경영학석사 학위논문

# Does Information Provision Lead to a Better Performance of E-Marketplace Sellers?

- An Empirical Analysis -

# 정보의 제공은 판매자에게 도움이 되는가? 전자상거래에서의 판매 보조 도구 효과성 실증 분석

2021 년 8 월

서울대학교 대학원

경영학과 경영정보전공

박 재 상

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- An Empirical Analysis -

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이 논문을 경영학석사 학위논문으로 제출함
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# Abstract

With the emergence of new technologies and due to the recent COVID-19 pandemic, e-commerce and its subsequent e-marketplaces are constantly gaining attention. Simultaneous to the popularity, competition is becoming fierce for both e-marketplace operators and its participating sellers. As a result, they are striving for a competitive edge.

Incorporating decision-supporting services in e-marketplaces can be considered as a strategic activity for the platform operators, which can enhance the performance of sellers actively using such services. We therefore hypothesize that the usage of decision support systems will lead to an enhanced performance of e-marketplace participants, i.e., sellers.

By utilizing a secondary data provided by one of the leading e-marketplace operators in Korea, we have empirically found out that usage of decision support systems, namely, seller dashboard and review systems, lead to an increase in sales, which is the measurement of a seller's performance.

This study will serve as a literature for DSS effectiveness, e-marketplace success strategies, and will provide theoretical implications for the resource-based view and competitive dynamics theory by adding an empirical evidence for those field of study. Also, this study possesses managerial implications for not only e-marketplace operators seeking success, but sellers within the platform also.

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# Chapter 1. Introduction

## 1.1. Study Background

The emergence and its subsequent popularity of e-commerce have been fueled by recent advances in information systems and its surrounding infrastructures, namely, handheld mobile devices such as smartphones, and dissemination of broadband networks including high-speed ethernet and state-of-the-art wireless network technologies (Laudon & Traver, 2018). In addition, Shopify (2021) reported that the year 2020 has seen a significant spike of growth in e-commerce partly due to the worldwide pandemic of COVID-19. Due to numerous measures for preventing spread of the virus, offline stores were forced to shut down, making consumers flock to online stores. For example, according to Statistics Korea[①], the e-commerce sector in Korea has shown perpetual, strong growth over the years and is still exhibiting substantial growth. To illustrate this phenomenon, the fact that the Korean e-commerce sector size grew from 2.1 trillion Won to 133 trillion Won in 2019, roughly a 66-fold growth, which is equivalent to an approximately 26% consistent annual growth since its inception in the year 2000, and the recent five years reported a sound yearly growth rate of 24.5% on average may be worth pointing out. As a consequence, participating in e-commerce has become an imperative for conventional brick-and-mortar firms as well as businesses with online presence, and e-commerce platforms create opportunities for prospective as well as existing sellers by matching buyers

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① Statistics Korea is Republic of Korea's national agency responsible for statistics.

and sellers, and providing useful functions to both buyers and sellers.

An e-commerce platform, particularly e-marketplace, may consist of three types of players: buyers, sellers, and (a) market(platform) maker(operator) (Evans, 2003). E-marketplaces' success from the perspective of the operator may rely on various factors. One of the most important factors may be the size of usage, usually measured by the number of users, which consists of both buyers and sellers, or by the size of total transaction. The reason for this can be explained by the network effect, in which users receive value from the fact that everyone else uses the same service (Laudon & Traver, 2018). Therefore, the marketplace owner (and/or operator) deploys numerous measures to increase the numbers of both buyers and sellers, invigorating his/her platform to maximize revenue induced from fees and diversifying products sold in the marketplace. Examples for these measures include recommendation systems favoring buyers as well as sellers by acting as a marketing support tool (e.g., Lee & Hosanagar, 2019), and reputation systems for both stakeholders, and marketing (business) intelligence systems, also known as dashboards, for supporting sellers' decision-making. These devices help buyers by lowering search costs and aid them find better matching product or service available in the vast online marketplace. Reputation systems, such as review systems, help both buyers and sellers by enhancing trust between these two players, leading to an increased number of transactions (e.g., Chevalier & Mayzlin, 2006; Resnick & Zeckhauser, 2002). And information systems curated for sellers claim to assist them by enabling a more refined marketing activities, which leads, in theory, to a better financial performance, i.e., greater revenue and/or profit.

Although much attention has been drawn upon recommendation systems

and other vehicles such as reputation systems in the context of information systems research, the information systems catering the seller side have been relatively neglected albeit its theoretical and managerial implications. Due to intensifying competition and rapidly changing circumstances of the e-commerce industry, it is important for both sellers and marketplace operators to take timely strategic measures. To cope with these harsh circumstances, the marketplace operators are eagerly in pursuit of competitive edge by differentiating their services. This may include recommendation systems, easy payment services, often coined as a Fintech service and/or bundled with reputation systems, and seller dashboards, etc. Although such features can be easily mimicked and deployed across almost every firm in a short time frame, it is an undeniable fact that there exists a certain discrepancy in performance between successful and unsuccessful services despite the homogeneity of features e-commerce platform firms provide. In other words, the success of an online marketplace cannot be explained merely by the combination of service features that the firms provide. Rather, the focus should be narrowed down to a specific feature, mandating an inspection on the specific mechanism and its effects.

## 1.2. Research Goals and Question

Given with this context, we have focused on a major e-marketplace of South Korea providing its sellers with decision-supporting services. The e-marketplace, which is run by one of the leading IT companies in Korea has a distinct position in the e-commerce industry, especially among the online marketplace providers. By leveraging its dominant position in the online search engine providers of Korea, the firm and its affiliated marketplace can make a full use of the large existing userbase,

giving the company a substantial competitive edge. The firm also has more liberty in designing and implementing new services for the users of the marketplace, which is subsidized by the synergy created between the other platform, which can be easily reaped by the company with such popular platform. For example, since the company owns and operates the leading search engine service in Korea, it can create a more effective feature for the seller using their online marketplace such as providing a more detailed search query data for them, which would be difficult to do so if it were otherwise.

In spite of its leading position in the e-commerce industry in Korea, the firm is continuously striving to promote and implement inclusive growth. Since there exists a disparity across individuals with certain demographics, and firms with different organizational sizes in terms of IT capabilities (savviness), this can produce a significant divide in seller performance (Saini, 2005). In order to mitigate such predicament, multiple programs are set up aiming to boost performance of newcomers and SMEs (Small- and Mid-Sized Enterprises). In particular, the firm provides a dashboard for sellers in their marketplace platform. It aims to aid sellers seeking a larger revenue and/or profit by providing marketing information and insights, as well as raw data on their sales. The service provides information and insights to the sellers, namely sales analysis, and marketing analysis. For example, sellers are provided with their respective weekly sales trend. Sellers then can build sales and promotion strategies in accordance with the statistics provided. An illustrative image is given as the following figure. In addition, the e-marketplace also provides a service to the sellers which can be utilized for stimulating customers to present more reviews. For instance, sellers can setup a promotional event giving

customers a financial incentive when they review after their purchases to boost the number of reviews.

