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Decision-making under uncertainty

The role of Descriptive, Predictive and Prescriptive Analytics

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Författare	Felix Segui, Ingrid Weidler, Olle Stålhammar Holm
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Nyckelord	Deskriptiv analys, Prediktiv analys, Preskriptiv analys, Beslutsfattande, Disruptiva händelser
Forskningsfråga	Hur använder organisationer deskriptiv, prediktiv och preskriptiv analys för beslutsfattande under normala omständigheter och disruptiva händelser?
Syfte	Hur organisationer använder deskriptiv, prediktiv och preskriptiv analys i beslutsfattande under två förhållanden: stabila och disruptiva händelser. Genom att undersöka den praktiska användningen av dessa analysverktyg syftar studien till att ge insikter om hur dataanalysverktyg kan tillämpas under disruptiva händelser där etablerade mönster och rutiner bryts.
Metod	Studien använder en kvalitativ, abduktiv fallstudieansats med fokus på ICA-butiker i Sverige. Data samlades in genom semistrukturerade intervjuer med ägare och chefer. Resultaten analyserades med hjälp av mönstermatchning för att jämföra empiriska data med teoretiska ramverk.
Teoretiskt perspektiv	De teoretiska ramverken som används omfattar Dual-Process Theory och teorier om organisatoriskt beslutsfattande. Dessa kompletteras med insikter från krishanteringslitteratur samt forskning om deskriptiv, prediktiv och preskriptiv analys.
Resultat	Deskriptiv, prediktiv och preskriptiv analys är effektiva verktyg för beslutsfattande under normala förhållanden. Deskriptiv analys används för att observera försäljningssiffror, prediktiv analys för att förutse efterfrågan och planera lager och preskriptiv analys för att optimera operativa beslut som lagerhantering och produktdistribution. Under krissituationer minskar analysverktygens effektivitet då de baseras på historisk data.
Slutsats	Analysverktyg är effektiva för beslutsfattande under stabila förhållanden men begränsas under disruptiva händelser då de inte längre kan förlita sig på historisk data. Följaktligen understryks behovet av flexibla analysverktyg samt mänskligt omdöme för att stärka motståndskraften i föränderliga miljöer. Det gjorde att manuella anpassningar baserade på mänsklig intuition blev avgörande.

Title	Decision-making under uncertainty - The role of Descriptive, Predictive and Prescriptive Analytics
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Author	Felix Segui, Ingrid Weidler, Olle Stålhammar Holm
Advisor	Magnus Johansson
Keywords	Descriptive analytics, Predictive analytics, Prescriptive analytics, Decision-making, Disruptive events
Research question	How do organizations utilize descriptive, predictive and prescriptive analytics for decision-making during normal operations and disruptive events?
Purpose	To explore how organizations use descriptive, predictive and prescriptive analytics in decision-making under two distinct conditions: normal operating conditions and disruptive events. By exploring the practical application of descriptive, predictive and prescriptive analytics, the purpose of this study is to provide insights about how data analytics tools can be applied during disruptive events where established patterns are interrupted.
Methodology	The study adopts a qualitative, abductive, case study approach, focusing on ICA stores in Sweden. Data was collected through semi-structured interviews with owners and managers. The findings were analyzed using pattern-matching to compare empirical data with theoretical frameworks.
Theoretical perspectives	The frameworks applied are Dual-Process Theory and Organizational Decision-Making Theories, complemented by insights from crisis management literature and research on descriptive, predictive, and prescriptive analytics.
Results	Descriptive, predictive, and prescriptive analytics effectively support decision-making in stable conditions. Descriptive analytics tracks sales, predictive analytics forecasts demand and manages inventory and prescriptive analytics optimizes operational decisions such as inventory allocation and product distribution. During disruptions, reliance on historical data limited their usefulness, requiring manual adjustments and human intuition.
Conclusion	Analytics tools are efficient for decision-making during stable conditions but their reliance on historical data limits their effectiveness during crises. This underscores the need for adaptable tools and the integration of human judgment to enhance resilience and agility in rapidly changing environments.

Abstract

This study examines how descriptive, predictive, and prescriptive analytics are applied in decision-making during stable operations and disruptive events, focusing on the Swedish food retail sector during the Covid-19 pandemic. Using a qualitative case study approach with semi-structured interviews and pattern-matching analysis, the research reveals key differences in analytics usage. During stable conditions, analytics tools provide reliable insights and forecasts, enabling efficient decision-making. However, during crises, their reliance on historical data and static models limits applicability, emphasizing the critical role of human expertise in recalibrating systems and interpreting incomplete data. The findings highlight the importance of balancing data-driven tools with human judgment to navigate disruptions effectively. This study contributes to understanding the interplay between analytics and human decision-making and offers practical recommendations for improving organizational resilience in volatile environments.

Keywords: Descriptive analytics, Predictive analytics, Prescriptive analytics,
Decision-making, Disruptive events

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Felix Segui Ingrid Weidler Olle Stålhammar holm

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1.0 Introduction

Chapter one introduces the research topic, aiming to provide an understanding of the study's background and context. This is followed by a problematization that reviews previous studies on the topic and highlights the existing research gap. Finally, this chapter outlines the study's purpose and defines its scope and delimitations.

1.1 Background

In early human history, survival depended on instinctual, rapid decision-making, an evolutionary adaptation to survive in unpredictable, high-stake environments. While modern decision-making generally occurs in more controlled settings, decisions under crisis, such as the Covid-19 pandemic, reignited the need for swift responses amid uncertain conditions. Crises, with limited time and uncertain outcomes, drive decision-makers towards rapid, sometimes less rational choices (Eisenhardt, 1989).

Rational decision-making follows a structured, logical approach, theoretically aimed at identifying and diagnosing problems, prioritizing criteria, evaluating alternatives, to select the optimal solution. However, Simon's (1955) concept of bounded rationality, highlighted that pure rationality is constrained by limited information, cognitive biases and the complexity of problems and its environment. Consequently, decision-makers are required to rely on available knowledge, and make judgments based on incomplete information in complex and uncertain situations.

In times of crisis, these constraints become even more pronounced as decisions need to be made within shorter timeframes and with less reliable information (Colehower, 2023). The uncertainty during the Covid-19 pandemic exemplifies this, where demand imbalances and societal changes created significant global disruptions and posed major decision-making challenges. Apart from Covid-19, other recent events such as Russia's invasion of Ukraine, increased climate change and a volatile economic landscape has resulted in inflation surges, energy crises, supply chain volatility, cyber threats and economic recession (Sweco, n.d).

Recognizing difficulties from such events, organizations increasingly relied on advanced technologies to improve their decision-making process (Colehower, 2023).

In parallel, industry 4.0 is transforming the industrial landscape, introducing new technologies through the Internet of Things. The appearance of big data is one central aspect of this transformation. It is described by Gressel et al. (2020, p.270) as "*huge volume of data collected from different sources and in different formats that can be analyzed in real time*". These new technologies enable the interpretation and analysis of large sums of data quickly. From these analyses managers can gain insights into operations, forecast future outcomes and are recommended the most appropriate course of action (Gressel et al., 2020).

1.2 Problematization

In an increasingly unpredictable world, organizations face the challenge of making effective decisions amid uncertainty (Ericsson, n.d.). Big data analytics has emerged as a powerful tool, offering descriptive, predictive, and prescriptive capabilities to analyze past trends, forecast future outcomes, and optimize decision-making processes (Gressel et al., 2020). These analytical tools enable organizations to make well-informed data-driven decisions, aligning with the rational decision-making approach. However, according to Simon's (1955) concept of bounded rationality, fully rational decisions are nearly impossible to make since decision-makers often face constraints such as limited information, time and cognitive incapabilities. These challenges become pronounced during disruptive events, when uncertainty is heightened and established patterns and routines are interrupted (Johns, 2006; Li et al., 2024; Mithani et al., 2022).

The Covid-19 pandemic provides a recent example of a significant disruptive event, impacting both supply chains and consumer behaviors (World Economic Forum, 2024). With over 700 million Covid-19 cases across the world (WHO, 2024), governments turned to science and data-driven decision-making to navigate the unprecedented challenges posed by the crisis (Han et al., 2016). A survey conducted by Harapko (2023), involving 200 senior-level supply chain executives in 2020 and 2022, revealed that only 2% of companies felt fully prepared for the pandemic. During the Covid-19 crisis, organizations showed a significant shift in their approach to crisis management compared to previous crises. During

past periods of economic instability, technological investments were reduced. However, during the Covid-19 pandemic, 92% of companies maintained their technology spending (Harapko, 2023). This underscores the growing recognition of technology and its critical role in managing supply and demand volatility.

Food retailers play a vital role in maintaining societal stability by ensuring the availability of essential goods during disruptions. Their ability to navigate crises impact not only their operations but also the well-being of the broader community. Examining how food retailers leveraged data analytics to maintain operations during disruptions such as Covid-19 offers valuable insights into current practices and potential areas for improvement, making it particularly relevant in today's increasingly volatile world. Extensive research has explored how organizations can anticipate disruptive events through tools such as machine learning, social media, and other measurement technologies (Alsaedi et al., 2015; Mbonigaba & Vanitha, 2015; Park & Singh, 2023). Similarly, the theoretical application of analytics tools during disruptive events has been thoroughly studied (Ballesteros & Kunreuther, 2018; Wissuchek & Zschech, 2024). However, there remains a significant gap in the literature regarding the practical application of data analytics tools by organizations during disruptive events.

1.3 Research question

How do organizations utilize descriptive, predictive and prescriptive analytics for decision-making during normal operations and disruptive events?

1.4 Purpose

This study explores how organizations use descriptive, predictive and prescriptive analytics in decision-making under two distinct conditions: normal operating conditions and disruptive events, such as the Covid-19 pandemic. By exploring the practical application of descriptive, predictive and prescriptive analytics, the purpose of this study is to provide insights about how data analytics tools can be applied during disruptive events where established patterns are interrupted.

1.5 Delimitation

This study is delimited to examining the use of descriptive, predictive, and prescriptive analytics in decision-making within the food retail sector, specifically examining ICA stores in the south of Sweden. The geographic scope is restricted to the south of Sweden to ensure consistency in market conditions, regulatory frameworks, and cultural factors, while also enhancing the study's feasibility within the given timeframe. The decision to focus on the food retail sector acknowledges that different industries faced distinct challenges during the Covid-19 pandemic and may have applied data analytics techniques in varying ways. The pandemic serves as the primary context for analysis, representing a global disruptive event that introduced unprecedented challenges within a clearly defined timeframe.

2.0 Literature review

Chapter two presents the theoretical frameworks that will be used to analyze and discuss the research in this study, aiming to build a thorough understanding of the key concepts and frameworks relevant to the topic. The theoretical frameworks are divided into three categories: decision-making in organizations, disruption characteristics and data analytics within crisis management.

