UNDERSTANDING THE FACTORS DRIVING PRODUCT SEARCHES: AN ANALYSIS USING PANEL DATA

A Thesis

Submitted to the Master's Study Program of Economics at the Faculty Economics and Business in partial fulfillment of the requirements for the degree of

Master of Arts (M.A.)

by:

Pradanti Nolo Wigati

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UNIVERSITAS ISLAM INTERNASIONAL INDONESIA

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ABSTRACT

Pradanti Nolo Wigati
03212210010
pradanti.nolo@uiii.ac.id
Economics
Universitas Islam Internasional Indonesia

This study examines the factors that influence consumer product search behavior on e-commerce platforms, specifically focusing on the leading marketplaces in Indonesia, namely Shopee, Tokopedia, and Lazada using a panel data approach. This research analyzes the impact of organic and paid search strategies on organic traffic, which is an important driver for e-commerce performance. Utilizing data from 2019 to 2022, obtained from SEMrush, this study explores the effects of organic keywords, organic traffic cost, paid keywords, and paid traffic cost on the organic traffic of these platforms. In addition, the study also included dummy variables to assess the influence of the COVID-19 pandemic and peak seasons on consumer search behavior. The findings reveal that organic factors, especially organic keywords and traffic costs, significantly increase organic traffic, highlighting the importance of SEO (Search Engine Optimization) in e-commerce strategies. In contrast, paid search strategies show a complex relationship with organic traffic, with paid keywords negatively impacting organic traffic, while paid traffic costs show a more nuanced effect. The COVID-19 era and peak season were found to significantly alter search behavior, with the pandemic driving an important shift towards online shopping, thus intensifying competition in organic search. Economically, the results underscore the critical role of digital marketing in shaping consumer behavior and the broader implications for market efficiency in fast-growing Indonesia.

Keywords: *E-commerce, SEO, Organic Traffic, Paid Traffic, Consumer Behavior, SEMrush, Panel Data, Indonesia, Shopee, Tokopedia, Lazada, COVID-19 Impact, Peak Season.*

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ABBREVIATION DIRECTORY

CPC	: *Cost Per Click*
SEO	: *Search Engine Optimization*
SEM	: *Search Engine Marketing*
SME	: *Small and Medium Enterprises*
R&D	: *Research and Development*
COVID-19	: *Coronavirus Disease 2019*
ICT	: *Information and Communication Technology*
GDP	: *Gross Domestic Product*
AI	: *Artificial Intelligence*
IoT	: *Internet of Things*
P2P	: *Peer-to-Peer*
KPI	: *Key Performance Indicator*
B2B	: *Business-to-Business*
B2C	: *Business-to-Consumer*
API	*: Application Programming Interface*

CHAPTER 1
INTRODUCTION

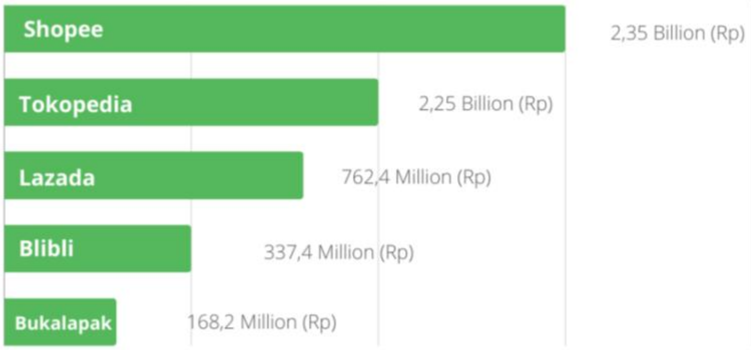
1.1 Background

The Internet already plays a significant part in helping human life carry out its daily tasks. Technology's rapid advancement has an indirect impact on competition. Businesses must offer the finest services possible, regardless of the constraints of human labor. To do this, they must have tools and procedures that enable humans to process metadata and obtain the essential information, whether in terms of time efficiency, security, or data accuracy. The Internet is a well-known medium with lots of benefits. The information can be shared by anybody, anywhere, at any time. The rise of electronic commerce is just one example of how the Internet's use significantly impacts trade and business. Today's technological advancements have led to worldwide shifts in people's habits, including how they buy and sell things. Traditionally, sales and purchases were made in person at a specific location (swap), transferring products straight from the vendor to the customer. However, as times have changed so quickly, information and communication technology has gradually changed. Media has become a more common form of information and communication technology.

As internet technology usage and penetration levels improve, online purchases, in particular, continue to rise (Rose et al., 2011). Online shopping alters the role of shopping as a way to pass the time or make purchases (Sazali, 2020). Online shopping is more convenient for the general public. Customers are highly pampered because they can order, transfer, and receive their things at home with just the touch of an index finger. Things are usually purchased online for significantly less money because they do not have as many overhead expenses as physical retailers. Indonesian consumers are increasingly choosing to make their purchases online. Some Indonesian customers think online shopping trends have been ingrained in their culture (Prayitno, 2016). The main advantages of virtual stores are the ability to save time and money, an extensive product range, easy delivery and payment choices, and stress-free gift-buying on holiday and pre-holiday days (Sammer et al., 2016).

The development of internet technology has fundamentally altered every aspect of human existence. This is because online websites are a great source of information for consumers (Hidayati et al., 2020). The e-commerce phenomena is mostly driven by the impact of technical advancements, particularly the internet. Online transactions and the creation of e-commerce platforms have been made easier by the expansion of the internet and the advancement of technology. However, this alteration not only modifies people's manual buying habits but also the interactions that take place. The interactions during physical shopping activities are the first interactions between people. However, people and technology interact in online buying activities, which promotes the development of different online shopping applications (Hardiyanto et al., 2020; Sazali, 2020; Mulyawan, 2020). The growth of e-commerce companies in Indonesia supports the public's ease of buying. E-commerce is one of the world's best sectors, expanding the fastest in the current digital era. Various promotional programs are available for buying and marketing products through e-commerce features. Particularly now that online buying is so popular, many e-commerce sites have emerged. Since e-commerce has grown, it has been used as a tool to carry out an online trade system.

Figure 1. 1 5 E-Commerce with the Most Visitors Throughout 2023



Source: databoks.katadata.co.id, Processed by Author (2024)

According to SimilarWeb data, Shopee is a marketplace e-commerce category that has attracted many users to its website since 2023 in Indonesia. From January to December 2023, Shopee's cumulative user base reached over 2.3 million, significantly outpacing its customers' expectations. Over the same period, there were roughly 1.2 million visitors to Tokopedia and 762,4 million visitors to Lazada. While the BliBli website has 337,4 million visitors, the Bukalapak website has 168.2 million visitors. Not only did the Shopee website outperform in number, but it also had the fastest rate of increase in visits. The number of visits to the Shopee website increased by 41.39% (year-to-date) between January and December 2023. Conversely, Tokopedia's website saw a decline of 21.08% (year-to-date), Lazada saw a decline of 46.72% (year-to-date), and BukaLapak saw a decline of 56.5% (year-to-date). The only rival of Shopee whose visits increased was BliBli, with a 25.17% (year-to-date) rise.

The Shopee application is one of the most well-liked e-commerce platforms now emerging in Indonesia due to the high interest in online shopping in society among both young and old. Indonesia, with the Shopee application being one of them. The importance of young customers in Internet shopping is growing (Alam et al., 2008). Younger consumers prefer online shopping because it is more accessible and affordable, offers a broader selection, saves time, and can be done anywhere at any time (Musyifah et al., 2016). Shopee is one of the e-commerce platforms that is very popular among Indonesian millennials. Students and other young people can easily access Shopee (Sofyan et al., 2021). Students' demands are becoming more varied and might be derived from their initial wishes or needs alone (Maulana & Asra, 2019).

The vast number of people who use the Internet and engage with digital media has created new business options and potential, known as digital marketing. According to Sawicki (2016), digital marketing is any method of using digital technology to connect with potential customers. Nearly 63% of Indonesian businesses registered in 2021 reported raising their budgets for digital marketing. The industry for digital marketing is expected to expand by 9% annually. According to Wardhana (2015), digital marketing tactics can impact a business unit's competitive advantage in product marketing by up to 78%. Digital marketing makes an adaptable digital relevance suite of marketing activities, organizations, procedures, and consumers possible. Notably, it results in a 20% yearly increase in consumers converting to digital media and the influx of youthful users into the purchasing ranks. (Bughin, 2015).

In e-commerce, enterprise marketing techniques are frequently employed. Blythe (2005) states that "marketing" encompasses all individual interactions. The term is used to describe all interactions that take place between people or businesses and their clients. It is the core idea of a market when buyers and sellers engage in profitable exchanges. E-commerce has grown in importance as one of the primary avenues for shopping in the expanding digital era. Online search engines are vital to the e-commerce ecosystem because they make it easier for customers to find their desired products. E-commerce businesses must be aware of the elements influencing consumer behavior when using online search engines to find products, as millions of people do so daily.

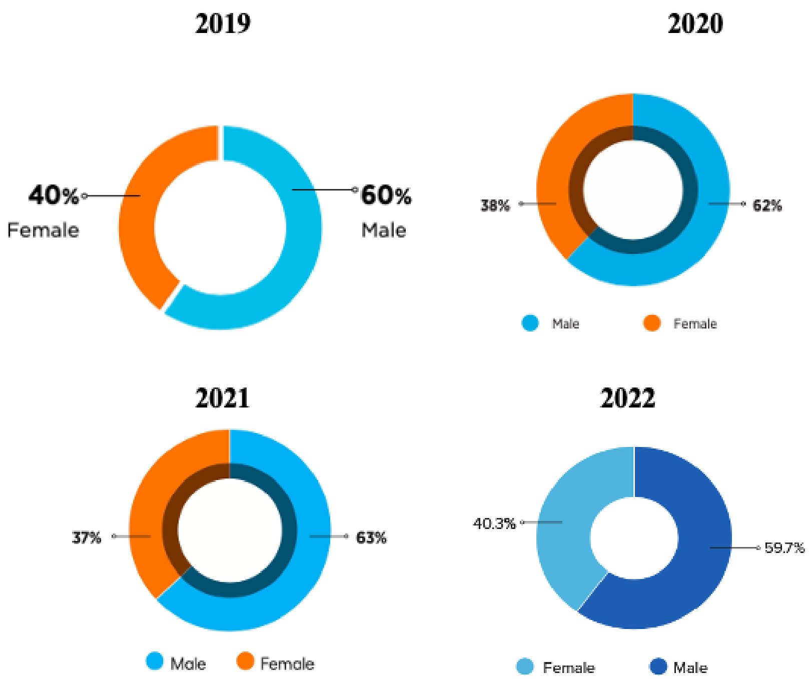
According to research from Ganiybay et al. (2023), e-commerce is highly highlighted, because it has become something important in terms of increasing contemporary business, which fundamentally reshapes traditional business practices. The advent of the internet revolutionized business operations, as it advanced the digital transformation of various industries. Eventually, there was a shift in e-commerce, where everyone's transactions were made electronically, and online marketplaces and transactions were digitized, becoming an important part of the global economic framework. Easier or arguably instant access to information from any location has become daunting for conventional business models, requiring companies to adapt faster to remain competitive. E-commerce can enable businesses to reach a wider audience by transcending geographical boundaries, thus facilitating market expansion. E-commerce has also led to more innovation, optimized supply chains, and increased efficiency in overall operations.

Additionally, e-commerce platforms are crucial for promoting entrepreneurship by providing opportunities for small businesses and start-ups to grow. These platforms have changed consumer behavior, shifting the trend towards more convenient and personalized shopping experiences. Traditional shopping, with face-to-face interactions and physical product exchanges, is increasingly being replaced by online shopping, which offers convenience, competitive prices, and a wide variety of products. This shift is driven by technological advances that make online transactions safer, faster, and easier. In Indonesia, the e-commerce sector has grown significantly, with platforms like Shopee, Tokopedia, and Lazada becoming well-known names.

These platforms offer a wide range of products, attractive discounts, and convenient delivery services, making them highly competitive. The convenience of shopping from home and the ease of comparing products and prices have made e-commerce a crucial part of Indonesia's retail sector. In short, e-commerce has transformed the business world by enabling companies to reach a global audience, promote entrepreneurship, and change consumer behavior. The digital transformation driven by the internet has made e-commerce an essential platform for businesses today, allowing for more innovation and efficiency in the global marketplace.

In 2019, consumers engaged in online transactions are dominated by males (60%). In 2020, the Covid-19 pandemic had accelerated digital transformation, resulting in the rapid development of e-commerce via digital platforms. In 2020, male shoppers had the highest engagement in online shopping. The rapid development of e-commerce in addition to the changes in consumer shopping behavior during the pandemic has increased online shopping activities through digital platforms. The Indonesian E-Commerce Association (idEA) projects that e-commerce growth in Indonesia will increase by more than 40% in 20211. In 2021, consumers shopping online are dominated by males at 63%. The graph in 2022 shows that the number of consumers making online transactions in 2022 is dominated by men. Below is an image of the number of consumers by gender according to Kredivo's research on Indonesian e-commerce consumer behavior in 2019-2022:

Figure 1. 2 Number of Consumers by Gender

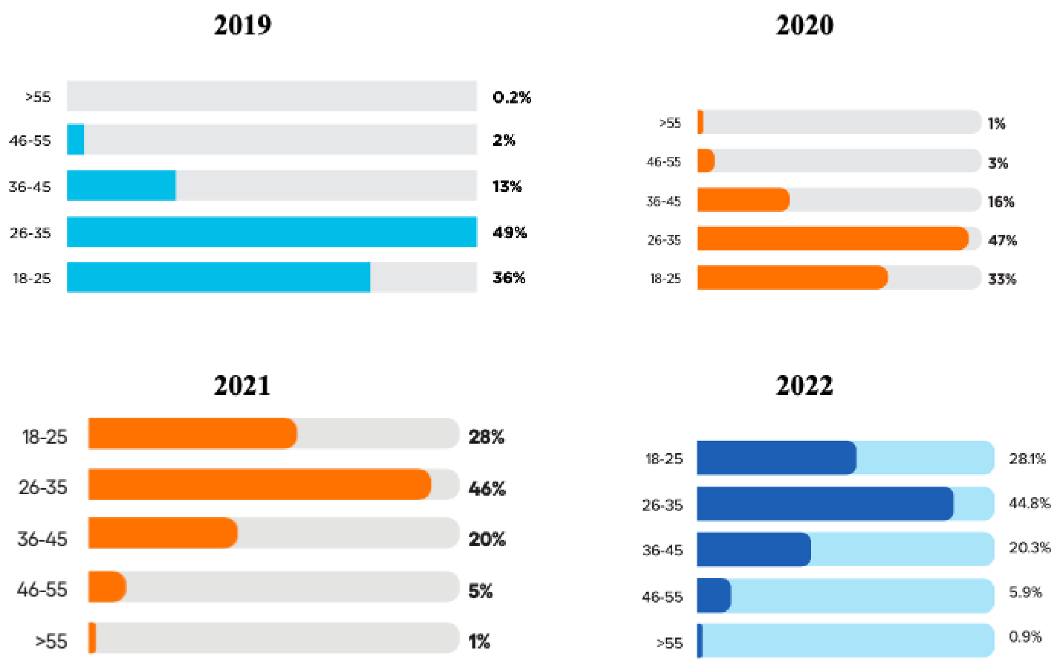


Source: Kredivo Corp (2019-2022), Processed by Author (2024)

In 2019, by age, 84% of these consumers were part of Generation Z and Millennials, or under 35 years old. In 2020, the report depicts online shopping patterns in Indonesia. As many as 80% of consumers are Generation Z and Millennials under 35 years old. Compared to the previous year, the proportion of online shoppers aged 36-45 increased from 14% to 16%. In 2021, by age group, more than 70% will be from Generation Z and Millennials aged 35 and below. According to Katadata (2021), the largest share of consumers who shop online are between 26 and 35 years old, reflecting the millennial generation that makes up the majority of the workforce in Indonesia. This age group of consumers generally have higher incomes than younger consumers and are comfortable with technology. According to Deloitte (2019), millennials are very familiar with digital technology due to their exposure to technological developments. Compared to the past two years, there has been an increase in the share of older consumers shopping online. As the pandemic has limited physical mobility, older consumers have started exploring the e-commerce marketplace for shopping. The share of online consumers aged between 36 and 45 has increased from 14% in 2019 to 16% in 2020, and now accounts for one-fifth of all consumers, at 20%.

According to Shahnaz (2023), In line with the decline in e-commerce visitors since September 2022, due to the lifting of Restrictions on Community Activities (PPKM) due to the Covid-19 pandemic which made people's mobility increase, thus increasing offline transactions. In 2022, it shows that the number of consumers making online transactions in 2022 is dominated by men. In addition, more than 70% of online consumers are Generation Z and Millennials under the age of 35. Interestingly, the number of consumers over 35 years old making online transactions increased from 20% in 2020 to 27% in 2022 over the past three years since the beginning of the pandemic. This group, commonly called Digital Immigrants, has started to learn and follow digital developments including online shopping. According to Kredivo's research on Indonesian e-commerce customer behavior in 2019–2022, the number of consumers by age group is depicted below:

Figure 1. 3 Number of Consumers by Gender



Source: Kredivo Corp (2019-2022), Processed by Author (2024)

Therefore, having a well-thought-out plan to optimize search engine optimization (SEO) is crucial for running an efficient website. SEO is a strategy used to increase the visibility and accessibility of websites for users (Hernawati, 2013). The process of making a website appear at the top of search engine results is known as SEO. Interest in marketing analytics, which involves collecting internet data and using data analysis techniques to find hidden patterns and metrics related to SEO strategies, is essential for improving business performance (Saura, 2021; Ponzoa & Erdmann, 2021; Iacobucci et al., 2019). Additionally, effective advertising is important for increasing organic traffic on e-commerce product feeds. According to the study "Learning to Advertise for Organic Traffic Maximization on E-Commerce Product Feeds" by Chen et al. (2019), researchers developed a machine learning method to optimize advertising bids to maximize organic traffic. This study emphasizes the need for a careful and flexible approach to maximize the effectiveness of e-commerce advertising. For e-commerce businesses, organic search accounts for the largest share of all traffic, as noted in a study by Cheng Jie et al. (2017).

