Customer Analytic in Vietnamese e-Commerce Firms: Status Quo and Its Influences on Firm Performance

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Abstract. This study presents the current situation of customer analysis of e-commerce enterprises in Vietnam. In addition, this study investigates the quantitative relationship between customer analytics adoption, innovation, and firm performance. We built a research model based on the literature review that claims that consumer analytics adoption not only has a favorable association with firm performance but also influences innovation, which leads to firm performance. After that, the authors tested the model using survey data from 154 Vietnamese e-commerce companies. The results show positive relationships between (i) applying customer analytics and innovation and (ii) innovation and firm performance. Innovation plays a mediating role in the relationship between customer analytics and firm performance. The findings encourage businesses to have a more perspective on the importance of working with customer data in e-commerce, promoting infrastructure upgrades, professional skills to quickly harness the full benefits of data analysis for decision support.

Keywords: Firm Performance · E-Commerce · Innovation · Customer Analytics

1 Introduction

1.1 Research Background

E-commerce is a global trend that helps consumers purchase products online conveniently. In Vietnam, there is fierce competition for market dominance in e-commerce. When physical contact is minimized and online sales are promoted, the Covid-19 pandemic in 2019 is a perfect chance to expand the e-commerce industry. The reality of this growth momentum, however, is not entirely positive. According to iPrice's research, the covid-19 pandemic has disrupted the market, the structure of industries has changed dramatically, electronic products and fashion no longer reign supreme instead, necessities have risen sharply [1] (Fig. 1).

As a result of this progression, customer analytics is critical for extracting insights from massive data in order to improve service innovation, product development, personalization, and management decision-making [2]. This has a significant impact on

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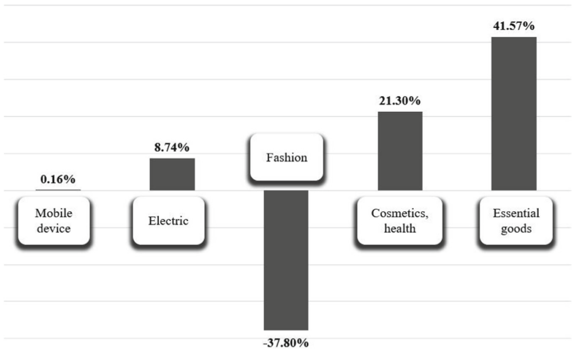

Fig. 1. Growth rate of traffic to the e-commerce industry (first six months of 2020 compared to the same period in 2019). Source: iPrice

enhancing business results and sales. Because the majority of e-commerce data is related to customer transactions, customer analytics assists firms in promptly adapting to market changes and assists in the formulation of firm's policies to increase their customer base. The integration and exploitation of such diverse data sources have much promise for competitive differentiation and strategic value creation [3].

Customer analytics aims to categorize customers based on their changing purchasing behavior over time and forecast future customer mobility [4]. However, despite its importance, present e-commerce enterprises in Vietnam do not appear to have used customer analytics' powerful capacity to improve firm performance. For that reason, the purpose of this study was to determine the current state of customer analysis and its impact on e-commerce firm performance, as well as the changes in business performance as a result of innovating methods for gathering and analyzing big data on customers.

1.2 Literature Review

We next review the relevant literature pertaining to (i) customer analytics in general, (ii) the impact of customer analytics on firm performance, (iii) customer analytics in e-commerce, (iv) customer data in the big data world, and (v) the mediating role of innovation.