2.1. Decision-Making in Organizations

Decision-making in business management involves numerous steps that connect thought to action (Talley, 2011). It is a critical process, where decision-makers impact the ability for organizations to improve performance and address organizational challenges (Porter, 1985). The decisions are impacted by cognitive abilities and emotional responses, which is examined in the field of behavioral economics (Schwartz, 2007). This research field explores why people sometimes act against or for self-interest and deviate from rational economic behavior (Frank, 2009). Kahneman (2011) elaborated on the duality of processing information, distinguishing between intuitive thinking (system 1) and conscious deliberate thinking (system 2). These two systems, as he presents it, interact and complement each other in decision-making processes. Decisions based on system 1 are driven by instinct, gut feeling and prior experience (Gilhooly & Murphy, 2005) and uses heuristics, rules of thumbs and mental shortcuts that simplify the decision-making process. This allows for quick decisions in familiar situations (Dane & Pratt, 2007). However, heuristics can lead to biases and impulsive decisions in unfamiliar contexts (Wray, 2017). Decisions based on system 2 are instead driven by breaking down decisions into step-by-step processes guided by rational thinking. It becomes possible to carefully identify and evaluate problems which lead to well-informed and reasoned choices. While decisions made with system 2 tend to be more reliable and accurate, they require more time due to the analysis (Gressel et al., 2020).

It is a common fallacy to assume that system 2 thinking always leads to better outcomes than system 1 thinking. Chick (2019) highlights that both systems can be rational and that emotions can influence rational decision-making processes both positively and negatively. Nonetheless, there is a more profound conceptual resemblance between a system 2 approach

and a rationalist approach, as both emphasize deliberate reasoning and structured analysis to guide decisions. When encountering a problem, rationalists follow a structured process: they identify and analyze the issue, consider various potential solutions, weigh these options carefully, and ultimately select the most effective course of action (Gressel et al., 2020). While this approach is preferred, the circumstances do not always allow for it. In 1955, Herbert Simon introduced the concept of bounded rationality, proposing that rational decision-making is inherently limited by constraints such as availability of information, cognitive biases, and the complexity of the problem and its surrounding environment.

These constraints are particularly evident in data-driven decision-making, where the accuracy and relevance of the data used can significantly influence the quality of knowledge produced. According to Moore (2017) the Data-Information-Knowledge pyramid is the transformation process from raw data to actionable knowledge. Data serves as the foundational layer, information is then derived from data by adding context, and knowledge emerges when this information is interpreted and applied. The quality of knowledge produced is directly dependent on the quality of the underlying data. If inaccurate or irrelevant data is used as the foundation, the resulting knowledge will be compromised, potentially undermining the effectiveness of decision-making processes within organizations. Therefore, managers play a critical role in defining the scope of relevant data to ensure the efficiency of data-driven decision-making processes. While data analytics offers organizations significant opportunities, the vast amounts of available data can become counterproductive if not properly managed. Without clear boundaries, employees may spend time analyzing data that does not contribute meaningfully to organizational goals, leading to inefficiencies and reduced productivity. To address this, managers must actively participate in identifying which datasets are most relevant to specific decisions. This managerial involvement not only prevents decision paralysis caused by data overload but also ensures that data analytics efforts remain aligned with strategic objectives (Gressel et al., 2020).

2.1.1 Data Analytics in Decision-making

Data analysis is the process of organizing, examining and interpreting collected data to identify patterns, trends and correlations between variables. This transformation of raw data into meaningful insights and knowledge provides a foundation for decision-making. Gandomi & Haider (2015) argue that the true potential of data is realized when it informs

decision-making. They emphasize that swiftly transforming vast volumes of data into actionable insights is essential to fully harness its value. By combining managerial expertise with data and market insights, decision-makers can gain a holistic view of organizational challenges and opportunities (Gressel et al., 2020). Today, companies are able to utilize analytics tools closer to the operational environment. Information as a Service (IaaS) has emerged as a consequence of the increased demand for easier and quicker access to reliable information and guidance. By creating a single version of the truth with the integration of real time data from different sources, users are able to be assisted with insights ubiquitously (Demirkan & Delen, 2013). Davenport (2006) presents how analytics-driven companies benefit from this approach:

> *So, like other companies, they know what products their customers want, but they also know what prices those customers will pay, how many items each will buy in a lifetime, and what triggers will make people buy more.* (...) *Like other companies, they know when inventories are running low, but they can also predict problems with demand and supply chains, to achieve low rates of inventory and high rates of perfect orders.* (Davenport, 2006, p. 2)

As illustrated with the insights from Davenport, analytics is used to establish what has happened in the past, anticipate what will happen in the future and also work as a tool for determining what actions to take to optimize and transform the organization. To understand the operational environment, organizations rely on descriptive analytics. This involves visualization of past and current data, which enables for identification of trends, detection of anomalies and inefficiencies (Gressel et al., 2020). Building on the insights and patterns from the data, organizations can integrate predictive analytics to forecast future scenarios. This emphasizes the importance of the quality of the descriptive data, since it serves as a foundation for further analytics (Delen & Demirkan, 2013). However, leveraging statistical modelling, scenario forecasting and machine learning algorithms in predictive analytics allow organizations to anticipate dynamic customer preferences, changing market conditions and detect potential risks (Brintrup et al., 2019; Gressel et al., 2020). Finally, based on the foundation created by descriptive and predictive analytics, prescriptive analytics is used to gain actionable insights and direct decision-makers to the most appropriate response (Mosavi

& Santos, 2020; Tamm et al., 2013). This includes areas such as customer segmentation, demand forecasting, churn prediction and fraud detection (Stryker, 2024). Kawas (2013) further suggests that prescriptive analytics can support decision-makers by for example recommending optimal production schedules based on forecasts, which minimizes costs, and ultimately increases revenue.

The relationship between the three approaches is iterative and not as hierarchical as presented above. Descriptive analytics provides clarity for decision-makers, improving the comprehension of the organization's situation. These mental models can refine the intuitive responses (system 1) by increasing familiarity with scenarios and situations. Conversely, predictive and prescriptive analytics engage more deliberate and methodological aspects (system 2) through analyses of forecasts, scenario planning and suggestions of optimization (Dane & Pratt, 2007; Gressel et al., 2020; Kahneman, 2011).

2.2 Disruption Characteristics

Disruptive events are significant occurrences within the external environment that interrupt established routines and challenge the operations of firms (Johns, 2006; Li et al., 2024; Mithani et al., 2022). These events, including natural disasters, geopolitical tensions, pandemics, economic shocks, cyberattacks, and technological advancements, not only threaten organizational stability but can also drive substantial transformation (Li et al., 2022; Mithani et al., 2022). Lu & Zhou (2024) elaborate how this poses threats to the stability of organizations which can significantly alter the way decisions are made as well as guide strategic actions (Al-Dabbagh, 2020; Li et al., 2022).

Paul and Chowdhury (2021) identified two main uncertainties brought on by the Covid-19 pandemic. The initial challenge stemmed from a shift in consumer demand for goods and the second was a shortage of raw materials, both creating operational challenges for businesses. Changes in demand were not limited to reduced purchasing power, as observed by Janssen et al. (2021) in Germany and Denmark regarding fresh fruits, but also included irrational consumer behavior, such as the surge in demand for toilet paper and other essentials (Donnelly, 2020). Shortage of goods on the other hand arose from disruptions at different

stages of the supply chain. For example, lockdowns and sick leaves impacted upstream supply chain actors, such as producers and raw materials suppliers (Massoud & Zoghi, 2024).

2.2.1 Crisis Management

There are several ways to enhance the resilience of a company or organization in order to minimize the impact of the damage posed by a disruption. Fifty years ago, Holling (1973), a psychologist and ecologist, presented a theory where he described that ecological systems have two fundamental properties: *resilience* and *stability*. His theory revolves around the ability for a system to absorb disturbances while maintaining its essential structure, *resilience*, and the ability of a system to return to an equilibrium state after a disturbance, *stability*. Ramezani & Camarinha-Matos (2020) expand the concept by distinguishing between resilience and the concept of antifragility, a term popularized by Taleb in his book Antifragile: *Things That Gain from Disorder* (2012). While resilience focuses on maintaining a "business as usual" outcome, antifragility is about thriving under stress by using disruptions as opportunities for growth and transformation. Ramezani & Camarinha-Matos (2020) exemplifies by discussing how agricultural retailer who experimented with e-commerce prior to the Covid-19 pandemic developed antifragile capabilities, which not only created value for the business during the pandemic, but also enabled for new business opportunities after the pandemic (Ramezani & Camarinha-Matos, 2020). Over time, the concept of resilience in management literature has evolved to hold a more profound significance when applied to organizations. Organizational resilience is defined as the capacity to anticipate potential risks, respond effectively to unforeseen events, and learn from these experiences to develop a dynamic capability that drives organizational adaptation and change (Duchek et al., 2020). Hence aligning more with the definition of antifragility. Below, four of the main concepts will be presented again.

Term	Description
Resilience	The ability to absorb disturbances while maintaining its essential structure
Organizational resilience	The capacity to anticipate, respond to and learn from potential risks in order to develop dynamic capability that drives adaptation and change
Stability	The ability to recover from disturbances
Antifragility	The ability to thrive under disturbances, and become more resilient for future events

Table 1: Description of crisis management vocabulary (Ramezani & Camarina-Matos, 2020; Duchek et al., 2020; Holling, 1973).

One critical focus is to recognize the inevitability of disruptions (Reddy et al., 2016). It shifts the focus from solely avoiding disruptions, to developing resilience that can respond effectively when disruptions occur. Pearson & Clair (1998) discusses the criticalness of early detection of crises in order for the organization to be prepared with appropriate responses. The disruption should thereby be targeted from both a resilient and stability perspective (Pearson & Clair, 1998; Reddy et al., 2016; Holling, 1973).

A distinction can be made between disruptions of predictable and unpredictable nature. While failures in production and supply shortages are examples of predictable disruptions, disruptions caused by extreme nature conditions are examples of unpredictable disruptions (Reddy et al., 2016). Ballesteros and Kunreuther (2018) further emphasize that unpredictable disruptions exceed the ability of conventional risk management methods to anticipate or prepare for them. These unpredictable disruptions are marked by causal ambiguity, where cause and effect relationships are unclear, and they are difficult to measure due to their diverse characteristics. As a result, organizations often struggle to rely on past experiences or historical data for preparation. In such situations, effective decision-making requires creative and flexible thinking while avoiding excessive reliance on improvisation or random actions (Al-Dabbagh, 2020).

Additionally, failing to make a decision or take action during unpredictable disruptions is often considered as one of the most critical mistakes in the decision-making process. Therefore, effective decision-making requires ongoing monitoring and evaluation of decision situations and their outcomes (Al-Dabbagh, 2020). This highlights the importance of balancing system 1 and 2. Aven (2018) argues that a system 2 approach is too narrow on its own and needs support from the holistic and creative system 1.