Grigoriou (2023) defines organic search as the process by which users utilize search engines like Google or Bing to find websites. Search engine algorithms, which rank web pages based on quality and relevancy independent of sponsored advertising, determine the results. Because organic search results are earned via hard work rather than sponsored, users tend to view them as more credible. In contrast to organic links, advertisers have direct control over the placement of their adverts, which are rated and shown based on real-time auction results (Baye et al., 2015). Shops decide how much money they want to spend and which keywords to bid on. Google assigns a quality score to each ad based on relevance, click-through rate, and the site's maximum spend for the keyword. The cost per click for advertisers is the same as the minimum amount needed to secure a specific position (a generalized second-price auction process), and they only pay when a link is clicked.

This study will examine the variables influencing consumer product search behaviour on e-commerce platforms, with a particular focus on Indonesia's Shopee, Tokopedia, and Lazada platforms, utilising a panel data approach. The information on organic and paid traffic, organic and paid keywords, and paid traffic expenses will be gathered via SEMrush, an internet analytics tool. By using panel data techniques, researchers can track how product search behavior changes over time and across different e-commerce platforms. This approach helps in identifying new trends and factors that significantly impact customer behavior. Researchers will also examine how specific SEO strategies are applied and their effect on how customers search for products. As a result, this research is expected to provide valuable insights that can help e-commerce businesses improve their marketing strategies, increase product visibility, and boost sales on their platforms.

1.2 Problem Statement

This research will look into the factors that affect how consumers search for products on different e-commerce platforms, focusing specifically on Shopee, Tokopedia, and Lazada in Indonesia, using a panel data approach. Data on organic and paid traffic, keywords, and advertising costs will be gathered from the SEMrush website, a tool for internet analytics. By using panel data techniques, researchers can analyze changes in product search behavior over time and across different platforms. This approach helps identify new trends and factors that significantly impact customer behavior. The research will also evaluate how specific SEO strategies are applied and their effect on product searches. Ultimately, this study aims to provide detailed insights that can help e-commerce businesses improve their marketing strategies, increase product visibility, and boost sales on their platforms.

By using panel data, this study will explore how various factors influence consumer product search behavior on different e-commerce platforms, focusing on Shopee, Tokopedia, and Lazada in Indonesia. Data on organic and paid traffic, keywords, and advertising costs will be collected using the SEMrush analytics tool. This approach will help track changes in search behavior over time and across different platforms, revealing new trends and factors that impact customer behavior. The study will also examine how specific SEO strategies are applied and their effects on consumer search behavior. The goal is to provide detailed insights that can help e-commerce businesses improve their marketing strategies, boost product visibility, and increase sales on their platforms.

The age-old corporate landscape has undergone a significant change due to the rapid growth of internet technology and its gentle integration into everyday life. It has ushered in a new era now known as digital marketing. This shift is especially noticeable in the world of e-commerce, where some of the platforms that many people know especially in Indonesia, or arguably the big players are Shopee, Tokopedia, and Lazada that are present in Indonesia. Search engine optimization (SEO) and paid advertising are two examples of a way or tactic in terms of digital marketing that significantly influences how customers can search for products online. This study aims to examine the impact of these financial digital marketing methods on customer behavior and firm success in e-commerce using a panel data approach.

Moreover, the strategies implemented by a resilient company must take into account external factors, including economic conditions, seasonal patterns, and significant events such as the COVID-19 pandemic, which influence customer search behavior. To provide a comprehensive overview of the fluctuations that occur, this research will analyze data over a time period that encompasses these variations. This approach will also help enhance the efficiency and customer experience of the e-commerce platform overall, ensuring that it remains resilient in the face of any market condition changes. The company must also optimize digital marketing activities, using insights from this research to increase visibility, attract more customers, and ultimately stimulate economic growth. Creating a successful company strategy requires an understanding of how customer behavior and the overall economic impact are influenced by digital marketing. In addition to adding to the body of knowledge on digital marketing and e-commerce, this study will offer e-commerce platforms useful suggestions for enhancing their marketing campaigns and achieving superior financial results.

1.3 Research Question

Given the background information, the research topics for this study are:

1. How do organic factors such as cost, and traffic affect organic traffic?
2. How different are the organic and paid factors affecting the organic search?
3. Do time-specific factors, such as COVID-19 and peak season, affect organic search?

1.4 Research Objectives

The study’s objectives are:

1. To analysis the Impact of Organic Factors on Organic Traffic
2. To Compare the effect of Organic Factors with Paid Factors on Organic Traffic
3. To evaluate the effect on organic search performance of particular times of the month, such the peak season and the COVID-19 epidemic.

1.5 Research Hypothesis

The research formulation created in this study, the research backdrop, and the hypothesis put out in this study are:

1. Organic factors such as cost, and traffic significantly impact increasing organic traffic
2. Compared to paid factors, organic variables have a greater impact on organic search
3. Specific time periods, such as the COVID-19 pandemic and the peak season, significantly affect organic search.

1.6 Research Significance

It is anticipated that this thesis will enhance future research as well as the examination of e-commerce platforms from the standpoint of panel data analysis and economic performance optimisation. The following are some advantages of this research:

1. Academic Contribution and Educational Value

   By offering a more comprehensive understanding of customer behavior on e-commerce platforms, this study advances the academic area. It analyzes the variables impacting product search behavior on marketplaces like as Shopee, Tokopedia, and Lazada using a panel data technique. This method makes it possible to track changes over time and across many platforms, providing information that may be used to improve theoretical models of digital marketing and consumer behavior. Furthermore, the study's conclusions regarding the efficacy of SEO tactics can support next e-commerce and digital marketing studies. The results of this study can be added to business, marketing, and technology-related course curriculums. This can help provide students with the knowledge and skills needed to succeed in the digital economy. Educational institutions can use this information to develop training programs and courses that address current issues and trends in e-commerce.
2. Government Implication

   This research can provide valuable insights about the e-commerce industry to governments, which can help in creating regulations and policies. Understanding consumer behavior on these platforms can assist in developing laws that protect consumer rights, promote fair competition, and support the growth of the digital economy. The study can also reveal trends that impact digital infrastructure and economic planning. Additionally, the findings can aid in developing educational programs that enhance people's digital skills.

3. E-commerce Platform

   The insights from this study can help e-commerce platforms enhance user experiences and optimize their marketing strategies. Platforms like Shopee, Tokopedia, and Lazada can use this information to adjust their SEO and advertising campaigns, making their products more visible and increasing sales by understanding factors that influence consumer search behavior. The results can also identify areas where these platforms can improve and adopt best practices to stay competitive. Additionally, this research can guide the development of new features and technologies to boost user satisfaction and improve search efficiency.

4. Societal Benefits

   The study offers insights on how e-commerce platforms can better meet consumer needs, benefiting society as a whole. It suggests ways to enhance customer satisfaction through personalized shopping experiences and improved search features. By highlighting the importance of digital literacy and security, the research can help customers become more knowledgeable and confident in using online shopping platforms safely and effectively. This increased confidence and engagement can strengthen the digital economy.

5. Entrepreneurial Support

   The study can assist small businesses and entrepreneurs by providing valuable insights into effective digital marketing strategies. By understanding consumer search behavior, small businesses can better position their products and compete with larger competitors. This can create more opportunities for growth and innovation in the entrepreneurial sector.

6. Economic Development

   The insights from this research can help boost the digital economy on a larger scale. By enhancing consumer satisfaction and making e-commerce processes more efficient, the study can drive economic growth and create more job opportunities in the digital sector. This could lead to a more vibrant economy that leverages digital technologies for development.

7. Global Relevance

   Although the study focuses on Indonesia, its findings may be relevant to other parts of the world as well. Businesses in different areas and e-commerce platforms can benefit from the insights and tactics found in this study. This may result in the acceptance of best practices globally, fostering the development of international standards for digital marketing and e-commerce.

This research is important for societal benefits and practical applications in the e-commerce business in addition to improving academic knowledge and shaping government regulations. Through offering an extensive examination of customer behavior on e-commerce platforms, the research contributes to the development of a digital marketplace that is more effective, competitive, and user-friendly. Additionally, it can stimulate more research and creative developments in digital marketing tactics, advancing our knowledge and comprehension of e-commerce procedures.

1.7 Thesis Outline

The following is an outline of this thesis:

CHAPTER 1: INTRODUCTION

Things that point the reader toward the primary problem are covered in Chapter 1. Chapter 1 is described sequentially, starting from the background of the problem, the way the issue is phrased, the goals, the advantages of doing research, and the writing process's structure.

CHAPTER 2: LITERATURE REVIEW

Chapter 2 covers the theoretical basis and conceptual framework, which is linear, and discusses the issues. The theoretical basis, or what is commonly called a literature review, is obtained from various sources, including books, international journals, annual reports, or official reports sourced from official institutional and government websites. Next is previous research obtained from Scopus-indexed international journals. At the end of this chapter is the hypothesis of the problem and the framework.

CHAPTER 3: METHODOLOGY

Chapter 3 covers the research approach used in analyzing the problem. Research methodologies, variable identification, data kinds and sources, data collection procedures, and data analysis techniques are all included in the research methodology.

CHAPTER 4: RESULT AND ANALYSIS

Chapter 4 includes matters relating to the general description of the research object, variables used in the study, and description of research results, including selection of estimation models, model analysis and hypothesis testing, statistical tests, proof of hypotheses, and thorough discussion of research results.

CHAPTER 5: SUMMARY & CONCLUSION

A general description of the research object, variables used in the study, a description of the research results, including the selection of estimation models, model analysis and hypothesis testing, statistical tests, the validation of hypotheses, and a detailed discussion of the research results are all covered in this chapter. Chapter 5 includes the final part of writing research results, including conclusions that answer the formulation of problem and policy recommendations based on research findings.

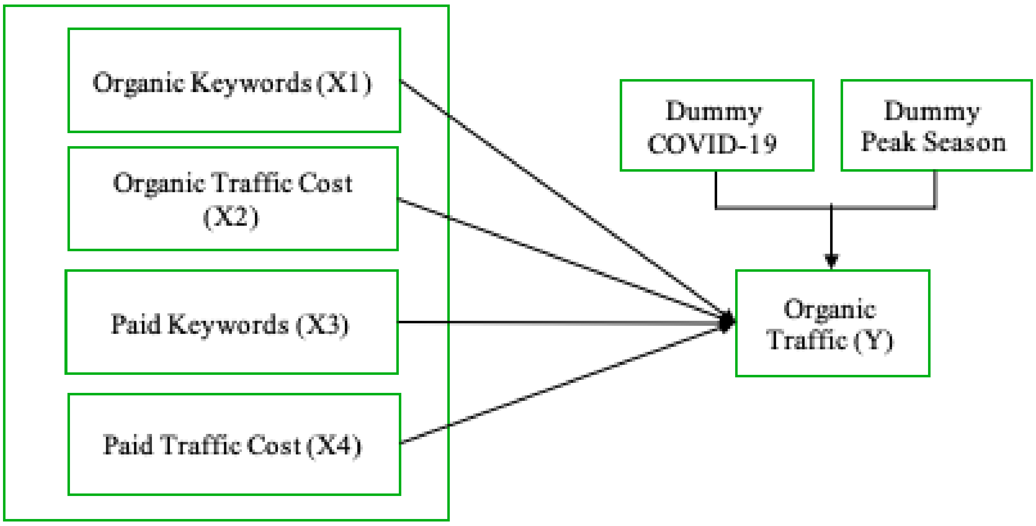
CHAPTER 2
INTRODUCTION

2.1 Conceptual Framework

The theoretical framework is the foundation of this research, linking relevant concepts and variables. This study visually depicts a theoretical framework, which shapes how various factors affect organic traffic on e-commerce platforms. The dependent variable, organic traffic, is directly affected by the first independent variable, organic keywords. Terms in user searches that match the content on a website are called organic keywords. The second independent variable, Organic Traffic Cost, refers to the expenses involved in driving organic traffic. This can include costs for creating content, using SEO techniques, and other unpaid methods to improve search engine rankings. The third independent variable, Paid Keywords, refers to the search terms used in paid advertising campaigns, such as Google Ads, which can indirectly affect organic traffic. The fourth independent variable, Paid Traffic Cost, includes the money spent on paid ads to increase website traffic. This covers costs like cost per click (CPC), cost per impression (CPM), and other related advertising expenses.

The next variable is the COVID-19 Period Dummy. This variable is used to identify the time when the COVID-19 pandemic affected the relationship between variables such as Organic Traffic, Organic Keywords, Organic Traffic Cost, and Paid Keywords. It suggests that the pandemic may have changed how these factors interact. Following that is the Peak Season Period Dummy, which indicates how seasonal changes can impact the relationships between these same variables. Then there is Organic traffic can be affected by the effects of peak season on consumer behavior and marketing tactics. Variations and trends in organic traffic on e-commerce platforms are due to the interactions between X1 (Organic Keywords), X2 (Organic Traffic Cost), X3 (Paid Keywords), X4 (Paid Traffic Cost), COVID-19 Period Dummy, and Peak Season Period Dummy. This more complicated matter is illustrated in the visual graph of this theoretical framework, which makes it easier to understand how different aspects affect the organic performance of a website in a dynamic online environment.

Figure 2. 1 Research Framework



Source: Processed by Author (2024)

The Summary and Identification of Research Gaps section summarizes the core findings derived from the literature review and describes the areas of deficiency in existing research that this study seeks to fill. Through an extensive examination of the literature, including studies on e-commerce platforms and consumer behavior, as well as insights gained from SEMrush data, several research gaps have been identified. These include the lack of a comprehensive understanding of the specific influence of Organic Keywords, Organic Traffic Cost, Paid Keywords, and Paid Traffic Cost on Organic Traffic on e-commerce platforms, especially in the context of Indonesian markets and platforms such as Shopee, Tokopedia, and Lazada. In addition, there are still few studies that examine the impact of these variables before and after the COVID-19 pandemic, as well as their interaction with seasonal variations denoted by "Peak Month". Addressing these gaps will contribute to a more comprehensive understanding of the factors that influence consumer product search behavior on e-commerce platforms and inform strategies to optimize online visibility and traffic.

2.1.1 Digital Economy

The emergence of the Digital Economy encompasses a variety of commercial endeavours that significantly depend on digitally transformed knowledge and data. The main technologies employed in the digital economy are cloud computing, AI, blockchain, IoT, data analytics, and any internet-based service. These new technologies use digital methods to gather, store, process, and disseminate information. Social ties are thus also changed since digital technologies foster innovation, create job opportunities, and support economic growth; the digitization of the economy has positive effects and increases efficiency. In addition, the digital economy affects every facet of society, transforming interpersonal relationships and bringing about significant societal transformations. The commercial potential of the digital economy has helped the world economy. (Brun et al., 2019; Kurniawan et al; 2022; Feshina et al., 2019).

The term "digital economy" refers to all online-based economic activities. A data-driven economy has emerged due to the capacity to collect, use, and analyze enormous amounts of machine-readable data to provide more relevant and personalized experiences. By leveraging the digital economy, companies may now develop new business models and generate economic value in ways that were unimaginable a few years ago. The financial industry is now a part of the digital economy since it employs technology to upend corporate models, markets, and daily operations. Consequently, it encompasses a wide range of industries, from recently emerging ones like digital to well-established ones like technology, media, and telecommunications (Morkovkin et al., 2020; Maisiri et al., 2019; Chang et al., 2022; Fedotova et al., 2019). Technology advancements affect online banking, e-commerce, and even "traditional" sectors like manufacturing and agriculture.

The foundation of the digital economy is the global network known as the Internet, which is now the most disruptive collection of technologies and enables the instantaneous flow of data worldwide. Remembering that thousands of technologies work together to enable connections, routing, and data transfer among all devices is crucial. The digital economy requires a paradigm shift in understanding, outlook, and business practices (Ghobakhloo, 2020; Dzyurdzya et al., 2022). Companies that wish to thrive in this new economy need to embrace digital technologies and cultivate a culture that is adaptable, innovative, and customer focused. The term "digital economy" describes how digital technology affects patterns of production and consumption, including how companies' market, conduct business, and receive payments for goods and services. These days, the phrase covers an incredible array of applications and technologies. These include the Internet of Things, blockchain, robotics, cloud computing, augmented and virtual reality, and autonomous cars (Digilina et al., 2019; Khadzhiev, 2019).

The term "digital economy" refers to a range of economic endeavours that use data to improve resource allocation and production. Big data, cloud computing, artificial intelligence, and other cutting-edge technology are included, along with creative uses like "new retail" and "new manufacturing." Constrained by physical space, traditional marketing methods are making way for more open forms of trade made possible by e-commerce platforms. These platforms allow trade to be more flexible and accessible, overcoming time and location restrictions. Nonetheless, issues like unfair corporate practices and information asymmetry continue to exist, driving up costs for consumers and undermining fair competition. Notwithstanding these obstacles, digital economy platforms present chances for increased consumer choice, increased corporate participation, and enhanced productivity through novel electronic payment systems. In general, businesses and consumers have both possibilities and challenges in the digital economy. (Ma and Gu, 2024).

2.1.2 E-commerce

The buying and selling of goods and services using electronic network, such as the Internet, is known as e-commerce (Kotler, 2017). Since the 1990s, this concept has gained popularity and transformed consumer and business behaviour, having a substantial impact on the world economy. E-commerce allows businesses to reach more customers, increase revenue, and cut costs. It also gives customers access to a wider range of products and services, makes shopping more convenient, and helps them save money. One of the biggest benefits of e-commerce is that it lets businesses connect with a global audience. According to Turban et al. (2018), the internet helps businesses overcome cultural and geographic barriers, allowing them to reach customers worldwide and grow their market. This means that small and medium-sized businesses can compete with larger companies. Furthermore, e-commerce enables businesses to offer personalized products and services based on customers' preferences and past purchases, which can improve customer satisfaction and loyalty.

Another major benefit of online shopping is the convenience it offers. Customers can browse and purchase products and services at any time, without being limited by store hours. Thanks to e-commerce platforms, people can shop from anywhere with an internet connection (Turban et al., 2018). This eliminates the need to visit a physical store, saving both time and money. However, e-commerce also has its challenges. One of the main issues is security in online transactions. Consumers are often hesitant to share their financial and personal information online due to risks like credit card fraud and identity theft (Kotler et al., 2017). To address these concerns, businesses need to implement secure payment systems and build trust with consumers through transparency and strong customer support.