1.2.1 Customer Analytics

The articles are collected mainly related to customer segmentation, which is a common customer analytics technique and a traditional concept in marketing [5]. Customer analytics models are frequently used in research publications to aid decision-making and are applied to typical case studies: in SMEs [6], in the retail industry [4, 7, 8], or in the financial institutions [9],… Lu et al. [6] developed a process model for data-driven decision-making that will serve as an overarching framework for critical business analytics life cycle stages. Visual analytics has informed customer sales strategy and donor fundraising strategy through recommendations to the respective senior management teams. However, most customer data is unstructured textual data collected at various times along the customer journey [10]. If only using visual analysis will be difficult, Kitchens et al. [3] have upgraded the analytical model that uses the IT infrastructure which builds a prototype system for a portfolio of advanced customer analytics apps for a company with a high proportion of single or rarely purchase clients, a challenge that cannot be solved by current customer analytics systems' fragmented approaches. When it comes to data analytics in general and customer analytics in particular, machine learning (ML) cannot be ignored, Giri et al. [4] can examine a customer's purchasing behavior and preferences by using ML methods and statistics. In addition to recommending modern models, Bijmolt et al. [11] listed the barriers to building customer analytics models: (i) Data quality, size of databases, and new types of data, (ii) Data ownership; (iii) Complexity of the models; (iv) Complexity of the models; (v) Usability of the results; and (vi) Integration in company processes.

1.2.2 The Impact of Customer Analytics on Firm Performance

The ability to analyze customer data has a significant impact on firm performance. Tomczyk et al. [12] developed and tested a model that describes how customer analytics might influence firm performance. The results show that the degree of formalization processing is the best predictor of financial business performance, followed by the scope of customer analysis. They discovered a positive association between customer-related data (customer attributes, customer-business relationships, customer opinions, etc.) and organization performance. In contrast to the study of data processing in businesses, Williams and Naumann [13] surveyed 3000 customers of a company to determine customer satisfaction levels, with the results bringing. There appear to be numerous advantages to enhanced customer satisfaction. At the analytical level of the firm, satisfaction is clearly linked to a number of measures that assess financial and market performance.

1.2.3 Customer Analytics in e-Commerce

A number of data mining technologies have been applied to electronic commerce research in the era of big data. Das [14] has built a prediction model to identify customers who are most likely to respond to the company's future offerings based on their prior purchase patterns. Experiments were conducted utilizing well-known classifiers such as Naive Bayes, KNN, and SVM. Wu and Chou [15] and Niu et al. [16] created a clustering method for classifying online clients based on their purchasing data across categories using a latent mixed-class membership clustering approach. The findings have ramifications for accommodating and incentivizing preferred search behavior on an e-commerce platform. Besides using transactional data, text data is also commonly used to analyze customer emotions [17]. Chen and Xu [17] contributed a semantic text analytics technique to elicit customers' most fundamental worries regarding online purchasing decisions. This study's practical implications are that merchants can more effectively adjust their products to satisfy more customers while also increasing sales performance.

1.2.4 Customer Data in the Big Data World

In applying big data analytics tools, INFORMS has proposed three levels of data analysis capabilities: descriptive analytics (i), predictive analytics (ii), and prescriptive analytics

(iii) [18]. In addition to these three levels, Vincent Whitelock [19] has mentioned two more levels in his research paper, namely: diagnostic analytics (iv) and discovery analytics (v). Organizations can engage with customers in various ways using information and communication technologies. These approaches open up numerous opportunities to capture value resulting from customer engagement behaviors, leading to advanced competencies that help firms sustain value creation over time [20]. In this topic, the authors often explore ways of integrating big data insights with automated and assisted processes related to key customer touchpoints to ultimately improve the customer experience [21–23].

1.2.5 The Mediating Role of Innovation

With the advancement of technology, firms can utilize it as an online marketing medium, also known as e-commerce, which is a new commercial approach that leads to improved product and service quality while lowering direct sales expenses [24]. After the implementation of e-commerce, Andrea Ordanini and Gaia Rubera [25] believed that the firm's innovative orientation is positively connected with the performance of IT innovators. Complementing the above point, Limthongchai and Speece [26]; Hardilawati et al. [24] also predicted that a favorable perception of E-commerce would lead to early adoption of the technology and have a positive and significant effect on marketing performance. This demonstrates the crucial role of innovation in e-commerce.

Based on the previous studies, the hypothesis was then developed:

H1: The application of customer analytics (CA) in e-commerce, characterized by data acquisition (DA), data storage and processing (SP), descriptive (DES), predictive (PRED), and prescriptive (PRES) analytics, positively affects innovation (INO).

H2: Innovation (INO) in e-commerce positively affects firm performance (FP).

