# BARRIERS TO DATA-DRIVEN DECISION-MAKING AMONG ONLINE RETAILERS

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**Abstract** This study investigates the barriers to data-driven decision-making among online retailers. The study seeks to deepen the previous knowledge by considering data-driven decision-making as a process and identifying the critical obstacles within its different (6) stages. Qualitative interview data (N=10) collected from Finnish e-commerce professionals are analyzed. The findings show that barriers to data-driven decision-making occur at all stages during the decision-making process. The barriers are mostly related to the employees' and the management's expertise in collecting, organizing, analyzing, summarizing, synthesizing, and prioritizing data. In addition, attitudinal, technical, and strategy-related barriers can hinder data-driven decision-making. The findings suggest that all the stages included in the data-driven decision-making process and the obstacles that prevent data-driven decision-making during the different stages should be carefully investigated and considered by online retailers.

**Keywords:**
data analytics,
data-driven decision-making,
online retailers,
e-commerce.

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## 1 Introduction

Decision-making is one of the most significant factors influencing an organization's performance as decisions guide the organization's all activities. The organization's failure or success depends primarily on its ability to utilize information and make decisions in a competitive business environment (Porter & Millar, 1985). The prevalence of information technology and the internet has enabled companies to collect large amounts of data and use it in their decision-making. More and more companies base their decisions on data-based analytics instead of management's "gut instinct" (Brynjolfsson, Hitt, & Kim, 2011). It has been noted that data-driven decision-making has many beneficial effects on an organization's performance and competitive advantage (Sumbal, Tsui, & See-to, 2017; Rialti et al., 2019). Data collection and analysis are considered necessary to facilitate the management's actions and decisions (Pohl, Staegemann, & Turowski, 2022).

Efficient use of data analytics is a crucial management tool for online retailers in particular (Phippen, Sheppard, & Furnell, 2004). Data analytics is the key to tracking customer behavior and gathering important information about the customer. Data analytics (also called marketing analytics) provides methods for measuring, analyzing, predicting, and managing a company's performance to maximize effectiveness and return on investment (Wedel & Kannan, 2016). Because of its importance, data has been called "the oil" of the digital economy (Wedel & Kannan, 2016). Furthermore, the online environment is constantly changing because of technological advancement. It forces online retailers to maintain their competitiveness and continually seek new ways to improve their business models and find new business opportunities based on data.

However, even though data-driven decision-making is highlighted nowadays, effective usage of analytics can be a big challenge for small companies in particular. It has been suggested that it may be hard to understand how to collect and utilize information strategically (Alford & Page, 2015). Previous research has shown that the most significant barriers to analytics usage include lack of resources, budgets, and skills (Chaffey & Patron, 2012), low-quality data, and inappropriate data analytics tools (Ghasemaghaei, Ebrahimi, & Hassanein, 2018). The involvement of top managers and a supportive organizational culture are also recognized as central issues in the deployment of data analytics (Germann, Lilien, & Rangaswamy, 2013;

Maxwell, Rotz, & Garcia, 2016). In addition, although the debate over data analytics has been lively, few studies have focused on examining the challenges of data-driven decision-making among online retailers and during their decision-making processes. Hence, this study seeks to deepen the previous knowledge by concentrating on online retailers' perspectives and considering data-driven decision-making as a process. The study aims to identify and describe the main barriers to data-driven decision-making at different stages of the decision-making process.

This study continues with the theoretical background in which the data-driven decision-making process is discussed. The theoretical section is followed by the methodology and the study's findings. The last section discusses the findings and gives some suggestions for future research.

## 2 Theoretical background: Data-driven decision-making process

Organizations' use of information in decision-making has been investigated in numerous studies (e.g., Choo, 1996; Nonaka & Konno, 1998; Rowley, 2007). Choo (1996) notes that organizations use information strategically in three areas. These include: making sense of changes in the operation environment, creating new knowledge for innovation, and making decisions about courses of action. In addition, data-driven decision-making has been discussed extensively (e.g., Brynjolfsson, Hitt, & Kim, 2011; Provost & Fawcett, 2013; Brynjolfsson & McElheran, 2016). Data-driven decision-making (DDDM) refers to activities where decisions are made based on the analysis of data rather than only based on intuition (Provost & Fawcett, 2013). Data is collected and analyzed so that the company can make better, more informed, and faster decisions. In the context of online retailing, data can include, for instance, clickstream, transaction, voice, and video data (Davenport, 2012). However, it has been noted that many companies that invest in data analytics cannot take full advantage of using data analytics tools (Ghasemaghaei, Ebrahimi, & Hassanein, 2018).