Another challenge of e-commerce is that businesses must continuously adapt to new technologies and changing consumer preferences. To stay competitive, companies need to incorporate the latest technology into their e-commerce strategies (Turban et al., 2018). They also have to keep up with evolving consumer demands, such as the growing interest in ethical and sustainable products. E-commerce has changed the way people shop and do business, making it a crucial part of the global economy. It involves buying and selling goods and services through electronic networks, primarily the Internet. The advantages of e-commerce include better operating expenses for firms. However, e-commerce also presents obstacles, such as the requirement for safe online transactions and the necessity for firms to adapt to evolving technologies and consumer preferences. According to Laudon & Traver (2017), there are five types of e-commerce classification as follows:

1. Business to Business (B2B)
    - Business partners who already know each other and have established long-standing company relationship
    - Recurring and mutually agreed information exchange
    - The commonly used model is peer-to-peer, where processing intelligence can be distributed by both actors. processing intelligence can be distributed by both business
2. Business to Consumer (B2C)
    - Accessible to the public, where information can be disseminated to the public
    - The services used are also intended for the public so that they are available to everyone. Many people
    - Services are used on demand, so the manufacturer must be able to respond well to consumer requests.
    - The system approach is client-server.
3. Consumer to Consumer (C2C)
    - E-commerce provides access to customers to sell products or services to other consumers through online media intermediaries.
    - It allows customers to sell their products or services to other users directly on the website.
4. Peer to Peer

    It is an e-commerce that uses the help of technology so that internet media users do not need to go to a web server first to send data directly.

5. Mobile Commerce (M-Commerce)

   An e-commerce system that uses digital device processes through wireless media for transactions, including smartphones, cell phones, notebook devices, and so on.

2.1.3 Search Engine Optimization (SEO)

Search represents one of the most important activities for Internet users (Pavlou & Fygensen, 2006). Although the exact algorithms used differ across search engines, major players in the field (e.g., Google) rank and display search results by taking into account the similarity of a website's content to the user's query, as well as the absolute "authority" of the site (Gori & Witten, 2005), which often relates to how many high-quality web sites link to the focal site in the search engine. In an e-commerce setting, two types of marketing activities can be conducted through search engines. First, in search engine advertising, companies pay to have links to their websites displayed in the "sponsored section" of a search engine results page. Second, in search engine optimization, companies strive to push the rankings of their websites higher in the organic search results (i.e., no payment made to the search engine) through a variety of techniques (e.g., changing the structure of the sites) or by hiring external consultants to develop specific techniques that will cause search engines to index their sites in higher positions (Delaney, 2006).

In their study The Impact of Search Engine Optimisation as a Marketing Tool, Ravneet Singh Bhandari and Ajay Bansal highlight the significance of search engine optimization (SEO) in the current digital environment, emphasizing its function in increasing website visibility and generating online traffic. Websites that use SEO are more likely to rank higher in search engine results, which increases the possibility of drawing visitors and making money. It is underlined that a website could rank lower in search results and have fewer visitors if it doesn't have adequate SEO. In comparison to more traditional tactics, SEO offers internet marketers a more affordable option for online marketing while giving them real-time insights into customer behavior. Moreover, SEO is described as an ongoing process that is required to maintain a website's visibility and relevance over time. The last phrase of the section, which states that SEO will be important as long as search engines exist, highlights the importance of SEO in the field of digital marketing. The study's conclusions broaden our knowledge of how SEO influences various marketing indicators and can be used to assist marketers in developing effective strategies. Numerous marketing factors were taken into account in the study, including user reviews, market share, customer online behavior, brand loyalty, brand recognition, product price, product information, brand image, and brand awareness. According to the empirical findings, SEO is the most important component in growing market share and enhancing product brand equity. Other aspects that come into play include product awareness, buying persuasion and consumer insights. These results imply that since SEO can have long-term effects on a variety of marketing variables, marketers should focus particularly on it. When comparing organic search and paid search, some key differences emerge. The differences between Organic Search and Paid Search (Baresquare, SEMrush, WebFX) are:

a. Cost
    1) Baresquare claims that organic search results have no direct cost per click. However, there are expenses related to SEO initiatives, including technological optimization, keyword research, and content production.
    2) Paid search: Starting in 2023, SEMrush will charge a fee for each click (PPC) or impression (CPM). Marketers place bids based on keywords, and the price might differ significantly based on the level of competition.
b. Placement
    1) Organic Search: Based on search engine algorithms, results show up organically. They are typically shown in SERPs beneath sponsored advertisements.
    2) Paid Search: Links to advertisements can show up above or below the organic results in the SERP. (SEMrush)
c. Credibility
    1) Users typically view organic search results as more reliable because they are derived from relevance and quality.
    2) Sponsored Search: Since users know this is a sponsored venue, it may be viewed as less reliable (WebFX).

d. Time to results
    1) Organic Search: Since SEO techniques entail gradually establishing authority and relevancy, they may take months to yield noticeable effects
    2) Paid Search: Upon activating the ad campaign, it can boost traffic and offer instant visibility (SEMrush).
e. Sustainability
    1) Organic Search: With steady SEO work, a website can sustain a high ranking and draw traffic indefinitely without incurring more expenses.
    2) Paid Search: When the advertising budget is depleted, traffic ceases. To keep visibility, constant investment is necessary (Baresquare | Act quickly) (SEMrush).

The elements that affect organic traffic to e-commerce sites have been covered in previous studies, such as those by Baye, De Los Santos, and Wildenbeest (2015). However, more research is required to understand how customers behave on e-commerce sites and what motivates them to use Internet search engines to find what they are looking for. Furthermore, research entitled "What's in a name? " was carried out by Michael R. Baye, Babur De Los Santos, and Matthijs R. Wildebeest. "Measuring Prominence and Its Impact on Organic Traffic from Search Engines" looks at how search engine organic traffic is affected by prominence in search results. This study examines the relationship between the quantity of organic traffic a website receives from search engines and various criteria that impact a page's prominence in search results, including site rank, position on search results pages, and display of site links and snippets.

2.2 Theoretical Framework

2.2.1 Consumer Behavior

According to Huang Huang et al., (2009), the idea that the Web makes all attributes "searchable" by consumers, there are differences in consumer perceptions, online search patterns, and purchasing behavior for the two types of products. The following is Consumer Information search and the Internet:

- Evaluating the quality of the product.

In the 1970s, Nelson suggested a framework for classifying items into search and experience categories based on consumers' ability to assess product quality prior to purchase. This framework is discussed in this section. Subsequent research revealed that experiences frequently convey confusing information, leaving customers uncertain even after purchase, despite Nelson's initial suggestion that experiencing goods provides assurance regarding quality after purchase. The growth of the Internet has significantly changed how we classify shopping methods. Experts say that online platforms now offer new ways for customers to research products before buying them. For example, websites can provide detailed product information, including expert reviews and user comments, which enhances the shopping experience before making a purchase.

Researchers studying decision-making argue that gathering information requires both mental and physical effort, with different types of information demanding different levels of effort. The text explains that every product has a mix of search and experience characteristics. Experience goods require customers to use or interact with the product to evaluate its quality, while search goods allow consumers to judge quality without direct experience. Even with the increased availability of information online, Nelson's initial classification remains valuable for understanding how consumers make decisions.

- Depth versus Wideness of Search.

  According to this study, a consumer's depth of search is determined by how long they spend analyzing content on a single website, and their breadth of search is determined by how many product websites they view. While the unit of analysis is web pages rather than attribute values, depth and breadth are comparable to the time-per-acquisition and number-of-acquisition variables used in process-tracing research (Bettman et al., 1993; Lurie, 2004). The study argues that evaluating search and experience attributes involves different levels of effort and that the depth of search is likely to be greater (and breadth lower) for experience goods than for search goods. Experience qualities, like how easy a camera is to use, are intrinsically subjective, marked by ambiguity and uncertainty, and challenging to assess. In contrast, search attributes, like price, are objective, diagnostic, and simple to compare. These variations may alter how customers interpret information.

  More specifically, search attribute information is usually provided in an easy-to-understand manner and should take less time to gather and process.

Examples of these qualities include price, color, shape, size, and other standard product specs. Furthermore, the fact that this data is frequently presented in online contexts in the form of tables or bullets facilitates comparisons across products. On the other hand, gathering data regarding experience attributes could entail looking through customer reviews and ratings, examining items, assessing product demos or videos, downloading digital samples from the website, and consulting independent product testing and recommendations.

Consumers must also combine information from various sources to assess the overall value of a product alternative, evaluate attributes at a more abstract level, or restructure information to make it comparable because experience attribute information is likely to be highly idiosyncratic (e.g., the type of information provided about a product will vary due to individual differences in product experiences and the description of these experiences by particular reviewers). Consumers need to absorb more information and, consequently, spend more time on each page of information due to the increasing uncertainty associated with experience qualities. According to information theory (Shannon and Weaver, 1949), more information can be acquired in fewer pages even though processing this information should require more work because each page of information on experience qualities reduces uncertainty to a larger extent.

- The issue of free-riding.

This section talks about how promotional inputs like product consultations and retail showrooms that aren't offered separately from actual products might lead to free-rider issues in internet retail. Online retailers spend a lot of money building educational websites, but buyers might use that information to decide what to buy and then look for less expensive options elsewhere, which would exacerbate the problem of free riders.

Compared to buyers of search products, the claim is that consumers of experience goods are less inclined to participate in free-riding behavior. This is due to the fact that assessing experience features takes more work, and data on these characteristics is frequently displayed differently on every website, increasing the initial cost of learning and decreasing the motivation for customers to look for less expensive options. Pre-purchase research also aids in lowering the perceived risk associated with online purchases, particularly for experiential items that require subjective evaluations. Customers are more likely to buy from reliable vendors who offer thorough product information, which helps to reduce the prevalence of free-riding.

- Methods of expressing experience attributes.

  This excerpt demonstrates how buyers can obtain information on experience attributes prior to making a purchase through the Internet as a retail channel. This change is facilitated by mechanisms like experience simulation, reliable third-party information, and customer feedback. For the purpose of anticipating product adoption and learning about other people's experiences, consumer feedback, such as product evaluations and online communities, is essential. Credible third-party data also sheds light on aspects of experience; examples of this are consumer reports' assessments. Moreover, multimedia information that simulates experiences provides online customers with a first-hand experience. The use of websites is probably going to rise as a result of these mechanisms, particularly among customers looking to experience goods. While there are easy ways to successfully disseminate information about search parameters, experience goods customers are more likely to invest time in reading in-depth reviews or watching multimedia content on reputable websites.

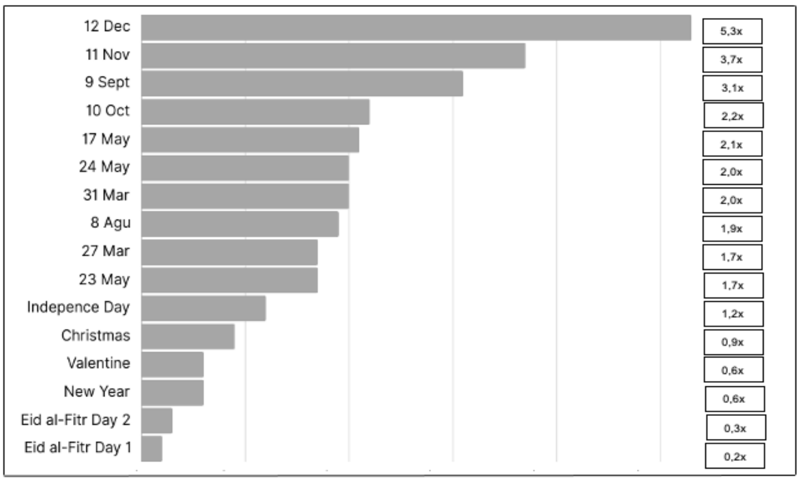
  These techniques might, however, have less of an impact on how customers behave while looking for specific goods. The question of whether these strategies boost the possibility of making a purchase on a website and whether the impacts vary for experience and search goods interests practitioners. There is a claim that the use of multimedia and other web design elements increases buy intentions by signaling reliability. Multimedia content that simulates experiences also encourages consumers to buy experience items. Experience products are thought to benefit more from these mechanisms in terms of increased purchase likelihood than search goods. Experience transfer mechanisms also lengthen customers' visits to websites, which lowers their perceived risk and creates cognitive lock-in, increasing the likelihood that they will make a purchase from a website.

2.2.2 The Impact of COVID-19 and Peak Season

The COVID-19 pandemic has resulted in major changes in consumer behavior, according to Tran et al. (2023), with the title Research Explaining Consumers' channel-switching behavior in the post-COVID-19 Period. During the pandemic, a significant number of new consumers have been drawn to digital consumption. The study results show that several factors significantly affected consumers' decisions to change their shopping habits after the pandemic broke out, including marital status, price, quality, convenience, and overall satisfaction with current and new shopping channels. More importantly, this study is one of the few to investigate the differences in determining factors regarding consumers' choices of online and traditional channels in the post-COVID-19 pandemic era. When choosing between online and traditional channels for purchases, factors including money, convenience level, time spent making purchases, technological proficiency, and the availability of a wealth of product information all play a major role.

There was a notable spike in product purchases during big events/festivals with special offers in the Kredivo statistics for 2019 and 2020. It is evident from the comparison data of transactions on these days that e-commerce transactions can be efficiently increased by online shopping events. Additionally, there is a spike in transactions in the week leading up to Eid or throughout the month of Ramadan. Below is an image comparing the average daily transaction volume with the transaction volume on the ten dates with the highest transaction volume in 2019:

Figure 2. 2 Comparing the average daily transaction volume with the transaction volume on the top ten dates with the highest transaction volume (2019)

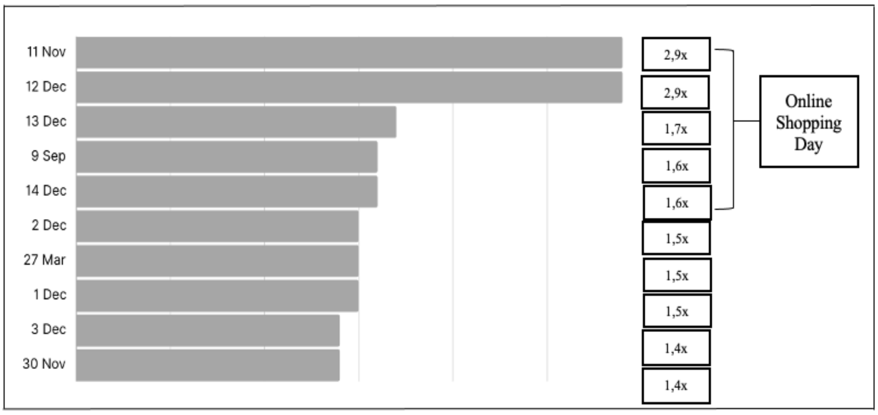


Source: Kredivo Corp, Processed by Author (2024)

The busiest shopping days in 2019 were National Online Shopping Day (December 12), Single's Day or Double Eleven (November 11), and Super Shopping Day (September 9) (Figure 2.2). Customers benefited from the sales that were being held throughout these times. A rise in transactions and a peak in shopping at the end of the year were caused by the huge number of customers taking part in e-commerce festivals. On December 12, the largest transaction value was almost 5.3 times the daily average.

Promotions and online shopping festivals are still successful in drawing customers, according to a Kredivo Corp. analysis. By the end of the year, there was a noticeable increase in the amount of online purchasing due to these e-commerce incentives. The following below is a comparison image of the average daily transaction volume with the transaction volume on the ten dates with the highest transaction volume in 2020:

Figure 2. 3 Comparing the average daily transaction volume with the transaction volume on the top ten dates with the highest transaction volume (2020)

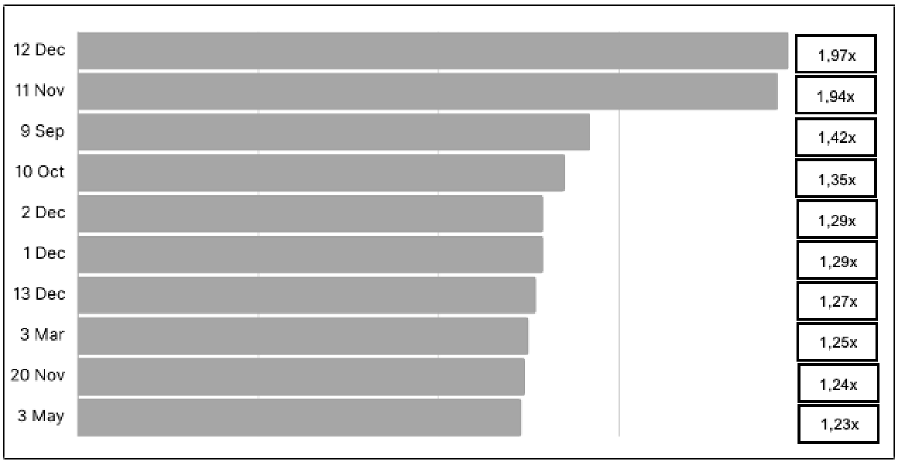


Source: Kredivo Corp, Processed by Author (2024)

In the 2020 figure, high transaction volumes usually occur during Harbolnas (National Online Shopping Day) celebrations, which fall on twin days such as September 9 (9.9), October 10 (10.10), November 11 (11.11), and December 12 (12.12). In addition, e-commerce businesses usually start discounts before or even a few days after these dates. During the two busiest dates in 2020, 11.11 and 12.12, the average daily transactions tripled from normal days.