**Figure 1. A screenshot of the decision support system**

With these context and facts, we seek to answer whether if these decision-supporting service actually leads to a better performance for the sellers or not. In order to analyze its intended effect, an empirical testing is needed, which will be elaborated in the following sections. The following sections include a review of background literature, an explanation of the research design, findings, and outcomes from the research, as well as the implications of the research. Finally, the limitations of the study and a discussion for further studies will be made.

# Chapter 2. Literature Review

## 2.1. E-marketplace

There have been numerous studies on e-commerce and online (electronic) marketplaces. For instance, Laudon and Traver (2018) defined e-commerce as 'the

use of the Internet, the Web, and mobile apps and browsers running on mobile devices to transact business. More formally, digitally enabled commercial transactions between and among organizations and individuals. Among these previous works, a research done by Bakos (1991) serves as an excellent source for conceptualizing the idea of e-commerce, more specifically, e-marketplace and its relevant strategies. While there have been various definitions of e-marketplace (See Table 1), those can be summarized as 'an electronic platform of buyers and sellers where sellers share their information on the products and/or services they sell.'

| **Research** | **Definition** |
|---|---|
| Malone, Yates, and Benjamin (1987) | Electronic intermediary that makes transactions easier between multiple buyers and sellers |
| Bakos (1991) | An inter-organizational information system that supports exchanging information about products between buyers and suppliers in the market |
| Kaplan and Sawhney (2000) | Internet-based agent system for business |

**Table 1. Definitions of e-marketplace**

E-commerce, as well as e-marketplace, generally lowers sales cost, and consumers can purchase an even wider variety of goods and services through electronic markets, when compared with conventional offline markets (Brynjolfsson, Hu, & Smith, 2003; Brynjolfsson & Smith, 2000). With these characteristics attracting large number of consumers to e-marketplaces, this in turn

creates network externalities and builds a favorable platform where sellers can enjoy a large userbase, resulting in a healthy two-sided platform market (Bakos, 1991; Li, Liu, & Bandyopadhyay, 2010). However, e-marketplaces typically exhibit wide disparities in terms of performance such as sales across sellers within the platform, and e-marketplace platforms as a whole also shows different levels of performance. Thus, practitioners including e-marketplace operators, online sellers as well as scholars are keen to find an explanation for certain online sellers demonstrating superior business performance than others. Research on the matter focused on the aspects including sellers' pricing strategies, use of reputation systems, and differentiation strategies.

| **Aspects** | **Findings** | **Related works** |
|---|---|---|
| Sellers' pricing strategies | Electronic market's higher price and supplier transparency increases competition among retailers. | Ghose and Yao (2011) |
| | Seller's external reservation price influences the final outcome of bids in the internet auction context. | Kamins, Drèze, and Folkes (2004) |
| | Stores with loyal customers can attain higher profits despite the diffusion of price-comparison shopping. | Kocas (2002) |
| | Successful e-marketplaces with low | Soh, Markus, and Goh |

| | | |
|---|---|---|
| | price transparency provide buyers with compensatory benefits. | (2006) |
| Reputation systems usage | The use of a 3rd party reputation system increases sellers' margins and total revenue. | Clemons (2007) |
| | The frequency of online reputation profile updates affects trader behavior. | Dellarocas (2006) |
| Differentiation strategies | Differentiation by utilizing discretionary attributes within online auctions affects sellers' outcome. | Bockstedt and Goh (2011) |
| | E-shops' personalization positively affects customers' purchase intentions. | Pappas, Kourouthanassis, Giannakos, and Chrissikopoulos (2014) |

**Table 2. Prior works on the aspects of successful e-marketplace sellers**

Our work is focused on the sellers' voluntary use and utilization of online decision support systems that a platform operator provides. Part of the work can be regarded as a study on reputation systems usage, since an online review system is incorporated into the decision-supporting system provided by the e-marketplace operator.

Additionally, e-marketplaces can be categorized into two different types:

business-to-business (B2B) marketplaces, and business-to-consumer (B2C) marketplaces (Pavlou & Gefen, 2004). The e-marketplace in question is a B2C marketplace such as Amazon, eBay, etc., which are geared toward end users.

## 2.2. Decision Support Systems

Decision support systems, commonly abbreviated as DSS, represents a vastly broad concept, which has various definitions from different areas rather than a single definition. Nonetheless, it generally represents a concept of the role of computers within the decision-making processes (Keen, 1980). Therefore, it can be said that the dashboard tool provided by the platform operator in question falls within the category of decision support systems. Alongside the dashboard tool, Cheung and Lee (2012) have posited that in today's e-commerce context, the eWOM (electronic word-of-mouth) systems changed the way businesses engage with consumers. Thus, eWOM systems, namely, the review system, can also be classified as a DSS aiding sellers within the e-commerce context. Here, eWOM refers to any statement made by potential, or actual customers about a product or company, which is made online (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004). With its importance, Sharda, Barr, and McDonnell (1988) have reviewed research that aimed to measure the effectiveness of decision support systems, which led to a finding of mixed contradictory results. Prior works consist of mostly empirical studies, with experimental studies being the dominant type.

In an experimental paper done by Todd and Benbasat (1992), they theorize that decision support systems (DSS) can reduce the cognitive burdens of users,

helping them make more effective, or accurate, decision making with increase in effort, or helping them make more efficient decision making with no impact on quality with decreased effort. The former idea is based on the theory of bounded rationality, and the latter on the cognitive cost perspective of behavioral decision theory. On the other hand, works such as done by Hoch and Schkade (1996) argue that when provided with decision aids that have adequate information processing capabilities, decision makers will use these tools to analyze problems in greater depth and, as a result, make better decisions. Therefore, it is open to question that decision support systems will lead to a better decision-making, measured by performance criteria, of a user. This will constitute the first part of our research.

Our study will empirically test these ideas using a real-world secondary data from an existing e-marketplace and its subsidiary services aiding online retailers. To our knowledge, there are not many literatures focusing on the seller side of a e-marketplace. Therefore, we hope this research will contribute to the stream as a novel work regarding suppliers' behavior rather than that of consumers.