H3: Innovation (INO) in e-commerce plays a mediating role in the impact of applying customer analytics (CA) on firm performance (FP).

1.3 Research Gap

Although e-commerce in Vietnam has been and is a sweet cake for domestic and foreign businesses to exploit, it is found that there are relatively few studies discussing the current situation of businesses that use data customers and how to analyze that data. In addition, the articles focus mainly on the use of data by companies to analyze customer behavior, customer satisfaction and loyalty, with little mention of the influence of customer analysis on business performance. Therefore, this study was conducted to present the current status of customer analysis of enterprises doing business in the field of e-commerce, thereby analyzing the influence of customer analysis on firm performance, and whether there is a link between regularly collecting and analyzing customer data will help improve firm performance.

Table 1. The observed variables

Variable	Reference
Data acquisition (DA)	[19, 23, 27–34]
Data storage and processing (SP)	
Descriptive analytics (DES)	
Predictive analytics (PRED)	
Prescriptive analytics (PRES)	
Innovation (INO)	[28, 35–38]

2 Research Methods

2.1 Research Model

The observed variables in this study's model are listed in Table 1. Because consumer data is the most important aspect of e-commerce, consumer data analysis follows the same stages as business analytics.

2.2 Sampling Method and Data Collection

The larger the sample size of the study, the smaller the error in the estimates will be, and the more representative, the population, will be. However, if a study collects a large sample of observations, it will take a lot of time, effort, and money. According to Hoang Trong and Chu Nguyen Mong Ngoc [39], the rule for determining sample size for exploratory factor analysis is that the number of observations (sample size) must be at least 4 or 5 times the number of variables in the factor analysis. According to Green [40], the minimum sample size to be achieved in the regression analysis is calculated by the formula: 50 + 8m (in which m number of independent variables).

In this study, there are all 21 observed variables that need to conduct factor analysis, so the minimum sample size needed is 105 observations. The survey subjects of the study are individuals/enterprises/households doing e-commerce business in Vietnam. These subjects can do business on popular social networks in this country (Facebook, Instagram, Zalo,…), on e-commerce platforms (Shopee, Lazada, Sendo,…), or on their own website already has a certain number of customers and is still doing e-commerce business.

The data was collected by the author using two methods:

a. The survey is designed on Google's tool (Google Forms) and sent to the pre-contacted respondents.
b. The survey was broadcast directly to the respondents.

Table 2. A summary of the characteristics of the sample

Characteristics		Number
Average number of orders per month	<500	46
	500–1000	63
	>1000	45
Years of operation	<3 years	44
	3–7	89
	7–15	18
	>15	3
Number of employees	<10	54
	10–150	88
	>150	12
Field of business	Electronics and technology products	37
	Furniture and household items	19
	Fashion and beauty	52
	Food and personal care	21
	Stationery	5
	Other	20
E-commerce business channels	Social networking sites like Facebook, Instagram, …	146
	Company/product website	61
	Domestic e-commerce platform (Lazada, Tiki, Shopee, …)	135
	International e-commerce platform	43
	Other Apps	45

Three major constructs and control variables make up the study. Five-point Likert scales were used to assess the constructs. CA adoption was graded on a scale of 1 ("never") to 5 ("always"). INO and FP were scored on a scale of 1 to 5 ("strongly disagree" to "strongly agree").

After the process of screening and removing the inappropriate answers, this research used 154 returned results to proceed to the next steps. A summary of the characteristics of the sample is shown in Table 2.

3 Result

3.1 Status of Customer Analytics

3.1.1 Data Acquisition

According to survey results, contemporary e-commerce enterprises in Vietnam collect data about their clients regularly: data related to customers' purchase history (49% usually frequently, 38% very often); data on customer demographics (53% often, 34% very often); customer feedback before, during and after purchase (53% often, 31% very often). This indicates that organizations are devoting an increasing amount of effort to extract meaning from data that frequently fails to meet practical needs [41]. Transactional data can help businesses find potential customers and segment their customers. The data referring to customer information will be used to build a recommendation system for each customer, increasing the customer's experience.

