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Barriers to and Enablers of Data-Driven Entrepreneurial Activities among SMEs in the Context of e-Commerce Platforms

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Barriers to and Enablers of Data-Driven Entrepreneurial Activities among SMEs in the Context of e-Commerce Platforms

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Abstract

The era of Big Data 1.0 has created an abundance of information that could provide insights to any onlooker. In parallel, the growth of e-commerce platforms has enabled SMEs to easily start a business. This study aims to identify significant organizational barriers and enablers of data-driven decision making (DDDM). Rooted in Resource-Based-View (RBV), Dynamic Capabilities View (DCV), and the Technology-Organization-Environment (TOE) Framework, this study explored the influence of owner-managers' perceived relative advantage, firm prioritization of organizational learning, and firm's dynamic capabilities. These factors were empirically tested using hierarchical multiple regression on a self-administered survey to 38 SMEs operating on Shopee Indonesia. The findings reveal that DDDM is positively influenced by the owner-manager's perceived relative advantage, with a moderating effect of the firm's prioritization of organizational learning. This study includes managerial implications aimed for SMEs on e-commerce platforms.

Keywords

Data-driven decision making (DDDM), Small-to-medium enterprises (SMEs), e-Commerce platforms, Indonesia

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1. Introduction

According to Provost & Fawcett (2013), we are currently in the Big Data 1.0 era, where firms are building capabilities to process large amounts of data to enhance their operations and efficiency. Technological advancements during this era have turned information scarcity into abundance, creating the potential to transform data into valuable information (Tihanyi et al., 2014). Through big data, the decision-making cycle is reimagined, as managers can now utilize big data to gain a deeper understanding of their businesses and improve overall performance and decision-making processes (Saggi & Jain, 2018).

Over the past years, evolving digital technologies have propelled the growth of e-commerce and opened opportunities for anyone to start an online business just one click away. With the inevitable rise of e-commerce, digitalization has become an indispensable business tool, and adopting such technology affects enterprise performance positively, particularly for small businesses (Borges et al., 2009; Petter et al., 2008; Sabherwal et al., 2006; Zhuang & Lederer, 2006). For instance, big data analytics (BDA) enables e-commerce firms to efficiently use data, drive higher conversion rates, improve decision making, and empower customers (Miller, 2013).

Decision making is often conducted in uncertain conditions. This uncertainty is often caused due to the lack of proper information interpretation (Petrakis, 2016; Milliken, 1987; Nutt and Wilson, 2010). Nowadays, decision making has become increasingly complicated and difficult due to abundance of information and fluctuating decision environments. Human decision making is especially more susceptible to biases and limitations when faced with the task of processing vast amounts of information (Wamba, 2017; Niu et al., 2009). Hence, with the modern information technologies and communication systems, managers can leverage big data to enhance their understanding of their businesses to improve performance and decision-making processes (Gupta & George, 2016; Niu et al., 2009).

Indonesia has the world's fourth-largest population, and is home to several of Southeast Asia's most impressive technology companies (Moore, 2017). 30 million of Indonesia's population transact online, creating a market of $8 billion (Das et al., 2018). E-commerce platforms have integrated into the typical lifestyle of Indonesian households, often even considered a necessity, projecting a predicted value of e-commerce to reach USD53 billion in 2025 (Google & Temasek, 2018). E-commerce has however not been fully implemented among Indonesian MSMEs, but has grown significantly in recent years, increasing 104.4% in 2018 (Setyowati, 2019). The Indonesian Ministry of Communication and Information (2018) reported that only 4.7 million micro-small-medium enterprises (MSMEs) used digital platforms in 2017, which constitutes a meager 7.4% of all MSMEs in Indonesia.

Small-to-medium enterprises (SMEs) are regarded as important on a local, national or even global basis as they play an important part in any national economy (Mullins et al., 2007). This ranges from European countries to developing countries such as Indonesia, where SMEs constitute 61.07% of the national GDP (Coleman, 2016; Coordinating Ministry for Economic Affairs of the Republic of Indonesia, 2021).

Recent technological advancements have led to a rise in platform economy, enabling the connection of dispersed networks of individuals to facilitate digital interactions between people (Deloitte, 2019). Buying and selling on e-commerce platforms have been increasingly popular due to the convenience and variety of available products opening new information channels between consumers and firms, especially for SMEs. E-commerce promises many benefits for SMEs, including improving financial performances, internal processes, and customer/supplier relationships through market expansion, improved information sharing efficiency and transactional efficiencies (Melville et al., 2004; Zhu, 2004; Zhu & Kraemer, 2002).

SMEs on e-commerce platforms such as Shopee, the biggest e-commerce platform in South-East Asia, are provided with additional support to make decisions based on data, such as providing the “Business Insights” feature - an overview on their enterprise’s marketing and financial analytics and have opportunities to attend seminars educating the sellers on making use of data-driven analytics (Shopee, 2019). Since 70% of Shopee’s 1.6 million merchants are SMEs, this should ease the struggle of significant IT investments when deciding to adopt data-driven decision making (DDDM) (Yasa, 2018). Despite having less technological and environmental barriers to adopt DDDM, other internal factors may affect SMEs’ adoption decisions. This is supported by related studies proposing that aside from external factors, organizational factors and even founder characteristics may impact a firm’s decision to adopt data-driven decision making (Reddy et al., 2022; Coleman et al., 2016; Ghobakhloo et al., 2011; Hill & Scott, 2004; Willetts et al. 2020, etc.)

Previous research has highlighted a reluctance among SMEs to adopt DDDM (Grabova et al., 2010). Empirical studies have shown that SMEs heavily rely on intuition and Personal Contact Networks (PCN) to enhance decision-making quality, often overshadowing the role of data analytics systems. There is an evident issue of scale, as SMEs indicated a reliance on DDDM only as their companies grow (Hill & Scott, 2004). This finding aligns with insights gathered during an interview conducted in the early stages of my research (see Part 1 of the Appendix), where an SME acknowledged the importance of analytics but expressed a preference for analyzing data at a more advanced stage of company development. Hill and Scott (2004) describe this situation as a two-edged sword. On one hand, there is a recognized need for effective data analytics in small firms, but on the other hand, challenges related to funding and system management arise. This poses a concern for SMEs aiming to outperform their competitors, as top-performing organizations prioritize the application of analytics over intuition (LaValle et al., 2013).

Academic research on the business value of big data is still limited (Wamba et al. 2015). Boonsiritomachai et al. (2016) observe that not only research in this field remains quite scarce, the majority focused on western and developed countries i.e. Australia (Elbashir et al., 2008), Northern Ireland (Hill & Scott, 2004), United States (Ramamurthy et al., 2008), Portuguese SMEs (Eiriz et al., 2018), Italian SMEs (Scupola, 2003). The goal of this research is to explore DDDM barriers and enablers from the perspective of top-management level in Indonesian SMEs. This point of view was taken as most decision making within SMEs are made by the owner-manager. In fact, the key enabler of strategic integration of big data into business processes is top management support (Polese et al., 2019). With this kept in consideration, the specific barriers and enablers explored are organizational factors, namely the owner-manager's perceived relative advantage of DDDM, firm's prioritization of organizational learning, and firm dynamic capabilities.

These aspects have been proposed as some of the most significant according to past research (i.e. Reddy et al. 2022), yet have never been empirically tested in the context of Indonesian SMEs. Therefore, this research aims to answer the question: What are significant organizational barriers to and enablers of data-driven decision making in the context of Indonesian SMEs operating on e-commerce platforms?

2. Theoretical Background

2.1 Data Driven Decision Making

2.1.1 Defining Data-Driven Decision Making

The success of business management depends on the performance of managerial functions such as planning, organizing, directing, and controlling (Turban et al. 2005). Niu et al. (2009) emphasize that to carry out these functions, business managers act as decision makers, as they are engaged in a continuous process of making decisions, such as drawing up a product plan, selecting a supplier and determining a product's price. Decision makers deal with various types of problems ranging from daily operation to long-term company strategies, where different decision-making tasks have different features and require different decision support techniques. In small businesses, decisions are generally made individually. However, should decisions be made in a group, conflicts may arise due to self-interests, varying expertise and resources.

Decision making is a reasoning process, either rational or irrational, and can be based on explicit or tacit assumptions (Simon 1979, Simon 1993). Rational decision making emphasizes fact collection and conducting research such as data analysis, surveys and interviews; whereas irrational decision making is based on assumptions and emotions. A rational decision-making model involves a cognitive process where each step follows in a logical order based on previous steps. Nowadays, firms can implement rational decision making with data, and make decisions that are data-driven, resulting in informed and objective decisions based on evidence. In fact, effective decision making can be attained when knowledge generated from big data analytics are used (Murdoch and Detsky, 2003).

Data-driven decision making in itself is a less common term in current research, and multiple terms such as business intelligence, e-business, data-driven culture, data science-strategy, and big data share similar concepts and are more frequently used.

The concept of DDDM first was first coined by Brynjolfsson et al. (2011) who defined it as the practice of basing decisions on the results of data analysis rather than purely on intuition. Provost and Fawcett (2013) propose that data-driven decision making stems from data science, which has a base of data engineering and processing, including big data technologies. Reddy et al. (2022) conducted a systematic literature review focused on creating a framework for enterprise data science strategy. Here "Data Science" is referred to as an umbrella term that encapsulates constituents such as Artificial Intelligence (AI), Machine Learning (ML), Big Data (BD), Big Data Analytics (BDA), Visualization, and Business Intelligence & Analytics (BI&A), Mathematics, Computer Science & Programming Skills, and Domain Knowledge.

The relevance of the human component and the ability to extract significant insights from data led to the reinterpretation of big data as a strategic asset that should encourage organizational members to make decisions based on the knowledge extracted and to foster decisions effectiveness (LaValle et al., 2011; Provost & Fawcett 2013).

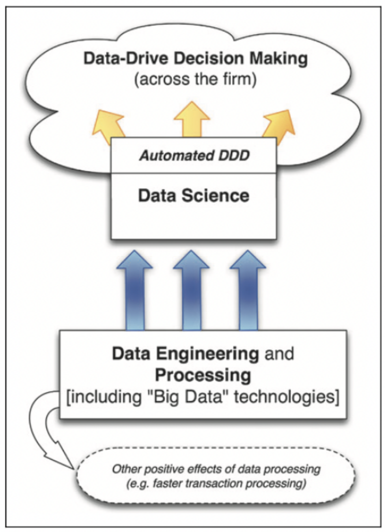


Figure 1: Data science throughout the organization (Provost and Fawcett, 2013).

Therefore I propose a definition of DDDM adapted from the depiction of data science in the context of closely related organization processes (Figure 1) proposed by Provost and Fawcett (2013). The visualization shows that DDDM is based on data science, which Provost and Fawcett (2013) suggest stems from BDA. Instead of being restricted to BDA, I propose data science to encompass a broader inclusion, adapting the 14 umbrella terms proposed by Reddy et al. (2022). According to their systematic literature review, data science is an umbrella of 14 terms of which their implementation have often been extensively examined in past research.

In Figure 2, through the implementation of any of the 14 umbrella terms, from which data is engineered and processed, is a data science system/strategy/culture developed in an organization (Provost & Fawcett, 2013). With data science, decisions can be made based on data analytics, even automating certain decision making processes (Brynjolfsson et al., 2011). As proposed by Lavalle et al. (2011), through DDDM a firm can become a top-performing organization, and reap the benefits of better asset utilization, increased financial performance, and increase their market value.

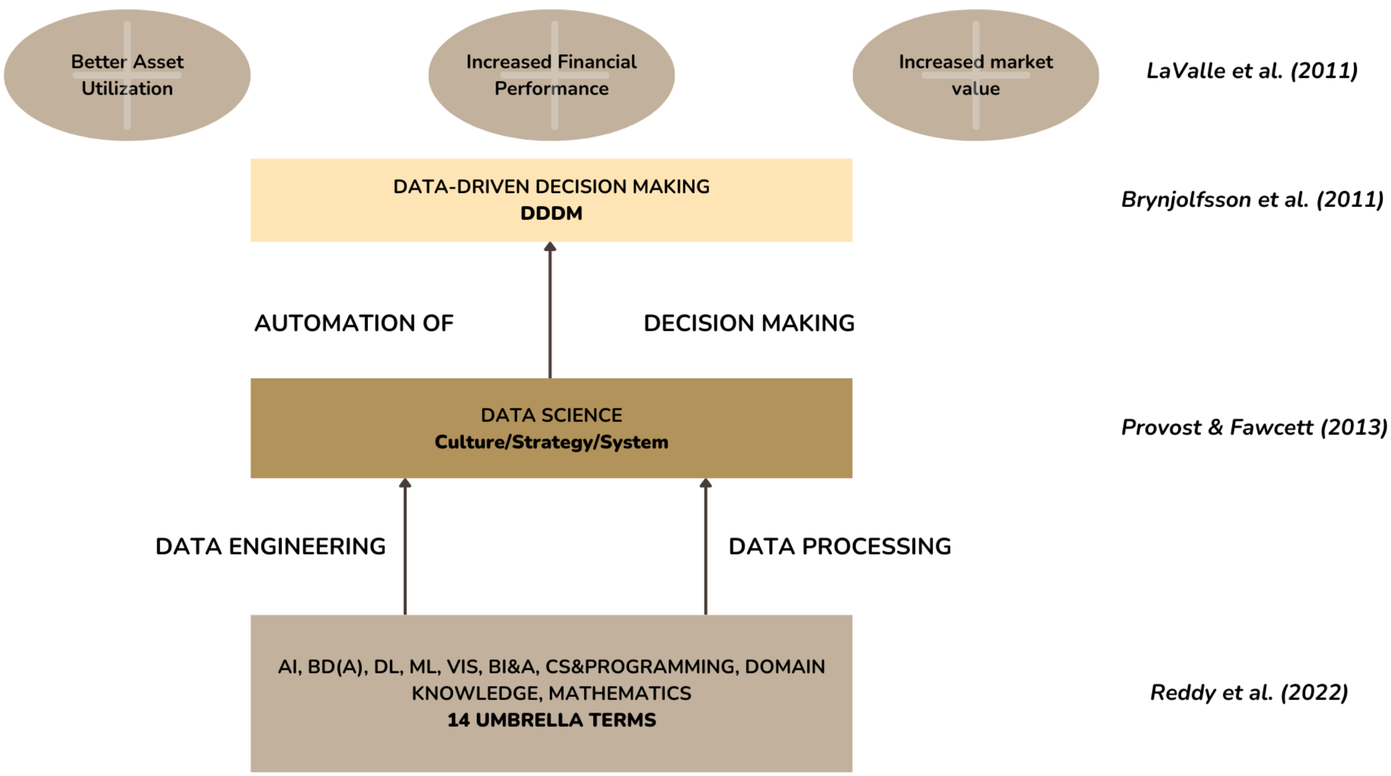


Figure 2: Constructed Definition of DDDM

2.1.2 Input and Output of DDDM

With a successful implementation of DDDM, firms would be able to enhance productivity, optimize asset utilization, improve financial performance (higher Return on Equity), and increase a firm's market value (Brynjolfsson et al., 2011). LaValle et al. (2010) observed that the top performing firms use analytics five times more than lower performers and approach business operations differently than their peers by putting analytics to use for all types of decision making, even for minor decisions. The systematic literature review of Reddy et al. (2022) concluded that successfully implementing a data science strategy provides strategic business values, both functional and symbolic. Functional values include an increased competitive advantage in terms of market share and when launching new products, operational benefits such as improved profits, as well as transformational values in terms of structure and capacity. Symbolic values range from a better reputation and brand value, to having Corporate Social Responsibility (CSR), and Environmental, Social and Corporate governance (ESG). The generation of knowledge from big data analytics also generates benefits for the whole value chain, including improving day-to-day activities such as prediction of consumer behavior, optimizing prices, and simplifying logistics that could also improve competitiveness (Chen et al., 2014).

The implementation of DDDM incurs both direct and indirect costs. Reddy et al. (2002) propose that the implementation of a data science strategy within a firm involve several firm resources, namely: business questions, business data, technology, infrastructure, human skills, core strategy connection. Direct costs associated with implementing such a system include expenses for hardware accessories, upgrades to increase processing power, consultancy support, installation engineers, networking hardware and software, overheads (including running costs), training costs, maintenance costs, and networking security measures like firewalls (Love & Irani, 2004). For the context of this research, the direct costs of implementation in this study should be minimum, assuming the companies solely rely on Shopee’s Business Insights feature. However, in general, adoption of Information Systems (IS) is also affected by indirect costs, such as the human factors (e.g. training and early cost of temporary loss in firm’s productivity) , which may be more significant than the direct costs (Love and Irani, 2004; Love et al., 2005).

2.1.2 Barriers of Data Driven Decision Making among SMEs

Various theories, including the Technology-Organization-Environment (TOE) framework, Resource-Based View (RBV), Dynamic Capability View (DCV), Knowledge-Based View (KBV), Organizational Learning Theory (OLT), Diffusion of Innovation Theory (DIT), Technology Acceptance Model (TAM), Task-Technology Fit (TTF), Information Systems Success Model (ISSM), Agency Theory (AT), Stakeholders Theory (ST), and Institutional Theory (ITh), have been used in previous literature to explain barriers to adopting Data-Driven Decision Making (DDDM). The TOE framework has emerged as a common foundation for analyzing the adoption of big data analytics systems, as evident in studies by Sun et al. (2019), Nguyen and Liaw (2020), and Lutfi et al. (2022). To enhance readability, this paper's literature review organizes the identified barriers within the TOE framework.