2.3 Data Analytics within Crisis Management

Having presented the theoretical application of descriptive, predictive, and prescriptive analytics in section (2.1.1), the focus now shifts to their theoretical utilization during disruptive events. While these tools are effective under stable conditions, their reliance on historical data and predefined patterns can pose challenges during crises. Ballesteros and Kunreuther (2018) highlight that traditional risk management approaches often fall short in addressing the unpredictability of such events, necessitating the integration of more flexible and adaptive analytics frameworks.

Descriptive analytics provide organizations with a snapshot of "what has happened" and "what is happening" by analyzing historical and current data. The insights allows managers to identify patterns and spot anomalies which is important in order to dynamically adapt to new circumstances (Ballesteros & Kunreuther, 2018). For example, organizations can use these insights to track inventory levels, monitor customer behaviors, and analyze variations in sales performance, which can be utilized for rapid decision-making during crises (Manyika et al., 2011; Wang et al., 2016). However, it does not only improve the decision basis at the moment, but also enhances the conceptual knowledge of decision-makers, enabling them to develop a better foundation for system 1 decisions later on (Dane & Pratt, 2007).

Predictive analytics enhances crisis management by forecasting potential future events and their impacts, building resilience and preparing for possible scenarios (AL-Ma’aitah, 2020; Singh, 2020; Qadir et al., 2016). With the advancements of big data, the predictions and analyses are able to be made closer to real time, meaning that shifts in trends and anomalies can be detected quicker (Manyika et al., 2011). The potential disruptions include both

downstream issues, like shifts in customer behavior, as well as upstream disruptions, such as supplier performance and transportation delays (Singh, 2020; Talwar et al., 2021). Park & Singh (2023) builds on this when presenting the risk alert tool, which utilizes big data analytics capabilities to signal for future risks. When supported by the right capabilities, such as infrastructure, knowledge management and human capital, it is an example of an effective tool for managing supply chain risk events.

With effective predictions, proactive measures can be implemented allowing organizations to mitigate risks before they occur. This is an objective for predictive analytics (Qadir et al., 2016), and it is related to building resilience according to Holling (1973), where a system, or organization in this case, is dependent on the ability to limit the degree of which it is affected by chocks and disturbances. Brintrup et al. (2019) further demonstrate how predictive analytics can identify high-risk suppliers, reducing vulnerability to disruptions in the supply chain.

Prescriptive analytics integrates descriptive and predictive insights to recommend actionable strategies (Mosavi & Santos, 2020). Providing a decision-making foundation is critical in times of crisis since the absence of decisions can lead to problems, and the need for optimized decisions are needed (Al-Dabbagh, 2020). It mitigates risks by detecting anomalies and trends by analyzing vast amounts of data in a short amount of time, which is not manageable for humans (Cote, 2021; Stryker, 2024). The systems that are used for prescriptive analytics are underexplored in academic literature, especially its application in crisis management. Wissuchek & Zschech (2024) identify three key applications: improving agility through dynamic pricing to address changing demand (Ballesteros & Kunreuther, 2018), enhancing scheduling to reduce bottlenecks and inefficiencies during urgent problem-solving (Al-Dabbagh, 2020), and optimizing resource allocation to prioritize critical areas and prepare for future crises.

The theoretical findings on the application of descriptive, predictive, and prescriptive analytics, drawn from Sections (2.1.1) and (2.3), are summarized in the table below. These findings are categorized into normal operating conditions and disruptive events.

	Normal operating conditions	Disruptive events
Descriptive	Visualizes past and current data to understand "what has happened" and "what is happening"	Detects anomalies and deviations from historical patterns to adapt to rapidly changing environments
	Identifies trends, detects inefficiencies and monitors operations to support informed decision-making	Monitors variations in trends related to inventory levels, customer behaviors and sales
	Provides reliable input data for predictive and prescriptive analytics	Enhances decision-maker's conceptual understanding to support intuitive responses
Predictive	Uses statistical models and machine learning to forecast future trends, including customer preferences and operational risks	Forecasts potential future events and their impacts to enhance crisis preparedness.
	Anticipates changing market conditions and detects potential risks	Builds organizational resilience by enabling proactive measures to reduce the impact of disturbances.
	Improves resource allocation and long term planning by generating reliable, data-driven forecasts	Functions as a risk alert tool to signal for potential risks
Prescriptive	Develops and assesses optimized courses of action to give actionable insights	Establishes a decision-making foundation under high-pressure scenarios, reducing risks of inaction or suboptimal decisions
	Creates optimal production schedules that minimizes costs and maximizes efficiency	Enhances organizational agility by dynamically mitigating rapidly changing demands and conditions
	Recommends strategies for demand forecasting, inventory management, and customer personalization to enhance data-driven decision-making	Decreases decisions based on randomness and improvisation
		Assists in resource allocation and improves scheduling capabilities, which is critical in crises to ensure that future preventive measures are emphasized and bottlenecks and inefficiencies are reduced

Table 2: Theoretical findings about the application of descriptive, predictive and prescriptive analytics during both normal operating conditions and disruptive events (Al-Dabbagh, 2020; Ballesteros & Kunreuther, 2018; Brintrup et al., 2019; Dane & Pratt, 2007; Davenport, 2006; Delen & Demirkan, 2013; Duchek et al., 2020; Gressel et al., 2020; Holling, 1973; Kawas, 2013; Manyika et al., 2011; Mosavi & Santos, 2020; Park & Singh, 2023; Qadir et al., 2016; Singh, 2020; Stryker, 2024; Tamm et al., 2013; Wang et al., 2016; Wissuchek & Zschech, 2024)

3.0 Methodology

Chapter three outlines the research methodology, covering the research approach, data collection methods, and analysis process. It introduces the selected theoretical frameworks and justifies their inclusion. The chapter also addresses potential validity, reliability, and generalizability concerns, along with ethical considerations.

3.1 Research Approach

This study adopts an abductive approach to examine how different big data analytics types are utilized for decision-making within the food retail sector during disruptive events, more specifically the Covid-19 crisis. The research is designed as a multiple case study focusing on store owners and managers from different ICA stores. According to Yin (2008), a case study is an empirical research that investigates contemporary events within real-life contexts, particularly when it is hard to tell when the event ends and its context begins. An abductive approach, as described by Bryman & Bell (2017), involves an iterative process of moving between data collected from participants and relevant theories, allowing the study to adjust its framework as new themes or insights develop. This approach is particularly well suited to the study's aim of understanding complex, real world contexts, as it allows the theoretical framework to evolve alongside emerging data patterns (Bryman & Bell, 2017).

To capture participants' experiences, a qualitative research strategy was chosen. According to Bryman & Bell (2017), qualitative methods are used for understanding participants' personal experiences, focusing on descriptions rather than numerical data to try to obtain a holistic view. In this study semi-structured interviews serve as the only method of data collection, offering a balance between guided questions and flexibility to allow participants to share insights openly (Bryman & Bell, 2017). The selected interviewees are employees and store owners in decision-making roles at different ICA stores, ensuring the collection of accurate and relevant data. To understand how data analytics are used during disruptive events a clear understanding of how they are used during normal operations is needed. This setup, combined with the theoretical framework, supports the study's aim of providing insights into how data

analytics tools can be applied during disruptive events when established patterns are disrupted.

3.2 Data Collection

This research gathers primary data through in-person, semi-structured interviews with owners, key managers and decision-makers from different ICA stores in the south of Sweden. Interviews follow a consistent template, ensuring each participant receives the same foundational questions, while also providing the opportunity to share their experiences. The semi-structured format enables follow-up questions and minor adjustments when needed, creating a balance between structure and flexibility during the interview (Bryman & Bell, 2017). Using a standard set of core questions enables comparison across responses and the ability to draw reliable conclusions. Each question is carefully formulated to reduce misunderstandings and ensure that all participants address the same topic. Furthermore, the interviews were conducted in Swedish to allow the interviewees to fully comprehend the questions and be able to elaborate their answers. They were subsequently transcribed in Swedish and translated into English. When transcribing the interviews they were anonymized to ensure the participants confidentiality.

3.2.1 Approach to Data Analysis

The data analysis adopts a qualitative approach, using insights from interviews as the primary data source to explore participants' experiences, perspectives and decision-making processes. A thematic analysis is conducted to identify recurring patterns and key concepts within the data, divided by the research question and the chosen theoretical frameworks. These frameworks, including rationalist, non-rationalist, and bounded rationality perspectives, as well as dual-process theory, are used to understand how decision-making is influenced by data inputs, situational context, and time constraints. Furthermore, the role of data analytics is analyzed in relation to descriptive, predictive, and prescriptive analytics, drawing connections between theoretical concepts and practical applications. The findings are then categorized to compare how the use of data analytics vary across different organizational decisions. This approach aims to integrate qualitative insights with theoretical analysis, providing a comprehensive understanding of the correlation between data, context, and decision-making.

3.2.2 Selection of Case

The study examines three different stores all operating within one single organization, the ICA-group. This approach enabled a comparison between stores, contributing to the study's generalizability. Interviewing individuals in similar positions across different stores ensures a fair comparison and enhances the accuracy of the conclusions. Interviews were conducted with individuals in four key positions within ICA stores to capture diverse perspectives and create a more holistic understanding. The roles were carefully selected for their decision-making authority and expertise on the subject. An overview of all participants is provided in the table below. The focus on the food retail sector is due to its societal impact making it both relevant and timely. Furthermore, pre existing contacts within the industry made the topic both engaging and feasible for analysis (Bell et al., 2019).

Case name:	**Role**	**Time and date**	**Place**
Tower	Store owner	5 Dec. 2024 at 15.30-17.00	ICA stores office
	Store manager	12 Dec. 2024 at 15.00-15.30	ICA stores office
	Department manager	5 Dec. 2024 at 15.00-15.30	ICA stores office
Knight	Store owner	2 Dec. 2024 at 14.00-14.35	ICA stores office
	Store manager	13 Dec. 2024 at 14.00-14.55	ICA stores office
	Department manager	13 Dec. 2024 at 15.00-15.15	ICA stores office
Bishop	Store manager	16 Dec. 2024 at 13.00-13.30	ICA stores office
	IT specialist	3 Dec. 2024 at 12.45-13.00	ICA stores office

Table 3: Overview of the interviewees

3.2.3 Selection of Respondents

To gather qualitative data eight interviews have been conducted at three different ICA stores in the south of Sweden. When selecting respondents for the interviews, a purposive sampling strategy was used to ensure that the individuals chosen were relevant and would provide valuable insights. Through purposive sampling, we deliberately selected participants who had specific knowledge or experience related to our research topic, ensuring that their

perspectives were directly applicable to our study's objectives. After the initial interview, snowball sampling was employed, where the respondent recommended additional participants who could provide further relevant insights. Interviewing respondents with different management positions within the ICA-stores provided a broader and more holistic view of their operations. Interviews were conducted with two store owners, three store managers, one IT-specialist and two department managers, all of which have worked within the ICA group for an extensive amount of time. Since our research question focuses on decision-making during disruptive events, with Covid-19 as a contextual example, it was essential to select respondents who already held their specific roles prior to the pandemic. While a larger sample size could have improved the accuracy and generalizability of our findings, we were constrained by time limitations, which led us to focus on a smaller group of eight participants. Nevertheless, by carefully selecting individuals at managerial positions who were representative of the broader population we are studying, we ensured that our sample was diverse enough to provide useful and reliable data within the scope of the study (Bell et al., 2019).