## 2.3. Platform Strategy

E-marketplace operators, or platform owners stive to successfully operate and grow their businesses. Therefore, the success of e-marketplaces and strategies enabling it are of both theoretical and practical importance. Related actions can be understood as part of a platform strategy, which consists of actions for attaining expansion into and operating in a given market by a networked business platform (Cusumano & Gawer, 2002). Business platform such as an e-marketplace is a nexus

of infrastructure and rules facilitating interactions between the network users (Eisenmann, Parker, & Van Alstyne, 2011).

Wang, Zheng, Xu, Li, and Meng (2008) have conducted a literature review on e-marketplace related studies. Through their meta-analysis, they have classified related works into 8 research themes: e-marketplace (EM) success, EM impact, EM adoption, EM design, Agents in EMs, EM and SMEs, EM and trust, and overview of EMs. Among these, EM success was the most interested topic for researchers, with subcategory consisting of market maker strategies, EM participation, EM characteristics, and environmental factors. Regarding our research subject, the factor of interest contributing to a success is the market maker strategies. Among the specific strategies, strategies of providing the right service are the most relevant subject for our study. For example, Guo (2007) have posited that EMs can increase their competitiveness by increasing its interoperability through constant improvement of an EM's function, leading to a success. Providing a decision support system for sellers within a e-marketplace can be understood as a similar strategic movement. In addition to the study above, there are numerous works regarding value proposition to its users as a method of increasing competitiveness and ultimately seeking success.

Also, one of the research topics worth noting is EM and SMEs, since the firm of our focus aims to actively support SMEs through various value propositions. A work done by Saban and Rau (2005) have found out that while EMs help SMEs by 'leveling the playing field' to some extent, SMEs suffer from lack of resource for conducting a more sophisticated marketing transactions. Given with this context, a e-marketplace extending its functionality with an intention of supporting SMEs can

be said that it is on a valid train of thought.

One theory explaining these measurements done by platform operators as well as the sellers within these platforms is the competitive dynamics theory, rooted in Schumpeter's "creative destruction" theory. The theory posits that a firm's performance is determined by its competitive actions, where competitive actions mean any externally oriented, specific, observable, market-oriented competitive move that a firm undertakes to improve its market position (Smith, Ferrier, & Ndofor, 2001). This can help explain the actions taken by sellers within the electronic marketplace as well as the strategic actions chosen by the platform operators themselves.

# Chapter 3. Hypotheses Development

## 3.1. Hypotheses and Research Model

To reiterate, our study is to empirically test whether a decision support system of an e-marketplace leads to an enhanced performance of sellers or not. In order to deploy an empirical research on the matter, research models along with hypotheses are needed. The following section elaborates on the process of developing the research model and its subsequent, as well as the related variables.

There are many ways of defining the performance of sellers. Since the subject of our study is sellers within e-marketplaces, drawing upon the research done by Ghose, Ipeirotis, and Li (2014), which serves as an excellent reference for modelling online retailing performance, will help modeling the research. While the manuscript has its focus on consumer behavior and search engine revenue, it helps

understanding and modelling the mechanism of online retailing and retailers' performance. Among its models, the most useful model for our research purposes is the modelling of clickthrough rate (CTR) and conversion rate (CR). The online browsing behavior of e-commerce consumers can be modelled with clickstream (or click path) data. The path typically contains the sequence of events reaching as far as actual purchases made by a consumer (Montgomery, Li, Srinivasan, & Liechty, 2004). Therefore, the click path can be understood as a funnel, with the best case of having every consumer clicking upon impression (i.e., a display of relevant content such as an advertisement of a product to the customer), and every click of consumers leading to an actual purchase. Then the clickthrough rate, which is *clicks/impressions*, is 1 (100%) as well as the conversion rate, calculated as *conversions/clicks*. The remaining rank modelling and rating model are out of our focus. The detailed models for each variable and related works (abridged list of entries only relevant to our research purposes) are described in the following table.

| **Model** | **Description** | **Related works** |
|---|---|---|
| Clickthrough rate model | Rank order and page number are significant determinant of clicks on the results of a search engine query | Rutz and Trusov (2011), Ghose and Yang (2009), Jerath, Ma, Park, and Srinivasan (2011), Ghose, Goldfarb, and Han (2013) |
| | Product price affects clicks | Dellarocas (2012) |
| | User ratings affect click-through | De los Santos and Koulayev (2013), Yao and |

| | | |
|---|---|---|
| | rates on search engines | Mela (2011) |
| | Product brand can influence consumers' perceptions of quality | Dodds, Monroe, and Grewal (1991), Nevo (2001) |
| | The number of competitors in the local market can affect consumers' clicks for a product online | Baye, De los Santos, and Wildenbeest (2016) |
| Conversion rate model | Price and quality as well as the volume and valence of online reviews will affect product sales | Chevalier and Mayzlin (2006), Ghose, Ipeirotis, and Li (2012) |
| | Screen position and page number are important factors that influence consumer demand on search engines | Rutz et al. (2012), Ghose and Yang (2009), Jerath et al. (2011), Rutz and Trusov (2011), Agarwal, Hosanagar, and Smith (2011) |

**Table 3. Clickthrough rate and conversion rate models and their affecting factors**

Following these prior works, we can model our research as the following conceptual figure.