According to research published in the Indonesian e-Commerce Consumer Behavior study, December 12 (12.12) and November 11 (11.11) have the largest transaction volumes in 2021, with an increase in transactions up to twice the average daily transaction. The following Figure 2.4 compares the average daily transaction volume with the transaction volume on the ten dates with the highest transaction volume in 2021:

Figure 2. 4 Comparing the average daily transaction volume with the transaction volume on the top ten dates with the highest transaction volume (2021)

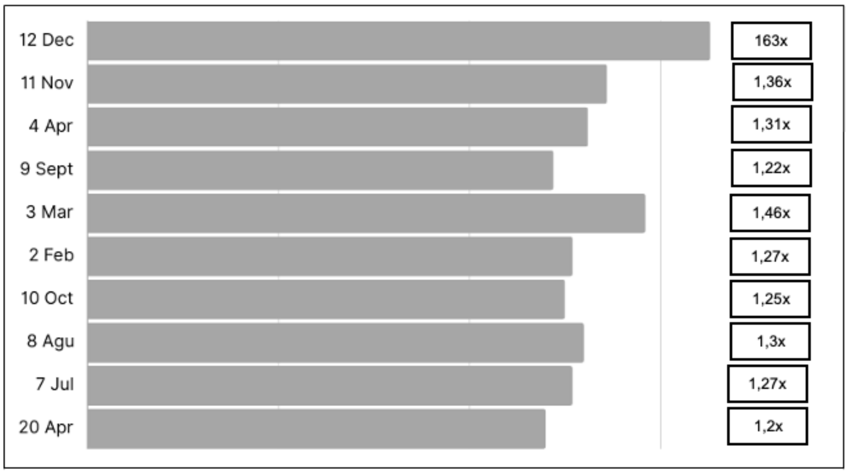


Source: Kredivo Corp, Processed by Author (2024)

In Figure 2.4, the number of transactions increased 1.5 times on the twin dates of September 9 (9.9) and October 10 (10.10) (Figure 2.3). These dates continue to attract consumers to try out various types of promotions provided by e-commerce, although the increase in transaction volume is not as large as the threefold increase in the previous year. According to BPS (2022), the macroeconomic environment in 2022 will also have an impact on this month-to-month pattern. In the fourth quarter of 2022, household consumption expenditure was recorded by the Central Bureau of Statistics as 4.48, a decrease from the third quarter of the same year (5.39).

Given that society had not yet fully recovered from the effects of the epidemic, the recession problem that worsened in the fourth quarter of 2022 was another reason why people refrained from consuming. On the other side, by charging customers service fees and reducing the number of promo options accessible, several e-commerce platforms have started to reduce promotions and concentrate on company continuity. Here's the graph for 2022:

Figure 2. 5 Comparing the average daily transaction volume with the transaction volume on the top ten dates with the highest transaction volume (2022)



Source: Kredivo Corp, Processed by Author (2024)

Based on "Report Consumer Behavior E-Commerce Indonesia 2023: Post-pandemic Economic Recovery and Shopping Trends", released by Kredivo in collaboration with Katadata Insight Center, of all the number of e-commerce transactions in 2022, consumers with the highest number of transactions will come from consumers who are married with a portion of 58.2%. The percentage of e-commerce transactions from single consumers is 38.7%, and the remaining 3.1% is from other groups.

2.3 Previous Study

There are previous researchers who are similar to this research, the first is research from Yang & Gose (2010), who examined the positive relationship between organic views and paid search ads in consumer responses. Sha Yang and Anindya Ghose (2010) conducted a study title “Analyzing the Relationship Between Organic and Sponsored Search Advertising: Positive, Negative, or Zero Interdependence?" Their research delves into the rising use of paid search advertisements by online marketers and aims to comprehend the relationship between sponsored advertisements and organic views from the same business. The findings indicate a favorable correlation between clicks on sponsored adverts and clicks on organic views, suggesting that having both types of perspectives can boost a business's earnings. This study provides valuable insights for company managers regarding the impact of search engine-based advertising.

In 2015, Ashish Agarwal, Kartik Hosanagar, and Michael D. Smith explored the question, "Do Organic Results Help or Hurt Sponsored Search Performance?" Their study examines the relationship between sponsored search adverts and changes in organic search results. By analyzing data from online retailers' advertising efforts, researchers found that while increased organic competition lowers click-through rates, it actually boosts the conversion rates of sponsored ads, leading to higher revenue. The study shows that organic competition has a greater negative effect on click performance compared to paid competition, but it improves the effectiveness of sponsored ads. In other words, while organic results can reduce the number of clicks on sponsored ads, they can also enhance the chances that those ads will lead to sales. This information helps marketers understand how the presence of organic search results influences the success of their paid advertisements, suggesting that organic competition might replace clicks but positively affect conversion rates.

Ron Berman and Zsolt Katona (2013) focused on "The Role of Search Engine Optimization in Search Marketing." Their paper investigates the impact of search engine optimization (SEO) on the competition between advertisers for organic and sponsored search results. They found that a positive level of SEO can enhance the search engine's ranking quality and visitor satisfaction. In the absence of sponsored links, SEO improves organic rankings only if the website's quality is positively correlated with its valuation for consumers. The presence of sponsored links accentuates these results, with high-quality websites benefiting more from SEO, leading consumers to start their search with an organic click. Although SEO can improve consumer welfare and the payoff of high-quality sites, it typically results in lower search engine revenue when advertisers spend more on SEO and less on sponsored links. The study also models the impact of the minimum bid set by the search engine, revealing an inverse U-shaped relationship between the minimum bid and search engine profits, suggesting an optimal minimum bid that decreases with higher SEO activity.

Ravi Sen (2005) investigated the "Optimal Search Engine Marketing Strategy" and found that consumers using search engines for informational purposes are more likely to trust and click on editorial links rather than paid placements. The study reveals that most online businesses prefer paying for sponsored placements over investing in SEO to rank higher in search results, as SEO is more costly, yields inconsistent outcomes, and does not always result in high search engine ranks. This means that retailers would likely spend more on SEO if it were cheaper and led to more stable search rankings. However, even if SEO and paid placement were equally expensive and consistently resulted in high rankings, most online retailers would still prefer paid placement for search engine marketing (SEM). These findings are especially important for advertising professionals who need to justify their spending on sponsored ads, even though consumers often prefer editorial links over these paid placements.

Finally, Michael R. Baye, Babur De Los Santos, and Matthijs R. Wildenbeest (2015) conducted a study titled "Search Engine Optimization: What Drives Organic Traffic to Retail Sites?" The study emphasizes the importance of SEO strategies for online retailers. Their findings show that investing in website quality and brand awareness helps attract more clicks on a retailer's link in organic search results. This investment also indirectly improves click-through rates by boosting search engine rankings. Factors like consumer demographics, search habits, and the visibility of brand names in searches also play a role in organic click rates. The study emphasizes that having a high-quality website is especially important for drawing organic traffic from higher-income individuals. Overall, the results suggest that incorporating investments in website quality and brand awareness into SEO strategies can enhance organic click-through rates and drive traffic from various online and traditional channels.

CHAPTER 3
METHODOLOGY

3.1 The Data

The main objective of this study is to understand consumer behavior in e-commerce platforms and analyze the factors that drive product search using panel data relevant to e-commerce platforms in Indonesia (Shopee, Tokopedia, Lazada). This research uses a quantitative approach which includes organic keywords, organic traffic costs, paid keywords, and paid traffic costs as independent variables and organic traffic as the dependent variable from 2019 to 2022. This analysis is performed on monthly data, which indicates that the observations in the dataset are collected at monthly intervals during the specified time period. While the data source used is secondary data obtained from the SEMrush website. The following research data was obtained:

Table 3. 1 The Variables

No.	Variable		Proxy	Measurement	Source
1.	Dependent	Organic Traffic	The total number of visitors who come to a website through organic search results.	Count of Visitors	SEMrush Website
2.	Independent	Organic Keywords	The total number of keywords for which a website appears in organic search results.	Count of Keywords	SEMrush Website

3.		Organic Traffic Cost	Estimated costs that would be incurred if getting that amount of organic traffic through paid advertising (Cost per Click - CPC).	Monetary Value	SEMrush Website
4.		Paid Keywords	The total number of keywords used in a paid advertising campaign to drive traffic to a website.	Count of Keywords	SEMrush Website
5.		Paid Traffic Cost	The total amount spent on paid advertising campaigns in a given period.	Monetary Value	SEMrush Website

6.		Dummy	**COVID-19 Era:** For dummy variables during pre-COVID in January 2019 - February 2020, the value is 0; during the COVID Era in March 2020 - December 2022, the value is 1. **Peak Season:** For the dummy variable of peak season on a specific date based on monthly report values one and otherwise for dummy variable beside the specific date of monthly report values 0.	Binary Indicator (coded as 1 for presence of the condition, 0 for absence)	

Source: Processed by Author (2024)

3.2 The Models and Variables

This research as an estimation model uses panel data analysis with organic keywords, organic traffic costs, paid keywords, and paid traffic costs as independent variables and organic traffic as the dependent variable. The following is this research for the estimation model:

$$\log(Y_{it}) = \alpha_{it} + \beta_1 \log(X_{1it}) + \beta_2 \log(X_{2it}) + \beta_3 \log(X_{3it}) + \beta_4 \log(X_{4it}) + \gamma_1 \ DCOVID_{it} + \gamma_2 \ Dpeakseason_{it} + \epsilon_{it} \quad \text{……………………………………………………………. (3.1)}$$

Where,

a) $\text{Log}(Y_{it})$ represents the natural logarithm of the dependent variable (Organic Traffic) for platform *i* at time *t*. Using the logarithm makes it easier to interpret the coefficients in terms of percentage changes.
b) $\text{Log}(X_{1it})$ is the natural logarithm of Organic Keyword.
c) $\text{Log}(X_{2it})$ is the natural logarithm of Organic Traffic Cost.
d) $\text{Log}(X_{3it})$ is the natural logarithm of Paid Keyword.
e) $\text{Log}(X_{4it})$ is the natural logarithm of Paid Traffic Cost.
f) $DpostCOVID_{it}$ is a dummy variable that equals 1 for the period after the COVID-19 pandemic and 0 otherwise.
g) $Dpeakseason_{it}$ is a dummy variable that equals 1 during the peak season and 0 otherwise.
h) α_{it} is the intercept.
i) β_1, β_2 , β_3, β_4 are the coefficients for the explanatory variables.
j) ε_{it} is the error term.

This estimation model was created to analyze the effect of research on independent variables on organic traffic using panel data. By applying a logarithmic transformation to the independent variables and also adding two dummy variables, namely for the post-COVID-19 period and the peak season, this model can also allow for a deeper understanding of the dynamics and changes in the effect of organic keywords, organic traffic costs, paid keywords, and paid traffic costs on organic traffic. With this approach, this research is expected to gain useful insights for more effective marketing and traffic management strategies.

3.3 SEMrush as an Analysis Tool

E-commerce SEO is the process of improving an online store's organic rankings and visibility in search engines like Google and Bing. Common tasks associated with e-commerce SEO include (Pol, 2023):

a. Performing keyword research.
b. Improving site structure.

c. Optimizing for on-page SEO elements (meaning making improvements to the web pages' content).
d. Creating quality content.
e. Building backlinks (links from other sites that point to the site).

Doing SEO for e-commerce sites is very difficult without specialized tools. Whether want to generate keyword ideas, find technical SEO issues, or build backlinks, e-commerce SEO tools help with almost all steps involved in the optimization process. SEMrush is one such tool that can be used. The SEMrush SEO tool covers various aspects of e-commerce SEO, such as (Pol, 2023):

a. Keyword research

   The Keyword Magic Tool can be used to find keywords for products and category pages. As well as blog posts.

b. Technical SEO

   The Site Audit tool can be used to audit websites for common technical issues, such as broken links, duplicate content, slow load speeds, and more.

c. On-page SEO

   Can use Page SEO Checker to confirm whether the pages are optimized

d. Link building

   Can use Backlink Gap to find link opportunities for e-commerce sites based on competitors.

3.3.1 Data Processing and Analysis Using SEMrush

Data from SEMrush was processed using the following steps:

a. Monthly Data Collection

   Data on organic and paid keywords, traffic costs, and organic traffic counts were collected monthly. For additional study, this data was extracted from SEMrush and stored in a spreadsheet file.

b. Data Merging

   Each e-commerce platform's monthly data was combined to create the one-panel dataset. This dataset includes time (month) and platform (Shopee, Tokopedia, Lazada) variables as panel entities.

c. Data Preprocessing

   To get rid of odd or missing data, data cleaning is done. Duplicate or irrelevant data is eliminated.

d. Descriptive Statistics

For every variable, descriptive statistics were computed in order to comprehend the data distribution. Trends and patterns are identified using data visualisation tools like histograms and line graphs.

e. Panel Data Regression Analysis

The link between the independent variables (organic traffic, organic traffic cost, paid traffic, and paid keywords) and the dependent variable (organic traffic) was examined using a panel data regression model. Three methods were used to conduct the analysis: the Random Effect Model (REM), the Fixed Effect Model (FEM), and the Common Effect Model (CEM). Model estimation and traditional assumption tests were carried out with the use of statistical software like Stata.

f. Model Selection and Evaluation

Hausman test is used to select between FEM and REM based on the presence of random effects. Goodness-of-fit measures such as R-squared are used to evaluate model performance. Classical assumption testing is performed to ensure the validity of the regression model.

g. Interpretation of Results

Regression results were interpreted to understand the impact of the independent variables on organic traffic. Trend analysis was performed to see changes in the effectiveness of SEO and PPC strategies over time.

To ensure the validity and reliability of the data retrieved from SEMrush, the following steps were performed:

k) Cross-Verification: Verifying SEMrush data with the e-commerce platform's internal data if available.
l) Consistency Check: Ensuring data consistency by conducting repeated sampling at different intervals.
m) Benchmarking: Comparing SEMrush data with other similar data sources to ensure accuracy (SEMrush, 2024).

3.4. Method

3.4.1 Panel Data

Gujarati (2012) explains that panel data, also known as pooled or longitudinal data, combines cross-sectional data and time series data. This research uses panel data, which combines information collected at different points in time with data from multiple sources. Specifically, this research focuses on three e-commerce platforms in Indonesia: Shopee, Tokopedia, and Lazada. While the analysis is conducted on monthly data, the time series data covers the last four years, from 2019 to 2022. The analysis used a multiple regression model with panel data using the Stata application. This approach made it possible to examine the relationship between the independent variables (Organic Keywords, Organic Traffic Cost, Paid Keywords, Paid Traffic Cost) and the dependent variable (Organic Traffic) across the three e-commerce platforms. Panel data estimation was chosen due to the nature of the dataset, which consists of repeated observations over time for the same individuals (i.e. e-commerce platforms). The panel structure enables modelling both within-platform and cross-platform variations in consumer behaviour, providing robust insights into the determinants of product searches in the e-commerce domain

3.4.2 Panel Data Advantages

Gujarati and Porter (2012) state that the following are benefits of panel data analysis:

a. Panel data analysis will openly promote variety by including certain individual variables in the calculation.
b. More information, improved variability, a reduction in the interaction between independent variables, greater degrees of freedom, and efficiency are all provided by panel data analysis.
c. It is more effective to investigate the dynamics of change using panel data
d. Time-series and cross-section data cannot measure or detect impacts that panel data can.
e. Compared to time-series and cross-section data, panel data enables researchers to examine more intricate behavioural models.
f. Panel data reduces bias by providing information for several thousand units.

3.4.3 Rationale for Panel Estimation

Panel data estimation is a useful method to combine information from different groups and time periods for more accurate analysis. This technique helps control for factors that are difficult to see or measure directly and that may change over time, but not across the entire group being studied (such as individuals, companies, or countries). When studying e-commerce platforms such as Shopee, Tokopedia, and Lazada in Indonesia, panel data estimation has several benefits. It allows each platform to have its own unique characteristics considered in the analysis, which is important when comparing the performance and strategies of different platforms over time. For example, Shopee may have a unique user interface or consistent marketing approach, and these specific features can be accounted for and controlled for in this study. The second advantage is that panel data improves the accuracy of econometric estimations. By collecting data from different groups and time periods, panel data increases the number of observations, thereby increasing the statistical power of the analysis. This is particularly useful when studying factors that affect the performance of e-commerce platforms, as it allows for more robust and reliable results. For example, the impact of a marketing campaign on sales can be evaluated more accurately with a larger data set spanning multiple platforms.

Thirdly, panel data can help solve the problem of endogeneity, which often affects cross-sectional and time-series analysis. Endogeneity happens when the explanatory variables are correlated with the error term, leading to biased and unreliable estimates. In the context of e-commerce platforms, this issue can arise if unobserved factors, like sudden changes in consumer preferences or economic conditions, affect both the independent variables (such as marketing costs or website features) and the dependent variables (like sales or website traffic). Panel data methods, especially fixed-effects and random-effects models, address this problem by accounting for unobserved differences and controlling for variables that change over time. Fourth, panel data helps research study changes over time and understand how things evolve. E-commerce platforms are always changing due to new technologies, shifts in consumer behavior, and changing market conditions. Panel data techniques can capture these changes by including variables that cause delays and by examining the relationships between variables over time. For example, the effect of a website redesign on customer retention may not be immediately apparent but can be seen after a few months. Panel data estimation can model these delayed effects and provide insight into how e-commerce performance changes over time.

In addition, panel data models can handle complex error patterns, such as serial correlation and heteroscedasticity, which are common in real-world data. Serial correlation occurs when errors are related across time periods, while heteroscedasticity refers to changes in error variability across observations. Ignoring these issues can lead to inaccurate estimates. Techniques such as generalized least squares (GLS) and feasible generalized least squares (FGLS) can overcome these problems, resulting in more precise and reliable estimates. In this study, the use of panel data estimation is very useful. The e-commerce industry in Indonesia is growing rapidly and varies greatly between platforms. By using panel data, this study can also control for the unique characteristics of each platform and trends over time, which can help us understand what factors lead to e-commerce success. In addition, panel data allows us to examine the impact of certain events, such as the COVID-19 pandemic, or peak seasons on e-commerce performance. By including variables for specific time periods and events, this study can evaluate how the pandemic has affected consumer behavior and platform performance over time.

Overall, the reasons for using panel data estimation in this study are to better account for differences that are not directly observed, improve estimation accuracy, address endogeneity, capture dynamic effects, and manage complex error patterns. This approach provides a comprehensive and robust framework for analyzing the factors that influence the performance of e-commerce platforms in Indonesia, providing valuable insights for researchers and industry professionals.