3.2.4 Semi-Structured Interviews

The interviews conducted have been semi-structured in accordance with the guidelines given by Bell et al. (2019). Semi-structured interviews give respondents the freedom to express their answers in their own words. Furthermore, it allows the interviewer to ask follow-up questions beyond the predetermined interview guide, allowing exploration into other topics that the respondents find relevant. This flexibility of the process is a key aspect of the approach as it enables the direction of the interview to be guided by the respondent’s answers while still being aligned with the study’s objective.

To ensure the interviews were both relevant and consistent, the questions were primarily derived from the research question and grounded in the theoretical framework and the study’s purpose. Hence, there was a focus on decision-making during uncertainty, the use of analytics tools and how the Covid-19 pandemic influenced the company’s usage of analytic tools to drive decision-making. This alignment enabled the comparison of empirical findings with theoretical concepts. The interview guide included headers of topics that would be touched upon during the interview as well as the main questions of interest for each category. Most

questions were intentionally open ended to encourage elaboration and sharing of own experiences. However, as the study is a multiple case study, some of the questions were more structured to ensure cross-case comparability in accordance with Bell et al., (2019) suggestions. Questions were carefully phrased to remain neutral, avoiding leading or suggestive wording, which allowed respondents to interpret and answer based on their own perspectives. This method promoted authentic and insightful responses, free from interviewer bias. Additionally, it facilitated the use of follow-up questions to thoroughly explore topics and ensure that all critical areas were addressed (Bell et al., 2019).

3.3 Theoretical Frameworks

The research question has been studied from the perspective of several theories and frameworks that can be divided into two main categories: decision-making in organizations and disruptive characteristics. The theories aim to give an understanding of how the environment, the data input and data analysis impact the decision-making process. Rationalist, non-rationalist and bounded rationality are all concepts that shape decision-making based on available data, the decision-maker's perspective on a situation, time constraints and other limitations they face. Dual process theory explains how humans have two distinct ways of making decisions depending on how quickly and well-thought through the decisions are. This theory is relevant as it enables the study to draw conclusions about the methodology differences when making decisions during normal operating conditions and disruptive events. Additionally, the study introduces several types of data analytics: descriptive, predictive and prescriptive, enabling a comparative analysis of the critical impact of data analytics on decision-making effectiveness and accuracy between normal operating conditions and disruptive events.

3.4 Validity and Reliability

When assessing the quality of a qualitative research study, reliability and validity are the primary criteria evaluated (Bryman & Bell, 2017). Validity and reliability involves critically evaluating the quality of the data gathered. This means assessing whether we obtained the information we aimed for, determining if the findings can be applied in another context, and considering whether the data we gathered is reliable (Jacobsen, 2002).

Specifically, validity, as explained by Bell et al., (2019), refers to whether the research accurately observes, identifies, or measures what it is intended to examine. LeCompte & Goetz (1982) categorize validity into, external and internal validity. This study aims to have high internal validity by basing the study's interviews on the theories chosen to further be able to see if there are correlations between theory and response. External validity refers to the degree of which things can be generalized across social settings. While this study aims for generalizability, the limited scope of three case studies conducted in Sweden presents challenges. To strengthen internal validity, data triangulation was employed within two out of three stores by conducting interviews with three individuals with different roles. This method allowed for cross-validation of responses within the same store, reducing the risk of individual biases and providing a more comprehensive understanding of each store's operations. Additionally, by comparing answers across all stores further enhanced the reliability of the findings by ensuring that patterns observed were not unique to a single store (Bell et al., 2019). This study aims at a heightened validity through a thorough literature review to ensure alignment with existing research and similar conclusions (Jacobsen, 2002). The references include peer-reviewed articles from Google Scholar, course literature from Lund University, and works by established authors and institutes, ensuring their trustworthiness. Furthermore, semi-structured interviews with experts in the area enhances the validity of the study. These interviews allowed for a deeper exploration of the subject, as they provided flexibility to examine specific areas of interest while maintaining a structured approach aligned with the research objectives.

Reliability can also be divided into internal and external reliability. External reliability refers to the degree a study can be replicated and achieve the same conclusions if replicated. External reliability is difficult to achieve since social settings change constantly. LeCompte & Goetz (1982) mean that people change their mind due to external changes in their surroundings and therefore replicability of qualitative research is hard to achieve. However, this study tries to attain external reliability by asking both general and specific questions to gain a holistic view. Internal reliability refers to the consistency of interpretation among researchers, ensuring that the entire research team understands and evaluates the answers and results in the same way. To ensure internal reliability all group members are asked to

elaborate their thoughts and opinions to try to eliminate misunderstandings. To mitigate the interviewer effect, one group member served as the primary spokesperson during all interviews, while the other two asked follow-up questions and took notes. This approach aimed to maintain consistency in how the interviews were conducted and to ensure that all participants were approached with a similar manner (Jacobsen, 2002).

3.5 Analytical Generalizability

Bryman & Bell (2017) raises concerns about the generalizability of qualitative research, like case studies. The context or environment being studied is often unfamiliar to the researcher, which makes it difficult to determine how applicable the findings are outside the specific case/cases. This case study has restrictive limitations to one industry and one crisis which affects the generalizability of the findings when different circumstances occur. Furthermore, Bryman emphasizes the importance of considering the timeframe for which research findings remain generalizable. Given the rapid pace of technological advancement, with new tools and methods continuously emerging, the technologies examined in this study may quickly become outdated. As a result, the relevance of the study's findings may diminish over time. However, the choice of industry, food retail, remains highly relevant, as it fulfills a fundamental societal need to access food regardless of the circumstances. Furthermore, using semi-structured interviews allows for a deeper understanding of the subject and information about what details are relevant only to this industry and which details are more general and therefore applicable in other industries. Qualitative research of this kind typically holds more theoretical value than practical generalizability to other industries or cases. Instead, it is often used to confirm existing theories or to further explore a hypothesis (Bell et al., 2019).

3.6 Approach to Analysis

3.6.1 Transcription

The interviews were transcribed to ensure accurate documentation and facilitate a detailed analysis of the participants' responses. The process of recording and transcribing allowed for the interviews to be paused and replayed, supporting a more thorough review of the empirical data (Bryman & Bell, 2017). Moreover, transcription was important for including precise quotes from participants, which is a key factor in enhancing the validity and credibility of the

study (Jacobsen, 2002). Since the interviews were conducted in Swedish, the transcribed material was later translated to English, with careful attention to preserving the participants' intended meaning and ensuring clarity in the translated text. Additionally, as the interviews were semi-structured, conversational fillers and non-verbal sounds were removed to enhance readability and coherence.

3.6.2 Coding

During the analysis, pattern matching (Yin, 2018) was used as a key analytical technique to compare empirical patterns with theoretical patterns. Pattern matching was valuable for identifying how different types of analytics; descriptive, predictive, and prescriptive, were utilized across various job roles and stores. By aligning the observed use of analytics tools with theoretical expectations, the analysis not only confirmed previously proposed patterns but also highlighted deviations that offered new insights into how data-driven decision-making operates during disruptive events. This approach is particularly valuable in case study research, where identifying consistencies between observed data and existing theories can strengthen the study's findings. Additionally, thematic analysis was utilized to systematically identify recurring themes across the data set. Thematic analysis involves a structured process of coding qualitative data to discover patterns, enabling the researcher to derive themes that reflect participants' experiences and perspectives. In this study, coding played a central role in the thematic analysis process. By categorizing qualitative data into relevant themes, the analysis facilitated comparisons between stores and between stable and unstable environments (Bell et al. 2019).

3.7 Ethics

Ethical considerations are a crucial part of research. Jacobsen (2002) identifies three key criteria for ethical research: informed consent, the right to privacy and accurate representations of data. Addressing these criteria helps protect participant's integrity and confidentiality.

Informed consent requires participants to fully understand the study's purpose and objective and to voluntarily and willingly attend the interview. To meet this requirement, we introduce

ourselves clearly, both during the interview but also before the interviews in writing. We explained the study's aim and outlined what participation would entail so that the interviewee would have, to the best of our ability, knowledge of the studies aim. To reassure ourselves that this information was understood and heard, a repetition of the information was given at the start of each interview.

The second criterion, "the right to privacy", is equally important. Jacobsen (2002) emphasizes the importance of anonymity, particularly when sensitive information is involved. To protect participants' identity, both the names of the different ICA stores and the names of the participants are not disclosed. Instead participants are referred to by their roles such as "store manager" or "owner". Additionally, we sought permission to reference their roles in the study and ensured that only relevant, non-personal information was collected to prevent any potential risks if the data were made public.

Finally, Jacobsen (2002) emphasizes that accurate representation of data requires presenting findings in a complete and contextually appropriate manner. To uphold this, we transcribed the recorded interviews shortly after they were conducted. However, as the interviews were made in Swedish and our text is written in English, a slight difference may appear when quoting the respondents from the interviews.

3.7.1 Use of AI

In this study, the AI tool ChatGPT has been primarily utilized as a generator for ideas. Terms such as "data" and "collection" were used to produce suggestions on related topics. Furthermore, AI was employed to clarify definitions and propose synonyms. Additionally, the chat function was used to explain academic concepts written in English by providing translations and clarifications in Swedish, which facilitated a deeper understanding of key terms and theories.

4.0 Results

Chapter four presents the findings from the conducted interviews. The interviews were conducted with managers and employees from ICA stores to explore how data analytics, namely descriptive, predictive, and prescriptive analytics, are used in decision-making during both normal operating conditions and disruptive events, with a particular focus on the Covid-19 pandemic.

4.1 CASE 1 - The Tower

Based on the interviews, the store Tower is a pioneer in the utilization of data and analytics. They have advanced tools, primarily related to enabling decision-making across different levels within the store.

4.1.1 Applicability of Analytics Tools

In the interview with the store owner, it was expressed that the company was well ahead of competitors when it comes to the applicability of data and analytics. The store primarily uses a tool performing two main tasks. The first is to forecast weekly sales and the second is to automate the ordering process. This tool is called MyICA application and is fundamental and utilized in everyday operations. The automated ordering process is triggered when products reach a critical stock level. The department manager explained that they use this tool on a daily basis:

> *There are several parameters which are integrated in order to optimize the logistic management of the autonomous system. It enables us to focus on other tasks that require humans instead of those that a computer can do for you.*

The store manager explains that the automatization is used every day. Without interference, the system would continue to order products undisturbed. However, the staff have the ability to intervene and manually adjust the order quantities. Sometimes, the system has data that is inaccurate, and therefore generates faulty orders. Hence, the staff is a vital part in confirming

or defying the quantities and other details related to the order. The store owner explains that this tool is updated dynamically with real time data on stock levels and consumption patterns. This means that it is reactive to both economic growth and decline. The store manager agrees with this standpoint when noting:

> *When consumption is low, the tool forecasts lower consumption for the weeks to come.*

It also accounts for recurring patterns related to specific events such as monthly paydays, pension payments, or yearly holidays such as Christmas or Easter. This enables for more accurate decision-making regarding changed consumer behaviour, not only in general, but also for specific products related to the specific event.