2.1.2.1 General Challenges for SMEs

Technological factors

Organizational resource availability was found to be a significant factor influencing SMEs' decisions to adopt Business Intelligence. The implementation of new IT normally requires a long-term investment involving high costs in IT infrastructure (Boonsiritomachai et al., 2016). Nguyen & Liaw (2020) have integrated “Data” as an important technological factor that requires separate examination which encompasses security, quality, class imbalance, and scalability. Technological factors often make use of DoI (Diffusion of Innovation) theory (Rogers, 1995). Out of these determinants, relative advantage and complexity were significant in BI adoption, consistent with prior research (Ghobakhloo et al., 2011; Grandon & Pearson, 2004; Ramamurthy et al., 2008). The higher the perception of relative advantage and the lower the complexity, the more likely an SME will adopt higher levels of BI technology (Boonsiritomachai et al., 2016).

Environmental Factors

The environmental context concerns factors external to an organization presenting constraints and opportunities for technological innovations (Tornatzky & Fleischer 1990). Wang et al. (2010) describe this as the arena in which an organization conducts its business, which includes the industry and dealings with business partners, competitors, and government. Environmental factors include competitive pressure, selection of vendors, absorptive capacity and organizational resource availability (Chong, 2008; Ghobakhloo et al., 2011; Ifinedo 2011; Tan & Lin, 2012). Reddy et al. (2021) highlighted external factors (e.g. non-transparency) in the market, lack of accessible talent, competency with vendors, and blindly mimicking other business models as possible adoption barriers.

However, not all environmental challenges pose barriers to the adoption of DDDM. The rapid growth of information technology increases competitive pressure, which drives a higher need to adopt advanced technologies that could improve performance. In fact, SMEs that do not use intelligence systems could even fail to compete effectively (Chang et al., 2010; Boonsiritomachai et al., 2016; Fogarty & Armstrong, 2009; Ghobakhloo et al., 2011).

However, the biggest challenges in adopting analytics are actually managerial and cultural (LaValle et al., 2011). The role of key organizational decision makers (predominantly owner-managers in SMEs) can make or break the implementation of data-driven decision making. Data-driven decision making relies on data-driven culture - a culture valuing evidence-based decision making and encourages transformation of data into meaningful insights. This culture can be sustained when the top management creates a unified vision of the approach to big data analytics (Rasmussen & Ulrich, 2015). Intelligence gleaned from data will be of little use to an organization if its managers fail to foresee the potential of newly extracted insights (Gupta & George, 2016).

2.1.2.2 Organizational Factors

Even when technological superiority is assured, it does not guarantee the adoption of IT innovation by organizations. This is because other social, organizational and individual factors may impact IT adoption (Segal, 1994).

This aligns with findings from Polese et al., (2019) where managerial commitment is said to significantly lessen cultural and technological barriers to big data strategies. Managerial commitment to big data projects contributes to the generation of a data-driven culture by sending the right signals to everyone in the organization (Adrian et al., 2018). 's The empirical study by Love and Irani (2004) identified that the most significant barrier is having no strategic vision is a major barrier to justifying IT investments, especially when expecting quick returns from such investments.

Not only will this culture address the firm's technological challenges, it mitigates low levels of employees' motivation, talent attrition, and enhances data acquisition and data management systems. Leading research and advisory firm Gartner Inc. predicted that through 2017, around 60 percent of big data projects will stop at piloting and experimentation stages and end up neglected due to lack of change in mindset and organizational culture (Gartner, 2017). In order to make big data initiatives successful, it is imperative that the decision makers understand the problem at hand, and take action with the right data, people, and problem solving techniques.

2.1.3 Enablers of Data-Driven Decision Making among SMEs

Reddy et al., (2022) categorized enablers for data science strategy into individual, organizational, and institutional factors. Individual enablers include top-management team support, storytelling techniques for visualization, and a high tolerance for complexity. Organizational enablers encompass elements such as organizational agility, compatible and complementary resources, data characteristics and data governance, training and knowledge management, alignment with strategy, alignment between business and IT, an ambidextrous culture for both exploiting and exploring opportunities, absorptive and dynamic capabilities, rewards and recognition, or/and/as well as collaboration with other organizations through formal and informal networks. Lastly, institutional enablers involve industry collaboration and compliance, establishment of a competence pool, engagement between industry and government, collaboration between industry and academia, and clear target market definition.

The role of founder/owner-manager characteristics is important in assessing the adoption of new technologies in small businesses, as they are often dependent on owner-managers' decisions and are likely to be more flexible in adopting new technologies (Eiriz et al., 2018). Past research shows conflicting effects of the owner-manager's education and IT knowledge on technological adoption. DDDM adoption is not necessarily dependent on the owner-manager's education. In fact, Mehrtens et al. (2001), found that SME owners with low levels of IT knowledge seek advice from staff with IT knowledge within their organizations or hire IT experts. Despite educational backgrounds, technology adoption is actually influenced by the innovativeness of the owner-manager (Thong, 1999).

Additionally, owner-managers' characteristics other than IT knowledge such as owner innovativeness and attitude towards IT adoption have been recognized as important factors that impact technology adoption in SMEs and have been integrated as factors affecting technological adoption (Chan et al., 2010; Fogarty & Armstrong, 2009; Ghobakhloo et al., 2011; Boonsiritomachai et al., 2016). Furthermore, Fernández & Nieto (2006) found that SMEs with innovative and non-risk-averse owners are more likely to apply distinctive and risky solutions. In this context, intelligence systems can be considered a risky investment due to difficulties in quantifying its return on investment (ROI).

Polese et al., (2019) concluded that DDDM adoption relies both on top management support (active role of leadership, management attitude, adoption of a proactive innovation mindset, data-driven culture of key organizational decision makers,) and change management (readiness in case of change in the business environment, facilitation of training and learning needs of employees and controls the change process). Change management is critical to successfully gaining insights from big data, as it reflects the organization's readiness in case of change. Change management relies on incremental successes to push data-driven decision making into the culture of the organization (Lamba & Singh 2018).

2.2 Existing Frameworks & Models

Upon exploring theoretical backgrounds surrounding data-driven decision making, were plenty of frameworks and models encountered. Several examples of such frameworks that specifically investigate barriers and enablers are briefly summarized in this section.

2.2.1 Existing Conceptual Models

As previously introduced in Section 2.1, Reddy et al. (2022) conducted a systematic literature review towards a conceptual framework for the enablers and barriers of data science strategy in an enterprise. Rooted in multiple theories including resource views, innovation adoption, and stakeholder theories, this study divides factors associated with Data Science Strategy into 4 main divisions: content, context, intent and outcome. Content includes data characteristics and governance; Context covers the technology and business environment aspects, Intent encompassess alignment with core strategy, managerial willingness, organizational agility, and leadership & culture; while Outcome highlights the business value of implementing data science. In Figure 3, 18 barriers and 18 enablers of enterprise Data Science Strategy were proposed based on their literature review. These barriers and enablers were separated based on individual, organizational, and institutional levels.

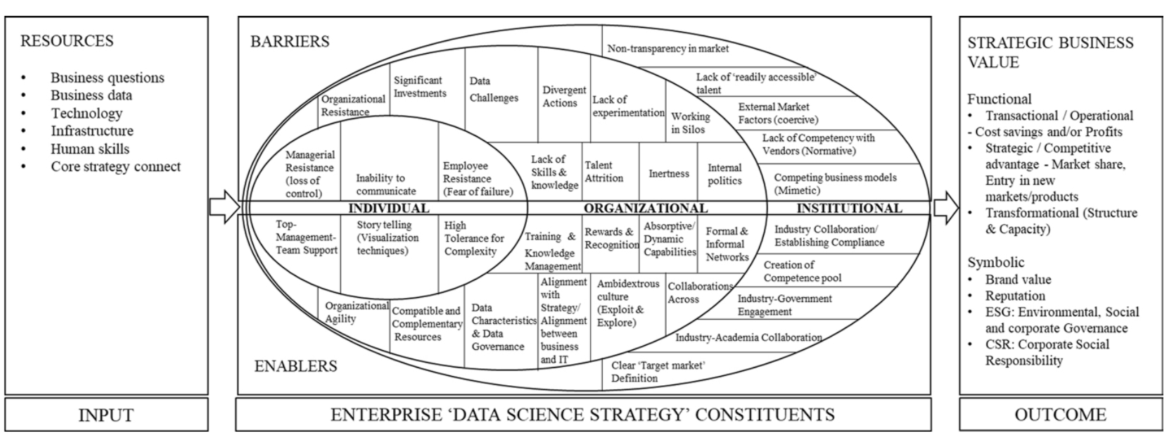


Figure 3: Conceptual Framework: Data Science Strategy (Reddy et al. 2020)

Specifically focusing on Tornatzky & Fleischer's (1990) TOE framework, Nguyen & Liaw (2020) identified barriers of big data adoption and proposed Data as an additional barrier. Based on previous research where data has been identified as the biggest barrier affecting organizational decisions to adopt big data, security, complexity, quality, storage class imbalance, analysis, visualization, performance and scalability are indicated as barriers. Recommendations for each encompassing barriers are suggested, including technical recommendations to solve possible Data hurdles. Their literature review found that security, complexity, infrastructure, and organizational culture repeatedly underlined as barriers.

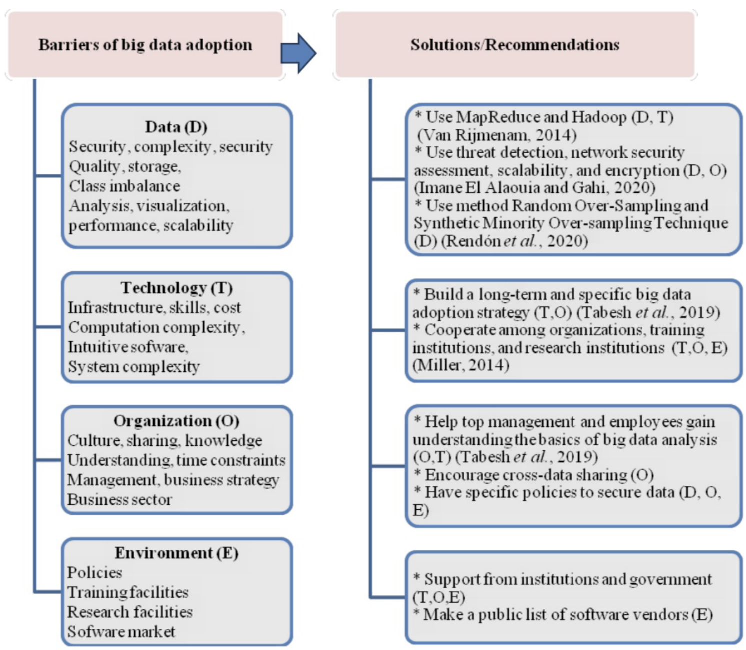


Figure 4: Barriers and Solutions for Big Data Adoption (Nguyen & Liaw, 2020)

2.2.2 Empirical Studies

Lutfi et al. (2022) performed a case study on factors influencing the adoption of big data analytics on 116 Jordanian SMEs. Similar to Nguyen & Liaw (2020), they based their factors on the TOE framework. Their study concluded relative advantage, organizational readiness, and government support having a positive relationship with big data analytics adoption; whereas, high levels of insecurity and complexity having negative relationships.

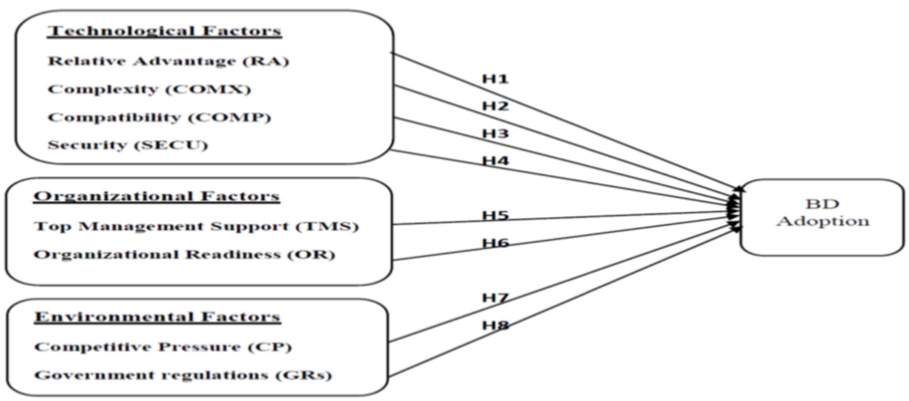


Figure 5: Research Model of Factors influencing BD Adoption (Lutfi et al., 2022)

Behl. et al (2019) developed a theoretical framework using Interpretive Structural Modelling (ISM) that categorized 11 enablers of adopting big data analytic tools in the context of Indian e-commerce startups. This theoretical framework was validated using the fuzzy analytical network process. Technical Expertise of Internal Staff and Training of Employees were identified as the most important enablers with ISM. They theorized that having strong technical capabilities internally would ease the process of adoption for the firm by reducing reliance on third party analytics firms to analyze data. Their results also highlighted the importance of Analytical Skill-set of Top Management and Data Consistency, despite realizing this would be more difficult for businesses in initial stages.

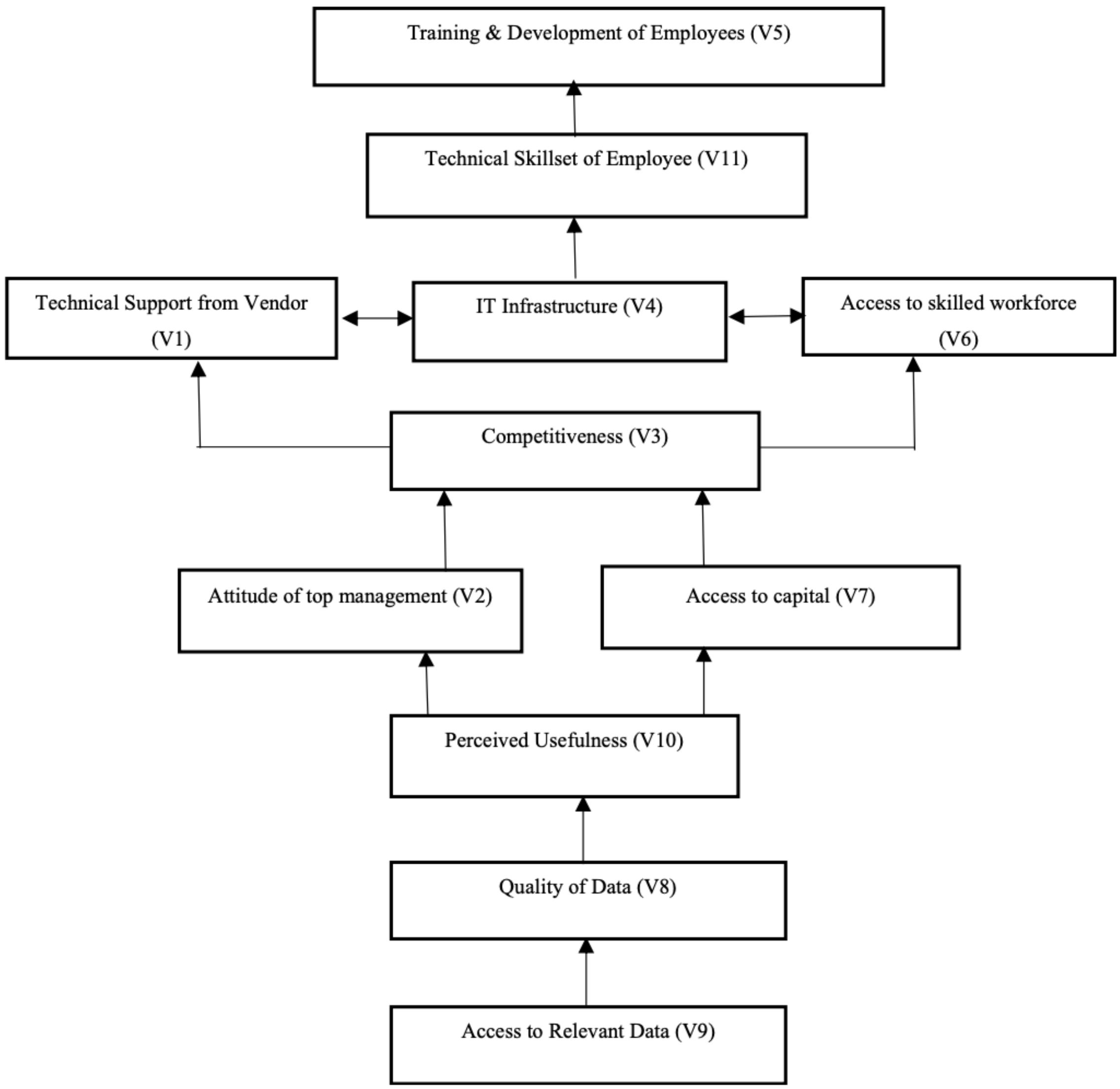


Figure 6: ISM framework for BDA adoption enablers (Behl et al., 2019)

2.3 e-Commerce Platforms & SMEs

2.3.1 e-Commerce Adoption

Web 1.0 Era

Web 1.0 was the origin of business adoption of internet technologies. In Web 1.0, businesses busied themselves with getting the basic internet technologies in place so that they could establish a web presence, build electronic commerce capabilities, and improve operating efficiency (Provost & Fawcett, 2013). This is the era of e-commerce adoption, where businesses began to build websites, create mailing systems, build extranet, intranet, EDI, ESCM, and EFT (Ghobakhloo et al., 2011).