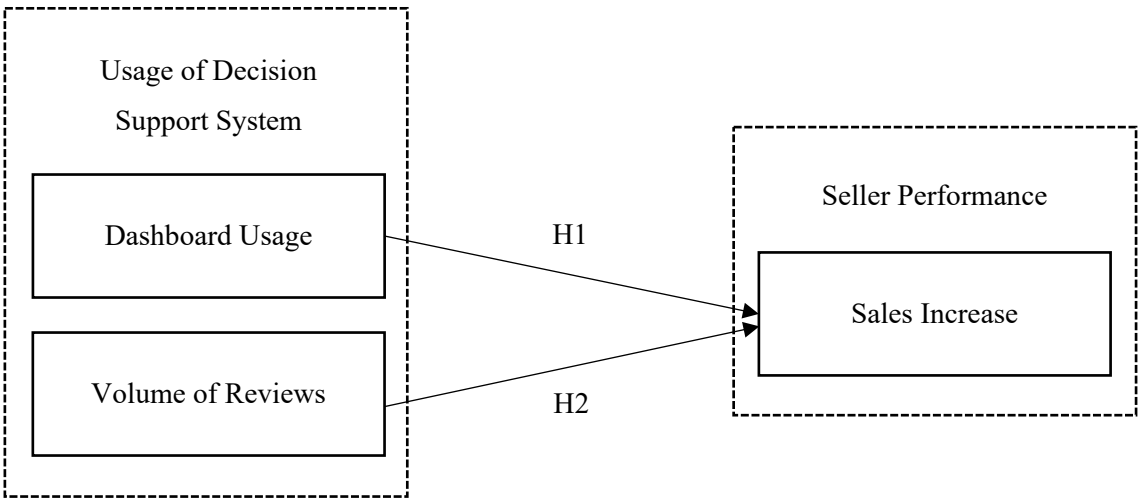


**Figure 2. Conceptual model**

It should be noted that, the e-marketplace operator's clickstream data does not distinguish sales derived from online traffic stemming from its own marketplace and that derived from the external traffic. Therefore, a significant proportion of sales may have been derived from outside the platform and were thus not captured in the clickthrough rate and/or conversion rate. Nonetheless, following the aforementioned model, we assume that higher clickthrough rate and conversion rate transitively means higher sales, i.e., almost a perfect correlation exists between the factors.

Resource-based view posits that sustainable competitive advantage can be achieved through developing superior capabilities and resources (J. Barney, 1991). J. B. Barney (2001) further defined that resources are all assets, capabilities, information, knowledge etc. controlled by a firm which enables the firm conceive of and implement strategies improving its efficiency and effectiveness. And

competitive advantage as when a firm is able to conduct a value creating strategy currently not implemented by other firms. Since the DSS in question is aimed to enhance the quality of each seller's decision-making by providing information, an improvement in sales performance based on the usage of such DSS can be explained with the theory.

Drawing upon the theories and research model elaborated above, we can build the following hypothesis:

*H1: The usage of the dashboard service will positively affect the increase in sales of an online seller.*

Actions, which is defined as a specific and detectable competitive move initiated by a firm, can therefore be measured in volumes (Chen & Hambrick, 1995). Therefore, the extent of decision support system usage, provided by the platform operator, can be measured by the pageview number of dashboard webpages.

We set volume of reviews as the proxy of measuring usage level of review systems for both customers and sellers because the review system tends to enlarge the volume of reviews by providing incentives to customers leaving reviews (Burtch, Hong, Bapna, & Griskevicius, 2018). Since the scope of the dashboard system does not include the functionality of managing customer reviews, we can build a separate hypothesis regarding the matter:

*H2: The volume of reviews will positively affect the increase in sales of an online seller.*

Here, we assume that a significant change in the volume of reviews only hinges on the usage of the review-stimulating function, i.e., the review system

provided by the platform operator.

As for the dependent variable, measuring objective financial performance such as sales amount, as the performance of a business is considered an ideal practice (Gnyawali, Fan, & Penner, 2010). Variables that can affect CTR and/or CR (see Table 3), and therefore sales, but does not fall into our primary interest will be added to the model as control variables or covariates.

# Chapter 4. Research Methodology

## 4.1. Propensity Score Matching

In order to accurately measure the effect of the decision support system usage on sellers' performance, we will incorporate a statistical matching technique, specifically, the propensity score matching (Rosenbaum & Rubin, 1983). Although the dataset was obtained by randomly selecting 10,000 stores from a particular category, this cannot prevent the bias arising from confounding factors that affect the outcome. To suppress this bias, propensity score matching (PSM) is conducted where it tries to match the covariates between the treatment group and control group. PSM creates a unified score derived from covariates and commences an algorithm finding the best match with balanced scores.

For our research, the control group refers to online stores that have not used the decision support system during the time window. Treatment group members, on the other hand, began using the dashboard during the time window. The time window and criterion for classifying each groups' member will be elaborated in the following section.

The quality of matching process can be assessed by standardized mean difference of covariates of each group.

## 4.2. Variables

Since our research aims to distinguish control group members and treatment group members, we have categorized stores into treatment group and control group as the following figure.

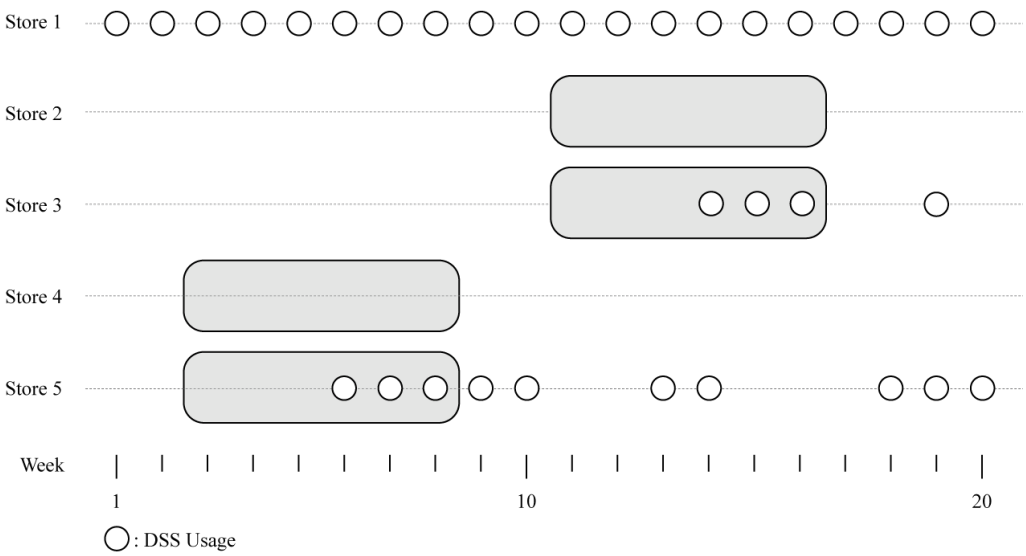


**Figure 3. Example of treatment group and control group categorization**

With a 6-week time window selected, stores that did not use the decision support system, i.e., 0 pageview of DSS webpages, are classified as members of control group. Therefore, they are regarded as sellers that does not use the dashboard service provided by the e-marketplace operator. On the other hand, sellers that are classified as members of treatment groups must:

- Start using the dashboard within the 6-week time window, i.e., there

must not be any case of usage prior to the time window.

- Use the decision support system for 3 consecutive weeks, i.e., there must be a pageview greater than 0 for each week.

By this setting, 27 stores were eligible for being members of the treatment group. By using 1:5 nearest-neighbor method, and re-estimate option enabled, a total of 135 cases of control group were matched. Covariates and the assessment of matching process are elaborated below.