3.1.2 Data Storage and Processing

In the era of big data, storing and processing customer data is not easy. However, because the benefits of data are tremendous, corporations place a high value on it. E-commerce businesses very often evaluate customer data quality (49%), clean customer data (53%), backup customer data (41%), analyze, and exploit to support future decision making (50%). Data preparation aids businesses in generating high-quality data, resulting in high-quality patterns [42].

3.1.3 Descriptive Analytics

Descriptive analysis is a process of finding patterns and relationships in historical and existing data [43]. According to 2014 research conducted by CI&T, about 90% of companies use this very basic analysis technique, and only 35% of the companies surveyed said they use this technique consistently [44]. In this study, the authors found that up to 51% of businesses very often use descriptive analytics to visualize customer data. However, businesses are still limited in online data analysis (OLAP).

3.1.4 Predictive Analytics

Predictive analytics deals with "forecasting or predicting future probabilities and trends, and allows analysis of what would happen if it happened" [43]. About 55% of businesses surveyed regularly analyze customer loyalty and repurchase behavior forecasts. This could explain that attracting new customers is more expensive and more difficult in today's competitive environment for most companies.

3.1.5 Prescriptive Analytics

Prescriptive analytics sets out what actions should be taken to maximize good outcomes and minimize bad outcomes over a given period of time [43]. The surveyed units have also been exploiting data to propose business improvement plans, develop new products, or propose separate preferential policies for each customer group. There are still some firms that never or rarely perform customer analysis in their e-commerce business.

3.2 Analysis

The links between the constructs were investigated using confirmatory factor analysis (CFA). The first and second-order reflective constructs were investigated in this study. For each concept, reliability analysis was first tested. The second test was done utilizing AMOS and structural equation modeling (SEM) on the first- and second-order analyses. Finally, convergent and discriminant validity were examined to determine data validity.

3.2.1 Reliability and Validity

For each of the constructs, the Cronbach's alpha was calculated. Cronbach's alpha values for sub-constructs of CA (i.e., DA, SP, DES, PRES and PRED) were found as 0.79, 0.74, 0.81, 0.81 and 0.78, respectively. In addition, the Cronbach's alpha values of reliability for the constructs of INO and FP were 0.80 and 0.92, respectively.

The variable measurement model CFA started with a first-order analysis to see if the latent variables of CA's underlying sub-constructs could explain its adoption. Therefore, the first-order model complied to check the goodness of fit indices and found that the result was satisfactory (Chi-square/df = 0.98, GFI = 0.92, TLI = 1.00, and CFI = 1.00). The presence of the four sub constructions is confirmed by the first-order analysis.

Next, a second-order analysis was conducted with reflective indicators. Four items (DA, SP, DES, PRES and PRED) were perceived as products of the CA adoption. The second-order analysis revealed that all of the necessary fit indices were satisfied (Chi-square/df = 0.99, GFI = 0.92, TLI = 1.00, CFI = 1.00). In addition, the efficacy of these two models were checked by comparing the Akaike information criterion (CAIC) measurement. The result showed that the second-order CAIC measurement (375.65) was lower than the first-order CAIC measurement (399.60), which indicates that the second order model holds better parsimony [45] and better choices for the entire structural model.

Validity and reliability tests in CFA analysis were performed with Standardized Loading Estimates 0.5. The discriminant is shown in Table 3, in which the results are satisfying (Sig = 0.00).

3.2.2 Hypotheses Testing

Figure 2 shows the structural model's outcomes in relation to our hypothesis. The maximum likelihood method was used in SEM to calculate the model parameters.

To test our hypotheses, whole linkages between the exogenous variable of CA and the endogenous variables of INO and FP were statistically tested with fit indices. The GFI of the model is satisfactory (Chi-square/df = 1.00, GFI = 0.90, TLI = 1.00, CFI = 1.00).