Despite having limited resources, past research has shown that the lack of SME's resources does not significantly influence the decision to adopt e-commerce. Ghobakhloo et al. (2011) empirically proved that EC adoption within SMEs is affected by perceived relative advantage, perceived compatibility, CEO's innovativeness, information intensity, buyer/supplier pressure, support from technology vendors, and competition. Barriers and enablers of adopting e-commerce in past research are similar to those of Data-Driven Decision Making, frequently making use of the TOE framework.

Web 2.0 Era

This growth ushered in the era of Web 2.0, in which new systems and companies started to exploit the interactive nature of the web. The changes brought on by this shift in thinking are extensive and pervasive; the most obvious are the incorporation of social-networking components and the rise of the "voice" of the individual consumer (and citizen) (Provost & Fawcett, 2013). This era marks the rise of e-commerce platforms. In Indonesia, the boom of their e-commerce market occurred in 2021, becoming the ninth-largest e-commerce secretary globally after growing six times its value in three years. (McKinsey & Company et al., 2023).

2.3.2 Role of e-Commerce Platforms for SMEs

Reduce Coordination Costs

Information asymmetry is inherently attached to SMEs (Borges et al., 2009). e-Commerce platforms can act as the agency needed to reduce opportunism and give customers transparency on products and better online shopping experience which in turn increases customer satisfaction, customer engagement, and online sales growths (Esteve-Pérez & Mañez-Castillejo; Wirdiyanti et al., 2022).

Once customers recognize an enterprise's product or service brands, business performance will increase as more customers pay attention to the products and services, ultimately leading to their purchase. This result was empirically tested by Wirdiyanti et al. (2022), and is aligned with previous studies concluding a direct influence of e-commerce sellers' reputation and trustworthiness from customer online transaction experiences on their online purchase decisions (Dai et al., 2018 ; Nickel, 2009)

Financial Inclusion

Agyekum et al's., (2021) study on Southeast Asian countries concluded that the use of ICT-based services enhances financial inclusion of SMEs, as utilizing these services facilitates access to external credit facilities. E-Commerce platforms such as Shopee provide an automatic record of business transactions for each seller, providing banks the necessary business performance evidence. Before the rise of e-commerce, businesses applying for bank loans would face challenges because they lack trusted business records (Wirdiyanti et al., 2022). Through the sellers' online business transaction records, e-commerce platforms actually act as channeling agents by providing credit scoring for every merchant. The e-commerce platforms are able to connect merchants with their associated financial institutions and help financial institutions' credit decisions. This mechanism mitigates information asymmetries between MSMEs as e-commerce merchants and financial institutions, improves loan approval probability, and reduces loan acquisition costs (Scupola, 2003).

2.3.3 Implementing Data-Driven Decision Making

As previously mentioned in Section 2.1.3, there exists a multitude of theories regarding adoption of new technologies or innovation.

Diffusion of Innovation (DOI) Theory

Classic DoI theory identifies five innovation characteristics including, relative advantage (the degree to which an innovation is perceived as being better than the idea it supersedes), compatibility (the degree to which an innovation is consistent with existing business processes, practices and value systems), complexity (the degree to which an innovation is difficult to use), observability, (the degree to which the results of an innovation are visible to others), and trialability, (the degree to which an innovation can be experimented with) (Rogers, 1995; Rogers & Shoemaker, 1971). The most consistent innovation characteristics are Relative Advantage, Complexity, and Compatibility (Tornatzky & Klein, 1982).

Past research has named relative advantage as the most significant factor and most consistent predictor of IT adoption (To & Ngai, 2006; Premkumar, Ramamurthy, & Nilakanta, 1994). Considering the fact that in SMEs owner-managers make the most decisions, and support from top-management has been empirically proven to be a significant enabler of data science strategy adoption, it is hypothesized:

Hypothesis 1: The owner-managers' perceived relative advantage of DDDM is positively related with DDDM adoption.

Resourced Based View (RBV) Theory

Data science components related to innovation adoption can be classified as Tangible, Human, and Intangible resources from a Resource-Based View (Gupta and George 2016; Mikalef & Gupta 2021). Here, tangible resources comprise data, technology, and basic resources, such as time and investments. Human resources consists of technical (data-specific) and managerial (analytical and business acumen) skills. Finally, intangible resources indicate organization culture and learning abilities, which include data-driven approaches and Knowledge-Management Systems.

The intensity of organizational learning is one of the critical intangible resources needed to build 'Data Science' capabilities (Gupta & George 2016; Mikalef et al. 2020b). Lin & Lee (2005) conducted a study on the adoption of e-business systems among SMEs. Adoption was hypothesized to be affected by organizational learning, which is composed of training availability, technical expertise, knowledge level, and knowledge management (knowledge acquisition, knowledge application, and knowledge sharing).

Based on these findings regarding organizational learning, it is hypothesized:

Hypothesis 2: The firm's prioritization of organizational learning is positively related to DDDM adoption.

Several literature have examined the effects of big data systems on organizations using the dynamic capabilities view (Rialti et al., 2019). RBV is considered essentially static in its nature and inadequate to explain firms' competitive advantage in changing environments. As an extension of the resource-based view of the firm, the dynamic capabilities view postulates that a firm may achieve sustained competitive advantage based on the bundles of resources and capabilities it has under its control. In short, a firm's dynamic capabilities could explain how a firm maintains a competitive advantage in changing environments (e.g., Priem & Butler, 2001).

Dynamic Capabilities View (DCV) Theory

Over the past decade, the dynamic capabilities view of a firm has emerged as one of the most influential theoretical perspectives in the study of strategic management (Schilke 2014). Originating from the Schumpeterian logic of creative destruction, dynamic capabilities enable firms to integrate, build, and reconfigure their resources and capabilities in the face of changing conditions (Teece et al., 1997). Several researchers have assumed a direct relationship between firms' dynamic capabilities and their performance (Teece 2007). However, Zott (2003) claimed that dynamic capabilities may influence performance through a firm's bundle of resources of routines. Big-data analytics have a direct and an indirect effect on firm performance, with dynamic capabilities playing a strong mediating role (Wamba, 2017).

According to Barreto (2010), the dynamic capabilities view can be conceptualized as an aggregate multidimensional construct with four dimensions: the propensities to sense opportunities and threats, to make timely decisions, to make market-oriented decisions, and to change the firm's resource base. However, Barreto (2010) overcomes some important limitations of current definitions about dynamic capability such as vague, confusing, tautological, there is still room for improvement. First, this definition applies well to a perfect market-oriented economy, but not necessarily to transition economies. Li & Liu (2014) created an adapted definition of dynamic capabilities to better suit the Chinese context. Similar to Indonesia's conditions, due to inadequate market and legal support, dysfunctional competitive behavior of firms is widespread, the definition and dimensions of dynamic capabilities are not quite the same as Western countries. Reddy et al. 's (2022) literature review considers the development of dynamic capabilities as an important enabler for data science strategy, including tolerance for complexity and top management support. Thus it is hypothesized:

Hypothesis 3: The firm's dynamic capabilities are positively related to DDDM adoption.

Organizational learning has been considered a moderating variable when dynamic capabilities and competitive advantage are involved (Liu et al., 2018). As explained in Section 2.1.2.2, Mehrtens et al. (2001), found that SME owners with low levels of IT knowledge rely on employees skilled in IT. It would be difficult for SME owners to fully understand the perceived relative advantages of DDDM without the appropriate technical expertise and knowledge management. Given this possible relationship, it is hypothesized:

Hypothesis 4: The firm's prioritization of organizational learning moderates the relationship between the owner-manager's perceived relative advantage and DDDM adoption.

In order to contribute to a firm's data science capabilities, organizational agility/learning must be developed in order to contribute to the emergence of an overall "Data Science" capability (Mikalef and Gupta 2021). Agility and learning are often connected to an organization's dynamic capabilities (Rialti et al. 2019). Drawing on this possible relationship, the final hypothesis is posited:

Hypothesis 5: The firm's prioritization of organizational learning moderates the relationship between the firm's dynamic capabilities and DDDM adoption.

2.3.4 Summarized Conceptual Model

This study hypothesizes that DDDM adoption will be affected by the owner-manager's perceived relative advantage, the firm's prioritization of organizational learning, and firm dynamic capabilities. It is also hypothesized that the firm's prioritization of organizational learning could potentially moderate the relationship between the other two main effects and DDDM.

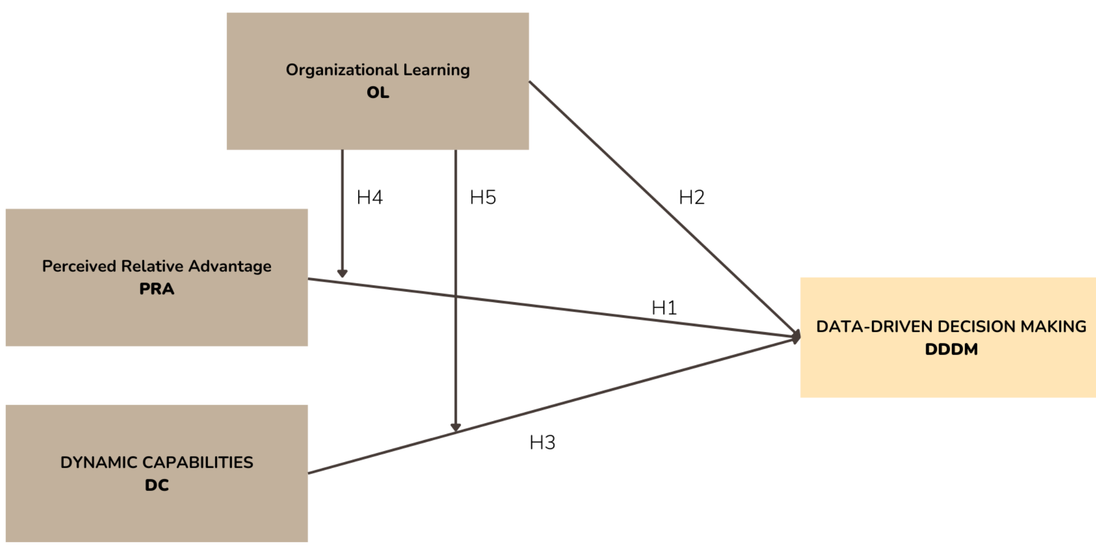


Figure 7: Proposed Conceptual Framework

3. Research Methodology

3.1 Data

3.1.1 Data Collection

This study performed quantitative analyses on a self-administered survey directed at Indonesian SMEs operating on the e-commerce platform Shopee. Despite attempts in collaborating with Shopee Indonesia to distribute the survey and properly conduct random sampling, due to conflicts regarding their company policies, the survey was eventually self-distributed across multiple social media platforms. The survey was designed on the survey platform Qualtrics, to allow for Indonesian translations within the same online environment. To test the translations and the clarity of the questions, a pilot survey and consultations with a local economics platform were conducted. The survey was then distributed to 244 respondents, of which 41 were returned. Out of these, 3 were filtered out as fake stores through a validity check with the provided store link. The final sample size amounted to 38 respondents, yielding a response rate of 15.6%. Aside from the limited timeframe of the study, the low response rate is most likely due to respondents not thoroughly reading the instructions and requirements of the survey, as the majority stopped filling the survey after the question requesting the provision of their Shopee store link. The demographic profiles of the respondents can be found in Table 1.

Adapted from Wirdiyanti et al. (2022), the survey comprises 5 parts: General Survey Information & Disclaimer, Respondent Data, SME Demographics, Awareness and Usage of Data-Driven Decision Making Tools, and Organizational Cultures. The survey can be filled anonymously, with the respondent data section having optional questions should respondents consent to participation in the random giveaway. The questions directly related to the analysis can be found in Table 2, while the full survey can be found in the Appendix.

Table 1. Demographic of Respondents			
Demographics	**Categories**	**Count (n = 38)**	**(%)**
Gender	Male	16	42%
	Female	22	58%
Age	20-30	26	68%
	31-40	6	16%
	41-50	1	3%
	50+	5	13%
Education	Junior High	1	3%
	Senior High	6	16%
	Vocational Studies	3	8%
	Bachelor's Degree	26	68%
	Master's Degree or Higher	2	5%
Number of Employees	Proprietary Owner	3	8%
	1 -- 5	28	74%
	6 -- 10	3	8%
	> 10	3	8%
Firm Age	< 1 Year	1	3%
	1 -- 5 Years	32	84%
	5 -- 10 Years	3	8%
	> 10 Years	2	5%
Store Location	Bali, Nusa Islands, and Sulawesi	3	8%
	JABODETABEK	19	50%
	Java	14	37%
	Sumatra	2	5%
Product Category	Fashion	15	39%
	Hobbies & Stationery	7	18%
	Electronics and Computers	3	8%
	Health and Beauty	3	8%
	Home and Living	2	5%
	Food and Beverage	8	21%
Operational Duration on Shopee	< 1 Year	9	24%
	1 -- 3 Years	21	55%
	> 3 Years	8	21%
Frequency of Using Shopee	Rarely	5	13%
	Sometimes	9	24%
	Very Often	10	26%

	Always	14	37%
Operational Platforms	Less than 3 Platforms	10	26%
	More than 3 Platforms	28	74%
Monthly Revenue	< 25 million Rupiah	28	74%
	25 Million Rupiah - 200 Million Rupiah	7	18%
	200 Million Rupiah - 1 Billion Rupiah	1	3%
	1 Billion Rupiah - 5 Billion Rupiah	1	3%
	> 5 Billion Rupiah	1	3%
Analytical Systems Used	Only Shopee Business Insights	22	58%
	Other Platforms	16	42%

3.1.2 Preliminary Analyses

Several preliminary analyses were conducted before the data analysis, including missing data analysis, response bias, and common method bias. Visualizations of the data such as boxplots and the full correlation matrix were also made and can be found in the Appendix.

Missing Data

Qualtrics allow the customization of setting questions as *required,* which was utilized to avoid issues of missing data. However during the distribution process, there was an error in one subquestion of the independent variables that led to one missing column. Attempts were made in contacting the respondents; however for the remaining 7 that did not respond, row mean imputation of the other “Organizational Learning” subquestions was performed. Other than the second column of Organizational Learning (OL2), no other rows had missing data.

Response Bias

To avoid response bias, the length of the survey was designed to be filled under 5 minutes to lessen cognitive burden (Bogner & Landrock, 2016). A clear statement regarding anonymity and the option to omit personal details was outlined in the beginning of the survey. The majority of questions were multiple choice incorporating a 5-Point Likert scale, with clear instructions in every subsection of the survey. To further reduce response biases, personal data was removed before the data was processed, and only used to contact respondents for the voucher giveaway.

Common Method Bias

Due to the independent and dependent variables being from the same source and self-reported by the respondents, common method bias might be a threat to this study. Applying a similar methodology from Sun et al. (2019), the common method bias can be mitigated with two methods. Following the guidelines by Podsakoff et al. (2003) and the methodology from Sun et al. (2019), several measures were taken to reduce common method bias during both the design of the study and the data collection process. Respondent-researcher anonymity during the data analysis process was ensured, clear instructions were provided, and independent and dependent variables were proximally separated in different sections of the survey (Podsakoff et al., 2003). Despite recommendations of adding a marker-variable, due to efforts in reducing the length of the survey this was ultimately excluded. To statistically determine threats of common method bias, Harman's one factor test was conducted (Greene & Organ, 1973). The first factor had 41% proportion variance explained, which is less than the recommended 50% cutoff (Podsakoff et al. 2003).

3.1.3 Measurement of Variables

As much as possible, all items were adapted from the extant literature and modified in the context of DDDM adoption to fit the needs of this study. Table 2 visualizes the variables used to analytically test the hypotheses.

Dependent Variable

DDDM is the dependent variable of this study. A score of DDDM adoption is constructed from 5 items adapted from Chaterjee et al. 's (2021) interview questions regarding organizational BA analytics system usage and Data Driven Culture in the organization. The 5 items were averaged, resulting in a final DDDM score for each firm.

Control Variables

Dummy variables were created for the survey items found in the Appendix. A stepwise regression was then performed to select the best possible baseline model, from which the variables *monthly_revenue, multi_platform_dummy, duration_shopee, founder_education* were included in the model with the best goodness of fit (R^2), F statistics and p-value. This aligns with related work where control variables included firm age, founder education, and revenue (Chaterjee et al., 2021; Wirdiyanti et al., 2021).

Independent Variables

The independent variables in this study are: the owner-manager's perceived relative advantage (PRA), firm prioritization of organizational learning (OL), and the firm's level of dynamic capabilities (DC). Each variable had 4 items, and 3 composite variables were created by taking the average of each item. Table 2 shows the construction of each item.

Table 2. Survey Item Constructs		
Construct	Sources	Item Statement
DDDM	Chaterjee et al. (2020)	DDDM 1: How often do you use such data analytic systems? DDDM 2: How often do you make decisions based on insights from data analytics systems? DDDM 3: I believe effective data analytics is necessary for faster and accurate decision making. DDDM 4: I believe data plays an important role in new product development. DDDM 5: I believe data plays an important role in improving business processes.
PRA	To & Ngai (2006), Brynjolfsson et al., (2011)	PRA 1: I believe data-driven decision making can increase firms' productivity. PRA 2: I believe data-driven decision making leads to better manage resources PRA 3: I believe data-driven decision making can contribute to increased financial performance. PRA 4: I believe data-driven decision making has the potential to increase a firm's market value.
OL	Lin & Lee (2005)	OL 1: My company has personnel that manages a data analytics system. OL 2: My company views employee training as a valuable investment. OL 3: My company has people with technical knowledge and skills. OL 4: My company has a set of procedures for launching a new product.
DC	Kademeteme & Twinomurinzi (2019), Li & Liu (2004)	DC 1: My company actively identifies major opportunities and threats. DC 2: My company can quickly address unsatisfactory customer issues. DC 3: My company can reconfigure resources in time to address environmental changes. DC 4: My company can effectively implement changes

3.2 Model

To test the proposed conceptual framework and the hypotheses, hierarchical multiple regression was performed. Before doing so, several tests were run to ensure the OLS assumptions were satisfied.