To suppress bias arising from confounding factors, we chose covariates for matching purposes. Variables that can affect the outcome, i.e., sales, clickthrough rate, and conversion rate, rather than the group membership were selected as covariates, which can be found in the following table. For the matching, value from the first week of the 6-week time window was selected, since we are interested in finding homogenous pairs from each group in terms of covariates.

| **Variable** | **Description** |
|---|---|
| ad_exp | Weekly advertising expenditure of a store. Since advertising affects rank order and page number of a store's product display, this can affect a seller's performance. |
| reviews | Newly added number of reviews made within a store per week. Volume of reviews can affect a seller's performance (Chevalier & Mayzlin, 2006; Ghose et al., 2012) |
| ratings | Weekly Average of newly created ratings by consumers on a seller's product. User ratings can affect a seller's |

| | |
|---|---|
| | performance (De los Santos & Koulayev, 2013; Yao & Mela, 2011). |
| returns | Weekly cost due to returns. Sales returns may affect a seller's performance. |
| months_since_open | Age of shop denoted in months (until the month of study; October 2020). Shop age can affect a seller's performance (Baum & Korn, 1996; Chen, Su, & Tsai, 2007). |
| indiv_corp | Binary variable denoting whether a store is run(owned) by an individual or a corporation. Due to differences in IT capabilities between the two, this may affect a seller's performance in the context of e-marketplace. |

**Table 4. Description of covariates**

With covariates set as above, a matching procedure was performed using the statistical language R, and the resulting covariate balance is shown in figure 6 below. We can see that each covariate's standard mean difference is balanced, i.e., difference close to zero, by the matching procedure. One thing to be noted is that the difference of *first_week* variable is exactly zero. That is because the matching was conducted using an exact match of starting week from each group for matching a pair. This is to suppress any effect of seasonality which can significantly affect the performance of a seller.

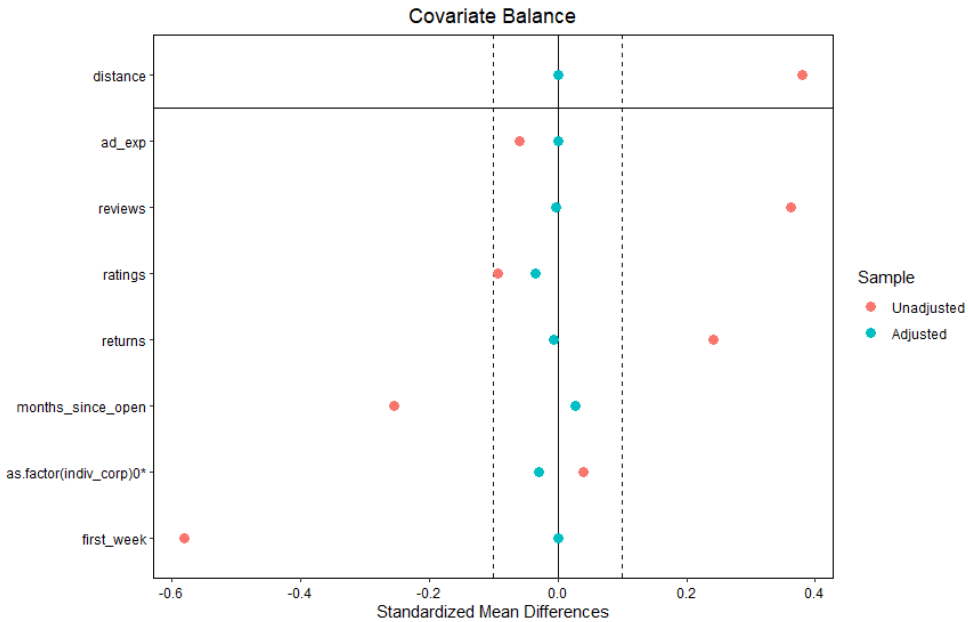


**Figure 4. Plot for assessing the matching of covariates**

# Chapter 5. Data Analysis and Results

## 5.1. Data Description

The collected data comes from one of the leading e-marketplaces in Korea. The data consists of randomly sampled 10,000 stores from each category, a total of 70,000 stores across 7 categories. Each store has 46 weeks of transaction and decision support system usage data. Although the main dataset covers a 46-week data, the rows with valid observation cover only the first 20 weeks (from September 9, 2019 to April 26, 2020). This is due to missing observations regarding the decision support system usage of each store. For the first part of our study, the home appliance category was selected as the focus of study. As a result, we were able to obtain a dataset with 334,884 rows with each row representing a specific store's weekly data.

The entire pooled dataset will be utilized in the subsequent analysis.

The columns of the data include the identification number for each store, pageview count for measuring the usage of decision support system, the average display rank order of each store's selling goods, number of queries responded, clickthrough rate, conversion rate, list of goods sold within a week, sales count, monetary amount of sales, advertising expenditure, weekly added number of reviews for each store, average ratings for goods sold, and refund cost. Along with these time-series data, cross-sectional data on characteristics of each store were also collected. This includes the opening year and month of a store, the age group of a store's owner, owner's gender, and a binary variable showing whether the owner of a store is an individual seller or a corporation.

The descriptive statistics can be founded in table 5. Note that the result obtained below is from a subset of the initial data, since the only valid observations of decision support system usage are available for the first 20 weeks, each row was truncated. For each store data, the 20-week average of each variable was computed.

| **Variable** | **Mean** | **Std. Dev.** | **Min** | **Max** |
|---|---|---|---|---|
| Usage | 1.5832 | 5.0873 | 0.0000 | 140.3500 |
| Sales | 479899.7994 | 3090675.6477 | 0.0000 | 101274240.0000 |
| Ad expenditure | 796.0090 | 15653.1671 | 0.0000 | 794860.5000 |
| Reviews | 2.1439 | 11.6000 | 0.0000 | 307.9500 |

| | | | | |
|---|---|---|---|---|
| Ratings | 4.4879 | 0.6035 | 1.0000 | 5.0000 |
| Returns | 15653.1671 | 429237.7019 | 0.0000 | 16274710.0000 |
| n= 5,259 | | | | |

**Table 5. Descriptive statistics**

The distribution of weekly average DSS usage and sales amount can be plotted as the following figures, respectively.