The data-driven decision-making process is typically pictured by dividing it into phases: collect, analyze and use (Maxwell, Rotz, & Garcia, 2016). One of the best-known models for data utilization in decision making is the DIKW pyramid, also known as the Information hierarchy, Wisdom hierarchy, and Knowledge pyramid

(Rowley, 2007). Even though the origin of the hierarchy is uncertain, it has been utilized in information science discussions for many years (Wallace, 2007).

The DIKW model explains how organizations can move from data (D) to information (I), knowledge (K), and wisdom (W) with their actions and decisions. Even though there are multiple interpretations of the model, the core idea is that each phase during the continuum is a step towards a higher level of understanding. Zeleny (2006) notes that the process includes the steps of know-nothing (data), know-what (information), know-how (knowledge), and know-why (wisdom).

This study mainly relies on Mandinach, Honey, and Light's (2006) interpretation of the DIKW model (Figure 1). Mandinach et al.'s version is supplemented with the help of related literature (e.g., Ackoff, 1989; Rowley, 2007). Mandinach et al. (2006) include only three main phases in the decision-making process: data, information, and knowledge. They also list six actions (collect, organize, analyze, summarize, synthesize and prioritize) that are crucial during the decision-making process.

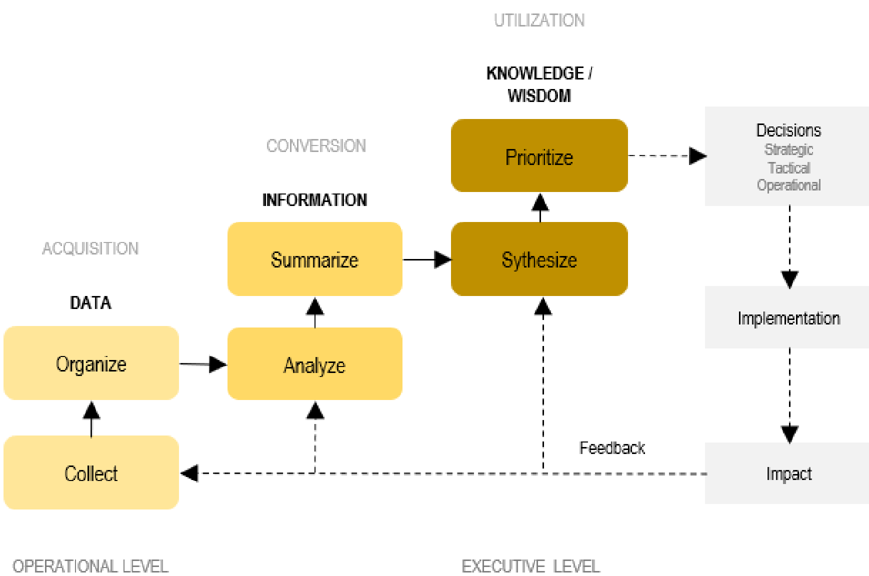


**Figure 1: Data-driven decision-making process. Adopted from Mandinach, Honey & Light (2006), Ackoff (1989), and Rowley (2006)**

According to Mandinach et al.(2006), data refers to the collection of facts in a raw or unorganized form. Data includes symbols that describe the properties of events, objects, and their environment (Baskarada & Koronios, 2013). Data can exist in any form, including numbers and characters. It does not have meaning in and of itself; hence, whether it becomes information depends on the people looking at the data. Important issues regarding data include how data is *collected* and *organized*. The organization must decide what data is collected and which data collection should be helpful. After the data is collected, it must be organized systematically to be made sense of.

Information comes into existence when raw data is *analyzed* and *summarized*. Data turns into information when it is further processed – when it is connected to a context and given meaning (Mandinach et al., 2006). It answers the questions of who, when, what, where, and how many (Ackoff, 1989). It is vital to produce targeted and concise summaries of information that can be transformed into usable knowledg*e* (Mandinach et al., 2006).

Knowledge is achieved when the organization *synthesizes* the available information and *prioritizes* the knowledge (Mandinach et al., 2006), meaning that it is used to achieve goals and guide action. Knowledge answers the how-to questions (Ackoff, 1989).

The concept of wisdom has received limited attention in the literature (Rowley, 2007) because it is difficult to distinguish between knowledge and wisdom. Zeleny (2006, p. 7) states that wisdom includes understanding why things should be done; it is a “socially accepted or experience-validated explication of purpose. “ As noted before, Mandinach et al. (2006) do not mention the wisdom-layer in their model, but similar ideas are included in *knowledge*.