3.2.1 OLS Assumptions

To test the OLS Assumptions, the following tests were run on each step of the hierarchical model. The test results for the final model are seen in Table 3 and Figure 10, while for the other models they can be found in Part 4 of the Appendix.

Normality

Histograms were plotted to check if the data was normally distributed. As seen in Figure 8 the independent variables, PRA, OL, DC had a skewed distribution. This is most likely due to the relatively small sample size;thus, log-transformation was applied to satisfy this assumption. After the transformation, a QQ-plot of the residuals (Figure 9) was visualized to confirm the normality of the distribution.

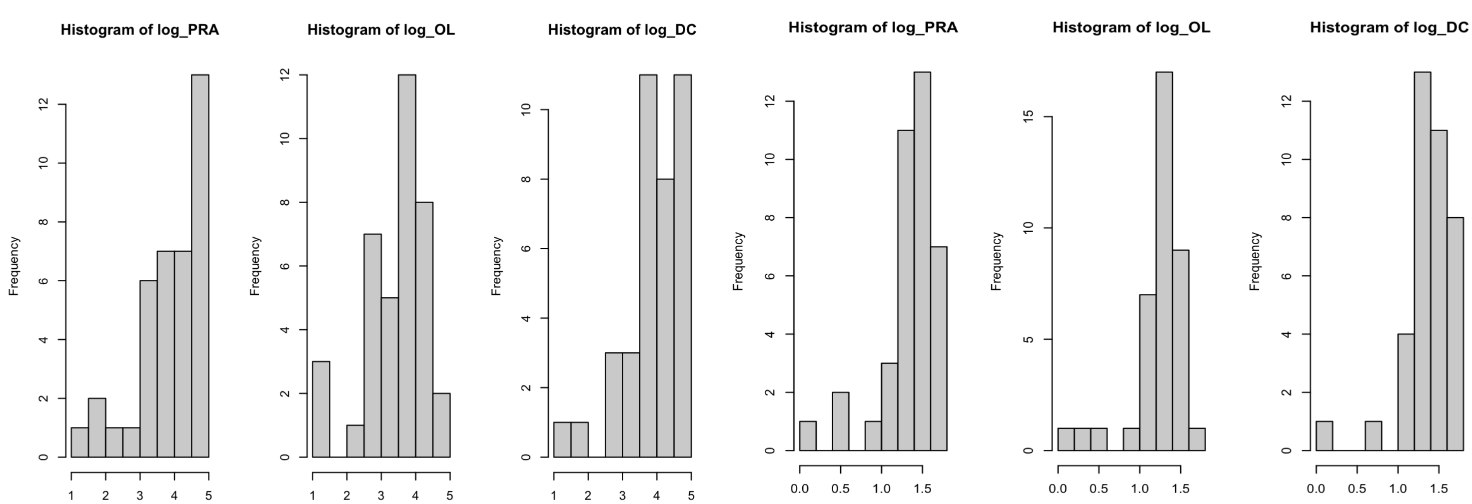


Figure 8: Histogram of Independent Variables before and after log-Transformation

Linearity

The linearity assumption is seen satisfied in the scatterplot of Figure 9. Despite the small sample, the Lowess smoother line on the scatterplot visualizing the fitted and residuals of the final regression model is relatively straight compared to the zero line.

Homoscedasticity

In the same scatterplot in Figure 9, the homoscedasticity assumptions can also be seen satisfied. The dispersion of the points are relatively constant along the range of independent variables, following no specific pattern. Therefore, homoscedasticity - the assumption of constant variance is satisfied.

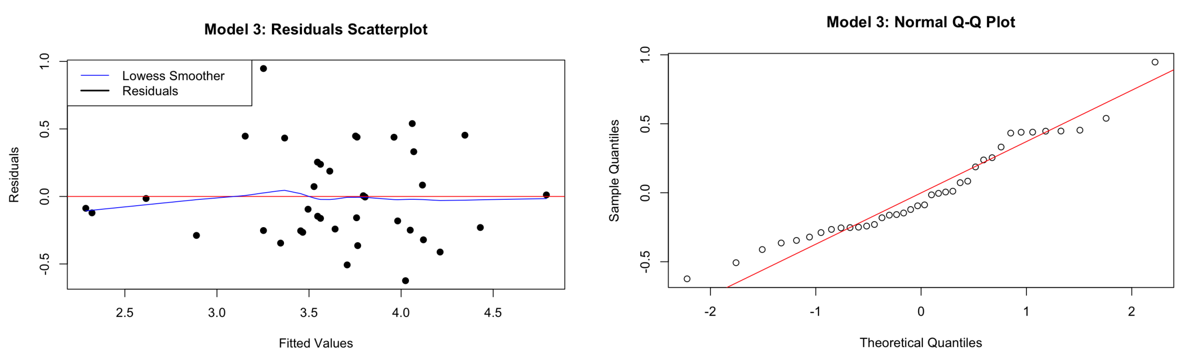


Figure 9: Descriptive Statistics Testing OLS Assumptions

Independence of Observations

To test the independence of observations, the Durbin Watson statistic was examined. The test statistic had a value of 1.898764, indicating evidence of no significant autocorrelation as it is close to a value of 2.

Multicollinearity

The correlation matrix of all the regression variables is visualized in Figure 10. It can be observed that the log transformation of DC exhibited high positive correlations with *log_OL* and *log_PRA*, with correlation coefficients of 0.81 and 0.79, respectively. These high correlations among the predictor variables indicate the possible presence of multicollinearity, which can pose a threat to the regression models. To assess the extent of multicollinearity, the Variance Inflation Factor (VIF) was calculated for all models and presented in Table 3. The first two models did not show any significant multicollinearity, as the VIF values for each variable were all below 5. However, when the interaction effects were introduced, the VIF values became extremely high, exceeding the threshold value 10, indicating a substantial presence of multicollinearity (Hair et al., 1998). To address this issue, the main effects were centered with the mean, resulting in improved VIFs below 10 for the main effects and control variables. Notably, the interaction effects *log_PRA*log_OL* and *log_DC*log_OL* exhibited VIFs of 42.429348 and 41.392372, respectively. Based on this analysis, it is evident that multicollinearity is indeed present to a certain extent, which can be attributed to the small size of the dataset. Therefore, it is important to acknowledge this limitation in the analysis.

Table 3. VIFs of the Hierarchical Regression Model Variables

VIF	Model 1	Model 2	Model 3	Model 3 (Centered)
monthly_revenue	1.049568	1.163728	1.328641	1.328641
multi_platform_dummy	1.068259	1.215784	1.338027	1.338027
duration_shopee	1.176759	1.66988	1.904925	1.904925
founder_education	1.163005	1.24018	1.386417	1.386417
log PRA		1.2408	**90.198179**	**3.300255**
log OL		3.105546	**15.309302**	**3.873157**
log DC		3.427456	**84.303876**	**8.080046**
log PRA*log OL		4.633509	**176.722454**	**42.429348**
log DC*log OL			**164.927747**	**41.392372**

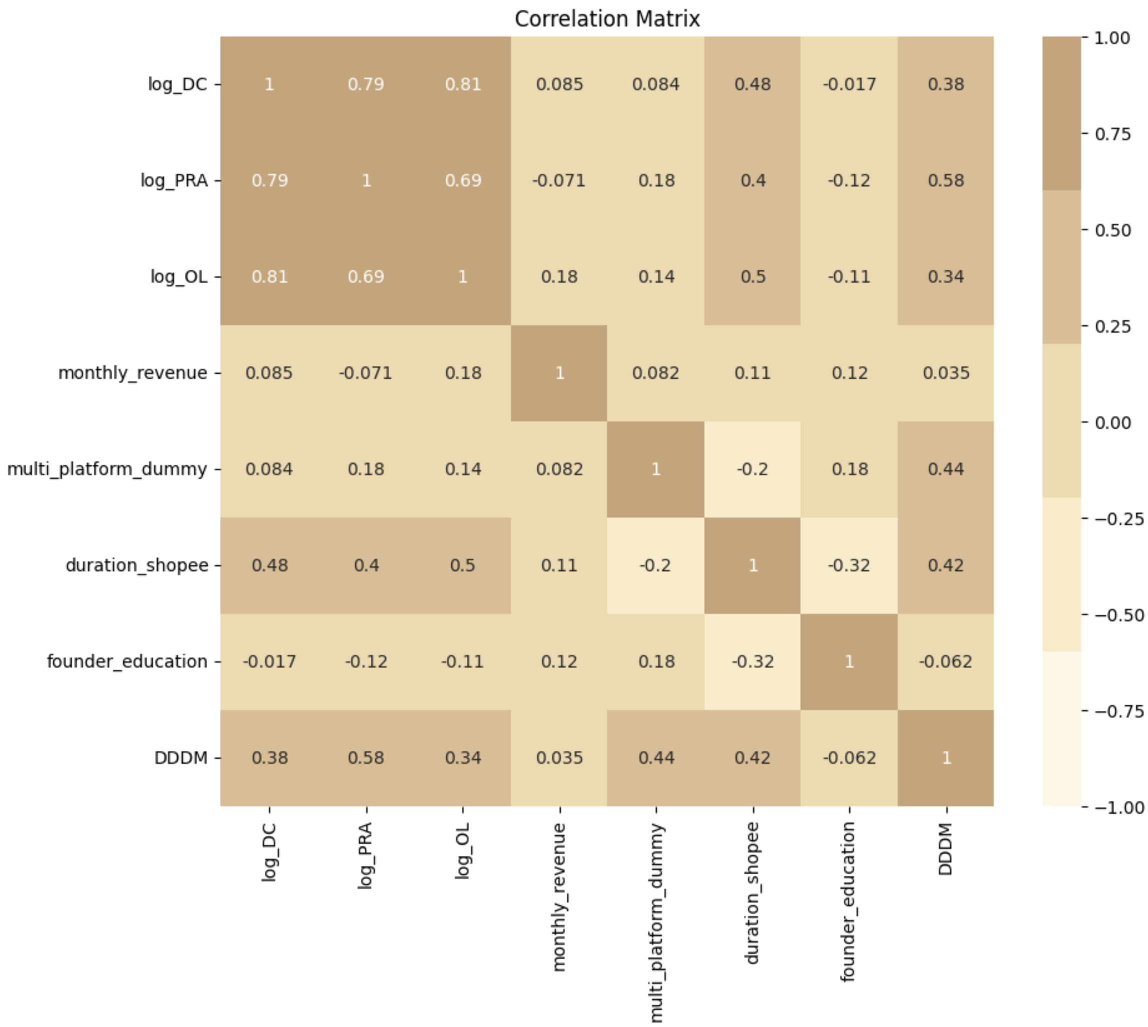


Figure 10: Scatterplot of variables in the multiple regression

3.2.2 Hierarchical Regression Analysis

Since the OLS assumptions were relatively satisfied, a hierarchical regression analysis could then be performed to analyze the impact of the proposed control and independent variables on DDDM. The mathematical representations of the relationship between the predictors and the dependent variables are quantified in three separate equations.

The first multiple regression (Model 1) can be equated as follows:

$$DDDM_i = \alpha_0 + \sum \beta_{ci} C_{ci}^{(1)} + \epsilon_i^{(1)}$$

With this baseline model, DDDM is modeled with the coefficients (β_{ci}) corresponding to the control variables (C_{ci}) including *monthly_revenue, multi_platform_dummy, duration_shopee, founder_education.*

The second multiple regression (Model 2) incorporates 3 additional variables, the main effects, to test Hypotheses 1-3.

$$DDDM_i = \alpha_o + \sum\beta_{ci}C_{ci}^{(2)} + \sum\beta_{mi}M_{mi}^{(2)} + \epsilon_i^{(2)}$$

Here the main effects (M_{mi}) are included alongside the control variables. The coefficients (β_{mi}) represent the effects of the main effect variables (*PRA, OL, DC*) on DDDM.

The third multiple regression (Model 3) extends the analysis by incorporating interaction effect variables, to test Hypotheses 4 and 5.

$$DDDM_i = \alpha_o + \sum\beta_{ci}C_{ci}^{(3)} + \sum\beta_{mi}M_{mi}^{(3)} + \sum\beta_{ii}I_{ii}^{(3)} + \epsilon_i^{(3)}$$

In this final model, the interaction effects (I_{ii}) are introduced alongside the control and main effect variables. The coefficients (β_{ii}) represent the effects of these interaction effects (*OL*PRA* and *OL*DC*) on DDDM.

In all three equations, $DDDM_i$ represents the dependent variable, β_i represents the coefficients, C_{ci} represents the control variables, M_{mi} represents the main effects, I_{ii} represents the interaction effects, while α_0 and ϵ_i represent the intercept and residuals respectively.

4. Results

Table 4 portrays the results from the hierarchical regression analysis. Upon adding the main and interaction effects in a stepwise manner, it can be seen through the values of the Residual Standard Error, Adjusted R-squared (R^2), and F-Statistics that values are gradually improving. The residual standard error gradually decrease from 0.4826 in Model 1 to 0.3968 in Model 3, suggesting close predictions to the actual observed values. Adjusted R^2 is selected to evaluate the goodness of fit by measuring the proportion of variance in the dependent variable. It is a corrected version of R^2 adjusting for the number of predictors and taking into account the sample size, giving a more accurate representation on how the model generalizes to the newly added predictors. There is a gradual increase in the Adjusted R^2 from 0.4118 in Model 1 to 0.6023 in Model 3, indicating improved goodness of fit. The F-test is also included in the table to determine the overall statistical significance of the regression model, evaluated with both the F-statistic and p-value. In all three models, the F-Statistics remain similar; while the p-values decrease gradually with values under p<0.05 for all three models, indicating an overall significant relationship between the model and dependent variable.

Table 4. Results of Hierarchical Regression Analysis

Variables	**Model 1**	**Model 2**	**Model 3**
Coefficient	2.06242(3.646)***	1.59103 (2.966) **	2.23944 (4.285)***
monthly_revenue	-0.05179 (-0.567)	0.03369 (0.396)	0.11027 (1.304)
multi_platform_dummy	0.78676 (4.281) ***	0.66309 (3.829)***	0.58364 (3.451) **
duration_shopee	0.51000 (4.013)***	0.46075 (3.446)**	0.35350 (2.659) *
founder_education	0.01463 (0.157)	0.03240 (0.382)	0.01622 (0.194)
log PRA	-	1.18698 (3.264)**	1.23615 (3.542)**
log OL	-	-0.49505 (-1.314)	-0.72380 (-1.941) •
log DC	-	-0.38726 (-0.764)	0.52880 (0.849)
log PRA*log OL	-	-	3.44220 (2.388)*
log DC*log OL	-	-	-2.77520 (-1.919) •
Residual Standard Error	0.4826	0.4263	0.3968
Adjusted R^2	0.4118	0.5412	0.6023
F-Statistic	7.477 (on 4 and 33 DF)	7.234 (on 7 and 30 DF)	7.227 (on 9 and 28 DF)
p-value	0.0002107	4.28E-05	2.34E-05

The table is read as coefficient(t-value). *** p <0.001 ; ** p< 0.01; * p<0.05; • p <0.1

4.1 Control Variables

Four control variables were included in each multiple regression. The operational duration on Shopee and the dummy variable of operating on multiple platforms both had positive relationships with DDDM and were significant in all 3 models, despite the decrease from a 99% to 95% confidence level. For Model 1, Model 2, and Model 3 the coefficients are 0.51, 0.461, 0.354 and 0.787, 0.663, 0.584 for *duration_shopee* and *multi_platform_dummy* respectively. Based on the results of the last model, which has the best overall model performance, it can be interpreted that holding all other variables constant, for every year the operational duration on Shopee increases, there is an estimated increase of approximately 0.35350 units in DDDM. When *multi_platform_dummy* changes from 0 to 1 (operating on more than 3 platforms), there is an estimated increase of approximately 0.58364 units in DDDM, holding all other variables constant.

Similar to the results of the study on e-commerce adoption by Wirdiyanti et al. (2022), revenue and founder education had no significant effect on DDDM. In the correlation matrix in Figure 10, both revenue and founder_education even had correlations close to 0.

4.2 Main Effects

From all three main effects in Model 2, only the owner-manager's perceived relative advantage had a statistically significant ($p < 0.05$) relationship with DDDM. The t-value of 3.264 and 3.542 in Models 2 and 3 respectively indicates that the coefficient is statistically significant at the 0.05 level, suggesting a strong association between *log_PRA* and *DDDM*. For every 1% increase in *log_PRA, DDDM* is estimated to increase significantly by approximately 1.187% Model 2, holding all other variables constant. As *log_PRA* was centered in Model 3, the coefficient of 1.236 can be interpreted as: 1% increase of PRA from its geometric mean (1.345), DDDM will increase by roughly 1.236%. Therefore with the results from all two models, Hypothesis 1 is accepted.