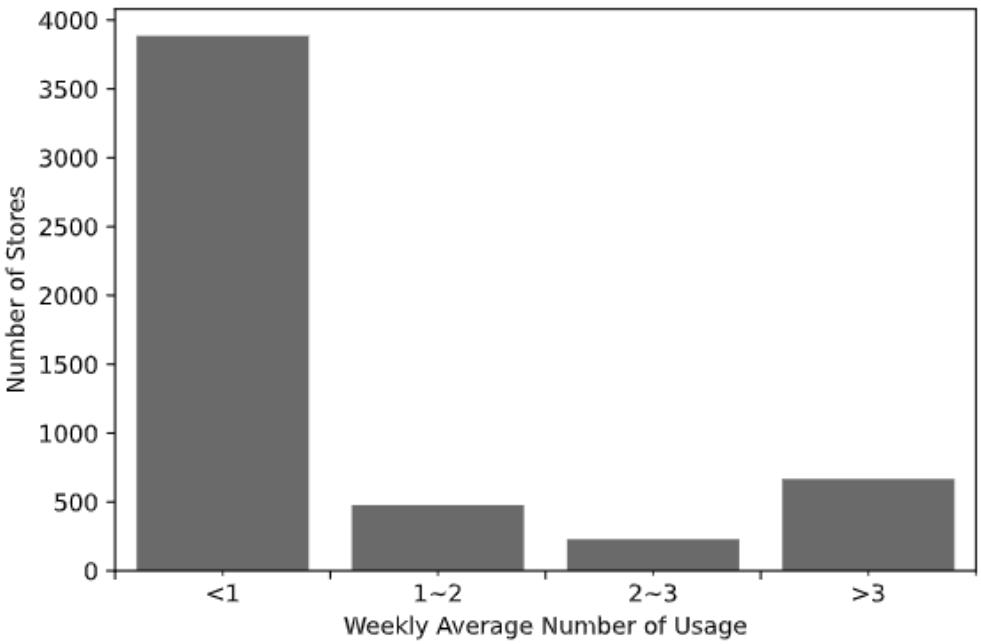


**Figure 5. Distribution of the weekly average dashboard DSS usage**

The distribution graph on DSS usage is considerably skewed to the right, meaning an overwhelming number of stores from the sample exhibit low or no usage. As with the classification of cases explained in the subsequent sections, stores without any usage will be classified as a control.

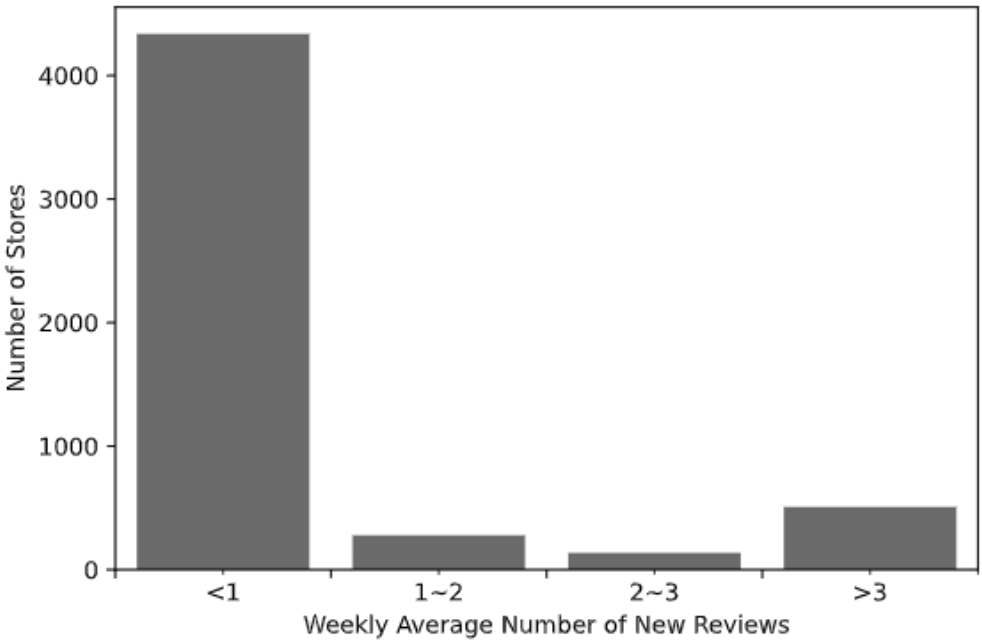


**Figure 6. Distribution of the weekly average new reviews**

The weekly average number of new reviews created shows a similar heavily right-skewed distribution as the dashboard usage shown above.

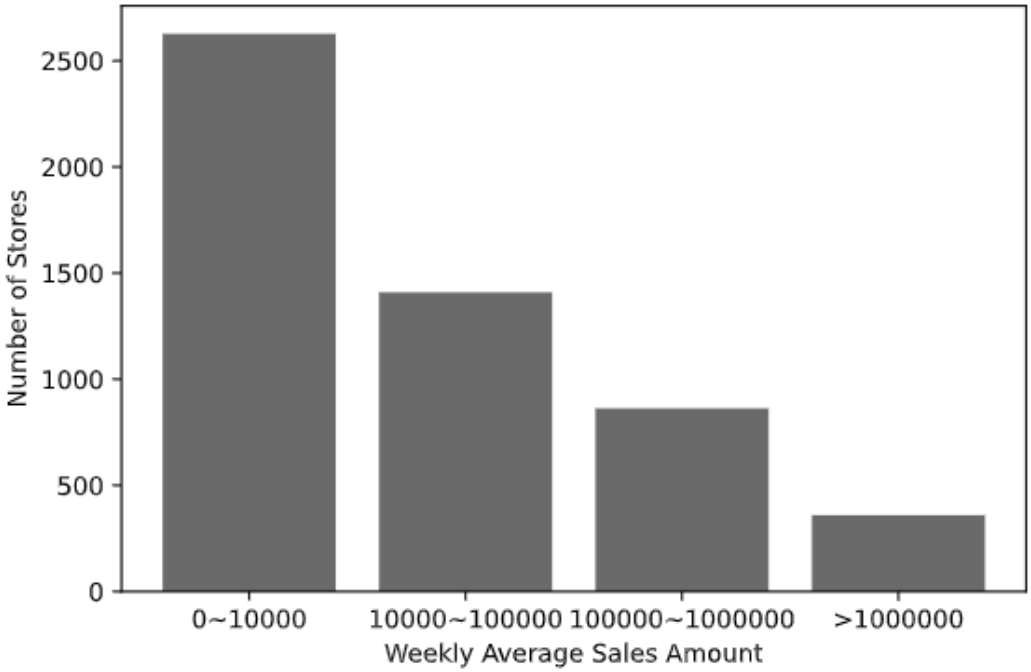


**Figure 7. Distribution of the weekly average sales amount by each store**

The distribution of average sales amount conveys a similar pattern with the decision support system usage. Note that due to the data collection process, only stores with at least one sale during the initial 46-week timeframe were selected. This implies the possibility of stores having no sales during the 20-week subset. Cases with empty data, i.e., all values being zero, were discarded in the subsequent analysis phase.