The department manager highlights the value of being able to use the technology to support the majority of their decisions with data. The store owner elaborates on this and believes that their advancements are related to having the courage to frequently try new technologies and new ways to use data and analytics.

4.1.2 Data-driven Decision-making vs Human Intuition

The forecasting tool, according to the store manager, is useful for a wide range of people in the company. It is mentioned that it allows for decisions to not be based on guesses, but rather forecasts and statistics. Data and analytics is considered to be the foundation for decisions, but a degree of human judgment is included to secure accuracy and avoid data related faults. The owner explains that the analytics tool has empowered staff to make decisions without consulting upper management. The department manager experienced that this has enabled a big shift in confidence among the staff in everyday decisions. These types of decisions have previously been a time consuming process, where managers have been forced to move back and forth from the office and the store to instruct and make decisions regarding small details, such as how a product should be displayed to the customer.

According to the owner and store manager, human judgment is particularly critical in tasks involving interpersonal or subjective assessments. The store manager elaborates with an example:

> *In a recruiting process, machines can handle basic evaluations, such as checking educational qualifications and experience. However, determining whether a candidate will fit well with the team and contribute to the company in the long run requires human judgment.*

The owner also highlighted the importance of human judgment during the Covid-19 pandemic, where rapidly changing circumstances made it essential for decision-makers to rely on their expertise and adaptability. During this period of uncertainty, they manually decreased the ordering quantities by 20% compared to the forecasts generated by the automated ordering tool. A similar approach was taken during the inflation surge that began in 2021. They mean that their technology is unable to recognize these types of situations. At other times, they are diverging from the system, relying on human intuition completely.

4.1.3 Disruptive Events - Crisis Management and Adaptability

It was suggested by the store owner that data and analytics was not really of considerable value during the Covid-19 pandemic. The inability of the systems to account for the fluctuating demands limited the systems to provide reliable information. Instead, they manually adjusted the parameters in the forecasting tool, which resulted in a more cautious ordering behaviour, which was in line with the target to minimize waste. However, over time, the forecasting tool adapted to the changing consumer patterns to some extent. According to both the store manager and owner, it is adjusting faster to changing consumer patterns, enabling them to increasingly rely on data-based decisions. The owner also mentioned that the tool is becoming more accurate when more data is being gathered, especially the dynamic forecasting that adjusts for changing consumer purchasing power and patterns.

Another consequence of the change in consumer behaviour was the hoarding of certain products. The owner discussed how products such as toilet paper, canned food, dry yeast and powdered milk were hoarded which led to depleted stock levels. This forced them to seek

external suppliers to mitigate the loss of sales opportunities. The store manager emphasized the difficulty with this situation:

> *At times, we had to source suppliers on our own for products that were hoarded. It also created ripple effects, where the depletion of one product sometimes resulted in an increased demand for a substitute product, or even related products.*

Meanwhile, the department manager highlighted the human aspect of consumer patterns, explaining that in future crises, the items being hoarded could be entirely different, making it challenging to prepare effectively.

Within the inventory management, the store manager highlighted that the staff have information regarding when an order is placed, its estimated time of delivery and what is included in the order. They also have a system that indicates how much stock space is needed for the products which enables the staff to be prepared in advance. This is supported by the department manager, who explains that this facilitates the process of managing the delivery. The stock levels are updated by the system in real time. However, when asked about whether they have insights of the status of shipment in real time, all three of the interviewees at Tower said no. They are solely notified of a disruption by sms or a phone call.

The store owner highlighted their technological capabilities, including the use of heat cameras during the Covid-19 pandemic. This technology identified highly populated areas, or "hot spots," providing valuable insights for redistributing products that contributed to crowding. This approach helped minimize congestion (decreasing the risk of spreading the virus) and improve the store layout. However, despite these technological advancements, the store lacked an online shopping platform. The store manager noted that this limitation led to missed sales opportunities and reduced the store’s ability to support customers who were unable or hesitant to visit in person, impacting its efforts to fulfill social responsibilities.

4.1.4 Future prospect of Data and Data Analytics utilization in Decision-making

The owner expressed enthusiasm for advancing the company's data analytics infrastructure, with a particular focus on integrating AI in the company. The owner hopes to collaborate with young people who share an ambition to grow within the company through technological advancements. There is a focus on the progress being made both within the company and in the broader market, with developments particularly in enabling more immediate feedback on decisions across various contexts. The owner states:

> *It is very important for my staff to be able to have an idea of what consequences their actions have. Like with the example we spoke about before, when you make an adjustment on the shelves, it is very important to go back the next week, and see… ah! The result of my action was this or that.*

Furthermore, the store has a well developed system to identify staffing needs across different times and departments. For instance, since bread is primarily sold in the morning, this signals a need for additional personnel in that department during those hours. While this data is currently used as support for manual scheduling, there is a belief that AI will streamline the process in the future. In general the owner mentions that they will keep developing and investing in technology that generates value for the company. They work with this in an agile way, where they try new things, and either keep going if it turns out successful, or shut the project down if it does not generate enough value in relation to the time it consumes. The downside, the store owner explains, of increasingly relying on technology and digitalization in general, is that the system and business becomes more vulnerable to cyber attacks. This is something that both the owner and store manager fears will occur more frequently in the future. These events pose threats to systems that are essential for daily operations. The store owner adds that a cash withdrawal machine, located just outside their building has allowed them to continue their operations when the checkout system is disabled.

Another disruptive event that bears similarities to the one caused by the Covid-19 crisis is Russia's full scale invasion on Ukraine. With the geopolitical instabilities, the store owner explains that there has been an increased emphasis on being prepared by having extra stock of dry food in their warehouse.

4.2 CASE 2 - The *Knight*

At Knight, department managers have 16 to 34 years of experience at ICA. Despite their practical knowledge, the store manager insists all decisions be data-driven and supported by statistical analysis.

4.2.1 Applicability of Analytics Tools

The store owner emphasizes the daily use of data, which is primarily collected through the MyICA application. The department managers rely on this resource to make decisions regarding how to organize the product displays, including shelf space allocation, which the store manager explains is being done by analyzing statistics and graphs generated from inventory data. According to the store owner, this utilization of data should be standard for all store and department managers. The store manager explains:

> *You can pull up statistics on practically everything here. We have the total sales figures, which you can then break down by product category or even a single product. Below that, you can see the total number of sales, and you can select a specific timeframe, here is for today, but you can also choose past week, past 14 days, month or year to see how it varies depending on the time of the year. Here you have the current stock and how many items come in a package, and these numbers are used with data on weekly sales to know how many should be displayed on the shelf to optimize the space.*

The MyICA application automatically generates and sends new orders to producers based on mathematical algorithms that accounts for quantities sold, inventory levels and stock capacity at the product shelves. The store owner noted significant improvements of this function over the past few years. Human interaction is still applied to some extent. For example, when ordering discounted products or holiday-specific items, the store owner and manager adjust quantities manually. In these cases, they use data as a guideline but rely on judgment for the final decisions.

The MyICA application is Knight's most frequently used tool and it is utilized daily by nearly all staff members. According to the department manager, the application is connected to

handheld scanning devices, carried by the store staff, allowing them to scan, modify or verify inventory levels in real time. The department manager highlights two primary uses of the data collected by the scanning devices. First, it is used to optimize the rearrangement of products on the shelves, by determining the benefits of giving products more or less space. Additionally, at what shelf levels each product should be located in order to both strategically expose specific products to increase sales, but also to have best-selling products easily accessible. Secondly, the floor staff can identify inventory discrepancies by comparing the expected number of products, according to the device, with the actual quantity present. The discrepancies can occur due to theft or products disappearing in the warehouse or during delivery.

The store manager and the store owner uses the MyICA application primarily to track the profit and sales progress of the store. These sales statistics include information about where the sales occur and at what time of the day, which allows them to to allocate employees to the right place at the right time. Furthermore, the store manager highlights that the data is updated in real time through various systems. These systems include floor staff scanners, cashier inventory updates and customer-count sensors. However, apart from updating the inventory systems, real time data is not used.

4.2.2 Data-driven Decision-making vs Human Intuition

The owner explained that data from up to 18 months back is collected and used in the MyICA application. This ongoing data collection, from scanning machines and the cashier system, enables the system to continuously update and adapt to changing consumer behaviours, like seasonal demand. Therefore, orders for everyday items can be automated and sent to the supplier without any human intervention. However, for special occasions with unique products, this process is in need of manual intervention. The store manager explained that historical sales data and other internal data points provide a useful foundation for decisions. However, external events, such as inflation, business cycles, and availability of supply must be accounted for by human judgment to ensure more precise forecasting. The store manager highlighted an example of an external event that significantly changed the consumer patterns. A relocation of a bus station introduced a new customer base, with a different set of purchase habits. The store manager explains:

We recently got a new bus-station just outside the store and saw an increase of about 3000 new customers each week. We waited two weeks to see if this trend would sustain, and then took a decision to reschedule the staff so we could cope with the increase in demand.

4.2.3 Disruptive events - Crisis Management and Adaptability

During times of crises, the store owner admitted that they lacked a predefined plan for how to proceed. Reflecting on the situation, the store owner stated:

No one saw it coming, there was no way of knowing this would happen and that it would have such a big impact on us and our consumption patterns.

When the pandemic struck, the store faced challenges as certain items unexpectedly sold out quickly. This sudden surge in demand overwhelmed suppliers, creating a gap between supply and demand. This, according to the store owner, posed challenges, where they had to find alternative solutions to replenish stock. The store manager further explained that during a crisis, the ICA group disables the manual ordering function of its central warehouse to ensure that products are distributed equally among all ICA stores. As a result, each store had to find new products from alternative suppliers by themselves, both locally and internationally. This, however, according to the store owner, created a moral dilemma, where products that need to be sourced, do not necessarily meet the criterias of product quality as they might not align with ICA's protocol regarding product quality and legislation. The owner also mentioned that the store started to invest more money in enabling a digital shopping experience for its customers. Additionally, with the online shop in place, new types of data were possible to collect. The owner explained that:

We want to find suitable options for all of our customers, we know that elderly people should stay inside and feel like it's our responsibility to give them an opportunity to do so and still be able to shop from us.

The store manager further elaborates on a more recent crisis. When the news started announcing the date for Russia's invasion on Ukraine, the store manager realised that, similarly to the pandemic, some specific products, like dry goods and canned foods, increased in sales. Recognizing this trend, the store manager proactively placed an order to have additional stock on those items. This additional stock ensured that the store could meet demand in the following weeks, resulting in profits compared to other stores that experienced shortages.