Organizational learning has a negative relationship with DDDM in both Models 2 and 3, yet is only marginally significant ($p < 0.10$). Previous research consider $p<0.05$ to be a point of significance for variables, therefore, further research is required to properly evaluate this relationship. Yet, with the current findings, Hypothesis 2 is rejected.

Dynamic capabilities has a negative relationship with DDDM in Model 2, but has a positive relationship with DDDM in Model 3. Yet, this relationship is inconclusive as the p values are well above 0.05 in both models;thus, rejecting Hypothesis 3.

4.3 Moderation Analysis

Organizational learning is a significant moderator for the relationship between perceived relative advantage and DDDM. With a coefficient of 3.442 and a p-value of 0.02395, the relationship between the interaction effects *log_OL*log_PRA* and *DDDM* is positive and significant, allowing for Hypothesis 4 to be accepted. This coefficient indicates that the effect on DDDM of a 1% change in PRA from its geometric mean of 1.345 differs depending on the value of OL. Specifically, a 1% increase in PRA from its geometric mean of 1.345 is associated with a 3.44% increase in DDDM, but only when OL also increases by 1% from its geometric mean of 1.233.

There seems to be a negative relative relationship (coefficient of -2.77520) between *log_DC*log_OL* and *DDDM*. However, the p-value was 0.065227, indicating 90% confidence and above the general 0.05, thus requiring further research to validate this inconclusive relationship, and therefore refuting Hypothesis 5 of this study.

5. Conclusion & Discussion

This study aimed to answer the research question: What are significant organizational barriers to and enablers of data-driven decision making in the context of Indonesian SMEs operating on e-commerce platforms? In Section 2 of this study, a comprehensive literature review was undertaken to identify and examine the key barriers and enablers that are associated with data-driven decision making (DDDM). It was observed that organizational factors hold greater importance compared to environmental and technological factors, particularly in the context of this study where decision making is predominantly led by owner-managers, and technological and environmental factors remain relatively constant due to the advantages of operating on an e-commerce platform. With this, 5 hypotheses were formulated:

Hypothesis 1: The owner-managers' perceived relative advantage of DDDM is positively related with DDDM adoption.

Hypothesis 2: The firm's prioritization of organizational learning is positively related to DDDM adoption.

Hypothesis 3: The firm's dynamic capabilities are positively related to DDDM adoption.

Hypothesis 4: The prioritization of organizational learning moderates the relationship between the owner-manager's perceived relative advantage and DDDM adoption.

Hypothesis 5: The prioritization of organizational learning moderates the relationship between the firm's dynamic capabilities and DDDM adoption.

A hierarchical regression was performed to test these hypotheses, as elaborated in Section 3. The results of this study revealed that the relationship between the owner-manager's perceived relative advantage with DDDM is statistically significant, which allowed support for Hypothesis 1. DDDM is greatly influenced by the owner-manager's perceived relative advantage of DDDM, indicating that a better understanding of the advantages of DDDM will result in a higher adoption of DDDM. This aligns with results from past research, where relative advantage has a positive significant relationship in e-commerce and BDA adoption (Lutfi, 2022; Ghobakhloo et al., 2011; To & Ngai, 2006; Premkumar et al. 1994).

Considering the lack of resources SMEs often have, before putting in time, human, and financial resources into a new innovation such as DDDM, it is vital to understand the benefits in order to take the necessary steps to adopt DDDM. Furthermore, support was also given for Hypothesis 4, as the relationship between the perceived relative advantage and DDDM adoption was found to be moderated by the firm's prioritization of organizational learning. This suggests that the extent to which organizational learning is prioritized enhances the relationship between perceived advantage and adoption, and can be explained as, only with the correctly perceived understanding of DDDM, can all employees (regardless of their technical skills) fully understand and carry out DDDM.

The other two hypothesized main effects had inconclusive results as the statistical significance was lacking ;thereby, rejecting Hypothesis 2 and 3. Although Gupta & George (2016) and Mikalef et al. (2020) both put forward that the intensity of organizational learning is one of the critical intangible resources needed to build 'Data Science' capabilities, it is important to realize the setting of both studies. Mikalef et al. (2020) performed a systematic literature review that still required empirical testing, while Gupta & George (2016) did not perform their studies on SMEs; let alone in a country where the economy is still developing. Besides the prioritization of organizational learning, having a culture that promotes DDDM specifically is also important, to ensure the entire firm has a unified vision of implementing DDDM (Rasmussen and Ulrich, 2015).

Similar to the case of organizational learning, where multiple conceptual frameworks such as Rialti et al. (2019) and Reddy et al. (2022) hypothesized a possible relationship between firm dynamic capabilities and DDDM, it is crucial to highlight that these proposed relationship has not been empirically tested and to understand the difference in economic and cultural aspects of Indonesia. Dynamic capabilities has indeed been considered as a mediator between big data analytics and firm performance (Wamba et al., 2017; Mikalef et al., 2020). Yet, when postulating a relationship with emerging IT adoption, Kademeteme & Twinomurinzi (2019) empirically rejected their hypotheses of a positive relationship. In fact Fuller-Love (2006) claimed that absorptive capacity did not affect BI adoption unless the owner-managers perceive the technology as necessary, will they become more likely to adopt it.

Hypothesis 5 of this study was also refuted, as the moderating relationship of the firm's prioritization of organizational learning between the firm's dynamic capabilities and DDDM was significant at a p-value <0.1 but not at the 0.05 level. In Indonesia, only 7.4% of MSMEs operate on online platforms, representing a small demographic with access to the internet and resources to operate an online business. The empirical study of Liu et al. (2018) revealed that the moderating role of organizational learning on dynamic capabilities only had a significant relationship in one model for competitive advantage but none for differential strategy, and that the relationship depends on the external market conditions. The tradeoff between having to adapt quickly to situations (dynamic capabilities) and prioritization of organizational learning can occur depending on different market conditions and what the SME is focused on at certain time periods. It is important to further study this dynamic, if possible in a longer time period instead of one specific point in time.

It is essential to note that while Hypotheses 2, 3, and 5 did not yield statistically significant results in this study, their outcomes provide valuable insights for future research and suggest potential avenues for further investigation.

Furthermore, the observations made by the Bank of Indonesia shed light on the cultural constraints that hinder the embrace of digitalization among SMEs. These constraints influence lower levels of human intellectual capital, as SME staff, even those designated as "IT specialists," may lack sufficient digital literacy to effectively adopt DDDM practices. Additionally, the Bank of Indonesia highlights that only a limited number of SMEs, despite having access to internet facilities and networks with fellow entrepreneurs, professionals, and the government, actually take advantage of the wealth of information available for business growth and advancement. Specifically for Hypothesis 3, although in the survey SMEs claimed they prioritize and value organizational learning, the extent to which they have capable IT personnel, and the extent to which DDDM-specific training is not explored. The aforementioned cultural constraints may pose barriers to fully utilizing their available capital. This cultural constraint is also related to the firm's dynamic capabilities, the extent of agility is not specified, and it is unclear if the SMEs are taking full advantage of available resources and networks to advance digitally (Bank of Indonesia BI Institute, 2022).

As for the control variables, only the dummy variable of operating more than 3 platforms and operational duration on Shopee had positive significant relationships. This can be explained as a higher operational duration increases familiarity with the platform, and allows for time to discern the analytics offered by the platform. Operating on multiple platforms causes dispersed information, which requires constant organization of information and making decisions according to platform-specific insights. Meanwhile, operating on one platform does not require complicated data analysis, where quick decisions could be made merely looking at financial data i.e. sales. Similar to the results of the study on e-commerce adoption by Wirdiyanti et al. (2022), revenue and founder education had no significant effect on DDDM. This is consistent with results from the theoretical research in Section 2.1.3, stating adopting data-driven decision making does not require high education levels or investment. Especially when operating on Shopee, the analytics platform Business Insights is free of charge, along with complementary training resources on how to fully implement DDDM.

5.1 Key Findings

Figure 11 summarizes the estimated relationships of the proposed conceptual framework. These findings can allow for conclusions to be drawn regarding significant barriers and enablers of DDDM adoption that apply to Indonesian SMEs on e-commerce platforms. For this specific context, the following barriers are identified. Firstly, having an unclear understanding of the benefits of DDDM will prevent adoption. Secondly, an even bigger barrier is having low prioritization of organizational learning when the understanding of DDDM advantage is low. These barriers can be tackled by the following enablers. First, having owner-managers understand the benefits of adopting DDDM, and once this understanding is built, also prioritize an organizational learning culture within the firm, specifically one that promotes a unified vision of DDDM.

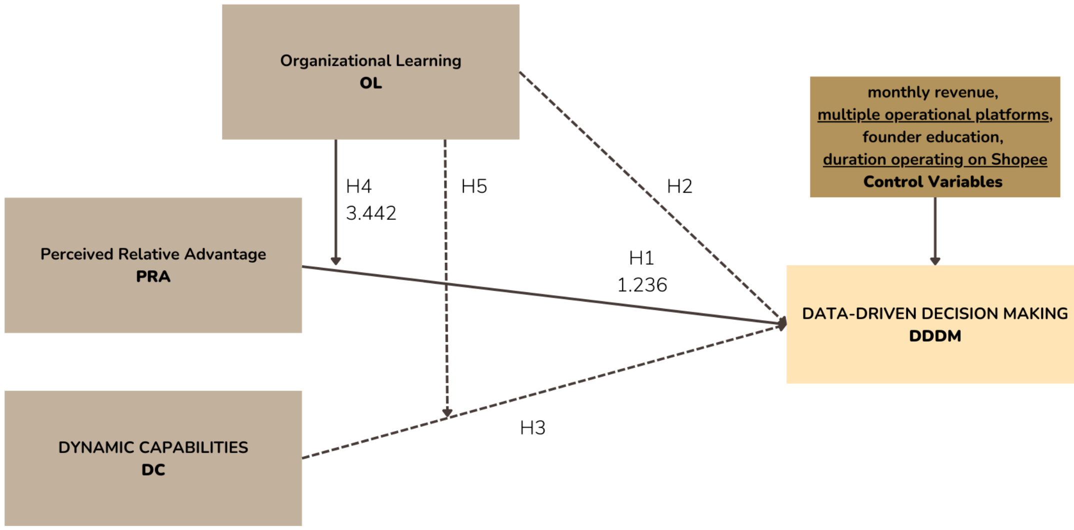


Figure 11: Estimated Relationships within the Conceptual Framework

5.2 Limitations

The dataset is a major limitation in this study;therefore, it is important to carefully consider the findings of this research given the small sample size. As shown in descriptive statistics in Part 4 of the Appendix, there are outliers present to a certain extent, yet as the sample size was too small to be reduced, they were not removed, possibly causing more noise in the model results. The results found inconclusive relationships, some variables being positive and negative, drastically changing as more variables were added, and multiple insignificant relationships, which could be attributed to the small sample size.

This study was also static as the dataset captured one point in time, thus the changes in DDDM adoption and the impact of DDDM (i.e. improved financial performance and innovation) were not studied. Jao (2013) emphasized that adoption is a preliminary stage, and is further followed by adaptation and usage. The following stages are required to be studied to properly decipher the link with success factors.

This study had a specific subject of SMEs operating on Shopee Indonesia. Although Shopee is the biggest e-commerce platform in South-East Asia, there exists other platforms that SMEs operate on, including offline stores, as only 7.4% of Indonesian MSMEs operate on digital platforms (Ministry of Communication and Information of Republic Indonesia, 2018).

Thus, given the narrow research context, researchers should be careful when generalizing these findings, especially from an international perspective, as the results may only be generalizable to countries with a similar industrial infrastructure.

5.3 Theoretical Implications & Future Work

This paper contributes to existing research by painting a broader picture of how SMEs operate, as in general there is limited data on SMEs due to their sheer number and diversity. As mentioned in Section 2.1, data-driven decision making (DDDM) is still an uncommon term, this paper attempts to solidify its definition by connecting multiple perspectives including terms falling under the Data Science umbrella, such as Big Data (Analytics), Business Intelligence, and Information Systems. From the performed literature review, it was concluded that organizational factors, specifically building an organizational culture rooted in DDDM is crucial to adopt DDDM.

To the best of my knowledge, this field has limited English studies with Indonesia as the subject of research. Forsooth, Indonesia has an incredibly interesting economic profile, as it is a developing country with high growth potential. As its economy relies majorly on SMEs, it could serve as a subject in future research agendas focusing on SMEs.

Extending upon the identified limitations in Section 5.2, it is recommended to retest the proposed hypotheses with a broader and larger sample size. It could also be interesting to investigate different stages of adoption, and the impact on firm performance and innovation. This applies to research within Indonesia, where it could be interesting to test the same hypotheses across other e-commerce platforms; as well as other countries, to check the generalizability of these findings in countries with different industrial and economic infrastructure.

5.4 Managerial Implications on e-Commerce SMEs

As previously explained in Section 4 and 5.1, for this study DDDM adoption is most influenced by the owner-manager’s perceived relative advantage. Therefore, in order to adopt DDDM, as key decision-makers in the firm it is crucial to be aware of the benefits of DDDM and develop a better understanding of DDDM.

DDDM can improve productivity levels, maximize the utilization of assets, improve financial performance, and increase a firm's market value (Brynjolfsson et al., 2011). With these benefits in mind, it will be easier to create a unified vision on DDDM throughout the firm. Developing an organizational culture that values DDDM as highlighted in Section 2; where other factors influencing DDDM are explained in more detail, is essential for adoption. This can be further enhanced by prioritizing organizational learning. Organizational learning in this context includes having personnel technically skilled to manage a data analytics system, viewing employee training as a valuable investment, and having set procedures to launch products. This may seem to require significant investments in terms of time, human, and financial capital; however, there exists recommendations that are free of charge. Shopee offers a free seller training center, complete with tutorials and guidelines on multiple aspects, including extracting insights from data. Shopee’s Business Insights could serve as a start of having a data analytics platform before deciding to invest in more sophisticated data analytics platform. In fact, this study found that not all sellers are aware of the BI platform, as only 58% of respondents make use of this free platform.

Should it be difficult to hire full-time and skilled employees to manage the data analytics platform, outsourcing vendors could also be an option, and compensate for the difficulty in recruiting IT professionals and the costs of providing required IT training for employees (Thong, 1999). However, as there are a variety of IT vendors to select from, it is important to select a vendor suiting the firm’s current needs and resources (Hiziroglu & Cebeci, 2013).

LaValle et al. (2013) have created a guideline on adopting DDDM that could also serve as a reference. First, gather the necessary resources and tools to adopt DDDM. Second, set a specific goal where to begin DDDM. For example, focusing on successful historical sales if production innovation is a goal, or looking at marketing data to decide new launch days if improving marketing is the goal. Choose the initial goal that aligns the most with current business goals to further incentivize the implementation. Realize that it is easy to get distracted, therefore it is important to focus and prioritize the necessary changes to successfully follow through. Thirdy, implement long-term goals, which should be broken down to smaller steps. Insights from data is not strict to one period, and may require looking at the bigger picture. It is also vital to re-evaluate the analytics model and business vision for continuous improvements.

6. References

Agyekum, F. K., Reddy, K., Wallace, D., & Wellalage, N. H. (2022). Does technological inclusion promote financial inclusion among SMEs? Evidence from South-East Asian (SEA) countries. *Global Finance Journal*, *53*(100618), 100618. https://doi.org/10.1016/j.gfj.2021.100618

Bank of Indonesia BI Institute. (2022, August 22). *Challenge of Culture-based SMEs Digitalisation*. Www.bi.go.id. https://www.bi.go.id/en/bi-institute/BI-Epsilon/Pages/Tantangan-Digitalisasi-UMKM-Berbasis-Budaya.aspx

Barreto, I. (2010). Dynamic Capabilities: A Review of Past Research and an Agenda for the Future. *Journal of Management*, *36*(1), 256–280. https://doi.org/10.1177/0149206309350776

Beheshti, H. M., Hultman, M., Jung, M.-L. ., Opoku, R. A., & Salehi-Sangari, E. (2007). Electronic supply chain management applications by Swedish SMEs. *Enterprise Information Systems*, *1*(2), 255–268. https://doi.org/10.1080/17517570701273221

Behl, A., Dutta, P., Lessmann, S., Dwivedi, Y. K., & Kar, S. (2019). A conceptual framework for the adoption of big data analytics by e-commerce startups: a case-based approach. *Information Systems and E-Business Management*, *17*(2-4), 285–318. https://doi.org/10.1007/s10257-019-00452-5

Bogner, K., & Landrock, U. (2016). *GESIS Survey Guidelines Response Biases in Standardised Surveys*. https://doi.org/10.15465/gesis-sg_en_016

Boonsiritomachai, W., McGrath, G. M., & Burgess, S. (2016). Exploring business intelligence and its depth of maturity in Thai SMEs. *Cogent Business & Management*, *3*(1). https://doi.org/10.1080/23311975.2016.1220663

Borges, M., Hoppen, N., & Luce, F. B. (2009). Information technology impact on market orientation in e-business. *Journal of Business Research*, *62*(9), 883–890. https://doi.org/10.1016/j.jbusres.2008.10.010

Brackett, M. H. (2001). Business Intelligence Value Chain. *DM Review*, 1–6.

Brynjolfsson, E., Hitt, L. M., & Kim, H. H. (2011). Strength in Numbers: How Does Data-Driven Decisionmaking Affect Firm Performance? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1819486

Chang, S.-I., Hung, S.-Y., Yen, D. C., & Lee, P.-J. (2010). Critical Factors of ERP Adoption for Small- and Medium- Sized Enterprises. *Journal of Global Information Management*, *18*(3), 82–106. https://doi.org/10.4018/jgim.2010070104

Chen, C. (2014). Data-intensive applications, challenges, techniques and technologies: A survey on Big Data. *Information Sciences*, 314–347.