## 5.2. Data Analysis

With control and treatment groups set as above, we have conducted a linear regression analysis to check whether there is a significant difference in performance between the two groups. The regression model can be written as the following equation:

$$SalesIncrease_i = \beta_0 \cdot Treatment_i + \beta_1 \cdot IndividCorp_i + \beta_2 \cdot \ln(AdExp_i) + \beta_3 \cdot \ln(Reviews_i) + \beta_4 \cdot \ln(Ratings_i) + \beta_5 \cdot \ln(Returns_i) + \beta_6 \cdot \ln(MonthsSinceOpen_i) + \varepsilon_i$$

Where the dummy variable *Treatment* denotes the membership of store *i*. In other words, if store *i* is in the control group, then the value of *Treatment* is 0, and 1 if otherwise. By introducing this binary variable to the equation, we can now compare the sales increase of each store group depending on the usage of decision support system.

*SalesIncrease* was derived by computing the difference in percentage during the 6 weeks of each store's case. Also, the covariates raw values were substituted with logarithm values[②] due to its distribution.

Also, we have extended the research by utilizing a difference-in-differences (DD) method for testing hypothesis 1. With treatment and control groups set according to the conditions above, the effect of dashboard DSS on sales increase can be measured by differentiating the effect of treatment versus the treatment group and the control group (Angrist & Pischke, 2008). This will take the form of the following equation:

$$\ln(Sales_{it}) = \beta_0 + \beta_1 \cdot Treatment_i + \beta_2 \cdot Time_t + \beta_3 \cdot (Treatment_i \times Time_t) + \beta_4 \cdot AdExp_{it} + \beta_5 \cdot Reviews_{it} + \beta_6 \cdot Ratings_{it} + \beta_7 \cdot Returns_{it} + \beta_8 \cdot MonthsSinceOpen_i + \varepsilon_{it}$$

With other variables remaining the same as the previous model, *Time* variable is added to the model as the dummy variable denoting whether the data is

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② To be exact, the transformation was done using the formula *ln(x+1)*, due to values with zero.

ex ante or ex post. That is, the variable is 0 if the store data is situated in the start of the 6-week time window (prior to the start of DSS usage), and 1 if it is in the end of the window (3 weeks after the first DSS usage). The coefficient of interest is $\beta_3$, being the effect of dashboard DSS usage on sales increase.

For testing hypothesis 2, we have implemented a fixed effects regression. The full dataset of 7 categories was utilized, and the panel data was not classified into control and treatment groups for this phase. Our model for this can be written as follows:

$$Sales_{it} = \alpha_i + \beta_1 \cdot Reviews_{it} + \beta_2 \cdot Bizadv_{it} + \beta_3 \cdot AdExp_{it} + \beta_4 \cdot Ratings_{it} + \beta_5 \cdot Returns_{it} + u_{it}$$

To further deal with sampling bias, data of 100 stores from each category were randomly selected as a stratified sampling process. Variable *Bizadv* denotes the pageview of the dashboard DSS by each seller or store.

## 5.3. Results

The result of the preliminary regression analysis can be seen in the following table.

| Variable | Coeff. | Std. Err. | t | p>\|t\| |
|---|---|---|---|---|
| *Treatment* | 1727.1789 | 626.657 | 2.756 | 0.007** |
| *IndivCorp* | -721.1281 | 516.367 | -1.397 | 0.165 |

| | | | | |
|---|---|---|---|---|
| ln(*AdExp*) | - | - | - | - |
| ln(*Reviews*) | 910.9987 | 384.427 | 2.370 | 0.019* |
| ln(*Ratings*) | -1016.2882 | 494.805 | -2.054 | 0.042* |
| ln(*Returns*) | 8.9695 | 44.409 | 0.202 | 0.840 |
| ln(*MonthsSinceOpen*) | 146.5891 | 144.495 | 1.014 | 0.312 |
| *Note*. ***$p < .001$, **$p < .01$, *$p < .05$, $^{\dagger}p < .10$ | | | | |

**Table 6. Result table of regression analysis for testing hypothesis 1**

According to the result shown above, the coefficient of variable *Treatment* is significantly positive, which means stores utilizing the dashboard had larger increase in sales compared to the control group. And hypothesis 1 is therefore supported. However, according to the extended analysis of DD method exhibits an equivocal result.

| Variable | Coeff. | Std. Err. | t | p>\|t\| |
|---|---|---|---|---|
| *(Intercept)* | 11.9834 | 0.197 | 60.800 | 0.000*** |
| *Treatment* | -0.4394 | 0.285 | -1.542 | 0.124 |
| *Time* | -0.1726 | 0.165 | -1.047 | 0.296 |
| *AdExp* | - | - | - | - |
| *Reviews* | 0.0644 | 0.012 | 5.183 | 0.000*** |

| | | | | |
|---|---|---|---|---|
| *Ratings* | 0.1835 | 0.037 | 4.974 | 0.000*** |
| *Returns* | 0.0000 | 0.000 | 5.659 | 0.000*** |
| *MonthsSinceOpen* | -0.0097 | 0.003 | -3.240 | 0.001** |
| *IndivCorp* | 0.6023 | 0.168 | 3.577 | 0.000*** |
| *Treatment×Time* | 0.4817 | 0.406 | 1.187 | 0.236 |
| *Note*. ***$p < .001$, **$p < .01$, *$p < .05$, $^{\dagger}p < .10$ | | | | |

**Table 7. DD regression result**

While the coefficient of the interaction term *Treatment×Time* shows a positive value, which means an aligned pattern with the previous result, it is not significant ($p > .05$). Note that variable *AdExp* is not available in the results of analyses despite its inclusion in the research model. This is due to the fact that as a result of the matching process, only stores with no advertising expenditure were selected for pairing. Therefore, the variable *AdExp* had to be discarded from the analyses.