H1 was shown to have strong support in that CA adoption, as measured by DA, SP, DES, PRED, and PRES analytics, has a beneficial impact on INO. The results show that firms often use customer data analysis tools to increase their competitiveness through innovation related to business models, new products, new customer policies, etc… Depending on the purpose and size of the data, e-commerce businesses will

Table 3. The discriminant

	Estimate	SE	CR	P
INO ↔ BA	0.183	0.0065	126.32	0.00
INO ↔ FP	0.258	0.0064	116.74	0.00
FP ↔ BA	0.101	0.0065	137.35	0.00

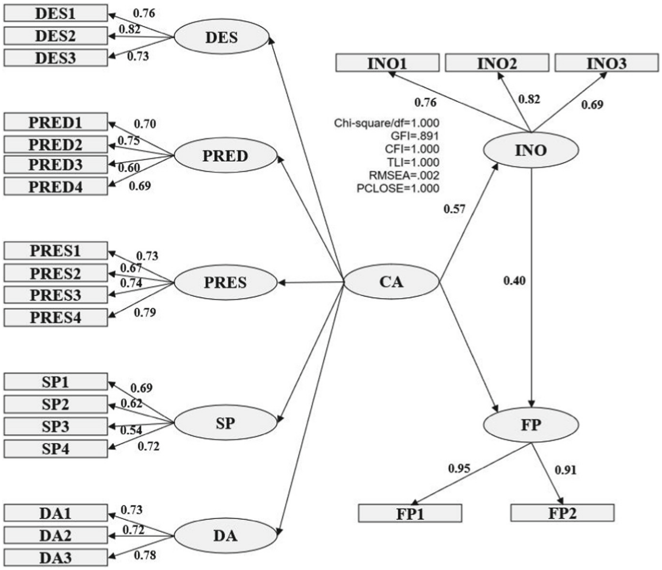

Fig. 2. The structural model's outcomes

apply different analytics methods (descriptive, predictive, or prescriptive analytics) and promote the data preprocessing (data collection, storage, and processing) to produce important, useful information.

The hypothesis H2, which states that INO has a favorable and significant influence on FP, received strong support. This hypothesis complements Darroch's [46] opinion. He supposed that empirical evidence backs up the idea that a company with a knowledge management competence will be more innovative and perform better since it will use resources more efficiently. Especially in e-commerce, an industry heavily dependent on information technology, innovations are extremely necessary to determine businesses' competitiveness and survival.

INO, according to H3, mediates the link between CA and FP adoption. According to mediation analysis, only through the mediation role of INO did the adoption of CA have a favorable effect on FP. A Sobel test was used to prove the mediation effect and determine whether it was statistically significant [46]. The Sobel test result indicated that there is a significant ($p < 0.005$) support for H3, indicating that INO serves a mediating role in the relationship between the adoption of CA and FP.

4 Conclusions

This study explores the current situation of customer analysis of e-commerce businesses in Vietnam. Businesses have gained insight into the importance of data collection, storage, and processing. At the same time, businesses also flexibly use descriptive analytics, predictive analytics, or prescriptive analytics tools to support decision-making. The study also discovered the positive relationship between applying customer analytics to corporate innovation, innovation on firm performance and the mediating role of innovation in the relationship between customer analytics and firm performance.

Research also helps future strategic planners focus more on using customer data to generate useful and valuable information. From there, e-commerce businesses have a better overview and work hard to invest, innovate in business activities, and improve firm performance.

Our research looks at the effect of INO in mediating the relationship between CA adoption and FP. This relates to the need to effectively communicate corporate knowledge and decisions made through procedures to achieve acceptable results. CA well used promotes client orientation and aids in achieving better FP. Simultaneously, greater integration with other business domains aids in achieving better FP. The results show that they have the same opinion as Vincent et al. [47]. Overall, the findings show that excellent performance is strongly and positively associated with innovation. Furthermore, the offered framework for CA adoption adds value to a company by allowing it to improve business operations to achieve the FP while also giving it a competitive advantage in the market.

The limitation of this study is that the survey sample size, although quite representative of different groups of business sizes and business fields, is still relatively small (154 samples). Solutions to overcome data collection and analysis barriers have also not been provided, only focusing on providing evidence for the positive relationship between CA, INO, and FP. Future studies can conduct surveys on a broader scale and conduct in-depth interviews with different groups of enterprises, analyze and find solutions to data collection and analysis activities in the operation of E-commerce business is carried out effectively.

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