Chong, S. (2008). Success in electronic commerce implementation. *Journal of Enterprise Information Management*, *21*(5), 468–492. https://doi.org/10.1108/17410390810904247

Coleman, S., Göb, R., Manco, G., Pievatolo, A., Tort-Martorell, X., & Reis, M. S. (2016). How Can SMEs Benefit from Big Data? Challenges and a Path Forward. *Quality and Reliability Engineering International*, *32*(6), 2151–2164. https://doi.org/10.1002/qre.2008

Cooper, A. (1996). *Business Intelligence*. Executive Protection Inst .

Coordinating Ministry for Economic Affairs of the Republic of Indonesia. (2021, July 21). *Dukungan Pemerintah untuk Mendorong UMKM Go Digital dan Go Global - Kementerian Koordinator Bidang Perekonomian Republik Indonesia*. Ekon.go.id. https://ekon.go.id/publikasi/detail/3180/dukungan-pemerintah-untuk-mendorong-umkm-go-digital-dan-go-global

Dai, Y. (Nancy), Viken, G., Joo, E., & Bente, G. (2018). Risk assessment in e-commerce: How sellers' photos, reputation scores, and the stake of a transaction influence buyers' purchase behavior and information processing. *Computers in Human Behavior*, *84*, 342–351. https://doi.org/10.1016/j.chb.2018.02.038

Das, K., Tamhane, T., Vatterott, B., Wibowo, P., & Wintels, S. (2018). *The digital archipelago: How online commerce is driving Indonesia's economic development*. McKinsey & Company. https://www.mckinsey.com/~/media/McKinsey/Featured%20Insights/Asia%20Pacific/The%20digital%20archipelago%20How%20online%20commerce%20is%20driving%20Indonesias%20economic%20development/FINAL_The-digital-archipelago-How-online-commerce-is-driving-Indonesias-economic-development.ashx

Davis, C. D., Hills, G. E., & LaForge, R. W. (1985). The Marketing/ Small Enterprise Paradox: A Research Agenda. *International Small Business Journal: Researching Entrepreneurship*, *3*(3), 31–42. https://doi.org/10.1177/026624268500300302

Deloitte. (2019). The rise of the platform economy. In *https://www2.deloitte.com/content/dam/Deloitte/nl/Documents/humancapital/deloitte-nl-hc-the-rise-of-the-platform-economy-report.pdf*.

Edzai Kademeteme, & Hossana Twinomurinzi. (2019). The role of SME dynamic capabilities on the evaluation of existing ICT. *Proceedings of the South African Institute of*

Computer Scientists and Information Technologists 2019, *9781450372657*, 1–8. https://doi.org/10.1145/3351108.3351119

Eiriz, V., Barbosa, N., & Ferreira, V. (2018). Impacts of Technology Adoption by Small Independent Food Retailers. *Journal of Small Business Management*, *57*(4), 1485–1505. https://doi.org/10.1111/jsbm.12413

Elbashir, M. Z., Collier, P. A., & Davern, M. J. (2008). Measuring the effects of business intelligence systems: The relationship between business process and organizational performance. *International Journal of Accounting Information Systems*, *9*(3), 135–153. https://doi.org/10.1016/j.accinf.2008.03.001

Esteve-Pérez, S., & Mañez-Castillejo, J. A. (2008). The Resource-Based Theory of the Firm and Firm Survival. *Small Business Economics*, *30*(3), 231–249. https://www.jstor.org/stable/40650909

Fernández, Z., & Nieto, M. J. (2006). Impact of ownership on the international involvement of SMEs. *Journal of International Business Studies*, *37*(3), 340–351. https://doi.org/10.1057/palgrave.jibs.8400196

Fogarty, G., & Armstrong, D. B. (2009). Modelling the interactions among factors that influence successful computerisation of small business. *Australasian Journal of Information Systems*, *15*(2). https://doi.org/10.3127/ajis.v15i2.513

Fuller-Love, N. (2006). Management development in small firms. *International Journal of Management Reviews*, *8*(3), 175–190. https://doi.org/10.1111/j.1468-2370.2006.00125.x

Garter. (2017). *Top Trends in the Gartner Hype Cycle for Emerging Technologies, 2017*. Www.gartner.com.

https://www.gartner.com/smarterwithgartner/top-trends-in-the-gartner-hype-cycle-for-emerging-technologies-2017

Ghobakhloo, M., Arias‐Aranda, D., & Benitez‐Amado, J. (2011). Adoption of e‐commerce applications in SMEs. *Industrial Management & Data Systems*, *111*(8), 1238–1269. https://doi.org/10.1108/02635571111170785

Google, & Temasek. (2018). *e-Conomy SEA 2018*. https://www.thinkwithgoogle.com/_qs/documents/6730/Report_e-Conomy_SEA_2018_by_Google_Temasek_v.pdf

Grabova, O., Darmont, J., Chauchat, J.-H., & Zolotaryova, I. (2010). Business Intelligence for Small and Middle-Sized Enterprises. *SIGMOD Record* , *39*(2), 39–50. https://doi.org/10.48550/arXiv.1102.0115

Grandon, E. E., & Pearson, J. Michael. (2004). Electronic commerce adoption: an empirical study of small and medium US businesses. *Information & Management*, *42*(1), 197–216. https://doi.org/10.1016/j.im.2003.12.010

Greene, C. N., & Organ, D. W. (1973). An Evaluation of Causal Models Linking the Received Role with Job Satisfaction. *Administrative Science Quarterly*, *18*(1), 95. https://doi.org/10.2307/2391931

Gupta, M., & George, J. (2016). Toward the development of a big data analytics capability. *Information & Management*, 1049–1064.

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (1998). Multivariate Data Analysis. *Prentice-Hall*.

Hill, J., & McGowan, P. (1999). Small business and enterprise development: questions about research methodology. *International Journal of Entrepreneurial Behavior & Research*, *5*(1), 5–18. https://doi.org/10.1108/13552559910259829

Hill, J., & Scott, T. (2004). A consideration of the roles of business intelligence and e‐business in management and marketing decision making in knowledge‐based and high‐tech start‐ups. *Qualitative Market Research: An International Journal*, *7*(1), 48–57. https://doi.org/10.1108/13522750410512877

Hill, J., & Wright, L. T. (2000). DEFINING THE SCOPE OF ENTREPRENEURIAL MARKETING: A QUALITATIVE APPROACH. *Journal of Enterprising Culture*, *08*(01), 23–46. https://doi.org/10.1142/s0218495800000036

Hiziroglu, A., & Cebeci, H. İ. (2013). A Conceptual Framework of a Cloud-Based Customer Analytics Tool for Retail SMEs. *Periodicals of Engineering and Natural Sciences (PEN)*, *1*(2). https://doi.org/10.21533/pen.v1i2.24

Ifinedo, P. (2011). AN EMPIRICAL ANALYSIS OF FACTORS INFLUENCING INTERNET/E-BUSINESS TECHNOLOGIES ADOPTION BY SMES IN CANADA. *International Journal of Information Technology & Decision Making*, *10*(04), 731–766. https://doi.org/10.1142/s0219622011004543

Jao, J. (2013). *Why big data Is A must In ecommerce.* www.bigdatalandscape.com/news/why-big-data-is-a-must-in- ecommerce

Kristoffersen, E., Mikalef, P., Blomsma, F., & Li, J. (2021). The effects of business analytics capability on circular economy implementation, resource orchestration capability, and firm performance. *International Journal of Production Economics*, *239*, 108205. https://doi.org/10.1016/j.ijpe.2021.108205

Lamba, K., & Singh, S. (2018). Modeling big data enablers for operations and supply chain management. *The International Journal of Logistics Management*, 629–658.

Lavalle, S., Lesser, E., Shockley, R., Hopkins, M., & Kruschwitz, N. (n.d.). *Big Data, Analytics and the Path From Insights to Value W I N T E R 2 0 1 1 V O L . 5 2 N O. 2 R E P R I N T N U M B E R 5 2 2 0 5*.

Lin, H., & Lee, G. (2005). Impact of organizational learning and knowledge management factors on e‐business adoption. *Management Decision*, *43*(2), 171–188. https://doi.org/10.1108/00251740510581902

Lin, T. T. C., & Tan, M. (2012). Exploring organizational adoption of cloud computing in Singapore. *19th ITS Biennial Conference, Bangkok 2012: Moving Forward with Future Technologies - Opening a Platform for All*.

Lin, T., & Tan, M. (2012, December 1). Exploring the organizational adoption of cloud computing in Singapore. *2012 International Telecommunication Society, Bangkok, Thailand*.

Liu, C.-H., Horng, J.-S., Chou, S.-F., Huang, Y.-C., & Chang, A. (2018). How to create competitive advantage: the moderate role of organizational learning as a link between shared value, dynamic capability, differential strategy, and social capital. *Asia Pacific Journal of Tourism Research*, *23*(8), 747–764. https://doi.org/10.1080/10941665.2018.1492943

Love, P. E. D., & Irani, Z. (2004). An exploratory study of information technology evaluation and benefits management practices of SMEs in the construction industry. *Information & Management*, *42*(1), 227–242. https://doi.org/10.1016/j.im.2003.12.011

Love, P. E. D., Irani, Z., Standing, C., Lin, C., & Burn, J. M. (2005). The enigma of evaluation: benefits, costs and risks of IT in Australian small–medium-sized enterprises. *Information & Management*, *42*(7), 947–964. https://doi.org/10.1016/j.im.2004.10.004

Lutfi, A., Alsyouf, A., Almaiah, M. A., Alrawad, M., Abdo, A. A. K., Al-Khasawneh, A. L., Ibrahim, N., & Saad, M. (2022). Factors Influencing the Adoption of Big Data Analytics in the Digital Transformation Era: Case Study of Jordanian SMEs. *Sustainability*, *14*(3), 1802. https://doi.org/10.3390/su14031802

McKinsey & Company, Tey, T., & Wintels, S. (2023, April 23). *Indonesia ecommerce growth opportunity: Reseller market* . Www.mckinsey.com. https://www.mckinsey.com/industries/retail/our-insights/resellers-the-unseen-engine-of-indonesian-e-commerce

Mehrtens, J., Cragg, P. B., & Mills, A. M. (2001). A model of Internet adoption by SMEs. *Information & Management*, *39*(3), 165–176. https://doi.org/10.1016/s0378-7206(01)00086-6

Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Review: Information Technology and Organizational Performance: An Integrative Model of IT Business Value. *MIS Quarterly*, *28*(2), 283–322. https://doi.org/10.2307/25148636

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, *58*(3), 103434. https://doi.org/10.1016/j.im.2021.103434

Miller, G. (2013). *6 ways To use “big data” To increase operating margins By 60 %*. http://upstreamcommerce.com/blog/%202012/04/11/6-ways-big-data-increase-operating-margins-60-part-2

Milliken, F. (1987). Three types of perceived uncertainty about the environment: State, effect, and response uncertainty. *Academy of Management Review*, 133–143.

Ministry of Communication and Information of Republic Indonesia. (2018). UMKM Go Online. In *https://www.theindonesianinstitute.com/wp-content/uploads/2018/10/Paparan-UMKM-versi-1.1.pdf*.

Moore, B. (2017). Digital Indonesia: Connectivity and Divergence. In E. Jurriens & R. Tapsell (Eds.), *Cambridge University Press* (pp. 256–275). ISEAS–Yusof Ishak Institute. https://www.cambridge.org/core/books/digital-indonesia/99D4B12CE99CAC86C73610D2590F7CB5

Mullins, R., Duan, Y., Hamblin, D., Burrell, P., Jin, H., Jerzy, G., Ewa, Z., & Aleksander, B. (2007). A Web Based Intelligent Training System for SMEs. *Electronic Journal of E-Learning*, *5*(1), 39–48. https://eric.ed.gov/?id=EJ1098860

Murdoch, T., & Detsky , A. (2013). The inevitable application of big data to health care. *Jama*, 1351–1352.

Nguyen, G. T., & Liaw, S.-Y. (2020). BIG DATA APPLICATION: FROM IDENTIFYING BARRIERS TO FINDING SOLUTIONS. *International Journal of Economics, Business and Management Research*, *Vol. 4, No. 12; 2020*(2456-7760).

Nickel, P. J. (2009). Trust, Staking, and Expectations. *Journal for the Theory of Social Behaviour*, *39*(3), 345–362. https://doi.org/10.1111/j.1468-5914.2009.00407.x

Niu, L., Lu, J., & Zhang, G. (2009). *Cognition-driven decision support for business intelligence : models, techniques, systems and applications*. Springer.

Nutt, P., & Wilson, D. (2010). Handbook of decision making . *John Wiley & Sons*.

Petrakis, P. (2016). Secular stagnation, faltering innovation, and high uncertainty: New-era entrepreneurship appraisal using knowledge-based thinking. *Journal of Business Research*, 1909–1913.

Petter, S., DeLone, W., & McLean, E. (2008). Measuring information systems success: models, dimensions, measures, and interrelationships. *European Journal of Information Systems*, *17*(3), 236–263. https://doi.org/10.1057/ejis.2008.15

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Polese, F., Troisi, O., Grimaldi, M., & Romeo, E. (2019). *A BIG DATA-ORIENTED APPROACH TO DECISION- MAKING: A SYSTEMATIC LITERATURE REVIEW*.

Premkumar, G., Ramamurthy, K., & Nilakanta, S. (1994). Implementation of Electronic Data Interchange: An Innovation Diffusion Perspective. *Journal of Management Information Systems*, *11*(2), 157–186. https://www.jstor.org/stable/40398110

Priem, R. L., & Butler, J. E. (2001). Is the Resource-Based "View" a Useful Perspective for Strategic Management Research?. *The Academy of Management Review*, *26*(1), 22–40. https://doi.org/10.2307/259392

Provost, F., & Fawcett, T. (2013). Data Science and its Relationship to Big Data and Data-Driven Decision Making. *Big Data*, *1*(1), 51–59. https://doi.org/10.1089/big.2013.1508

Rahayu, R., & Day, J. (2016). E-commerce adoption by SMEs in developing countries: evidence from Indonesia. *Eurasian Business Review*, *7*(1), 25–41. https://doi.org/10.1007/s40821-016-0044-6

Ramamurthy, K. (Ram), Sen, A., & Sinha, A. P. (2008). An empirical investigation of the key determinants of data warehouse adoption. *Decision Support Systems*, *44*(4), 817–841. https://doi.org/10.1016/j.dss.2007.10.006

Rasmussen, T., & Ulrich , D. (2015). Learning from practice: how HR analytics avoids being a management fad. *Organizational Dynamics*, 236–242.

Reddy, R. C., Bhattacharjee, B., Mishra, D., & Mandal, A. (2022). A systematic literature review towards a conceptual framework for enablers and barriers of an enterprise data science strategy. *Information Systems and E-Business Management*, *20*(1). https://doi.org/10.1007/s10257-022-00550-x

Rialti, R., Marzi, G., Ciappei, C., & Busso, D. (2019). Big data and dynamic capabilities: a bibliometric analysis and systematic literature review. *Management Decision*. https://doi.org/10.1108/md-07-2018-0821

Rogers, E., & Shoemaker, F. (1971). *Communication of innovations A cross-cultural approach. New York, NY The Free Press. - References - Scientific Research Publishing*. Www.scirp.org. https://www.scirp.org/reference/ReferencesPapers.aspx?ReferenceID=494275

Rogers, L. (1995). Innovation Diffusion Theory . *Information Seeking Behavior and Technology Adoption*, 261–274. https://doi.org/10.4018/978-1-4666-8156-9.ch016

Sabherwal, R., Jeyaraj, A., & Chowa, C. (2006). Information System Success: Individual and Organizational Determinants. *Management Science*, *52*(12), 1849–1864. https://doi.org/10.1287/mnsc.1060.0583

Saggi, M., & Jain, S. (2018). A survey towards an integration of big data analytics to big insights for value-creation. *Information Processing & Management*, 758–790.

Schilke, O. (2014). On the contingent value of dynamic capabilities for competitive advantage: the nonlinear moderating effect of environmental dynamism. *Strategy Management* , 179–203.

Scupola, A. (2003). The Adoption of Internet Commerce by SMEs in the South of Italy: An Environmental, Technological and Organizational Perspective. *Journal of Global Information Technology Management*, *6*(1), 52–71. https://doi.org/10.1080/1097198x.2003.10856343

Segal, H. P. (1994). Future imperfect : the mixed blessings of technology in America | WorldCat.org. In *www.worldcat.org*. Amherst : University of Massachusetts Press,. https://worldcat.org/title/28222570

Setyowati, D. (2019, January 17). *Lampaui Target, 10 Juta UMKM, Petani, dan Nelayan Go-Online - Katadata.co.id*. Katadata.co.id. https://katadata.co.id/berita/2019/01/17/lampaui-target-10-juta-umkm-petani-dan-nelayan-go-online

Shopee. (2019, July 29). *Seller Education Hub*. Seller.shopee.ph. https://seller.shopee.ph/edu/article/8

Simon, H. (1979). Rational decision making in business organizations. *American Economic Review 69*, 493–513.