To sum up, organizations first need to acquire data, convert it into usable information and, finally, utilize the engendered knowledge and wisdom in decision-making to be data-driven. Following these ideas and the decision-making framework presented in Figure 1, the empirical investigation of this study aims to find out:

- what prevents online stores from collecting and organizing data
- what prevents data from being analyzed and summarized

- what prevents the synthesis and prioritizing of the obtained information.

The methodology used to find answers to these questions is described in the next section.

## 3 Methodology

As this study aimed to identify and describe the barriers to data-driven decision-making among online retailers, a qualitative approach was selected. The data was collected by interviewing ten Finnish e-commerce professionals with more than four years of experience in spring 2021. The interviewees included, for instance, CEOs, managers, and web analysts. The interviews of those working in different positions were aimed at gaining a broad view of the topic of the study. A detailed description of the participants is provided in Appendix 1.

The interview guide was semi-structured as the aim of data collection was to explore the participants' thoughts and beliefs about the research topic. Similar themes were discussed with each participant. The exact questions, however, varied within the discussions. The discussed themes included the professional background of the interviewees and their perceptions of data-driven decision-making and data analytics in Finnish online stores. The discussed topics included, for instance, the importance of data analytics in the context of e-commerce and the benefits and problems associated with data-driven decision-making. The average length of the interviews was 38 minutes.

The interviews were recorded and transcribed. After that, the written data was analyzed with the qualitative data analysis software NVivo. All the barriers mentioned by the interviewees were first picked from the data and named according to their content. As a result of several rounds of coding and interpretation, the barriers were eventually grouped into four descriptive themes under the six main phases of the data-driven decision-making process framework presented in Figure 1. These findings are discussed next and are summarized in Appendix 2.

# 4 Findings: Barriers to data-driven decision-making among online retailers

The findings indicate that various issues can be barriers to data-driven decision-making among online retailers. Barriers exist at every phase of the decision-making process. The findings show that barriers are mostly linked to staff and managers' (1) *expertise*. In addition, (2) *attitudinal*, (3) *technical*, and (4) *strategic* barriers were identified. The barriers occurring at the different stages of the data-driven decision-making process are discussed next.

## 4.1 Data collection

The analysis shows that barriers in data collection are related to attitudes, expertise, and technical issues. The identified attitudinal barriers included prejudices and unwillingness to invest in analytics. The participants concluded that even though data analytics' benefits are highlighted in today's discussions, all online retailers may not have a positive attitude towards analytics.

> "The difference in attitudes is staggering. Attitudes may be like night and day. [...] Some companies may have an internal culture where data is seen as a threat that destroys jobs." -P5

The expertise barriers were linked to a lack of knowledge and understanding of data analytics. Online retailers do not always understand the possibilities of data analytics or do not have the necessary knowledge on how to collect data.

> "You often hear e-commerce retailers being told that data is the king, but nobody really tells you how to use it." -P3

The technical barriers were related to platforms and combining different sources of data. The participants stated that the platforms used by online retailers do not always support data collection in the best possible way. Combining partners' systems and different platforms in data collection is challenging as the various data sources may not communicate with each other.

> "Analytics is not so simple because there are so many platforms, Google, Facebook, marketing platforms, e-commerce platforms, and they don't communicate with each other in a snap of a finger." -P9

### 4.2 Organizing

Only expertise barriers, including lack of systematicity, problems in managing collected data, and information overload, were identified concerning the organizing phase. The participants noted that data structuring and organization are often unsystematic. This is typically related to the amount of data and information overload: there is so much data that it is unknown what should be done about it or how it could be organized sensibly.

> "The biggest problem is that there is too much data." -P10
> "Even though there is a lot of data, there is no knowledge of how to segment it to make sense of it." -P6

### 4.3 Analyzing

Analysis-related barriers included expertise and technical barriers. The identified expertise barriers included lack of routines, amount of analysis, skills, and knowledge. Technical barriers were affiliated with data quality: the collected data can be of poor quality, and thus it is challenging or even impossible to proceed with it.

It was concluded that data analysis often lacks routines. In the worst case, the analysis is not done at all. In other cases, the analysis is done randomly, for example, when there is some time available. The participants addressed that even though most online retailers collect data at some level, they often lack knowledge about analysis, and wrong issues are paid attention to.