4.2.4 Future prospect of Data and Data analytics utilization in Decision-making

The store manager explained that beyond storing data to improve system accuracy and reliability, they do not take additional measures. The store pays an annual fee to the ICA group to support the continued development of the MyICA application, as well as research for improving existing systems and developing new ones.

The owner admitted that they still do not have a plan for potential upcoming crises because of their unpredictable nature, both in terms of when they are due to occur and in regards to which products are going to be hoarded. The store owner stated that there is no economic incentive to prepare for uncertainty and, as a result, prefers to respond to disruptions as they arise. The store manager stated that staying informed about global events allows for some calculated guesses, such as the invasion of Ukraine, but that there is limited predictability. As these disruptions are rare, a constant overstock of items such as dry goods and preserves are not financially sustainable in the long run.

4.3 CASE 3 - The Bishop

Interviews with the IT-specialist and the store manager at the ICA store Bishop revealed that data-driven decision-making is highly prioritized. However, as many full-time employees have spent many years at the store, they possess a strong foundation of knowledge and often rely on their expertise and intuition to complement data insights.

4.3.1 Applicability of Analytics Tools

In the interview with the store manager it was explained that KPI's are central components of their weekly planning process and that these indicators are stored and visualized in an

application called MyICA. It is further explained that store managers use these key metrics to identify areas of improvement and evaluate whether staffing levels can be adjusted to optimize costs. The Manager elaborates by saying:

> *Staff is our primary cost and therefore a lot of emphasis is placed on minimizing the unnecessary costs related to overstaffing.*

The IT-specialist described significant changes in scheduling practices as a result of new technologies and analytics tools. The store manager supports this by explaining that, until just a few years ago, their staff hours were manually recorded in Excel each week to oversee staff scheduling and workload distribution. This process, according to the store manager, has since then been replaced by an automated HR system that records hours worked and generates salary specifications based on the collected data, which streamlines operations. The system also updates in real time, allowing for easier budget monitoring and optimization of staffing hours.

The store manager highlighted that analytics tools are most frequently utilized in managing procurement. This is particularly true for departments such as fruit and vegetables as well as meat and fish departments, where a continuous supply of fresh ingredients is essential. However, for these specific products, there is significant amounts of human intervention, as these decisions need to be confirmed by deliberate human analyses to avoid faults from the automated ordering tools. The store manager explains:

> *I am only stressed when we make a faulty order in the departments with goods prone to deterioration as our goal is to minimize waste. Therefore, these kinds of decisions need to be managed by staff as well as the data system. Minimizing waste has been a key mission for us for at least the past 30 years.*

In contrast to the non-automated ordering processes, The IT specialist explained that the purchasing procedures for departments that manage dry goods, preserved products, and household tools are almost fully automated, requiring minimal human intervention. These

processes are entirely operated by a system. The IT-specialist and the manager acknowledged that they are aware of stores with more extensive use of new tools and techniques.

4.3.2 Data-driven decision-making vs Human Intuition

The Bishop store has been collecting data for several decades. However, they explained that only data from the past 18 months is actively used as the basis for their decision-making. The Manager shared:

> *Data from more than 18 months back does not really give us too much to work with as trends change so often, of course during holiday seasons like christmas and easter, older data could potentially give us more valid information.*

The store manager explained that the majority of their decisions are made by combining insights from the data with careful judgment. Both the Manager and the IT Specialist noted that some decisions cannot rely on data alone. These decisions often need to be made on the spot, without time for detailed analysis. For example, the Manager described how staff identify deteriorating products, such as defected fruit, and decide whether to discard them or repurpose them into discounted bundles of lower-quality items.

The manager further clarified that all major decisions are expected to be supported by data to ensure that they align with the store's mission and to minimize the risk of errors. However, they emphasized that data alone is not always sufficient when it comes to upholding the store’s core values. Human judgment plays a crucial role in areas such as selecting local alternatives and eco-friendly products, which may not always align with purely data-driven profitability metrics. The manager elaborated by saying:

> *If we were to rely solely on data to maximize our profits, we would not have as many local alternatives. These are not the ones that we earn a lot of money on. However, some people choose us on the terms that we are a sustainable business.*

The Manager also added that human judgment plays a crucial role when evaluating supplier discounts, as decisions must consider factors beyond just cost savings, such as storage capacity, product demand, and the store's overall strategy.

4.3.3 Disruptive events - Crisis management and Adaptability

The Bishop store faced significant challenges during the Covid-19 pandemic. The manager recalled conducting a crisis meeting the same night as the lockdowns were announced, recognizing the potential negative impact on the store. This negative effect was primarily due to the anticipated loss of the store's regular customer base: the commuters. The manager highlighted that the store relied significantly on commuter traffic, which drove demand for pre-prepared meals and grab-and-go products. With the onset of the pandemic and the disappearance of commuters, customer traffic dropped by nearly 50%, resulting in a 40% decline in sales. Consequently, the store had to adjust its assortment and product availability to align with the shifting demand. The store manager pointed out that their online shop was a key success factor during the pandemic, as it enabled many elderly customers to continue shopping. As a result, significant emphasis was placed on updating the website and ensuring a seamless and user-friendly shopping experience.

In addition to the shifts in customer demand patterns, the IT specialist mentioned that Covid-19 caused staffing challenges and a slight increase in raw material prices from subcontractors. These changes affected the store's ability to rely on previous data, as nearly all previously saved data became irrelevant. This made human judgment and experience more important for managing the crisis. The IT specialist added:

> *Most decisions were based on gut feeling, we used the old classical trial and error method and tried to figure out how to get a grip of what we were doing, and what we should do. We could not know if our actions were correct, we were operating completely blind.*

Both the store manager and the IT specialist explained that after a few weeks of lockdowns and manual ordering, the system began to adapt by identifying a decrease in demand for certain products and an increase in others. While the systems accounted for some adaptiveness regarding the ordering quantities during the pandemic, human interference was still prevalent, where they manually adjusted the amounts to recalibrate the systems to the new consumer behavior. The store manager noticed that there was an increase in wasted fresh products during the first weeks of the pandemic as neither the system nor the managers that handled procurement could predict the amount that would be consumed. The store manager also

highlighted that one of the key lessons learned during this period was the ability to identify their regular customer base, as commuter shoppers had stopped visiting the store. This understanding of new consumer patterns also prompted adjustments to the product range.

When inflation impacted Sweden, the manager explained that the Bishop staff applied lessons learned from the Covid-19 pandemic, such as reducing the stock of premium products. They recognized that the economic downturn had created a more price-sensitive customer base and focused on lowering margins to maintain customer satisfaction. The manager explained that it was a daily task to analyze the pricing strategies of competing stores to ensure that their prices remained competitive. The manager and IT specialist noted that the mass distribution of crisis-of-war newspapers triggered similar trends in consumer demand compared to those seen during Covid-19. Customers began stockpiling items such as preserves, toilet paper, and water.

Lastly, both the manager and IT specialist explained that the pandemic forced them to put other investments in infrastructure and staffing on hold due to the uncertainty surrounding the future. This was identified as one of the key long-term challenges resulting from the pandemic.

4.3.4 Future prospect of Data and Data Analytics utilization in Decision-making

The Bishop store recognizes the growing importance of data and analytics in its decision-making processes and they have plans to expand their use of such tools in the future. Both the Manager and IT-specialist emphasized the need for more advanced tools to enhance accuracy in their predictions and minimize reliance on manual interventions, which is explained to cause more errors. The store manager also underscores the importance of maintaining a balance between data-driven insights and human judgment, particularly in decisions that reflect the store’s values, such as promoting sustainability. The IT specialist further explained that there is an increasing risk of cybersecurity attacks and acknowledged that their current cybersecurity measures are underdeveloped. They emphasized that relying solely on automated and digital systems could make the store's operations fragile and vulnerable to potential threats.

4.4 Summary of empirical findings

Table 4 provides a summary of the findings on how descriptive, predictive, and prescriptive analytics were utilized and created value for decision-makers during both normal operating conditions and disruptive events.

Analytics Type	Normal operating conditions	Disruptive events
Descriptive analytics:	MyICA dashboards and handheld scanners identified inventory discrepancies (e.g., theft or delivery issues), enabling immediate corrective actions Visualized KPIs (e.g., daily sales, turnover rates and purchasing trends) guided decisions on product placement and staffing needs Built confidence and facilitated decentralized decision-making, especially those at tactical and strategic level by providing all employees with accessible, easy-to-understand metrics.	Offered real time tracking of shifting consumer behavior during Covid-19, allowing managers to adjust inventory and staffing dynamically Enabled managers to identify new demand patterns (e.g., panic buying of non-perishable goods) and adapt operations accordingly Enhanced managers' conceptual knowledge, enabling structured yet flexible decision-making during volatile periods
Predictive analytics	Reduced manual workload by integrating predictive models into the MyICA application, aligning orders with projected demand Enabled proactive planning through scenario analyses (e.g., preparing for holiday demand spikes) With assistance of human judgment, it enabled pre-crisis measures like stockpiling for Russia's invasion of Ukraine, improving operational continuity	Initially, it was not utilizable from a forecasting perspective. However, with time, it adapted to changed consumer patterns and provided ordering insights for managers It was utilized with human intervention, where parameters and metrics were changed manually, allowing the tool to still function. Hence, creating value by maintaining operational continuity

Prescriptive analytics	Tools like MyICA, dynamic forecasting systems, and AI enhance decision-making in procurement, staffing, budgeting, and anomaly detection Automated processes (e.g., stock ordering) optimized operations Optimized shelf-space allocation and inventory management Empowered decision-making across staff levels with data-backed recommendations	Given that descriptive and predictive insights are reliable, MyICA application effectively identifies and successively adapts to patterns in consumer demand, supporting decisions on procurement and inventory management for both general and event-specific products Supported the decision-making process of implementing online stores by identifying customer segments (e.g., elderly shoppers) The use of heat cameras provided insights into product placement strategies to help minimize the risk of spreading the Covid-19 virus

Table 4: Summary of the empirical application of descriptive, predictive and prescriptive analytics during normal operating conditions and disruptive events

5.0 Analysis

Chapter five presents the analysis of the study's results by connecting them to the theoretical frameworks and situating them within the appropriate context. The results distinguish between normal operating conditions and disruptive events to highlight the differences and deepen the understanding of their usability during disruptive events. The analysis begins with descriptive analytics, followed by predictive and prescriptive analytics. Lastly, an analysis on strategies for adapting to disruptive events is presented.

5.1 Utilization of Analytics Tools

5.1.1 Descriptive Analytics

Descriptive analytics form the foundation of data-driven decision-making by providing summaries and insights from historical and current data. These insights are critical not only for understanding the current state of operations but also for informing more advanced methods like predictive and prescriptive analytics (Demen & Demirkan, 2013). This dependency on descriptive analytics is highlighted by the general findings from the interviews with the three ICA-stores.