Simon, H. (1993). *Protocol analysis: Verbal reports as data*. Psycnet.apa.org. https://psycnet.apa.org/record/1993-97655-000

Sun, S., Hall, D. J., & Cegielski, C. G. (2019). Organizational intention to adopt big data in the B2B context: An integrated view. *Industrial Marketing Management*, *86*(2020), 109–121. https://doi.org/10.1016/j.indmarman.2019.09.003

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, *28*(13), 1319–1350. https://doi.org/10.1002/smj.640

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7%3C509::AID-SMJ882%3E3.0.CO;2-Z

Thong, J. Y. L. (1999). An Integrated Model of Information Systems Adoption in Small Businesses. *Journal of Management Information Systems*, *15*(4), 187–214. https://doi.org/10.1080/07421222.1999.11518227

Tian, H., Dogbe, C. S. K., Pomegbe, W. W. K., Sarsah, S. A., & Otoo, C. O. A. (2020). Organizational learning ambidexterity and openness, as determinants of SMEs' innovation performance. *European Journal of Innovation Management*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/ejim-05-2019-0140

Tihanyi, L., Graffin, S., & George, G. (2014). *Rethinking governance in management research*. Academy of Management Journal,.

To, M., & Ngai, E. (2006). *Predicting the Organisational Adoption of B2C E-Commerce An Empirical Study. Industrial Management and Data Systems, 106, 1133-1147. - References - Scientific Research Publishing*. Www.scirp.org. https://www.scirp.org/(S(351jmbntvnsjt1aadkposzje))/reference/referencespapers.aspx?referenceid=1771521

Tornatzky, L. G., & Klein, K. J. (1982). Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. *IEEE Transactions on*

Engineering Management, *EM-29*(1), 28–45. https://doi.org/10.1109/tem.1982.6447463

Tornatzky, L., & Fleischer, M. (1990). *The Processes of Technological Innovation. Lexington Books, Lexington. - References - Scientific Research Publishing*. Scirp.org. https://www.scirp.org/reference/ReferencesPapers.aspx?ReferenceID=1771512

Turban, E., Liang, T. P., & Aronson, J. E. (2005). Decision support systems and intelligent systems. *Pearson Prentice Hall*, *7th*.

Ulrika Jägare. (2019). *Data Science Strategy For Dummies*. John Wiley & Sons.

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, *122*(0148-2963), 889–901. Sciencedirect. https://doi.org/10.1016/j.jbusres.2019.09.022

Wamba, S. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, 356–365.

Wang, Y.-M., Wang, Y.-S., & Yang, Y.-F. (2010). Understanding the determinants of RFID adoption in the manufacturing industry. *Technological Forecasting and Social Change*, *77*(5), 803–815. https://doi.org/10.1016/j.techfore.2010.03.006

Willetts, M., Atkins, A. S., & Stanier, C. (2020). A STRATEGIC BIG DATA ANALYTICS FRAMEWORK TO PROVIDE OPPORTUNITIES FOR SMES. *INTED2020 Proceedings*, *2340-1079*, 3033–3042. https://doi.org/10.21125/inted.2020.0893

Wirdiyanti, R., Yusgiantoro, I., Sugiarto, A., Harjanti, A. D., Mambea, I. Y., Soekarno, S., & Damayanti, S. M. (2022). How does e-commerce adoption impact micro, small, and medium enterprises' performance and financial inclusion? Evidence from Indonesia. *Electronic Commerce Research*, *22*(4). https://doi.org/10.1007/s10660-022-09547-7

Yasa, A. (2018, March 30). *Mayoritas Penjual Shopee Merupakan UMKM*. Bisnis.com. https://ekonomi.bisnis.com/read/20180330/12/755433/mayoritas-penjual-shopee-merupakan-umkm.

Zhu, K. (2004). The Complementarity of Information Technology Infrastructure and E-Commerce Capability: A Resource-Based Assessment of Their Business Value. *Journal of Management Information Systems*, *21*(1), 167–202. https://doi.org/10.1080/07421222.2004.11045794

Zhu, K., & Kraemer, K. L. (2002). e-Commerce Metrics for Net-Enhanced Organizations: Assessing the Value of e-Commerce to Firm Performance in the Manufacturing Sector. *Information Systems Research*, *13*(3), 275–295. https://doi.org/10.1287/isre.13.3.275.82

Zhuang, Y., & Lederer, A. L. (2006). A resource-based view of electronic commerce. *Information & Management*, *43*(2), 251–261. https://doi.org/10.1016/j.im.2005.06.006

Zott, C. (2003). Dynamic Capabilities and the Emergence of Intraindustry Differential Firm Performance: Insights from a Simulation Study. *Strategic Management Journal*, *24*(2), 97–125. https://www.jstor.org/stable/20060516

7. Appendix

Appendix 1: Initial Interview with Shopee e-Commerce Seller

An interview was conducted with the founder of @bobbi.id, an online-based retail SME operating on the e-commerce platform Shopee. Founded in September 2021, the SME single-handedly consists of a founder with a higher education in Fashion Business. The SME's current decision making is mainly based on marketing strategies and selective financial performance, as well as the owner's intuition. Surprisingly, the decision making process is not data-driven, and not based on the "Business Insights" feature provided by the e-commerce platform. When asked what it would take to implement data-driven decision making, the answer was to wait for the growth of a company, and only then hire a skilled employee to do so. This was mainly due to the lack of time and unawareness of the benefits from data-driven decision making. The founder quoted that peers owning SMEs often hire BI services to sort out and create recommendations from the SMEs' business intelligence data.

Appendix 2: *Business Insights* Offered to Sellers of Shopee Indonesia

Image 7.2.1: *An overview of the "Business Insights" feature (SHOPEE, 2019).*

1. Dashboard
Get an overview of your shop's performance based on key metrics, buyer statistics, as well as your best-selling products and categories.

2. Product
Examine the overall and individual performance of your products and identify those that can be improved.

3. Sales & Service
Examine the overall and individual performance of your products and identify those that can be improved. Evaluate your customer service performance by looking at enquiry rate, chat response rate, and conversion rate.

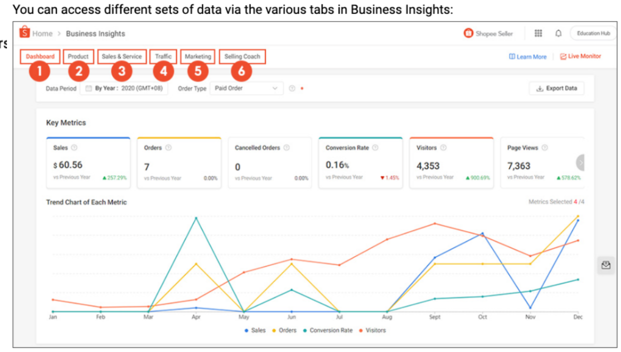
4. Traffic
Analyse the traffic performance of your shop and product detail pages on both App and PC through page views and visitors

5. Marketing
Review your marketing performance across various Marketing Centre tools. Analyse your Shopee LIVE performance.

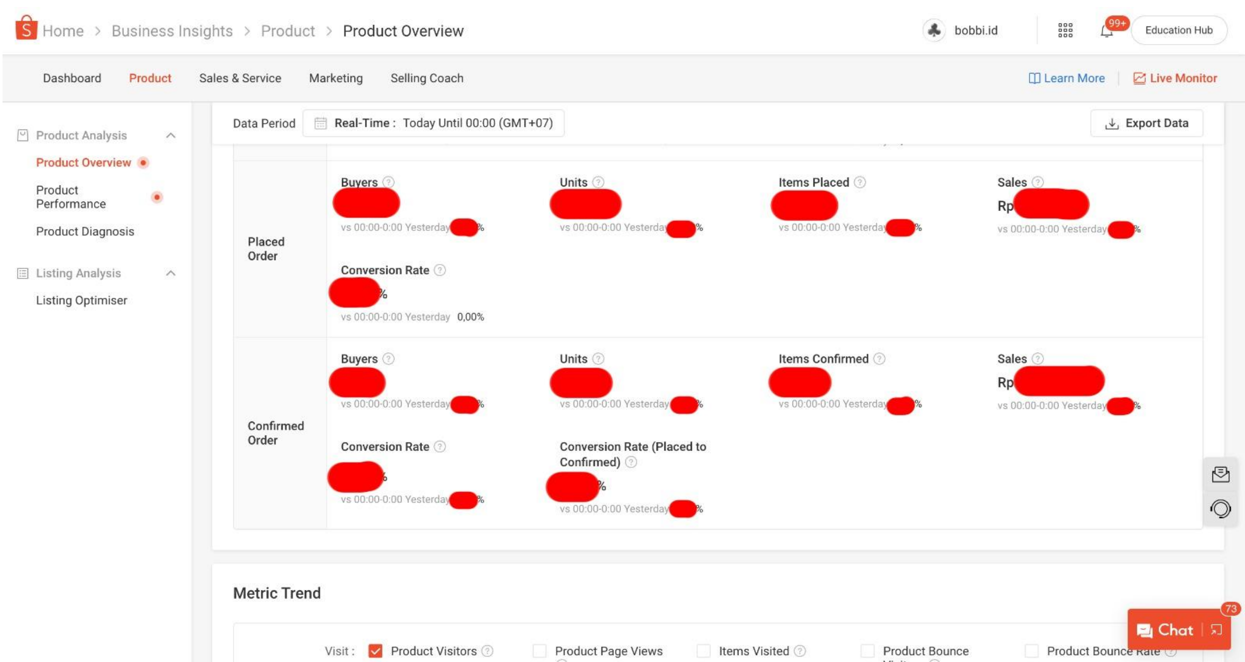
6. Selling Coach
Get personalized recommendations and insights on your listings.

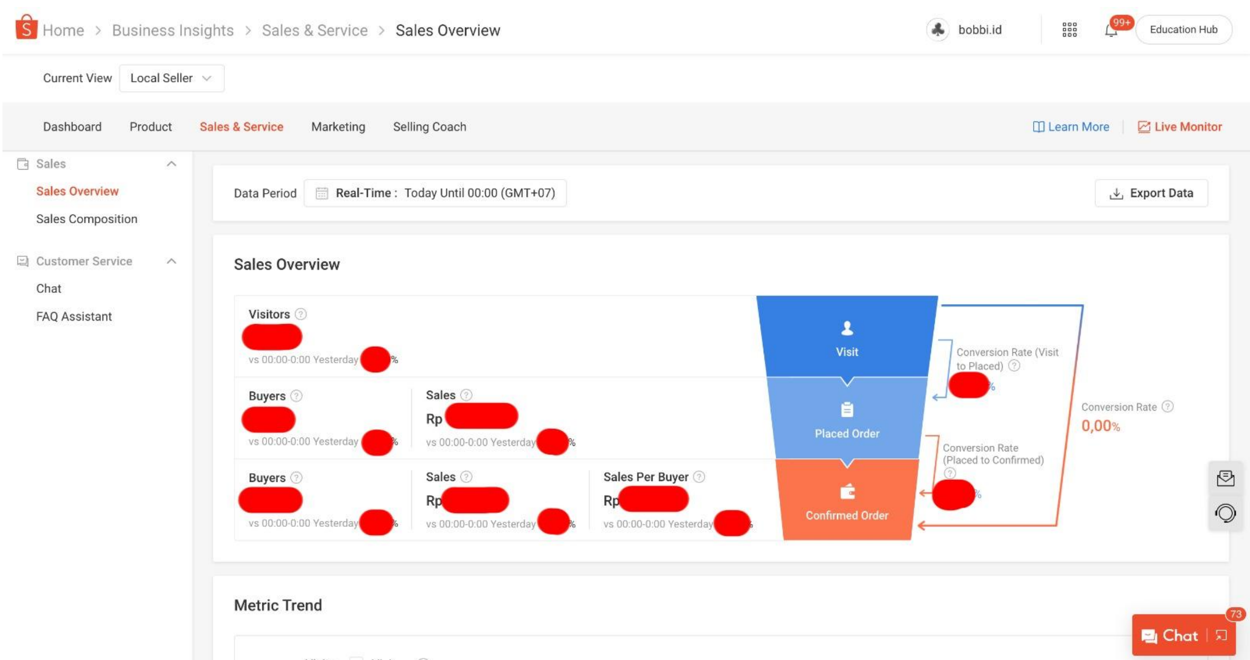
You can access Business Insights via Shopee App or Seller Centre.

You can access different sets of data via the various tabs in Business Insights:



Images 7.2.2-7.2.4: *Actual images from the "Business Insights Feature"*




Home > Business Insights > Sales & Service > Sales Overview
bobbi.id
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Education Hub
Current View
Local Seller
Dashboard
Product
Sales & Service
Marketing
Selling Coach
Learn More
Live Monitor
Sales
Sales Overview
Sales Composition
Customer Service
Chat
FAQ Assistant
Data Period
Real-Time : Today Until 00:00 (GMT+07)
Export Data
Sales Overview
Visitors
vs 00:00-0:00 Yesterday
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Sales
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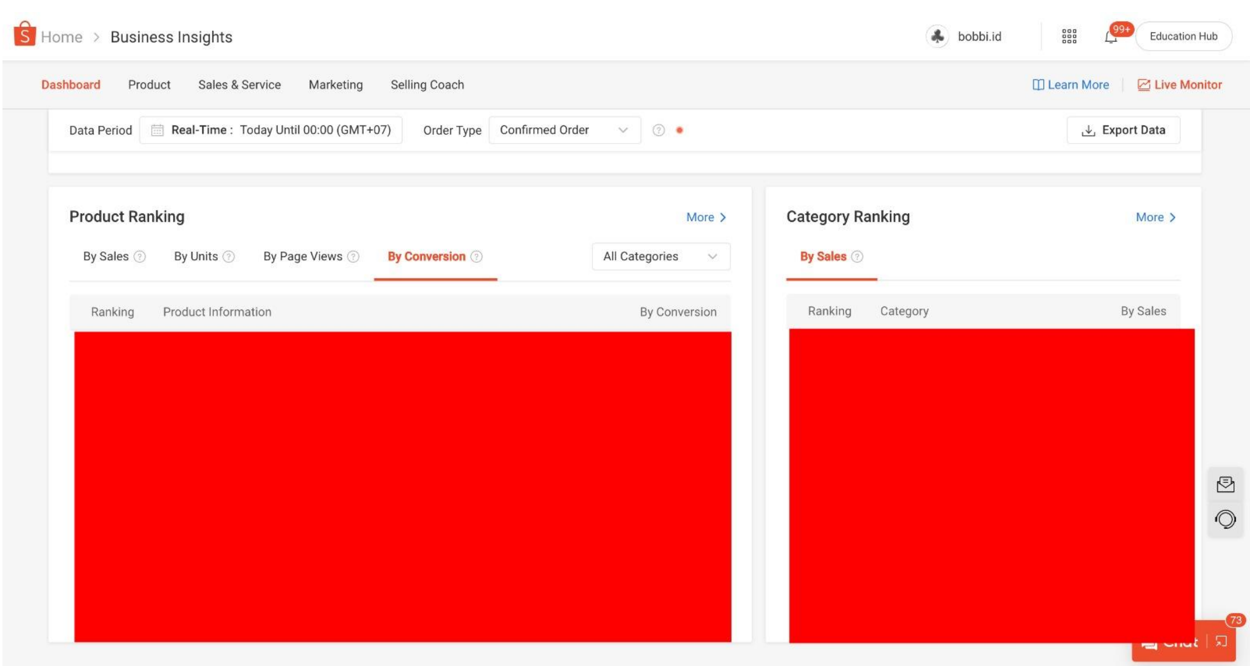
Home > Business Insights
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99+
Education Hub
Dashboard
Product
Sales & Service
Marketing
Selling Coach
Learn More
Live Monitor
Data Period
Real-Time : Today Until 00:00 (GMT+07)
Order Type
Confirmed Order
Export Data
Product Ranking
More >
By Sales
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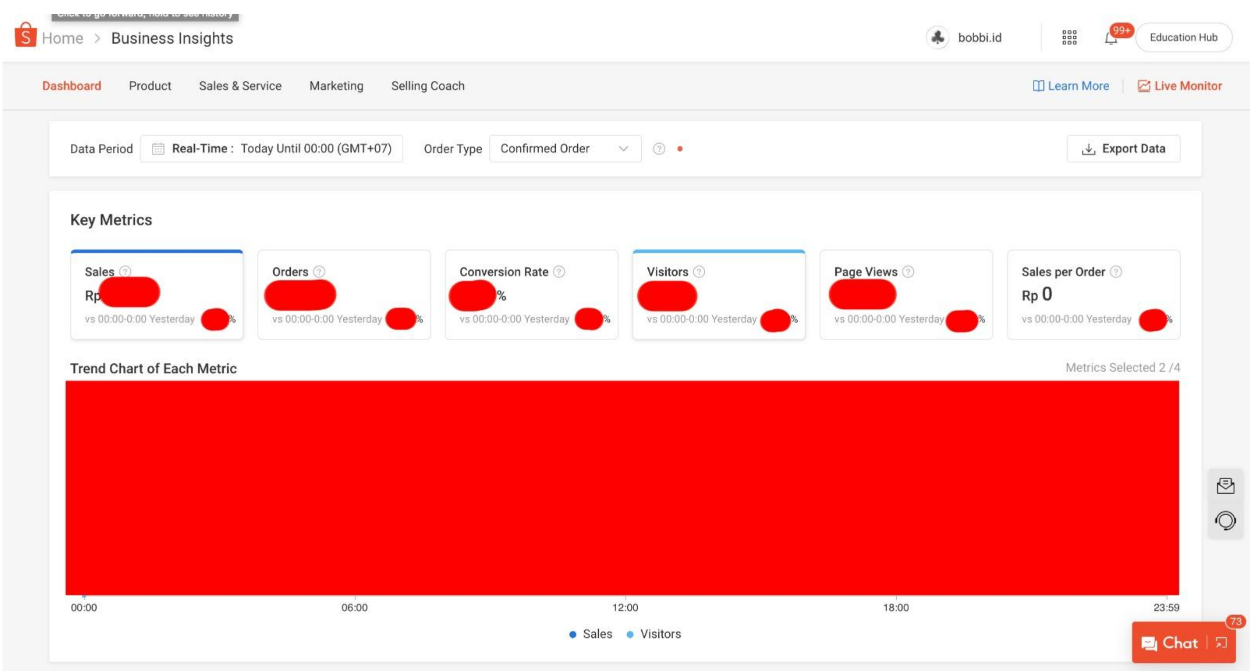