The result of the fixed effects model can be found in the table below.

| **Variable** | **Coeff.** | **Std. Err.** | **t** | **p>\|t\|** |
|---|---|---|---|---|
| *Reviews* | 43419.9787 | 1015.372 | 42.763 | 0.000*** |
| *Bizadv* | 6431.8926 | 3131.865 | 2.054 | 0.040* |

| | | | | |
|---|---|---|---|---|
| *AdExp* | 1.3066 | 0.272 | 4.804 | 0.000*** |
| *Ratings* | -3079.7837 | 5854.428 | -0.526 | 0.599 |
| *Returns* | 1.2376 | 0.029 | 42.415 | 0.000*** |
| *Note*. ***$p < .001$, **$p < .01$, *$p < .05$, $^{\dagger}p < .10$ | | | | |

**Table 8. Fixed effects regression result**

Through the panel regression analysis, we were able to discover the positive marginal effect of *Reviews* on sellers' sales by observing the parameter. Therefore, hypothesis 2 is also accepted.

To sum up, the results of the analyses indicate that the usage of dashboard service leads to a better performance in terms of sales amount. The first model demonstrates that the seller group who have utilized the decision support system had significantly higher sales increase than that of those who haven't, and the result of the second model is aligned with the former model, albeit its statistical insignificance. The last model using the fixed effects model also showed a positive relationship between the extent of DSS usage and the amount of sales revenue. This further supports the hypothesis that the usage of dashboard service will lead to a better performance of sellers who incorporate it in their operations. And from the final model, we were able to obtain the result that sellers with more reviews exhibited a greater revenue. Therefore, sellers may leverage the functionality of the online marketplace tool stimulating buyers to create more reviews in order to enhance their business performance. These findings suggest that the usage of decision support systems leads to a better performance of e-marketplace sellers in terms of sales

revenue.

# Chapter 6. Discussion and Conclusion

## 6.1. Implications

DSS is a widely researched area with diverse topics of research. Among those topics, the effectiveness of DSS have been long studied, but is still a popular field of study especially with the emergence of IT in recent years. This study will serve as an evidence supporting that decision support system helps users make a better decision, which is measured by performance outcomes. Additionally, for the case of platform strategies, this research will contribute to the literature, especially for the electronic marketplaces' strategic decision striving for success as well as research interested in aiding SMEs in e-marketplaces. To our knowledge, most of EM research are focused on consumers' purchasing behavior and welfare rather than sellers' performance on the platform. This is quite striking since EMs are a prime example of two-sided market, but the themes of related research were leaned to the buyer-side. We believe this serves as a novel work focusing on the seller side of the platform rather than the consumer or the platform as a whole. Also, our study will serve as a literature empirically supporting the resource-based view and the competitive dynamics theory.

Furthermore, with the surrounding changes in commerce, e-marketplaces are gaining attention alongside the steep growth despite its long-time presence. This is favorable for the firms within the e-commerce industry, but it also means a

foreshadowing fierce competition among the players. In light of these circumstances, e-marketplace operators as well as the sellers within the marketplace are constantly seeking for technologies and services that can bring a competitive advantage to them. We believe this study can shed a light to a relatively disregarded service of seller dashboard along with the review system, which has a potential to benefit sellers and ultimately the platform itself.

## 6.2. Limitations and Further Research

This study comes with some caveats. The foremost point is that the research model with clickthrough rate and conversion rate set as the dependent variable were not supported by the data analysis. We suspect that the data was not well defined as data used in other studies. More specifically, since the current clickthrough ratio and conversion ratio data cannot distinguish internal and external web traffic, a more detailed, thorough clickstream data with controlled environment in terms of source of web traffic, will be needed to derive a more accurate result. Second, the criterion for classifying treatment group is arbitrary, and due to limited data, cases with full usage of DSS had to be discarded by design. This can be mitigated by performing a robustness check, and by obtaining more data.

This study can be further extended in several ways. First, we can include variables measuring IT savviness or the effect of learning in the model. Although information for marketing activities is provided by the dashboard service, not every store owner can fully utilize it due to differing savviness. Consequently, the platform operator provides a consultancy service and a learning program to enhance the effect

of information provision. Therefore, further including this factor to the research model as a moderating factor will show a different result. Also, given with the reality that many sellers incorporate 3rd party analytics tools in their operations, introducing a new variable for that will produce a different intriguing result. Lastly, with additional data, the research model with the difference-in-differences methodology may produce significant results.

## 6.3. Conclusion

In this study, we have empirically shown that whether providing information to sellers via decision support system leads to a better performance in an e-marketplace or not. Drawing upon previous literature, we have hypothesized that usage of decision support systems such as seller dashboard and review system will lead to a better seller performance. During the procedure of developing hypotheses, we have acknowledged the fact that there are numerous ways to measure a seller's performance. We have unified the measurements into a single funnel model postulating that higher clickthrough rate and subsequent conversion rate leads to a higher sales amount. Therefore, the dependent variable was selected as the increase in sales, which represents the sellers' performance. The consequent 2 hypotheses posit that the use of decision support systems will enhance sellers' performance.

Through secondary data provided by one of leading e-marketplace operator in Korea, we were able to empirically test the hypotheses. The testing was done utilizing matching algorithm to refine the dataset and derive more accurate results. The results partially supported hypothesis 1, which argues that the usage of seller

dashboard decision support system will lead to a better seller performance in terms of boost in sales, and supported hypotheses 2, which posits that stores with a greater number of reviews will show superior performance.

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# 국문 초록

IT의 발전과 함께 특히 최근 COVID-19 팬데믹의 영향으로 전자상거래는 꾸준한 성장과 관심을 받고 있다. 하지만 이와 동시에 경쟁 역시 치열해지고 있기 때문에, 전자상거래 플랫폼 운영사들과 플랫폼에 참여하는 판매자들은 경쟁우위를 점하게 위해 노력을 하고 있는 실정이다.

이를 위한 한가지 전략적 방안으로는 전자상거래 플랫폼 내에 의사결정 지원도구를 제공함으로써 판매자들을 돕는 방법이 있다. 이에 따라 실제 이러한 의사결정 지원도구가 실제 전자상거래 플랫폼 참여자에게 도움이 될 것이라는 가설을 세우고 연구를 진행하였다.

한국의 한 전자상거래 플랫폼의 데이터를 제공받아 분석한 결과, 대시보드 및 리뷰 시스템의 의사결정 지원도구를 사용한 경우 매출이 증가하여 판매자의 실적이 유의미하게 개선되었다는 사실을 확인할 수 있었다.

본 연구는 의사결정 지원도구의 효과성, 그리고 전자상거래 플랫폼 성공 요인에 관한 문헌으로서 그 의의가 있다고 할 수 있고, 자원기반이론 및 역동적 능력 이론에 관한 실증이라는 점에서 의의를 찾을 수 있다. 또한, 전자상거래 플랫폼 운영사뿐만 아니라 판매자들에게도 경영적인 시사점을 줄 수 있을 것이다.