Utilization of descriptive analytics during normal conditions

In all three of the ICA stores studied, the MyICA application was central for utilizing descriptive analytics. The application delivers real time data visualizations, including dashboards and graphs that highlight key performance indicators such as daily sales, turnover, and customer purchasing trends, all of which are used to guide decision-making. Gressel et al (2020) highlights one of the main tasks of descriptive analytics is to provide visualizations and insights into the questions of what is happening and what has happened. This aligns with Gandomi & Haider’s (2015) assertion that the potential of data is only realized when it is transformed into actionable insights that directly inform decisions. By enabling managers to process large volumes of data at high speed, the application allows the stores to fully capitalize on the value of their data.

At Tower and Knight, descriptive analytics is embedded into daily operations through handheld scanners used by all employees. These scanners provide simple, easy-to-read statistics, allowing decision-makers to make choices of higher accuracy with confidence. The manager at Tower emphasized that these statistics have enabled employees at all levels of the organization to make both tactical and strategic decisions without needing reassurement from top management. The manager at Tower emphasized how this accessibility built confidence and contextual knowledge among employees, allowing them to also rely on intuitive decision-making for future challenges. This exemplifies Dane & Pratt's (2007) argument that increased familiarity with reliable data strengthens decision-makers' intuitive decision-making capability in general.

Descriptive analytics also facilitated operational monitoring across the stores. Descriptive analytics helped identify operational discrepancies. For example, at Tower and Knight, managers used MyICA's real time stock data to detect and address mismatches between projected and actual inventory levels, reducing problems caused by theft or delivery issues. Additionally, descriptive analytics is used to monitor trends over daily, weekly and seasonal periods by categorizing sales data based on product type and time frame. This ensures that both manager and employees can make informed decisions grounded in reliable data. At Bishop, Knight and Tower, almost all products are displayed based on descriptive sales statistics, guiding decision-makers with optimized exposure of products. These empirical insights Further strengthen the theoretical applications of descriptive analytics provided by Davenport (2006).

Utilization of descriptive analytics during Disruptive events

During disruptive events, the reliability of descriptive analytics is weakened as consumer behavior and market conditions shift dramatically, often rendering historical data irrelevant. This limitation was observed across all of the ICA stores during the Covid-19 pandemic. For instance, the store manager at Bishop noted that sales patterns and customer behavior deviated from historical trends. This deviation was partly due to the lockdowns, where one of the stores, Bishop, experienced a 50% decrease in commuter traffic, making pre-pandemic data on product assortment and staffing ineffective.

Their inability to rely on historical data reinforces Ballesteros & Kunreuther's (2018) perspective that unpredictable disruptions have unquantifiable and inherently unpredictable effects. Consequently, ICA managers were compelled to adopt a more intuitive decision-making approach. Interviews revealed a consensus among managers that gut feeling and trial and error methods became essential when descriptive analytics became obsolete. This limitation highlights the need for manual adjustments and managerial expertise to interpret and adapt to real time data effectively. The unreliability of information illustrates Simon's (1955) concept of bounded rationality, where decision-makers face constraints such as irrelevant or incomplete data. Furthermore, the reliance on gut-feeling and human judgment aligns with Kahneman's (2011) system 1 approach, where instinct and rules of thumbs become central in the decision-making process. However, while system 1 decision-making can be efficient in the absence of reliable data, it also introduces risks of biases and errors. One example of such an instance was expressed by the store manager at Bishop, explaining that there was an increase in food waste during the first weeks of the pandemic, due to the new reliance on human intervention and decreased support from analytical tools. The imbalances in supply and demand that Covid-19 entailed changed how decision-makers confronted problems and made decisions. Their usual reliance on system 2 thinking and deliberate analyses of decisions were challenged during this period.

Despite these challenges, descriptive analytics still played a valuable role by both visualizing drastic changes in consumer demand and playing a supportive role by improving manager's conceptual knowledge, which in turn enhanced their confidence in using system 1 approaches. This Aligning with Dane & Pratt's (2007) claim that descriptive analytics can support intuitive responses during uncertain environments. A practical example of this comes from the owner at Tower, who described an emerging tool at their ICA. This tool allows all employees to continuously monitor whether actions, like rearranging a shelf, have a direct impact on sales, showing how constant feedback contributes to building knowledge and making more informed decisions. As Moore (2017) explains, raw data gains value first when it is interpreted and transformed into actionable insights. During crises, this process becomes even more critical, as Aven (2018) highlights the importance of system 1 thinking to encourage creative problem solving and rapid responses. However, creativity alone is insufficient, decision-making must still follow a structured process to avoid reliance on randomness or improvisation. Al-Dabbagh (2020) argues that the key to effective

decision-making lies in balancing the flexibility and adaptability of creative thinking with the stability of structured approaches.

5.1.2 Predictive Analytics

Predictive analytics builds on descriptive insights to forecast future trends and potential scenarios, enabling proactive and strategic decision-making. It uses historical data, statistical modeling and advanced algorithms to identify patterns and trends, reflecting Brintrup et al.'s (2019) view of predictive analytics as a vital tool for anticipating and mitigating risks. This importance is reflected in the experiences shared by ICA stores, who used it extensively both during normal operating conditions and during disruptive events.

Predictive analytics under normal conditions

From the interviews, it became evident that during normal operating conditions predictive analytics enables ICA stores to anticipate sales, restructure inventory levels and plan staffing allocation. For instance, at Knight, the department manager highlighted how predictive models within the MyICA application provided accurate forecasts for product demand and projected sales. This functionality, supported by the stores' automated ordering system, reduces manual workload and ensures inventory replenishment in alignment with anticipated demand. Such precise, data-driven processes align with Kahneman's (2011) system 2 thinking, where deliberate and analytical approaches drive decision-making.

Beyond inventory management, predictive analytics facilitates scenario planning and resource optimization (Qadir et al., 2016). For example, at Tower, forecasting tools identified recurring demand cycles, such as monthly paydays, allowing managers to adjust procurement proactively. This approach reduced waste and ensured stock availability during peak demand periods. Similarly, at Bishop, predictive analytics helped managers strike a balance between avoiding overstocking and meeting customer needs, demonstrating its strategic value in maintaining operational efficiency and customer satisfaction.

Given the empirical insights, predictive analytics tools were also utilized for resilience planning. At Knight, the store manager used forecasts and scenario-planning to prepare for Russia's invasion of Ukraine by stockpiling high demand items like preserves and dry goods.

This decision, although primarily driven by human intuition, was supported by predictive insights derived from descriptive historical data. When patterns similar to those observed during the pandemic began to reemerge, the combination of contextual knowledge, data analytics tools, and managerial expertise proved crucial in guiding effective action. This proactive measure highlights the capacity of predictive analytics to strengthen resilience by mitigating potential disruptions, aligning with Duchek et al.'s (2020) theory that resilience is rooted in adaptability and preparedness. By proactively addressing stock shortages, the store reduced the potential damage associated with lost sales.

Predictive analytics under disruptive events

The efficacy of predictive analytics is reliant on stable and consistent historical data. This dependency becomes a significant limitation during disruptive events such as the Covid-19 pandemic. At Bishop, the inability to quickly adapt to changes in the external environment rendered predictive analytics models ineffective until the point where new data allowed for recalibration. During this interim period, managers relied on manual adjustments to align order quantities with real time observations. These adjustments played a crucial role in shortening the recalibration period, as the system recognized the manual changes and interpreted it as indicators of changed patterns. This demonstrates that predictive analytics alone failed to provide actionable insights. It also highlights the concept of bounded rationality (Simon, 1955) , where information is increasingly limited during disruptive events. Furthermore, these insights support Brintrup et al.'s (2019) findings that predictive tools require consistent and reliable input data in order to function properly. The predictive analytics systems are inherently coded to interpret and make decisions based on historical datasets, which rendered them incapable of adapting to the rapidly changing consumer patterns during crises. This lack of real time adaptability underscores a key limitation of predictive analytics and reinforces the necessity of manual intervention. Similarly, staff at Tower were forced to intervene and manually reduce automated ordering by 20% to address the volatility of consumer demand. This intervention also highlights the importance of human oversight in ensuring that predictive outputs remain relevant in uncertain contexts.

Russia's invasion of Ukraine further illustrates the limitations of merely relying on data-driven predictive analysis during crises. While predictive tools were unable to fully anticipate the changes in consumer behavior, the store manager at Knight demonstrated how

human judgment could effectively complement predictive analytics. Using insights gained from the Covid-19 pandemic, the store manager anticipated surges in demand for non-perishable items like preserves, dry yeast, and toilet paper, manually adjusting orders before the crisis escalated. This intervention highlights the important role of experienced managers in complementing predictive systems during volatile conditions.

5.1.3 Prescriptive Analytics

Prescriptive analytics represents the most advanced stage of data-driven decision-making, combining insights from descriptive and predictive analytics to recommend actionable strategies. It employs optimization models, simulations and advanced algorithms to identify the best course of action, balancing effectiveness with efficiency (Tamm et al., 2013).

Prescriptive analytics under normal conditions

During normal operating conditions, prescriptive analytics tools are important in enhancing operational efficiency, reducing costs and improving customer satisfaction. At ICA stores, prescriptive analytics is integrated into the MyICA application for multiple purposes, such as staff scheduling, inventory management, pricing strategies, and promotional event planning. For example, at Knight, the MyICA application utilizes prescriptive analytics to suggest optimal staff schedules by analyzing historical sales patterns and peak hours. This is a benefit that Kawas (2013) also highlights, and it ensures that staff allocation aligns with demand, which improves both efficiency, cost optimization and customer service.

Similarly, inventory management at Bishop demonstrates the use of prescriptive analytics to optimize shelf arrangements by recommending product placements based on demand and profit margins. This enables products to be positioned more strategically, ultimately enhancing customer satisfaction and boosting profits. At Tower, data from heat cameras is another parameter used in prescriptive analytics for product placement. By monitoring customer flow and movement within the store, this data enables managers to optimize product placement based on observed movement patterns. As Tower and Knight utilize handheld scanners, these prescriptive insights allow store staff to make decisions in real time. This is a possibility that has been enabled with the advancements of technological developments such

as IaaS which provides a more objective decision-making foundation (Demirkan & Delen, 2013).

Prescriptive analytics is also used to foster sustainability and waste reduction by optimizing inventory management practices. At Bishop, managers used prescriptive suggestions to minimize food waste by aligning order quantities with real time sales data and expiration dates. This approach ensures that shelves remain stocked with fresh products while reducing overstocking and spoilage, benefiting both the environment and the store's profitability. This aligns with Frank's (2009) idea that rational decision-making can align individual and societal interests. It also addresses situations where decision-makers' cognitive constraints can be mitigated, by using the directives and suggestions from prescriptive analytics.