3.4.4 Parameter Estimation of Panel Data Regression Model

Panel data analysis can be done in three ways, common effect, fixed effect model method, and random effect model approach. A description of the three methods is:

a. Common Effect Model (CEM)

   The Pooled Least Squares (PLS) method, which aggregates all observations for every variable, can be used to estimate panel data. Since this method is time-invariant, it indicates that there are no variations in any individual over different times, hence all cross-section objects have the same intercepts. (Porter & Gandhi, 2012).

b. Fixed Effect Model (FEM)

   Gujarati (2003) describes the Fixed Effect paradigm as a paradigm that postulates that variances in intercepts might explain individual differences. The fixed effect model estimates panel data with a consistent slope but different intercepts by using a dummy variable strategy. This estimating approach is commonly referred to as the Least Square Dummy Variable (LSDV) method. Dummy variables are added to the LSDV approach in order to estimate and explain the different intercepts.

c. Random Effect Model (REM)

   This model will estimate panel data indicating the possibility of a relationship between disturbance variables over time and across individuals. In the random effects model, the differences in intercepts are accommodated by the error term of each individual. The advantage of using the random effects model is to address heteroskedasticity. This model is also known as the Error Component Model (ECM) or the Generalized Least Square (GLS) method. Including dummy variables in the fixed effects model represents our ignorance about the true model. However, as a consequence of using the fixed effects model, the degrees of freedom decrease, thereby affecting the efficiency of parameters. This issue can be overcome by using the Random Effects method, which involves disturbance variables (error terms). This model will estimate panel data indicating the potential relationship between disturbance variables over time and across individuals (Widarjono, 2013). Due to the correlation between disturbance variables in the random effects model, the OLS method cannot be used to obtain efficient estimators. Therefore, the appropriate method to estimate this model is Generalized Least Squares (GLS) (Widarjono, 2013). The GLS (Generalized Least Squares) method is OLS applied to transformed variables that meet the assumptions of ordinary least squares (Gujarati, 2004). Thus, the estimator obtained through the GLS method is the BLUE (best, linear, unbiased) estimator. Hence, it does not require testing of classical assumptions.

3.4.5 Panel Data Regression Model

Several tests may be performed in order to determine which is best for managing panel data, including:

a. Chow Test

According to Ghozali (2018), the Chow test determines the most appropriate common or fixed effect model for estimating panel data. The basis for decision-making is as follows:

1. If the probability value for cross-section chi-square > 0.05 is significant, then H0 is accepted, so the common effect model is used.
2. If the probability value for cross-section chi-square < 0.05 significant value, then Ha is accepted, so the model used is a fixed effect model.

The following hypothesis guides the execution of this test.

H0: Common Effect Model

Ha: Fixed Effect Model

b. Hausman Test

According to Ghozali (2018), the Hausman test determines which model approach best fits the real data. It will compare two types of approaches: fixed effect and random effect. The following is the basis for decision-making:

1. If the probability value for cross-section random > significant value of 0.05, then H0 is accepted, so the model used is a random effect model.
2. If the probability value for random cross-section <0.05 significant value, then Ha is accepted, so the model used is a fixed effect model.

The following hypothesis is used in this test:

H0: Model of Random Effect

Ha: Model of Fixed Effect

c. Lagrange Multiplier Test (LM Test)

Whether the random effect model is preferable to the fixed effect model depends on which model approach is best determined using the LM test. The following is the basis for decision-making:

1. If the Breusch-Pagan cross-section value > 0.05 significant value, then H0 is accepted, so the common effect model is used.
2. If the Breusch-Pagan cross-section value < 0.05 significant value, then Ha is accepted, so the random effect model is used.

The following is the hypothesis that the LM Test formed:

H0: Common Effect Model

Ha: Random Effect Model

3.4.6 Classical Assumption Test

Testing the traditional assumptions is required once the appropriate model has been identified in the panel data regression equation. In order to ensure that the independent variables are not biased, the classical assumption test is used to assess whether a panel data linear regression model using Ordinary Least Square (OLS) can be used. The conventional assumption tests in this study include the autocorrelation, multicollinearity, heteroscedasticity, and normality tests.

A). Normality Test

The purpose of the normality test is to ascertain if the distribution of each variable is normal. The statistical test is deemed invalid if this assumption is broken, particularly with small sample numbers. A normal or nearly normal distribution characterises a well-designed regression model (Ghozali, 2018). The Jarque Bera test and its probability, which determines whether the data is regularly or abnormally distributed, are used in this study to test for normalcy. The theory that was applied is as follows:

$H0$: Residuals are not normally distributed

$H1$: Residuals are normally distributed

The formula used is:

$$JB = n\left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right] \tag{3.2}$$

With,

JB: Jarque Bera

n: Number of data

S: Skewness coefficient

K: Kurtosis coefficient

In this case, to ascertain whether the data is dispersed normally or abnormally, under the following conditions in particular:

1. The data is normally distributed if the Jarque Bera probability value > 0.05 is significant.
2. The data is not normally distributed if the Jarque Bera probability value < 0.05 significant value.

B). Multicollinearity Assumption

The purpose of the multicollinearity test, according to Ghozali and Ratmono (2018), is to determine whether the regression model discovered a strong or perfect correlation between independent variables. The Variance Inflation Factor (VIF) and tolerance value are used to test for multicollinearity, which helps identify if there are issues with variables being too closely related. The commonly used value indicating the presence of multicollinearity is a tolerance of £ 0.10 or equal to a VIF value of ³ 10 (Ghozali, 2018).

C). Heteroskedasticity Test

The goal of the heteroscedasticity test, according to Hsiao (2014), is to ascertain whether the error variance is the same for each individual caused by time (t) as well as between firms (i). Because this data includes diverse sizes, a useful regression model exhibits Heteroscedasticity or one in which Heteroscedasticity is absent. The heteroscedasticity test, according to Hsiao (2014), consists of two parts:

1. Cross Section Heteroscedasticity

   Sectional View Heteroscedasticity resulting from Company data is known as Heteroscedasticity.

2. Period Heteroscedasticity

   Observed Heteroscedasticity resulting from year (time) data is known as Heteroscedasticity.

3.4.7 Hypothesis Testing

Only some models or equations the computation process generates are suitable for estimating the independent variable. In this instance, the sample regression model's goodness of fit can be used to gauge its accuracy in estimating its true value. The partial test (t-test), statistical F test, and coefficient of determination (R^2) can be used to quantify this test.

a) t-statistic test

A partial test or t-test is used to determine the significance of the effect of each independent variable on the dependent variable. Tests were carried out using a significance level of 1%, 5%, and 10% or alpha = 0.01, 0.05, and 0.1. If the t-test value < 0.01, 0.05, 0.1, the independent variable significantly affects the dependent variable. Conversely, if the p-value > 0.01, 0.05, 0.1, the independent variable has no significant effect on the dependent variable. The hypothesis formula is:

H0 = independent variable has no significant effect on the dependent variable.

H1 = independent variable has a significant effect on the dependent variable

b) Statistical F test (simultaneous)

According to Ghozali (2013), the F test aims to show whether all the independent variables have a simultaneous effect on the dependent variable. If the significance level of F is less than 5% or alpha <0.05, then the effect of the independent variable on the dependent variable has a significant effect simultaneously. Conversely, if the significance level F > 0.05, the effect of the independent variables on the dependent variable has no significant effect simultaneously. The F-test hypothesis formula is as follows:

H0 = independent variable has no significant effect on the dependent variable simultaneously

H1 = independent variable has a significant effect on the dependent variable simultaneously

c) Determination coefficient test (R^2)

The coefficient of determination aims to measure how much the model's ability to explain the independent variables. R2 values range from 0 to 1. The closer to 1, the better the model can explain the independent variable and provide almost all the information needed to predict the dependent variable. Vice versa, if it is close to 0, then the model's ability to explain the independent variable is still limited.

3.5 Operational Variables

3.5.1 Dependent Variables

The following are the dependent variables:

Organic Traffic (Y). The traffic received from unpaid search results. The number of visitors to a website arriving through unpaid search results. This is a key indicator of the effectiveness of a website's SEO strategy.

3.5.2 Independent Variables

The dependent variables are as follows:

a. Organic Keywords (X1)

   User-inputted keywords or search terms associated with the content of the website. the quantity of keywords that search engine results pages (SERPs) show the website as ranking highly for. These keywords increase the website's organic traffic.

b. Organic Traffic Cost (X2)

   This refers to the costs associated with increasing organic traffic, such as SEO strategies and content production. The approximate expense of obtaining an equivalent volume of traffic via sponsored search. This measure aids in determining the importance of organic traffic.

c. Paid Keywords (X3)

   Terms that are tangentially related to organic traffic and are employed in paid marketing. The quantity of terms that the website displays sponsored search ads for. These may have varying effects on organic traffic, but they do contribute to overall visibility.

d. Paid Traffic Cost (X4)

   Investments in paid advertising to increase website traffic. The cost incurred for paid search traffic, which provides insights into the investment in paid search strategies.

e. Dummy Variables

   There are two dummies, which include:

   1. COVID-19 Period: Represents the period affected by the pandemic.
   2. Peak Season Period: Represents peak shopping seasons.

CHAPTER 4

DISCUSSION

4.1 Descriptive Analysis

The results of the data analysis done on the dataset are presented in this chapter. The analysis uses Panel data regression models for both inferential and descriptive statistics. The goal is to comprehend how several predictors, including organic keywords, traffic cost, paid keywords, paid traffic cost, the effect of COVID-19, and peak seasons, relate to organic traffic. The results obtained from panel data models with fixed effects, random effects, and dynamic panel data are thoroughly addressed. Descriptive statistics sums up the main features of the dataset. The table below displays the mean, standard deviation, minimum, and maximum values for every variable in the dataset.

Table 4. 1 Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Obs
Organic Keywords	3296903	2190519	17630	6681951	144
Organic Traffic Cost	3.31e+07	5.85e+07	578248	3.83e+08	144
Paid Keywords	773.0139	679.4739	45	2970	144
Paid Traffic Cost	41524.74	111574.1	263	783108	144
Organic Traffic	8.58e+07	8.27e+07	7647012	3.00e+08	144

Processed by Author (2024)

Based on Table 4.1, the descriptive statistics reveal various insights into the dataset spanning from 2019 to 2022. The following paragraphs explain each variable used in the study, focusing on their mean, standard deviation, minimum, and maximum values. The variable Organic Keywords reflects the number of organic keywords. The average score of organic keywords across the observations is approximately 3296903. The lowest count of organic keywords recorded is 17630, whereas the highest count is 6681951. This demonstrates significant variability in organic keyword usage, as indicated by a standard deviation 2190519. The large range and high standard deviation suggest that the usage of organic keywords fluctuates greatly among different observations, potentially due to varying strategies or resources allocated to SEO efforts over time. The high mean substantial variability in organic keywords indicates that organic keyword strategies vary significantly among entities. This might be the result of variations in SEO spending, content marketing strategies, and industry-specific elements affecting keyword relevancy.

The cost related to organic traffic is measured by the Organic Traffic Cost variable. The price ranges from 578248 at the cheapest to 3.83e+08 at the top, with an average of 3.31e+07. The standard deviation of 5.85e+07, which shows a significant degree of variability in the cost of organic traffic, reflects this wide range of values. This variance can be ascribed to variations in the scope of activities, competitiveness in the market, and evolution of digital marketing tactics over time. It appears that some entities engage considerably in organic traffic optimisation while others spend nothing, based on the large range and high standard deviation of organic traffic costs. Different degrees of market rivalry, different strategic priorities, or disparities in how companies value their efforts in organic traffic could all have an impact on this disparity.

The average amount of paid keywords utilised is 773.0139, according to data on keywords. A minimum of 45 sponsored keywords and a maximum of 2970 are shown in the data, with a standard deviation of 679.4739. This implies that the paid keywords used in the observations varied significantly. The fluctuations in the use of sponsored keywords may be influenced by campaign goals, budgetary restrictions, and the changing environment of paid search advertising. The considerable spread in the number of paid keywords indicates diverse paid search advertising approaches. Organisations may alter their keyword usage in response to financial limitations, campaign objectives, or shifts in the long-term efficacy of sponsored search tactics.

The average value of the Paid Traffic Cost variable, which accounts for the expenses related to paid traffic, is 41524.74. The fees show a wide variation of paid traffic charges, with a minimum of 263 and a maximum of 783108, together with a large standard deviation of 111574.100. This broad range illustrates the varied paid traffic campaign sizes and intensities that different businesses performed during the study period. The vast range of paid traffic expenses is indicative of the various paid advertising campaign sizes. Some entities may allocate significant resources to paid traffic, while others may adopt more conservative spending strategies, resulting in substantial cost variability.

For Organic Traffic, the organic traffic numbers reveal an average value of 8.5e+07. The minimum value observed is 7647012, while the maximum value is 3.00e+08. The standard deviation is 8.27e+07, suggesting that the data points are spread widely around the mean. This wide dispersion indicates that some entities experienced significantly higher organic traffic, possibly due to successful SEO strategies, content quality, or brand popularity. The large dispersion in organic traffic highlights the varying success levels of different entities in attracting organic visitors. Content quality, SEO effectiveness, brand recognition, and industry dynamics likely contribute to this variability.

4.2 Current Situation

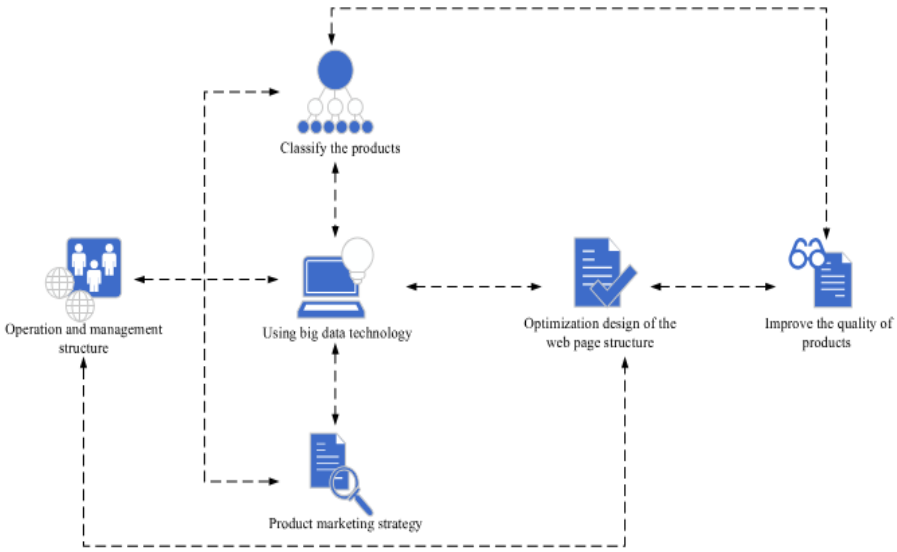
4.2.1 E-commerce Development in Indonesia

E-commerce has become a major industry in Indonesia, growing rapidly in recent years. This growth is driven by more people using mobile internet, government support for e-commerce, and the overall rise in the country's digital economy. Recent data shows that Indonesia's online retail sector was worth $53 billion in 2021, with a yearly growth rate of 49%, according to a report from Google, Temasek, and Bain & Company. The report also predicts that by 2025, Indonesia's e-commerce sector will reach a value of $104 billion, continuing to be a leader in the digital economy (Jayani, 2021).

The widespread use of mobile internet in Indonesia is a key reason for the country's growing e-commerce activity. According to research by the Asosiasi Penyelenggara Jasa Internet Indonesia (APJII), with over 200 million users in 2022 more than 77% of the country's population Indonesia has one of its highest percentages of internet users in a long time (APJII, 2022). E-commerce businesses play a significant role in this evolution. The growth of social media platforms like Instagram, Facebook, and WhatsApp has also made it easier for e-commerce businesses to market their products and connect with potential customers. Even if e-commerce has grown significantly in Indonesia, there are still a lot of obstacles to the sector's development. A major obstacle that the Indonesian e-commerce industry needs to overcome is people's mistrust of the security of online transactions. Trust and security are factors that influence consumers' decisions to make purchases in the marketplace, according to research by Agustiningrum and Andjarwati (Agustiningrum & Andjarwati, 2021).

Even with its difficulties, Indonesian e-commerce still has a lot of potential. One of the main potentials is the government's dedication to developing e-commerce throughout the country. The rise of e-commerce is being encouraged by the Indonesian government, which has realised its importance for the country's digital economy. In 2021, the government unveiled the e-Commerce Roadmap for 2021–2024 with the intention of creating an environment that will facilitate the expansion of e-commerce throughout the country (Rizkinaswara, 2021). The agenda includes projects like increasing digital literacy, improving infrastructure, and providing incentives to e-commerce businesses. For e-commerce businesses to establish a suitable structure for product management, they must classify products according to particular product kinds, make full use of big data technologies, and create product marketing plans to cater to various customer demands. Because design management is so convenient, e-commerce businesses may plan their operations and management structure, optimize their web structure, and make it easier for customers to make decisions. However, when it comes to product design, e-commerce businesses prioritize how their offerings may enhance and improve the customer experience. As seen in Figure 1, this can raise the product's quality and increase its marketability.

Figure 4. 1 Developing a sensible structure for product management



Source: Ma & Gu (2024)

A product's architecture develops gradually over time. Businesses essentially don't discuss product architecture in the early phases of digitization, or it's limited to distinct systems. Business lines are closely controlled by the product department's management, and they each grow separately and in a somewhat closed environment. The following are the fundamentals of product architecture (Ma & Gu, 2024):

(1) Guarantee the product architecture's scalability.

(2) Ensure that it is extremely abstract and standardized.

(3) Define boundaries clearly within the product architecture.

(4) Take the product matrix relationship network into consideration.

4.2.2 Comparative Analysis of E-commerce Platforms

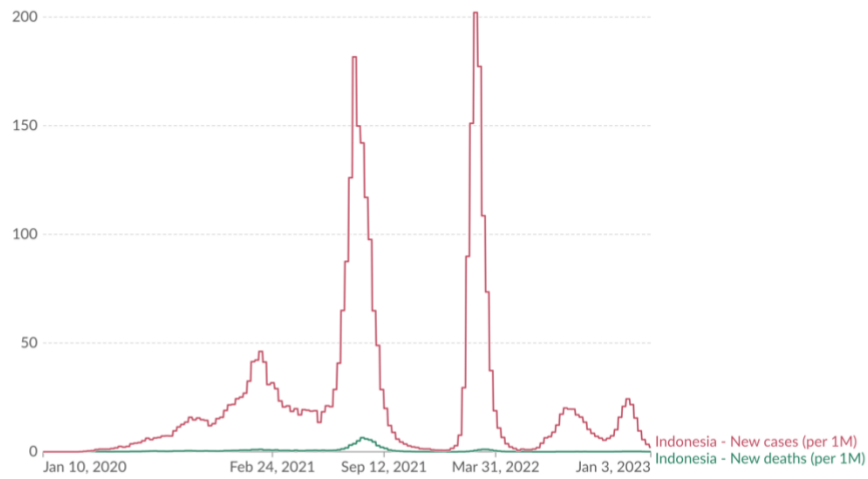
Research by Tinambunan (2019) covers assessing the quality level of the Shopee and Lazada sites using the Webqual 4.0 technique and descriptive statistics and analysing differences in quality on the two sites. Three-dimensional Webqual methods of information quality, interaction, and use are used in this study. Respondents who use Lazada and Shopee in Jakarta provided the data. The Shopee website has an average score of 43.22%, while Lazada has an average score of 37.69%. Based on the statistics, it can be said that both of these websites fall into the good category. For Lazada, the quality of use variable is the sole variable that affects customer happiness; however, for Shopee, all three of the examined variables had an impact on customer satisfaction.