> " The biggest challenge is that wrong things are measured." -P6

This was partly explained by the fact that there is a shortage of employees with data-analysis skills. If the analysis is perceived as necessary, it may not be possible to hire staff for it.

> "The biggest problem is that there are not enough people or not enough skilled people. [...] That is why I'm working with a lot of customers at the same time: they can't get people recruited." -P5

### 4.4 Summarizing

Expertise barriers characterized the summarizing phase. It was noted that summarizing the analysis results can be difficult if the analysis does not provide information on relevant issues or the findings are not outlined understandably.

> "Many times, you see that customers have metrics, but they don't match the objectives. For instance, you don't measure the right things for the objectives." -P6

The identified barriers also included overanalyzing and misinterpretation. If the analysis is made too complicated, it also makes obtaining sensible summaries and results challenging. The analysis might also be performed incorrectly, which distorts the received results.

### 4.5 Synthesizing

Expertise barriers were also highlighted in the synthesizing phase. It was noted that online retailers might ignore the overall picture when considering the different analyses and summaries. Some aspects of business are looked at very closely, but at the same time, other important issues are overlooked. In addition, the participants concluded that online retailers do not have enough knowledge of how to combine different analyzes. Also, analyses and results can be interpreted differently at the different levels of management and employees.

Outsourcing the analysis process to consults was raised as a problem related to synthesizing. Consultants do not typically have access to all the necessary information, and because of that, they do not understand the company's overall operations. Hence, the information provided by consultants may be fragmented and does not take into account all the matters relevant to the business.

> "Buying from outside is not a solution. [...] You should be able to make different assumptions based on the data, test them, and do continuous iterative testing. It requires that you are inside the business. " -P10

In addition to expertise, some attitudinal barriers were identified. It was noted that the differences in staff expertise in data analytics could be huge. As employees do not have a common understanding of the topic, communication problems occur when synthesizing the information. Furthermore, it was suggested that the most skilled employees might show negative attitudes toward the employees with less data-analytics skills. One of the interviewees called these employees "data snobs," as the following quote demonstrates.

> "It can easily create a situation where someone is a bit of a data snob. [...] You don't want to talk about it when you are at such a different level, even though you should be talking about it." -P2

### 4.6 Prioritizing

Prioritizing barriers included attitudinal, expertise, and strategy-related barriers. The attitudinal barriers were characterized by willingness and courage. It was highlighted that routines and old ways of doing things often limit the utilization of data analytics in decision-making. Making data-analysis-based decisions can be perceived as challenging. It was reported that online retailers might not have the willingness or courage to change old habits and make decisions based on data analysis. Instead, managers use their gut instinct and experience when making decisions.

> "I think the biggest challenge is that you don't dare to make decisions based on analytics. [...] People do not dare to make enough use of information." -P4

However, if there is motivation and willingness to make data analytics-based decisions, the lack of expertise can be an obstacle. It is challenging to integrate data and analytics into decision-making and act based on analyses. Related to this, lack of strategy was an essential obstacle. In many cases, data-driven decision-making is not part of the online retailer's strategy. It means that conclusions are based on speculation, not facts.

"There is easily too much data, making it easier to do it (decisions) by using gut instinct. [...] The decision is based on guessing because you haven't been able to form a truly coherent conclusion." -P10

## 5 Discussion

This study has discussed the barriers to data-driven decision-making among online retailers. The study has sought to deepen the previous knowledge by considering data-driven decision-making as a process and identifying and describing the main barriers at different stages.

First, the study aimed to understand what prevents online stores from *collecting and organizing* data. The findings show that even though data collection is pictured as necessary (Pohl, Staegemann, & Turowski, 2022), especially in e-commerce, it may not appear as such to online retailers. Instead, quite surprisingly, data collection may generate prejudices and unwillingness to engage in the process. The negative attitudes can act as significant barriers to data-driven decision-making. They stall the process right from the start, and if attitudes toward data and data-driven decision-making are negative, the company is unlikely to invest in analytics. Data collection may also be omitted due to a lack of expertise and understanding. The benefits of the data are not understood, or the data cannot be collected due to a lack of skills. In terms of data organizing, deficiency of systematicity, problems in managing collected data, and information overload were identified as significant barriers. Earlier studies support these findings. It has been noted that, especially for small businesses, it may be hard to understand how to utilize data (Alford & Page, 2015) or how to organize it. In addition to attitudinal and expertise barriers, it was concluded that technical factors might also be an obstacle to data collection. E-commerce platforms nor partner companies' systems do not always support data collection and organizing. Hence, the compatibility between different platforms and systems that are included should be further investigated and improved to help online retailers' data collection and organizing.