(Source: Courtesy of the SME interviewee)

Appendix 3: Full Survey

Part 1: Respondent Data

1. Name
2. Email
3. Age
4. Gender
    a. Male
    b. Female
5. Role within Company
6. Education Level
    a. Elementary
    b. Junior High
    c. Senior High
    d. Vocational Studies
    e. Bachelor's Degree
    f. Master's Degree or Higher

Part 2: SME Demographics

7. Store Name
8. Shopee Store Link
9. Number of Employees
10. Firm Age (Years)
11. Main Location of Store

   a. JABODETABEK
   b. Jawa Timur
   c. Jawa Barat
   d. Jawa Tengah
   e. Sumatra
   f. Bali, NTT, NTB
   g. Kalimantan
   h. Sulawesi
   i. Other

12. Product Category
    a. Fashion
    b. Hobbies & Stationery
    c. Electronics and Computers
    d. Health and Beauty
    e. Home and Living
    f. Sports and Outdoors
    g. Food and Beverage
    h. Automotive
    i. Tickets and Vouchers
    j. Other
13. How long have you been operating on Shopee?
    a. < 1 Year
    b. 1-3 Years
    c. 4-6 Years
14. How often do you use Shopee to sell your products
    a. Never
    b. Rarely
    c. Sometimes
    d. Very Often
    e. Always
15. What other platforms do you use to sell your products?
    a. No Other Platforms
    b. Physical Stores
    c. Social Media (Facebook, Instagram, Twitter, etc.)
    d. Chat Applications (Whatsapp, Line, etc.)
    e. Tokopedia
    f. Bukalapak
    g. Blibli
    h. Other
16. Average Revenue per Month
    a. < 25 million Rupiah
    b. 25 Million Rupiah - 200 Million Rupiah
    c. 200 Million Rupiah - 1 Billion Rupiah
    d. 1 Billion Rupiah - 5 Billion Rupiah
    e. > 5 Billion Rupiah

Part 3: Awareness and Usage of Data-Driven Decision Making Tools
Data-driven decision making (DDDM) is the practice of basing decisions on the analysis of data rather than purely on intuition. DDDM has been proven to increase firms' productivity, better financial performance, and increase a firm's market value. Examples of implementing DDDM include using analytics to justify actions (e.g. restocking certain products due to a high sales volume), using insights to guide strategies (e.g. holding sales on Mondays as most traffic are on Monday evenings), or using insights as reference for day-to-day operations.

DDDM is usually based on data analytics systems that allow organizations to analyze all their data, identify patterns, and generate insights. Examples are PowerBI, Microsoft Excel, Tableau, SAS, and many more.

Shopee offers Business Insights, a data analytics system on the Shopee App and Seller Centre that gives you a comprehensive overview of your sales trends and performances. It helps you understand potential areas of improvements and allows you to: Interpret trends and identify insights through historical data, deep dive into product level data and customize your strategy, understand the sales metrics and boost your sales, monitor your real-time performance. You can access different sets of data via the various tabs in Business Insights: Dashboard, Product, Sales & Service, Traffic, Marketing, Selling Coach. More information can be found in https://seller.shopee.ph/edu/article/8

17. What type of data analytics systems do you use?
    a. Shopee Business Insights
    b. Other Platforms
    c. Both Shopee Business Insights and Other Data Analytics Platforms
    d. None
18. How often do you use such data analytic systems?
    a. Never
    b. Rarely
    c. Sometimes
    d. Very Often
    e. Always
19. How often do you make decisions based on insights from data analytics systems?
    a. Never
    b. Rarely
    c. Sometimes
    d. Very Often
    e. Always
20. I believe effective data analytics is necessary for faster and accurate decision making.
    a. Strongly disagree
    b. Somewhat disagree
    c. Neither agree nor disagree
    d. Somewhat agree
    e. Strongly agree

21. I believe data plays an important role in new product development.
    a. Strongly disagree

b. Somewhat disagree
c. Neither agree nor disagree
d. Somewhat agree
e. Strongly agree

22. I believe data plays an important role in improving business processes.
    a. Strongly disagree
    b. Somewhat disagree
    c. Neither agree nor disagree
    d. Somewhat agree
    e. Strongly agree

Part 4: Organizational Cultures

23. Understanding of Data-Driven Decision Making Advantages

For the following 4 statements rate a score given the following scale: (1) Strongly disagree, (2) Somewhat disagree, (3) Neither agree nor disagree, (4) Somewhat agree, (5) Strongly agree.

1. I believe data-driven decision making can increase firms' productivity.
2. I believe data-driven decision making leads to better manage resources.
3. I believe data-driven decision making can contribute to increased financial performance.
4. I believe data-driven decision making has the potential to increase a firm's market value

24. Organizational Learning Culture

For the following 4 statements rate a score given the following scale: (1) Strongly disagree, (2) Somewhat disagree, (3) Neither agree nor disagree, (4) Somewhat agree, (5) Strongly agree.

1. My company has personnel that manages a data analytics system
2. My company views employee training as a valuable investment
3. My company has people with technical knowledge and skills.
4. My company has a set of procedures for launching a new product.

25. Company Adaptability to Change

For the following 4 statements rate a score given the following scale: (1) Strongly disagree, (2) Somewhat disagree, (3) Neither agree nor disagree, (4) Somewhat agree, (5) Strongly agree.

1. My company actively identifies major opportunities and threats.
2. My company can quickly address unsatisfactory customer issues.
3. My company can reconfigure resources in time to address environmental changes.
4. My company can effectively implement changes.

Appendix 4: Descriptive Statistics of Data

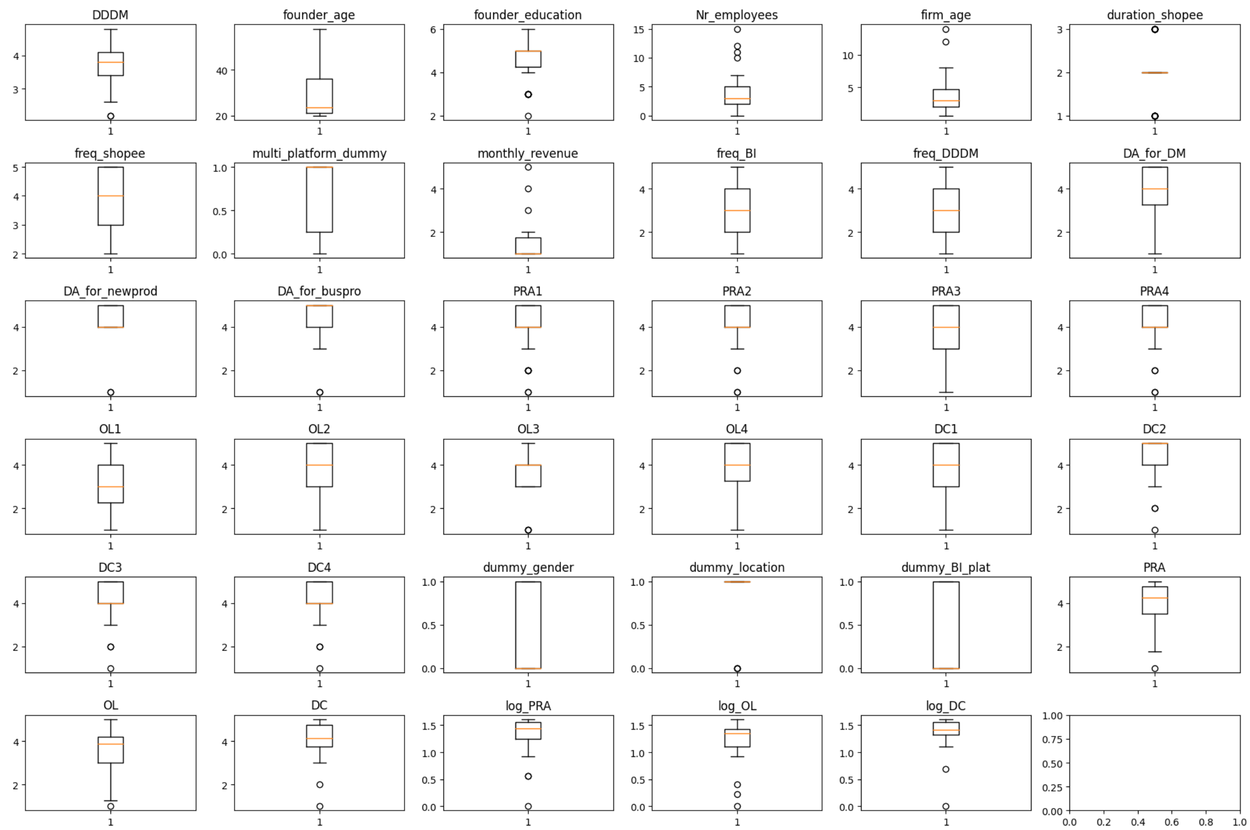

Figure 7.4.1: Boxplots of All Variables

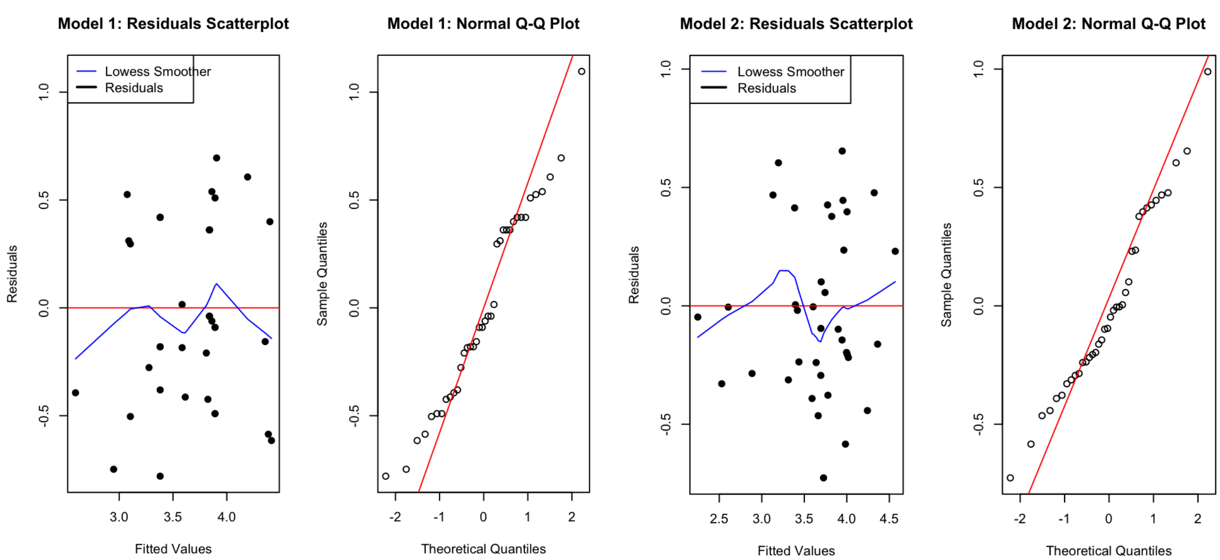

Figure 7.4.2: Visualization of OLS Assumptions for Models 1 & 2

Table 5. Complete Parameter Estimates				
Model 1				
	Coefficients:	**Estimate Std. Error**	**t value**	**Pr(>|t|)**
(Intercept)	2.06242	0.5657	3.646	0.000908 ***
monthly_revenue	-0.05179	0.0914	-0.567	0.574821
multi_platform_dummy	0.78676	0.18376	4.281	(4.281) ***
duration_shopee	0.51	0.12708	4.013	(4.013)***
founder_education	0.01463	0.09309	0.157	-0.157
log PRA				
log OL				
log DC				
log PRA*log OL				
log DC*log OL				
Residual Standard Error: 0.4826 (33 DF)	R^2: 0.4754	**Adjusted** R^2:0.4118	**F-Statistic:** 7.477 (4 and 33 DF)	**p-value:** 0.0002107
Model 2				
	Coefficients:	**Estimate Std. Error**	**t value**	**Pr(>|t|)**
(Intercept)	1.59103	0.53637	2.966	0.005866 **
monthly_revenue	0.03369	0.08501	0.396	0.694698
multi_platform_dummy	0.66309	0.17315	3.829	0.000609 ***
duration_shopee	0.46075	0.1337	3.446	0.001704 **
founder_education	0.0324	0.0849	0.382	0.705457
log PRA	1.18698	0.36362	3.264	0.002742 **
log OL	-0.49505	0.37685	-1.314	0.198923
log DC	-0.38726	0.5067	-0.764	0.45067
log PRA*log OL				
log DC*log OL				
Residual Standard Error: 0.4263 (30 DF)	R^2: 0.628	**Adjusted** R^2: 0.5412	**F-Statistic:** 7.234 (7 and 30 DF)	**p-value:** 4.282e-05
Model 3				
	Coefficients:	**Estimate Std. Error**	**t value**	**Pr(>|t|)**
(Intercept)	2.23944	0.52267	4.285	0.000195 ***
monthly_revenue	0.11027	0.08456	1.304	0.202813
multi_platform_dummy	0.58364	0.16911	3.451	0.001789 **
duration_shopee	0.3535	0.13294	2.659	0.012812 *
founder_education	0.01622	0.08357	0.194	0.847476
log PRA	1.23615	0.34896	3.542	0.001412 **

log OL	-0.7238	0.37294	-1.941	0.062415
log DC	0.5288	0.62291	0.849	0.403128
log PRA*log OL	3.4422	1.44173	2.388	0.023952 *
log DC*log OL	-2.7752	1.44615	-1.919	0.065227
Residual Standard Error: 0.3968 (28 DF)	R^2: 0.6991	**Adjusted** R^2: 0.6023	**F-Statistic:** 7.227 (9 and 28 DF)	**p-value:** 2.335e-05

Table 6. Constructed Dummy Variables

Column Names	Reference Group	Notes
dummy_gender	0: Female 1: Male	-
dummy_location	0: Bali, NTT, NTB, Sulawesi, Sumatra 1: Java & Jabodetabek	East and West Java are included in Java, as most trade is in these provinces.
multi_platform_dummy	0: Less than 3 store platforms 1: More than 3 platforms	Options for other platforms include: Physical Stores, Social Media (Facebook, Instagram, Twitter, etc.), Chat Applications (Whatsapp, Line, etc.), Tokopedia, Bukalapak,Blibli, Lazada, Kaskus

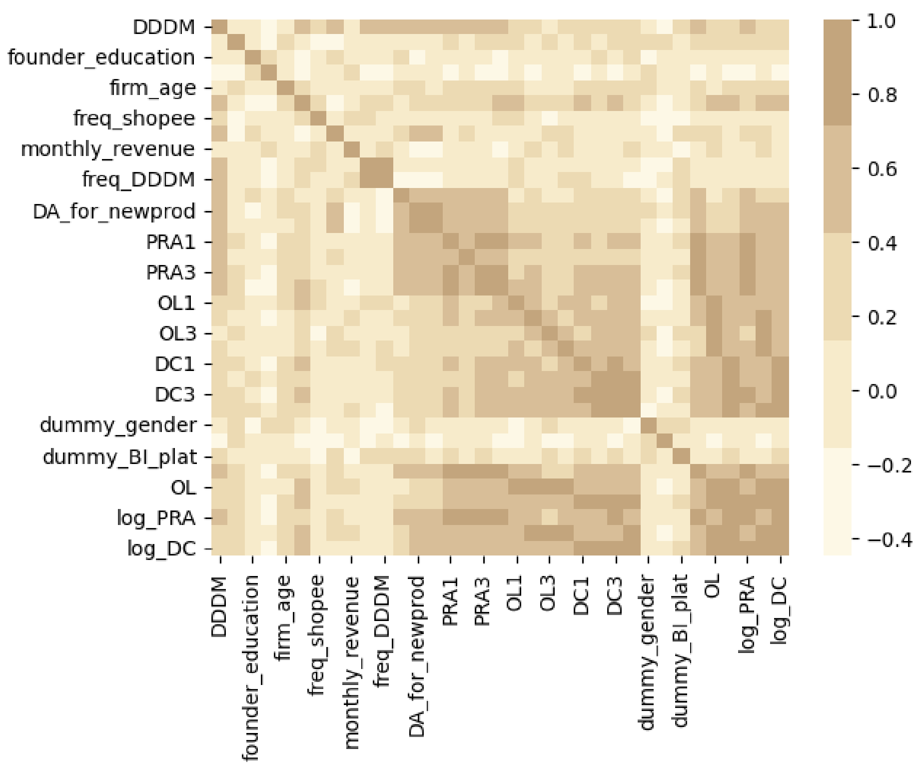

Figure 7.4.3: Correlation Matrix of All Variables