In addition, a study conducted by Suwasono (2020) examined how marketing stimulus, individual characteristics, and the decision-making process influence consumers' online purchases of Tokopedia. Data was collected using interviews and observation techniques through purposive sampling. A qualitative descriptive approach involves analyzing the data through reduction, display, and conclusion drawing. The results show that factors such as ease of access to goods, positive product reviews, and brand loyalty influence consumers' decisions to shop on Tokopedia. In addition, consumers tend to try new brands with positive reviews if they offer better products.

4.2.3 COVID-19 and Peak Season

The current research aims to understand the impact of various factors on organic website traffic, especially during crucial periods such as the COVID-19 pandemic and the peak season. The following is a detailed analysis of COVID-19 trends in Indonesia based on data from the Our World in Data Coronavirus Data Explorer. In this figure, the rolling average is seven days. Limited testing and challenges in attribution of cause of death mean the number of cases and deaths may not be accurate. On the figure, analyze the COVID-19 trend in Indonesia from January 1, 2020, to January 2023. The peak of the highest number of new cases was July 2021. Indonesia experienced the highest number of new cases in July 2021. This period marks the peak of the Delta variant wave, which caused a significant surge in infections. The healthcare system faced enormous pressure due to the high number of hospitalizations. Next for the highest number of new deaths is during the July-August 2021 peak. In line with the surge in new cases, the number of new deaths peaked around July to August 2021. The high mortality rate during this period can be attributed to the severe impact of the Delta variant and the pressure on medical facilities.

Figure 4. 2 Daily new confirmed COVID-19 cases and deaths per million people in Indonesia



Source: Our World in Data (2024)

The lowest number of new cases was in April 2020. There weren't many new cases in the early phases of the pandemic. The lowest number of new deaths in April and May 2020 can be linked to the early implementation of lockdown measures and limited testing to stop the virus's spread. In the early stages of the pandemic, there were not as many new deaths as there were new cases. The decreased numbers within this time frame are a result of the outbreak's early interventions and limitations. Due to the Delta variation, there were many waves of COVID-19 cases and fatalities that peaked around January 2021 and again in mid-2021. The overall trend of COVID-19 cases and deaths revealed a considerable increase starting in mid-2020. After a slow start in late 2021 and with occasional upswings, the fall lasted until 2022.

After reaching a peak in July 2021, the number of new cases started to trend downward, with a notable reduction taking place in late 2021 and early 2022. This can be attributed to higher vaccination rates and stricter public health regulations.

Following a peak in mid-2021, there was a reduction in both mortality and new deaths, with a notable decline towards the end of 2021 and lower levels continuing into 2022. This decline was due to better healthcare responses and improved treatment methods. Due to the Delta variants' greater transmission rates and severity, there was a sharp rise in cases and fatalities as well as their rapid emergence and spread. The healthcare system was overwhelmed during peak periods, leading to higher mortality rates. Mass vaccination efforts significantly contributed to the decline in severe cases and deaths. By the end of 2021, most of the population had received at least one dose of vaccine. Continued enforcement of health protocols, social distancing, and periodic lockdowns helped control the spread of the virus. So based on this data, this research was conducted in 2019, when COVID-19 had not started in Indonesia until 2022. 2022 is the decline of COVID-19 in Indonesia.

The COVID-19 pandemic accelerated digitalization, transformed the economy, and shaped consumer behaviour in the long run. The virtual landscape is becoming a saviour for many, driving innovation and adaptation in various sectors (Kirana, 2022). Understanding these dynamics is crucial for businesses to adjust their digital marketing strategies effectively. According to SocialPilot (2023) and AMW Group (2023), organic keywords are integral to search engine optimization (SEO) as they significantly enhance website visibility on search engine results pages (SERPs) and attract high-quality organic traffic. This traffic is cost-effective, highly relevant, and engages users effectively (Hardwick, 2021). The primary costs of generating organic traffic include keyword research, content creation, and technical SEO optimization (AMW Group, 2023; Hardwick, 2021), contributing to long-term cost-effectiveness and increased brand credibility (SocialPilot, 2023).

Research on paid keywords can significantly impact organic traffic by increasing brand awareness and presence in search engines. According to a study by Adlucent (2024), paid search advertising increases brand exposure, leading to higher brand recall and consideration. This increased awareness often results in more clicks on organic listings when users come across the brand again, thus improving organic search rankings and performance. Similarly, McGinley (2022) notes that running paid search campaigns can defend against competitors and drive higher overall website traffic. This is because paid advertising ensures visibility at the top of search results, complementing organic search efforts by creating a more prominent and repeatable presence on search engine results pages (SERPs). Charlie (2024) also highlights that combining paid and organic search strategies can optimize results, as the immediate impact of paid campaigns helps amplify and accelerate the benefits of organic SEO efforts over time.

According to Torkington (2021), the COVID-19 pandemic has permanently changed consumer behaviour. Many consumers are turning to online purchases, especially due to restrictions and the fact that they are working from home. Smartphone usage for online shopping has more than doubled since 2018. The peak season remains a critical period for online retailers. Organic traffic and sales experience significant fluctuations during this season. Consumers tend to look for the best prices, choose healthier options, and shop locally when possible. The impact on the e-commerce industry shows that changes in consumer behaviour during the pandemic have affected the e-commerce industry. Sales through online platforms continue to grow, while some industries have seen a decline in sales due to restrictions that keep people at home and shopping online. (Brewster, 2022). Consumers do not plan to return to how they shopped before the pandemic. These changes require online retailers to adapt and constantly understand the ever-changing consumer preferences.

In order to secure their survival, expansion, and advancement in today's quickly changing digital world, organizations are progressively adopting digital entrepreneurship, according to Alshaar (2023). The increased flexibility offered by digital technologies in coordinating various phases of company operations has led to the rise of the notion of digital business models. With the use of digital tools and the provision of digital products and services, digital entrepreneurship transcends traditional entrepreneurship. Information technology is crucial to corporate transformation in the digital age, claims Harto (2023). Information technology enhances consumer satisfaction, fosters product innovation, and increases operational effectiveness. This report also provides solutions and identifies challenges in the process of digital transformation. This study will use statistical modelling and quantitative analysis to look at these characteristics in the current setting and find out how the variables relate to organic traffic.

Peak seasons, i.e. major shopping events such as Black Friday and Cyber Monday, or major holidays, are particularly important for online merchants due to the large spikes in customer activity and spending. Online traffic increases significantly during these periods as people are more actively looking for deals, products and services. This increase in activity can have a significant impact on organic search traffic as people search for specific products, evaluate prices, and make purchase transactions. A business must also understand how organic search traffic varies during high-traffic periods to make the most of their SEO efforts and attract as many visitors or customers as possible. In addition, a business must maintain high search engine rankings during these times in order to compete on increasingly fierce search engines to attract and convert customers efficiently. In this case, "visibility" refers to the ease with which consumers can find a website when using search engines like Google to search for information, goods, or other services. When a website is highly visible, it shows up first in search results, increasing the likelihood that people will click through and visit it. In other words, good visibility increases the likelihood of a website attracting more organic visitors (without paid advertising).

4.3 Data Collection Method on SEMrush

The following are the functions of the Data Collection and processing methodology in SEMrush:

3. Monthly Data Collection

   Data on organic and paid keywords, organic and paid traffic costs, and organic traffic counts were collected monthly. This data was download from SEMrush and stored in spreadsheet format for further analysis.

2. Data Merging

   Monthly data from each e-commerce platform was merged into the one-panel dataset. This dataset includes time (month) and platform (Shopee, Tokopedia, Lazada) variables as panel entities.

3. Data Preprocessing

   Data cleaning was performed to remove missing or anomalous data. Irrelevant or duplicate data was also removed.

4. Descriptive Statistics

   Descriptive statistics for each variable were calculated to understand the data distribution. Data visualizations such as line graphs and histograms were used to spot trends and patterns.

5. Data Validation and Reliability

   a. Cross-Verification

      Verifying SEMrush data with the internal data of the e-commerce platforms if available.

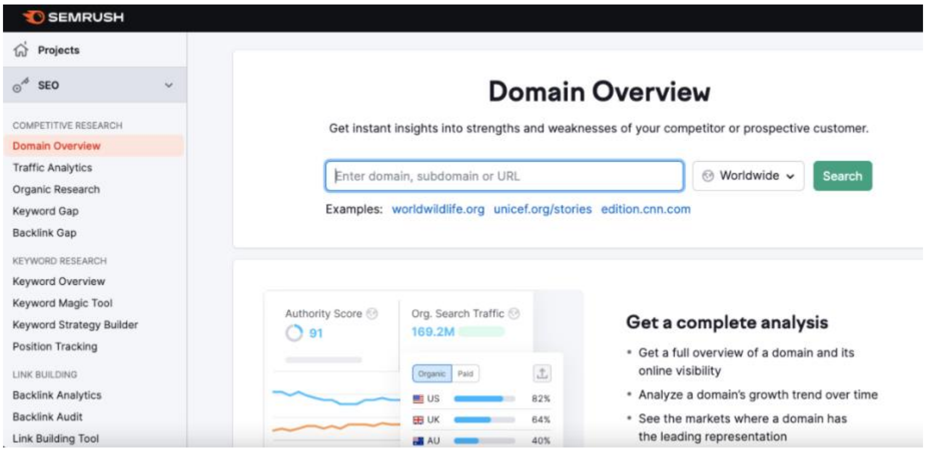
b. Consistency Check

Ensuring data consistency by conducting repeated sampling at different intervals.

6. Benchmarking

Comparing SEMrush data with other similar data sources to ensure accuracy. The following are the steps to retrieve Organic Keywords, Organic Traffic Cost, Paid Keywords, Paid Traffic Cost, and Organic Traffic data for Shopee, Tokopedia, and Lazada on the SEMrush website. First, open the semrush.com website and then log in; after the login is complete, the initial page will appear as shown below:

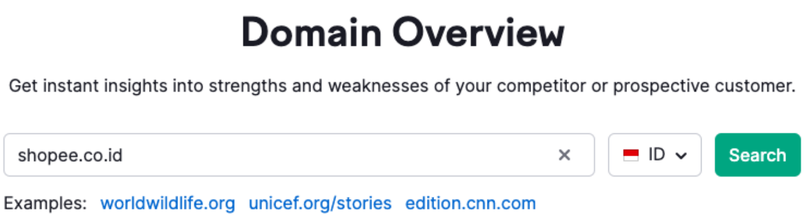
Figure 4. 3 Initial page view in SEMrush after login



Processed by Author (2024)

After that, continue to write what website if want to search, for this research, first write shopee.co.id as shown below:

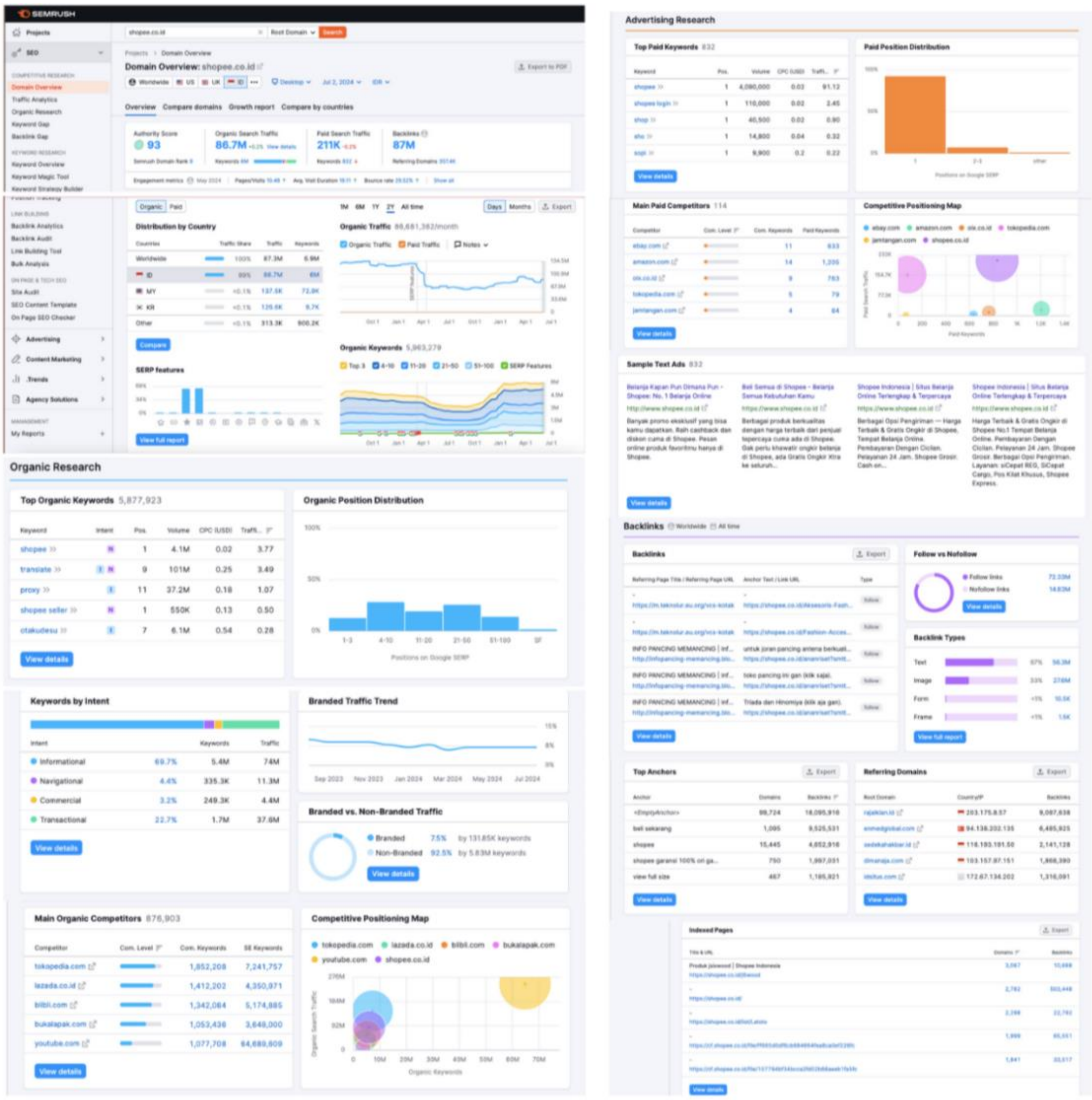
Figure 4. 4 Domain Overview



Processed by Author (2024)

After which the display appears as below:

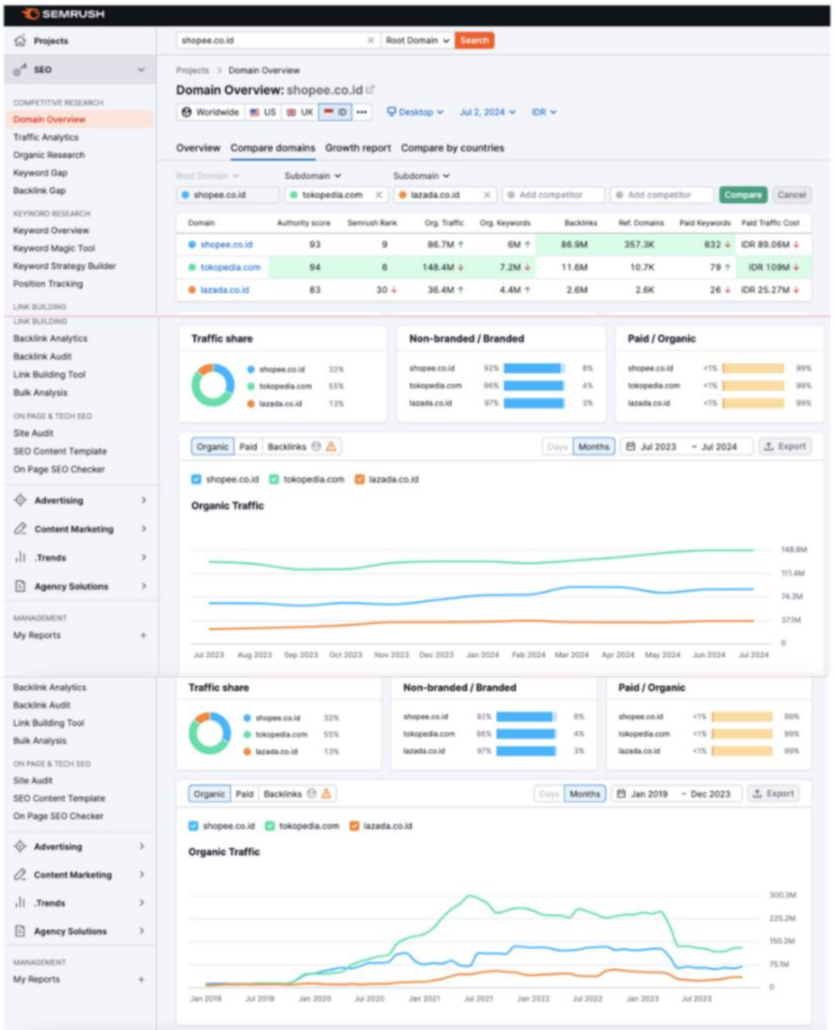
Figure 4. 5 Home page view in SEMrush



Processed by Author (2024)

After this page appears, then compare domains. The domains used are Shopee, Tokopedia, and Lazada; after that, change to IDR. After that, can see the Authority score, SEMrush rank, Organic Traffic, Organic Keywords, Backlinks, Referring Domains, Paid Keywords, Paid Traffic Cost.

Figure 4. 6 Home page Domain Overview in SEMrush



Processed by Author (2024)

4.4 Determining the Model in Panel Data Regression

Researchers ran a number of model specification tests to find the optimal model for panel data testing. The best panel data regression model, either the Random Effect Model (REM), the Fixed Effect Model (FEM), or the Common Effect Model (CEM), is chosen for testing. The Chow Test and the Hausman Test make up this exam.