Second, this study aimed to understand what prevents data from being *analyzed and summarized*. The findings demonstrate that analysis is often discouraged by a lack of expertise. Online retailers lack the skills to analyze the collected data. The analysis and summarization are characterized by randomness and lack of routines. The combination of lack of time and knowledge is a significant obstacle to adopting analysis (Alford & Page, 2015). The findings of this study suggest that the analysis problems are related to a shortage of professionals. Furthermore, the findings demonstrate that analysis and summaries are not always done on relevant themes, and the results of analyses are not appropriately reported. Thus, the usefulness of the data collection and analysis process is questionable and contributes to unnecessary work done in the company. Studies indicate that insights should be communicated in an accessible format to draw implications quickly and take further actions (LaValle et al., 2011), and summaries of analysis should be adjusted to fit the company's needs and decision-makers (Hanssens & Pauwels, 2016). However, the findings show that online retailers struggle with these issues. It is suggested, in line with other studies, that managers should carefully choose the best combination of data collection and analysis for their objectives because gathering and analyzing unnecessary data is confusing and a waste of resources (Phippen, Sheppard, & Furnell, 2004; Weischedel & Huizingh, 2006; Welling & White, 2006).

Third, this study investigated what prevents companies from *synthesizing and prioritizing* the obtained information in decision-making. The findings show that online retailers lack knowledge of synthesizing different analyzes and information. Also, the information obtained through the various data collection and analysis stages may not be prioritized in decision-making. Routines and existing habits often limit the utilization of data analytics findings. Based on the findings, the lack of strategic planning is one of the fundamental barriers that prevent the practical usage of data analytics in decision-making. Despite many scholars (e.g., Weischedel & Huizingh, 2006; Chaffey & Patron, 2012) have noted that a solid metrics system has to be linked to both business and marketing objectives, the findings suggest that data-driven decision-making is not always a part of the online retailer's strategy and conclusions. Decisions are not based on data-driven facts. Decisions can be relatively unstructured and based on the manager's previous experience and intuition. It has been argued that the adoption of data analytics requires strategic decisions (e.g., involving staff in the implementation and selecting appropriate technology) to fully achieve its potential (Kohli & Melville, 2019). Likewise, the findings of this study highlight the importance of strategic decision-making. Doing analytics without a clear business objective does not bring apparent benefits (LaValle et al., 2011). Data collection and analysis will lack the ultimate purpose and basis if analytics is not integrated into the retailer's strategy. Online retailers should carefully choose the best combination of metrics for their specific business objectives (Phippen, Sheppard, & Furnell, 2004; Weischedel & Huizingh, 2006; Welling & White, 2006).

This study has briefly discussed the barriers to data-driven decision-making among online retailers. To sum up, the findings are similar to those presented by earlier studies: lack of resources and skills (Chaffey & Patron, 2012), low-quality data, inappropriate data analytics tools (Ghasemaghaei, Ebrahimi, & Hassanein, 2018), and the poor involvement of top managers and lack of supportive organizational culture (Germann, Lilien, & Rangaswamy, 2013; Maxwell, Rotz, & Garcia, 2016) are among the central obstacles in the deployment of data analytics. Future studies are encouraged to further the investigations presented in this study. All the stages included in the data-driven decision-making process and the barriers occurring at the different stages should be more carefully investigated.

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## Appendix 1: Description of the study participants

| Participant | Experiece with E-commerce (years) | Current job title | Main areas of expertise / curret job | Main industry |
|---|---|---|---|---|
| 1 | 12 | CEO | All tasks related to the management of an online store, especially marketing | Leisure producs |
| 2 | 6 | Marketing technology manager | Digital marketing | Leisure products |
| 3 | 4 | E-commerce manager | All tasks related to the management of an online store | Clothing |
| 4 | 10 | Entrepreneur, sales and marketing director | Marketing | Online store implementation services |
| 5 | 4 | Web analyst | Marketing analytics | Management consulting |
| 6 | 4 | Analytics expert | Data analytics and visualization | Advertising agency |
| 7 | >20 | Head of digital | Online business operations | Leisure products |
| 8 | 4 | CEO | All tasks related to the management of an online store | Leisure products |
| 9 | 4 | User acquisition manager | Customer acquisition | Games |
| 10 | >10 | CEO, online retailer (4 stores), board professional, consultant | All tasks related to e-commerce | Multiple, e.g., leisure & pet products |

# Appendix 2: Summary of findings