4.4.1 Chow Test

This test is conducted to determine which model is the best between CEM and FEM to be used in regression. The Chow test has the following hypothesis:

H0: Pooled least square model
H1: Fixed Effect Model

If the probability value is greater than the significance level α = 5% or 0.05 then H0 is chosen so that this study uses the CEM and there is no need to do the Hausman test. However, if the probability value is smaller than the significance level α = 5% or 0.05 then this research model uses the FEM and needs to do the Hausman Test. The following are the Chow Test results:

Table 4. 2 Chow Test Table

Chow Test	0.0000

Processed by Author (2024)

The Chow Test results in Table 4.2 show a probability value of 0.0000, this value is smaller than the significance level of 0.05 (0.0000 < 0.05). Based on this, H1 is selected. This means that the most appropriate model to use is the Fixed Effect Model compared to the Common Effect Model. Because the Chow Test results show that the more appropriate model to use is the Fixed Effect Model, a Hausman Test is needed to see which model is more appropriate to use between the Fixed Effect Model and the Random Effect Model.

4.4.2 Hausman Test

This test is conducted to determine which model is the best between FEM and REM to be used in regression. The Hausman test has the following hypothesis:

H0: Random Effect Model
H1: Fixed Effect Model

If the probability value is greater than the significance level α = 5% or 0.05 then H0 is chosen so that this study uses REM. However, if the probability value is smaller than the significance level α = 5% or 0.05 then this research model uses FEM. The following are the Hausman Test results:

Table 4. 3 Hausman Test Table

Hausman Test	0.0000

Processed by Author (2024)

The Hausman Test results in Table 4.3 show a probability value of 0.0000, which is highly significant at any level of significance (1%, 5%, 10%). With a p-value of 0.000, the correct model selection is the fixed effects model, because the Hausman Test results show that there is a significant difference between the fixed effects and random effects model estimates, and the fixed effects model is more suitable for this data.

4.4.3 Lagrange Multiplier Test

If the Chow test results choose the OLS model and the Hausman test chooses the Random Effect model, then the Lagrange Multiplier test is used to choose between OLS and Random Effect. The statistical hypothesis for this test is as follows:

H0: Pooled least square model

H1: Random Effect Model

Based on the output, the Probability of Chi Square is 1.0000 which means this data does not have enough evidence to reject the null hypothesis, which states that the variance of the random effect is not significantly different from zero. The following are the results of the Lagrange multiplier test:

Table 4. 4 Lagrange Multiplier Test Table

Prob>chi^2	1.0000

Processed by Author (2024)

4.5 Classical Assumption Test

Ensuring the validity and reliability of the derived coefficients is essential for panel data analysis. This dependability depends on the regression models' underlying classical assumptions being followed. These assumptions include no autocorrelation, consistent variance (homoscedasticity), linear relationships, and no perfect multicollinearity. To ensure our model is reliable, we need to check for and address any issues by performing traditional assumption tests. This section details the various assumption tests we used for analyzing panel data from Indonesian e-commerce sites like Shopee, Tokopedia, and Lazada. These tests are essential for confirming that our estimation results are both effective and consistent.

4.4.1 Heteroscedasticity Test

When the variance of the errors in a regression analysis is not consistent across all levels of the independent variables, this situation is known as heteroscedasticity. Violation of this homoskedasticity assumption can result in ineffective estimations, jeopardize the validity of statistical tests, and produce unreliable conclusions. It is imperative to address heteroscedasticity when examining e-commerce sites such as Shopee, Tokopedia, and Lazada to guarantee the veracity and robustness of the results. To improve the reliability of the regression model, it is important to identify and address heteroscedasticity. The results of the heteroscedasticity test show a p-value of 0.0000, indicating that there is heteroscedasticity. heteroscedasticity in this model. This means that the error variance (residuals) is not constant and varies with the level of the predictor. This heteroscedasticity can cause problems in the estimation of regression coefficients, such as making the estimated standard errors invalid, so the results of the t-test and F-test can be unreliable.

4.4.2 Multicollinearity Test

When two or more predictor variables in a regression model are highly correlated with each other, it is called multicollinearity. This can make it difficult to determine the individual effect of each variable. Reliable results in the analysis of e-commerce platforms such as Shopee, Tokopedia, and Lazada depend on an understanding of and attention to multicollinearity. Accurate conclusion-making can be hampered by multicollinearity, which can lead to inflated standard errors and shaky coefficient estimations. The outcome of the multicollinearity analysis is shown below:

Table 4. 5 Multicollinearity Test

Variables	VIF
Organic Keywords	3.43
Organic Traffic Cost	2.85
Paid Keywords	1.80
Paid Traffic Cost	1.45
Mean	2.38

Processed by Author (2024)

If the tolerance value (1/VIF) > 0.10 and the VIF value < 10, then there are no symptoms of multicollinearity (passes the multicollinearity test). From the table above, it can be seen that the VIF value of variable Organic Keyword is 3.43 < 10, then the value of variable Organic Traffic Cost is 2.85 < 10, then the value of variable Paid Keywords is 1.80 < 10, and the value of variable Paid Traffic Cost is 1.45 < 10, so it can be concluded that there are no symptoms of multicollinearity (passes the multicollinearity test).

4.4.3 Autocorrelation test

The results of this test indicate the presence of first-order autocorrelation in the panel data analyzed. With an F-statistic of 31.940 and a p-value of 0.0299, which is significant at the 5% significance level, the null hypothesis of no autocorrelation is rejected. This means that the residuals in the model are not fully independent and show a recurring pattern from one period to another. This kind of autocorrelation can cause the regression coefficient estimates to be inefficient and the standard errors to be biased, which may result in inaccurate statistical conclusions.

4.5 Model Estimation Result

4.5.1 The Fixed Effect Model

In panel data analysis, choosing the right model is very important to ensure the accuracy and validity of the estimation results. Based on the Hausman test that has been conducted, the fixed effects model (FEM) is chosen as the best model for this analysis. The fixed effects model is able to control for heterogeneity between individuals by assuming that differences between cross-sectional units are fixed and can affect the dependent variable. Therefore, the estimation results of this model provide a more accurate picture of the relationship between variables in the panel data analyzed. The results of the base model estimation are presented in the table below:

Table 4. 6 Baseline Model Table

Variables	FEM
LOGX1	0.2452434*** (0.000)
LOGX2	0.3063764*** (0.000)
LOGX3	-0.2052338*** (0.000)
LOGX4	0.0384277 (0.136)
COVID	0.0681493 (0.309)
Peak Season	0.0662373** (0.030)
cons	4.379407
R^2	0.8778
Prob F sig	0.0000

***p < 0.01 (significant at 1% level), **p < 0.05 (significant at 5% level), *p < 0.10 (significant at 10% level)
Processed by Author (2024)

On Organic Keywords, with a coefficient of 0.245, these results indicate that a 1% increase in organic keywords is associated with approximately 0.245% increase in product search behavior. The significant p-value of 0.000 confirms that this positive relationship is statistically significant at the 1% level, implying that expanding the reach of organic keywords substantially increases the likelihood of consumers finding the products they are looking for. On Organic Traffic Costs, with a coefficient of 0.306, the result suggests that a 1% increase in organic traffic costs is associated with a 0.306% increase in product search behavior. This positive and significant relationship, with a p-value of 0.000, indicates that higher investments in organic traffic significantly improve the chances of consumers finding the desired products. In Paid Keywords, the coefficient of -0.205 shows that a 1% increase in the use of paid keywords is associated with approximately a 0.205% decrease in product search behavior. The negative coefficient, coupled with a significant p-value of 0.000, suggests that an increase in paid keywords diminishes the likelihood of consumers finding the products they are searching for.

For Paid Traffic Costs, the coefficient of 0.038 implies that a 1% increase in paid traffic costs results in a modest 0.038% increase in product search behavior. However, the p-value of 0.136 indicates that this effect is not statistically significant, meaning that changes in paid traffic costs do not have a meaningful impact on product search behavior in this model. Regarding the COVID-19 variable, with a coefficient of 0.068, the result suggests that the presence of COVID-19 is associated with a 0.068% increase in product search behavior. However, the p-value of 0.309 indicates that this effect is not statistically significant, suggesting that the COVID-19 pandemic did not significantly alter product search behavior according to this analysis. For the Peak Season variable, with a coefficient of 0.066, the result indicates that during peak seasons, there is a 0.066% increase in product search behavior. The significant p-value of 0.030 shows that this effect is statistically significant at the 5% level, indicating that peak seasons significantly enhance the likelihood of consumers finding the products they are looking for. Finally, the R-squared value of 0.8778 suggests that approximately 87.78% of the variation in the dependent variable (product search behavior) can be explained by the independent variables in the model. The Prob > F value of 0.0000 indicates that the model as a whole is highly significant, implying that the independent variables jointly have a strong and significant impact on product search behavior.

4.5.2 Driscoll and Kraay Standard Errors

One of the issues that frequently arises in panel data analysis is the existence of cross-correlation, autocorrelation, and heteroscedasticity across cross-sectional units. These circumstances may lead to biased and inefficient standard error estimations, which would reduce the precision of the findings from statistical tests. The Driscoll and Kraay standard errors methodology is employed as a corrective technique to get around this issue. By estimating standard errors that are resistant to heteroscedasticity, autocorrelation, and cross-correlation across units, the Driscoll and Kraay standard errors addresses all three issues. Tsopmo et al. (2022) emphasized that this technique not only considers differences between groups, but also handles variations in the relationships between variables and takes into account the interrelationships among variables within each group.

In addition, the Driscoll and Kraay estimator is able to handle missing data and imposes no restrictions on the change in the number of individuals over time. It also offers a non-parametric variance-covariance matrix that produces consistent and robust standard errors, even in the presence of dependence between cross-sectional units. As such, it provides more reliable and unbiased coefficient estimates, overcoming the limitations found in other large-scale covariance matrix estimation techniques (Hoechle, 2007; Gehring et al. 2017). This method increases the reliability of the model estimate results and the trustworthiness of the statistical inference, particularly when dealing with panel data that spans a lengthy time period and has a large number of cross-sectional units. This study uses Driscoll and Kraay standard errors to make sure that all statistical conclusions are reliable and resilient to a range of issues that frequently arise with panel data.

4.5.3 Final Estimation

As part of the final stage in this analysis, the following are the final estimation results using the Fixed Effects model with Driscoll & Kraay standard errors. This approach was chosen to ensure that the estimates are free from autocorrelation, heteroscedasticity, and cross-correlation among cross-sectional units that often compromise the validity of results in panel data analysis. Using this model seeks to obtain the most accurate results, which will provide deeper insights into the influence of key variables on the dependent variable in the context of this study. Below are the final estimation results that integrate the necessary corrections to ensure validity and reliability:

Table 4. 7 Final Estimation

Variables	D&K Model FEM
LOGX1	0.2452434* (0.053)
LOGX2	0.3063764* (0.056)
LOGX3	-0.2052338* (0.077)
LOGX4	0.0384277 (0.487)
COVID	0.0681493 (0.437)
Peak Season	0.0662373 (0.254)
cons	4.379407
R^2	0.8778
Prob F sig	0.0048

***p < 0.01 (significant at 1% level), **p < 0.05 (significant at 5% level), *p < 0.10 (significant at 10% level)
Processed by Author (2024)

Considering the outcomes in the preceding table, in the LOGX1 coefficient of 0.245 (p-value 0.053) indicates that a 1% increase in organic keyword usage increases organic traffic by 0.245%, significant at the 10% level (*). Next is the coefficient for LOGX2 is 0.306 (p-value 0.056) indicates that a 1% increase in organic traffic costs leads to a 0.306% increase in organic traffic, significant at the 10% level (*). This suggests that as businesses invest more in optimizing organic traffic, possibly through better SEO practices or content improvements, they successfully attract more visitors who find their products through organic search. In LOGX3, the coefficient -0.205 (p-value 0.077) indicates that a 1% increase in the use of paid keywords can lead to a 0.205% decrease in organic traffic, which is also significant at the 10% level (*). This negative relationship may imply that heavy reliance on paid keywords may overshadow organic traffic, as users may prefer to click on paid ads, or may reduce the perceived authenticity of organic search results. Although this finding is not statistically significant, the coefficient of 0.038 (p-value 0.487) on LOGX4 indicates that a 1% increase in the cost of bought advertising can result in a 0.038% increase in organic traffic.

Although the impact is too modest to be conclusively determined, this slight rise might be the result of a spillover effect, where users who interact with sponsored ads first subsequently return through organic search. Showing a coefficient of 0.068 (p-value 0.437) on COVID-19, the data shows that during the COVID-19 era, organic traffic increased by 0.068%. While this increase is in line with the general shift towards online shopping during the pandemic, the effect is not statistically significant in this model, which suggests that the impact may be more complex or influenced by other factors. The coefficient of 0.066 (p-value 0.254) indicates that organic traffic increased by 0.066% during peak seasons, but this effect isn't statistically significant. The slight increase likely reflects higher consumer activity during major shopping periods, although it wasn't strong enough to show a clear impact when considering other variables in the analysis. The R^2 value measures how well the regression model explains the variability of the observed data. In the D&K FE model, the R^2 value is 0.8778, indicating that about 87.78% of the variation in organic traffic can be explained by the independent variables in the model. The probability for the overall model indicates whether the model is statistically significant. In the D&K FE model, the probability is 0.0048, which is less than the significance level of 0.05, indicating that the model is significant overall.

4.7 Discussion

4.7.1 Relationship Between Organic Keywords and Organic Traffic

In the context of e-commerce, particularly within the Indonesian market, the relationship between organic keywords and organic traffic is crucial for understanding how consumers find products online. Organic keywords refer to the specific words or phrases that users input into search engines, which then lead them to discover relevant websites through non-paid, or "organic," search results. The effectiveness of these keywords directly impacts the volume of organic traffic a website receives, which is critical for e-commerce platforms like Shopee, Tokopedia, and Lazada. A simpler daily term and marketing relevance, organic keywords are like "magic words" that help consumers find what they are looking for on the internet without the influence of paid advertising. For example, if someone searches for "cheap smartphones in Jakarta," the exact words used in this search are organic keywords. If an e-commerce platform has optimized its content with these keywords, it will most likely appear higher in search results, driving more visitors to its site. This increase in traffic is not just a number, but also means potential sales and greater visibility, which is crucial to maintaining competitiveness in a crowded online marketplace.

From a broader economic perspective, especially in an emerging digital economy like Indonesia, the strategic use of organic keywords has significant implications. As e-commerce continues to grow, the ability for businesses to attract organic traffic without incurring the costs associated with paid advertising is crucial for sustainable growth. This is especially important for small and medium-sized enterprises (SMEs) that may not have the large marketing budgets of larger companies. By effectively utilizing organic keywords, these businesses can level the playing field, reach customers more efficiently and contribute to a more competitive market landscape. In economic terms, the relationship between organic keywords and organic traffic can be viewed through the lens of consumer surplus and producer surplus.

When consumers find products through organic search results, they often do so with greater efficiency, reducing the time and effort spent searching. This increases consumer surplus, as they get more benefits from the search process at no additional cost. On the other hand, producers (or businesses) benefit from higher producer surplus due to the lower costs associated with acquiring traffic organically rather than through paid advertising. This can increase profit margins, which can be reinvested to further optimize the business, expand product offerings, or improve service quality, thus increasing overall economic productivity.

4.7.2 Effect of Paid Keywords on Organic Traffic

In the context of e-commerce, especially in Indonesia's fast-growing digital market, the interaction between paid keywords and organic traffic is an important aspect of online marketing strategy. Paid keywords are keywords that businesses bid for on search engines such as Google to have their ads appear prominently in search results. These ads usually appear at the top or bottom of search results, marked as "sponsored" or "ads". The goal is to attract immediate attention and drive traffic to the website, but the relationship between paid keywords and organic traffic is more nuanced.

In daily terms, paid keywords can be thought of as a business paying for a fast pass to the front of the line. When a business pays for certain keywords, like "best running shoes Jakarta," it ensures that their website appears prominently when someone searches for those terms. However, while paid keywords can drive traffic quickly, there's an ongoing debate about their impact on organic traffic the visits a website gets without paying for ads. Sometimes, an over-reliance on paid keywords can actually reduce organic traffic if users begin to associate the brand more with paid ads rather than finding it naturally in search results. In marketing, this balance is crucial: overuse of paid keywords might overshadow a brand's organic presence, potentially leading to a dependency on paid traffic, which can be costly in the long run.

From a broader economic perspective, the use of paid keywords can be both a boon and a challenge for businesses, especially in a competitive e-commerce environment like Indonesia's. On one hand, paid keywords provide an immediate influx of traffic, which can lead to quick sales and rapid market penetration. This is particularly beneficial for new businesses or those launching new products. However, the costs associated with paid advertising can be substantial, particularly in highly competitive sectors where the most valuable keywords can be expensive. For small to medium-sized enterprises (SMEs), this can strain their marketing budgets, leading to a reliance on paid traffic that may not be sustainable in the long term. In contrast, maintaining a strong organic presence can reduce these costs and lead to more sustainable growth.

In economic terms, the relationship between paid keywords and organic traffic can be analyzed through the concepts of **marginal cost** and **marginal revenue**. Each additional dollar spent on paid keywords represents a marginal cost, and the traffic or sales generated by that investment is the marginal revenue. Ideally, businesses aim for a balance where the marginal cost of acquiring traffic through paid keywords is less than or equal to the marginal revenue generated from that traffic. However, if the use of paid keywords starts to cannibalize organic traffic, the overall return on investment (ROI) may diminish over time. This is because the cost of maintaining paid traffic can exceed the benefits if it begins to replace organic traffic that would otherwise be free. Additionally, businesses must consider the **opportunity cost** of investing heavily in paid keywords over strategies that might enhance organic search rankings, which could provide a more sustainable and cost-effective source of traffic in the long term.

4.7.3 Impact of Paid Traffic Cost on Organic Traffic

In daily terms, paid traffic costs are the money businesses spend to get more people to visit their website through ads. For example, when a company pays for a banner ad on a popular website or a sponsored post on Instagram, that's paid traffic. The question then arises, does spending more on paid ads reduce the number of people who find the website organically, meaning through non-paid search results? In some cases, heavy spending on paid traffic might overshadow the natural discovery of the brand, leading consumers to associate the brand more with ads than with quality or relevance. From a marketing perspective, this is a delicate balance, overspending on paid traffic could potentially harm organic traffic by reducing the brand's perceived authenticity or by making it overly dependent on paid channels for visibility.

From a broader economic perspective, the impact of paid traffic costs on organic traffic can influence the overall health of a business and the e-commerce sector at large. When businesses heavily invest in paid traffic, they may achieve quick visibility and short-term sales boosts. However, this strategy might not be sustainable if it leads to a decline in organic traffic, which is often more cost-effective in the long run. For smaller businesses or those with limited marketing budgets, the high cost of maintaining paid traffic can divert resources away from other critical areas, such as improving the customer experience or investing in organic SEO strategies. In the context of Indonesia's growing digital economy, a heavy reliance on paid traffic can exacerbate disparities between large corporations with significant marketing budgets and smaller players who struggle to compete. This could lead to a less competitive market, where only those who can afford high paid traffic costs dominate, potentially stifling innovation and reducing consumer choice.

In economic terms, the relationship between paid traffic costs and organic traffic can be analyzed through the concept of **diminishing returns**. Initially, increasing paid traffic costs might lead to a significant boost in overall traffic and sales. However, as spending continues to rise, the additional benefit of each dollar spent may start to decrease, especially if it begins to cannibalize organic traffic. This phenomenon is particularly relevant in highly saturated markets, where the cost of acquiring traffic through paid channels becomes prohibitively expensive, while the marginal gain from additional traffic decreases. Another key economic concept is **cost-benefit analysis**. Businesses need to evaluate whether the benefits of increased paid traffic justify the costs, especially if these costs are reducing the effectiveness of organic traffic, which is generally less expensive to maintain. If the paid traffic costs overshadow the long-term benefits of building organic traffic, businesses might find themselves trapped in a cycle of high expenditure without corresponding gains in sustainable growth.

4.7.2 Influence of Dummy Variables (Peak Season and COVID era) on Organic Traffic

In everyday terms, peak season refers to times of the year when consumer activity is at its highest think of the holiday shopping season or major sales events like Indonesia’s "Harbolnas" (Hari Belanja Nasional). During these times, consumer demand surges, and more people are likely to search for products online, leading to a natural increase in organic traffic. The "COVID era" dummy variable, on the other hand, captures the period during the global pandemic when consumer behavior dramatically shifted. Many people moved to online shopping as physical stores closed or became less accessible. In marketing, understanding how these periods affect organic traffic can help businesses plan more effective campaigns. For example, knowing that organic traffic spikes during peak seasons might lead a business to invest more in SEO and content creation during these times to maximize visibility.

From a broader economic perspective, both peak seasons and the COVID era have profound implications for e-commerce and the overall economy. Peak seasons, such as the holiday shopping period, often contribute a significant portion of annual sales for many businesses, driving economic activity across multiple sectors. The surge in organic traffic during these times reflects increased consumer spending, which can boost revenues and stimulate the economy. On the other hand, the COVID era represents a unique disruption, where online channels became the primary mode of commerce for many consumers. The shift to online shopping not only increased organic traffic but also accelerated digital transformation across industries. This period highlighted the importance of having a strong online presence and adapting to sudden changes in consumer behavior, which is crucial for economic resilience.

In economic terms, the influence of peak seasons and the COVID era on organic traffic can be analyzed through the concepts of seasonal variation and external shocks. Seasonal variation refers to predictable changes in consumer behavior throughout the year, such as increased spending during holidays, which can significantly affect organic traffic patterns. Businesses that understand these patterns can optimize their strategies to take advantage of high-demand periods, thereby maximizing their revenues during these critical times. The COVID era, however, represents an external shock a sudden and unexpected event that disrupts normal economic activities. In response to this shock, businesses that quickly adapted to the surge in online demand were able to capture a larger share of organic traffic, translating into higher sales and potentially long-term customer loyalty. The ability to weather such shocks is a key aspect of economic resilience, as it allows businesses to maintain operations and continue contributing to the economy even during crises.

4.8 Robustness Test

This step is especially important in complex analyses, like those involving panel data or multiple regression models, where the potential for bias or model misspecification is higher. In this study, perform a series of robustness tests to validate primary results, ensuring that the conclusions drawn are both credible and valid. Robustness tests are an essential component of this process, as they allow researchers to confirm that their findings are consistent and not sensitive to specific model assumptions or methodological choices. In doing so, researchers can assess whether the estimated relationships between variables hold true under different conditions or when alternative methods are applied. Here, a one-period lag value is included to account for potential delayed effects on search behavior.

Table 4. 8 Robustness Test Table

Variables	D&K FE Model	FE Model	No Dummy Model	Add More 1 Variable
LOGX1	0.2452434* (0.053)	0.2452434*** (0.0000)	0.2875115** (0.045)	0.2690215** (0.040)
LOGX2	0.3063764* (0.056)	0.3063764*** (0.000)	0.3059667* (0.059)	0.2923533* (0.063)
LOGX3	-0.2052338* (0.077)	-0.2052338*** (0.000)	-0.2106679* (0.079)	-0.2003141* (0.072)
LOGX4	0.0384277 (0.487)	0.0384277 (0.136)	0.394561 (0.469)	-0.0568663 (0.433)
LOGX5				0.1482482* (0.084)
Dummy COVID-19	0.0681493 (0.437)	0.0681493 (0.309)		0.0619219 (0.473)
Dummy Peak Season	0.0662373 (0.254)	0.0662373** (0.030)		0.0584732 (0.294)
cons	4.379407	4.379407	4.197602	3.958912
R^2	0.8778	0.8778	0.8732	0.8911
Prob	0.0048	0.0000	0.0033	0.0035

***p < 0.01 (significant at 1% level), **p < 0.05 (significant at 5% level), *p < 0.10 (significant at 10% level).

Processed by Author (2024)

This robustness tests are essential to verify the reliability and stability of the results. This table provides a comparison across different models, namely the FE D&C Model, the FE Model, the No Dummy Model, and the model that includes one additional variable. The results from the analysis show that the variable LOGX1 (organic keywords) has a positive coefficient of 0.245 in the D&K FE model with a p-value of 0.053, which means that a 1% increase in the use of organic keywords is expected to increase organic traffic by 0.245%. This is significant at the 10% level, indicating that organic keywords play an important role in increasing organic traffic. In the FE model with no dummy, this coefficient remains at 0.245 with a lower p-value of 0.0000, indicating that a 1% increase in organic keywords increases organic traffic by 0.245%, significant at the 1% level. In the No Dummy model, the coefficient increases to 0.287

with a p-value of 0.045, indicating that a 1% increase in organic keywords increases organic traffic by 0.287%, significant at the 5% level. Meanwhile, in the model with the addition of one variable, the coefficient is 0.269 with a p-value of 0.040, indicating that a 1% increase in organic keywords increases organic traffic by 0.269%, significant at the 5% level.

For the variable LOGX2 (organic traffic cost), the coefficient is also positive with a value of 0.306 in the D&K FE model with a p-value of 0.056, indicating that a 1% increase in organic traffic cost is expected to increase organic traffic by 0.306%. This is significant at the 10% level. In the FE model, the coefficient is fixed at 0.306 with a p-value of 0.000, indicating a 1% increase in organic traffic costs increases organic traffic by 0.306%, significant at the 1% level (**). In the No Dummy model, the coefficient is 0.305 with a p-value of 0.059, indicating that a 1% increase in organic traffic costs increases organic traffic by 0.305%, significant at the 10% level. In the model with additional variables, the coefficient is 0.292 with a p-value of 0.063, indicating that a 1% increase in organic traffic costs increases organic traffic by 0.292%, significant at the 10% level.

In contrast, the variable LOGX3 (paid keywords) has a negative coefficient, indicating that an increase in the use of paid keywords has a negative impact on organic traffic. In the D&K FE model, the coefficient is -0.205 with a p-value of 0.077, meaning that a 1% increase in the use of paid keywords decreases organic traffic by 0.205%, significant at the 10% level. In the FE model without dummy, the coefficient remains at -0.205 with a p-value of 0.000, indicating that a 1% increase in the use of paid keywords decreases organic traffic by 0.205%, significant at the 1% level (**). In the No Dummy model, the coefficient is -0.210 with a p-value of 0.079, indicating that a 1% increase in the use of paid keywords decreases organic traffic by 0.210%, significant at the 10% level. In the model with additional variables, the coefficient is -0.200 with a p-value of 0.072, meaning that a 1% increase in the use of paid keywords decreases organic traffic by 0.200%, significant at the 10% level.

For the variable LOGX4 (paid traffic costs), the results vary between models, with insignificant coefficients in all models tested. For example, in the D&K FE model, the coefficient is 0.038 with a p-value of 0.487, indicating that a 1% increase in paid traffic costs increases organic traffic by 0.038%, but this result is not significant. In the FE model, the coefficient remains 0.038 with a p-value of 0.136, which is also not significant. In the No Dummy model, the coefficient is 0.394 with a p-value of 0.469, indicating that a 1% increase in the cost of paid traffic increases organic traffic by

0.394%, but this is also not significant. In the model with added variables, the coefficient is -0.056 with a p-value of 0.433, indicating that a 1% increase in paid traffic costs decreases organic traffic by 0.056%, but this result is also not significant.

The variable LOGX5 (paid traffic) in the model with the addition of one variable shows a positive coefficient of 0.148 with a p-value of 0.084, which means that a 1% increase in paid traffic is expected to increase organic traffic by 0.148%, significant at the 10% level (*). For dummy variables, the COVID-19 dummy shows a positive coefficient of 0.068 with a p-value of 0.437 in the D&K FE model, indicating that the COVID-19 era is expected to increase organic traffic by 0.068%, but this result is not significant. Similar results are also seen in the FE model and the model with additional variables, where the coefficient remains insignificant. In contrast, the Peak Season dummy shows a positive coefficient of 0.066 with a p-value of 0.030 in the FE model, indicating that the peak season increases organic traffic by 0.066%, significant at the 5% level (**).

Overall, the R-Squared (R^2) values of these models show that the FE and R&D FE models are able to explain about 87.78% of the variation in organic traffic, while the No Dummy model explains 87.32%, and the model with additional variables explains 89.11%, indicating a good model in explaining data variation. The probabilities of these models are all significant, with the lowest value of 0.0000 in the FE model, indicating that these models are overall highly significant and valid in explaining the relationship between the independent variables and organic traffic.

CHAPTER 5
CONCLUSION

5.1 Conclusion

This research underscores the economic principle of market signalling, where organic keywords act as signals that effectively attract consumers, similar to how strategically positioned advertisements can maximize market reach. The powerful influence of this digital marketing tool reflects the fundamental economic theory of supply and demand, where appropriate and relevant information (supply) is aligned with consumer search and desire (demand). The notable efficacy of such strategies in the data reflects their critical role in increasing visibility and, by extension, sales potential in the digital marketplace.

In addition, the COVID-19 pandemic has triggered significant structural shifts in consumer behavior, exemplifying the concept of market adaptation in response to external shocks. This shift has highlighted market adaptability and the importance of agility in digital marketing strategies. The reduced predictability of peak seasonality, as observed in the variability of its impact across models, suggests a transformation in consumer consumption patterns. These changes may stem from market saturation, evolving consumer preferences, or increased competition among online retailers. Each of these factors calls for a re-evaluation of traditional peak season strategies, advocating a more dynamic approach to attract consumers and capitalize on emerging market trends.

5.2 Policy Recommendation

When e-commerce platforms seek to optimize their digital shelf space through strategic investments in SEO, they engage in what economists call productive efficiency, where resources are allocated in a way that maximizes output at the lowest cost. This approach allows companies to target consumer segments more precisely, thereby improving overall market efficiency. Such strategies help transform traditional marketing efforts into highly efficient digital campaigns that not only increase market penetration, but also improve producer and consumer welfare by maximizing consumer surplus and producer surplus.

In addition, the emphasis on balancing organic and paid digital strategies introduces the concept of marginal utility in digital marketing spend. For e-commerce platforms, understanding the diminishing return on investment in paid marketing compared to organic strategies is critical. This allows them to allocate budgets in a way that allows every additional dollar spent to yield the maximum possible increase in consumer engagement and conversion. This kind of optimization is critical in maintaining cost-effectiveness while driving scalability in operations, a crucial element in sustaining long-term growth and competitive advantage in the rapidly evolving digital marketplace.

This strategic implementation not only meets pressing market demands, but also contributes significantly to the broader economic landscape by improving digital literacy, fostering technological adaptability and ensuring sustainable economic growth. This holistic approach is aligned with modern economic theories on technological change and the innovation economy, which state that the diffusion of new technologies and business practices is critical to overall economic resilience and growth.

5.4 Limitation of the Study

This study has some limitations. First, the study only focuses on major e-commerce platforms-Shopee, Tokopedia, and Lazada- excluding smaller or niche platforms that may have different dynamics and performance metrics. Secondly, the data analyzed covers the period 2019 to 2022, which captures recent trends but potentially misses long-term developments and the impact of slower-changing factors such as the COVID-19 pandemic. In addition, this study concentrates on certain SEO metrics, such as organic and paid keywords, which may overlook other important elements such as user experience, email marketing, and social media interactions. The model used assumes a linear relationship between variables, which may not accurately reflect complex, non-linear interactions. In addition, external factors, including regulatory changes, competitive actions, and economic conditions, were not taken into account, which might affect e-commerce performance.

Finally, this study relied on data from SEMrush, a generally reliable source, but data quality issues may affect the validity of the results. These limitations highlight the need for future research to expand the data set, consider additional variables, and use more sophisticated models to provide a more complete understanding of the factors that influence e-commerce success. Further exploration into the elasticity of demand for online goods and services can reveal how sensitive consumers are to price changes and marketing efforts. Additionally, examining the externalities of increased digital consumption, such as data security and consumer privacy, can offer a complete view of the costs and benefits associated with the digital economy. These findings aim to connect microeconomic behaviors with macroeconomic policies, highlighting the link between digital marketing strategies and broader economic frameworks.

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APPENDIX

Appendix 1: Multicollinearity test

```
. vif

    Variable |       VIF       1/VIF
-------------+----------------------
LOGX1Organ~s |      3.43    0.291923
LOGX2Organ~t |      2.85    0.351255
LOGX3PaidK~s |      1.80    0.554740
LOGX4PaidT~t |      1.45    0.687499
-------------+----------------------
    Mean VIF |      2.38
```

Appendix 2: Heteroscedasticity test

```
. xttest3

Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (3)  =       86.85
Prob>chi2 =      0.0000
```

Appendix 3: Autocorrelation test

```
. xtserial LOGYOrganicTraffic LOGX1OrganicKeywords LOGX2OrganicTrafficCost LOGX3PaidKeywords LOGX4PaidTrafficCost dummy_covid dummy_peak_season

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,       2) =     31.940
           Prob > F =      0.0299
```

Appendix 4: Hausman

	(b) fe	(B) re	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
	Coefficients			
LOGX1Organ~s	.2452434	.3462862	-.1010428	.
LOGX2Organ~t	.3063764	.4003452	-.0939689	.
LOGX3PaidK~s	-.2052338	-.2522664	.0470326	.
LOGX4PaidT~t	.0384277	-.0109242	.049352	.
dummy_covid	.0681493	-.1857653	.2539146	.
dummy_peak~n	.0662373	.04678	.0194572	.

```
                 b = consistent under Ho and Ha; obtained from xtreg
      B = inconsistent under Ha, efficient under Ho; obtained from xtreg

  Test:  Ho:  difference in coefficients not systematic

                chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                        =      146.76
              Prob>chi2 =      0.0000
              (V_b-V_B is not positive definite)
```

Appendix 5: Driscoll & Kraay

```
Regression with Driscoll-Kraay standard errors   Number of obs     =       144
Method: Fixed-effects regression                 Number of groups  =         3
Group variable (i): ID                           F(  6,      2)    =    208.10
maximum lag: 3                                   Prob > F          =    0.0048
                                                 within R-squared  =    0.8778
```

LOGYOrganicTraffic	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
LOGX1OrganicKeywords	.2452434	.0587106	4.18	0.053	-.0073679	.4978546
LOGX2OrganicTrafficCost	.3063764	.0760688	4.03	0.056	-.0209212	.6336739
LOGX3PaidKeywords	-.2052338	.0606295	-3.39	0.077	-.4661017	.055634
LOGX4PaidTrafficCost	.0384277	.0454161	0.85	0.487	-.1569821	.2338376
dummy_covid	.0681493	.0707634	0.96	0.437	-.2363212	.3726198
dummy_peak_season	.0662373	.0418069	1.58	0.254	-.1136434	.246118
_cons	4.379407	.2782709	15.74	0.004	3.182104	5.57671

Appendix 6: Fixed Effect Model (FEM)

```
. xtreg LOGYOrganicTraffic LOGX1OrganicKeywords LOGX2OrganicTrafficCost LOGX3PaidKeywords LOGX4PaidTrafficCost d
> ummy_covid dummy_peak_season, fe

Fixed-effects (within) regression               Number of obs     =        144
Group variable: ID                              Number of groups  =          3

R-sq:                                           Obs per group:
     within  = 0.8778                                         min =         48
     between = 1.0000                                         avg =       48.0
     overall = 0.8501                                         max =         48

                                                F(6,135)          =     161.66
corr(u_i, Xb)  = 0.3138                         Prob > F          =     0.0000
```

LOGYOrganicTraffic	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
LOGX1OrganicKeywords	.2452434	.0429277	5.71	0.000	.1603457	.3301411
LOGX2OrganicTrafficCost	.3063764	.0303152	10.11	0.000	.2464222	.3663305
LOGX3PaidKeywords	-.2052338	.038305	-5.36	0.000	-.2809894	-.1294783
LOGX4PaidTrafficCost	.0384277	.0256018	1.50	0.136	-.0122047	.0890602
dummy_covid	.0681493	.066805	1.02	0.309	-.0639705	.2002691
dummy_peak_season	.0662373	.030246	2.19	0.030	.00642	.1260545
_cons	4.379407	.2191635	19.98	0.000	3.945969	4.812845
sigma_u	.15562252					
sigma_e	.14976252					
rho	.51918183	(fraction of variance due to u_i)				

```
F test that all u_i=0: F(2, 135) = 30.13                     Prob > F = 0.0000
```