Prescriptive analytics during disruptive events

The effectiveness of prescriptive analytics is decreasing during disruptive events due to the reliance on descriptive and predictive outputs, which often falter when patterns are disrupted. Ballesteros & Kunreuther (2018) highlight that traditional risk management frameworks and analytics tools, which depend on historical data, often fail to adapt effectively to rapidly evolving conditions. During the Covid-19 pandemic, ICA store managers observed these limitations firsthand. They were required to override system generated recommendations and use their judgment to address these challenges effectively. This resulted in a greater emphasis on system 1 thinking and intuition based decisions (Kahneman, 2011), where flexible and adaptive decisions were needed. Ballesteros & Kunreuther (2018) emphasizes the need for adaptiveness in order to cope with disruptive events. A practical example of prescriptive analytics during Covid-19 was shared by the store owner at Tower, where heat cameras identified crowded areas in real time. This data enabled decision-makers to reduce congestion by redistributing popular products from these hotspots.

5.2 Adaptation to Disruptive Events

The distinction between predictable and unpredictable disruptive events is critical in shaping managerial approaches (Ballesteros & Kunreuther, 2018). Predictable events, such as the war in Ukraine and the surge in inflation, enabled managers to prepare for disruptions and implement proactive measures, like adjusting inventory levels in advance. This enabled the

stores to develop resilience, aligning with Holling's (1973) concept of absorbing and responding to change.

In contrast, unpredictable events such as the pandemic required more reactive approaches where intuition and real time adjustments were essential to navigate the uncertainty. Moore (2017) emphasizes that decision quality is intrinsically linked to the relevance of the underlying data. However, as analyzed in section (5.1), the rapid changes in consumer behavior during the pandemic rendered pre-pandemic data ineffective. This challenged the applicability of analytics tools and forced the stores to rethink their strategies. Gressel et al. (2020) argue that managers must set clear directives to avoid the risks of overrelying on inaccurate or irrelevant information, a principle both Knight and Bishop applied when they pivoted toward a more digital solution with the online shopping platform.

Prior to the pandemic, both Bishop and Knight regarded digital shopping platforms as supplementary rather than central to their operations. The onset of lockdowns, accompanied by reduced in-store traffic and shifting consumer purchasing patterns, forced a reevaluation of this perspective. Tower, the only ICA store without an online shopping option, expressed regret during the interviews, acknowledging that they were ill prepared to serve customers remotely. In contrast, Bishop and Knight used the crisis as a catalyst for digital transformation, rapidly implementing online shopping platforms to meet shifting consumer needs. This aligns with Duchek et al.'s (2020) assertion that organizational resilience involves learning from events and building dynamic capabilities that drive change, as well as Taleb's (2012) concept of antifragility which demonstrates how systems can gain from disorder.

One significant advantage of adopting a digital business model was the ability to collect and utilize new, contextually relevant data to adapt to the evolving environment. Gressel et al. (2020) emphasize that the value of data depends on its applicability to the decision at hand. Through the online shopping option, ICA stores accessed real time customer insights, such as product preferences and delivery trends, which were more difficult to gather in traditional in-store settings. The ability to shift focus to these datasets underscores the adaptability of digital transformation in aligning operations with changing consumer and societal demands. It also exemplifies Al-Dabbagh's (2020) claim that inaction in decision-making during crises is a common fallacy. However, technological development also introduces new

vulnerabilities, particularly in areas like cybersecurity, which the IT specialist at Bishop described as underdeveloped. Consequently, while digital integration strengthens operations in some aspects, it may simultaneously increase fragility to potential disturbances in others.

6.0 Conclusion

Chapter six presents the conclusions drawn from the study in relation to its purpose and research question.

This study examined how organizations utilize descriptive, predictive, and prescriptive analytics in decision-making during both normal operating conditions and disruptive events, such as the Covid-19 pandemic. By comparing these conditions, the goal is to give an understanding on how these tools can be practically applied when established patterns are disrupted.

In normal operating conditions, analytics tools form a framework for data-driven decision-making. Descriptive analytics provides real time insights into inventory levels, sales trends, and other performance metrics, forming the foundation for strategic planning. Building on this, predictive analytics enables accurate demand forecasting and scenario planning, empowering managers to anticipate recurring events such as holidays or monthly paydays. Prescriptive analytics takes these insights further, offering actionable recommendations for resource allocation, waste reduction and operational efficiency. Together, these tools emphasize methodical and rational thinking, streamlining routine operations by leveraging automation to reduce human intervention and enhance efficiency.

Disruptive events, such as the Covid-19 pandemic, challenged the effectiveness of these tools by rendering historical data and established patterns unreliable. Descriptive analytics, while struggling to adapt to rapid behavioral shifts, still provided value by offering real time visibility into changing conditions. Predictive analytics required extensive manual recalibrations to address the lack of stable input data and prescriptive analytics became heavily dependent on human intervention to refine its recommendations. These limitations exposed the tools' reliance on static models, making them less effective in volatile environments.

The findings underscore the critical role of human expertise in bridging the gaps when data analytics becomes unreliable. During the pandemic, managers relied on their intuition and experience to recalibrate systems, interpret incomplete data, and make agile decisions to

maintain operational continuity. This interplay between human adaptability and analytics highlights the importance of complimenting advanced tools with managerial creativity and flexibility. By combining the strengths of analytics systems with human expertise, organizations can build the resilience needed to navigate an increasingly volatile world.

7.0 Discussion

Chapter seven discusses the findings within a broader context, explores implications for practitioners, and highlights the study's theoretical contributions. It further identifies opportunities for improvement and concludes with suggestions for future research.

This study aims to contribute to a deeper understanding of how data analytics tools are practically applied in dynamic real-world contexts, addressing the research gap identified in the problematization. Rather than offering a straightforward answer to the research question, the findings illustrate the interplay between data analytics, human expertise, and contextual factors that influence decision-making. By examining the roles of descriptive, predictive, and prescriptive analytics, the study highlights both their strengths and limitations in supporting organizational decision-making during stable and disruptive conditions.

A key finding is that these analytics tools rely heavily on consistent and historical data, which creates significant challenges during disruptive events. Predictive tools, in particular, depend on stable input data to function effectively, validating Brintrup et al.'s (2019) assertion. This is particularly evident in the case of automated ordering systems, which entirely rely on established consumer patterns. This study expands on this understanding by illustrating that during periods of disruption manual intervention becomes essential to ensure operational continuity as traditional patterns are rendered ineffective. For example, managers at ICA stores manually adjusted analytics models to recalibrate them for rapidly evolving consumer behavior, enabling the tools to adapt more effectively to new patterns. This reliance on human expertise highlights the critical role of decision-makers in bridging the gaps left by static data models.

The distinction between predictable and unpredictable disruptive events further underscores the complexities of solely relying on analytics tools. Predictable events, such as the Russia-Ukraine conflict, allowed managers to use predictive tools proactively, enabling measures like stockpiling essential goods. In contrast, the Covid-19 pandemic, an unpredictable disruption, exposed the fragility of analytics systems reliant on historical data. These findings align with Reddy et al. (2016), who argue that the predictability of an event

determines the strategies available to organizations. This study builds on their arguments by emphasizing the importance of human expertise and contextual knowledge, especially when analytics tools fail to deliver actionable insights in highly uncertain scenarios.

A finding closely tied to the pandemic and its societal transformation is the rapid shift to online shopping. This transition emerged as a way to address the limitations of digital analytics tools, which struggled to adapt to rapidly changing consumer behavior and societal shifts. By moving operations online, organizations could mitigate the challenges posed by unreliable analytics during the disruption, while also leveraging new opportunities for maintaining operations. However, this shift also introduced new vulnerabilities, such as cybersecurity risks when emphasizing the increased dependence on digital systems. As noted in the problematization, unlike past periods of economic instability, where technological investments were often decreased, the pandemic saw sustained investments in digital solutions (Harapko, 2023). This reflects the recognition of digitalization as an essential strategy for managing volatility. However, as Gressel et al. (2020) argue, the effectiveness of such investments hinges on aligning them with specific decision-making needs. Without this alignment, digital tools risk becoming liabilities rather than assets, particularly during disruptive events.

The implications for practitioners are clear: organizations must address the limitations of analytics tools by emphasizing the human aspect of decision-making processes. Given the critical role of human judgment in mitigating uncertainty when systems falter, organizations should prioritize the development of infrastructures and strategic plans that integrate human expertise alongside technological advancements. This includes educating staff, formulating structured contingency plans, and fostering a culture of adaptability to ensure that personnel are equipped with the clarity and the skills needed to respond effectively during crises. This study also makes two main theoretical contributions. First, it provides a practical example of how analytics tools are utilized in the food retail industry during disruptive events. Second, it enhances understanding of the essential role that human judgment and expertise play in effectively managing such situations.

As society and organizations increasingly turn to data-driven decision-making, it is essential not to overlook the human element. This is not a call to hinder technological progress but a reminder of the importance of preparing for the inevitable disruptions. Practitioners should

accept the inevitability of disruptive events, as highlighted by Reddy et al. (2016), and focus on fostering both reactivity and proactivity. Finally, the study underscores that resilience lies in the synergy between human expertise and analytics tools. While automation and digital tools can enhance operational efficiency, it is human intervention that ensures continuity when systems fail. Organizations must move beyond viewing analytics tools as replacements for human judgment and adopt a complementary approach where technology amplifies human decision-making.

7.1 Improvement opportunities

Validity and reliability are critical components of a well-conducted study, as discussed in the methods chapter. While this study involves quite a limited scope, three ICA stores and eight interviews, its design and execution ensure its findings remain robust and insightful. Generalizability could be enhanced by incorporating a broader sample of stores and regions. While the depth of the semi-structured interviews allowed for a detailed exploration of the subject, expanding the participant pool to include employees at various organizational levels, rather than focusing primarily on top management, could provide a more comprehensive understanding of data analytics utilization. This broader perspective would capture diverse insights and experiences, enriching the study's depth and applicability.

The reliability of this study can be questioned due to its reliance on interviews, a method that inherently carries the risk of misinterpretation. Subjective opinions shared by participants may have been influenced by their understanding of the questions, and similarly, responses may have been interpreted differently by the researchers. Acknowledging these challenges, several measures were taken to mitigate these risks and enhance the study's reliability. First, the topic and purpose of the study were thoroughly explained to all participants. This provided them with the necessary context to help them understand and respond accurately to the questions. Follow-up questions were tailored through the interviews to clarify responses and deepen the understanding of each participant's perspective. Second, questions anticipated to produce consistent answers were asked repeatedly across interviews to ensure alignment and validate the reliability of the responses. To further strengthen reliability, an additional step could have been taken by sharing the transcriptions with participants to confirm the accuracy of the statements. However, this would have required additional time from the participants, and

given the challenge of securing their initial participation as Christmas holidays approached, it was deemed impractical.

7.2 Further research

Our study offers valuable insights into the use of descriptive, predictive, and prescriptive analytics in decision-making under both stable and disruptive conditions, as well as the crucial role of human intuition in managing disruptive events. However, it also highlights areas that need further exploration.

Firstly, the study's focus on a single retail chain and one country limits the generalizability of its findings. Food retail stores, due to their societal importance, experienced a unique level of protection during the pandemic. Future research could investigate how organizations in different industries, cultural contexts and economic environments utilize analytics tools to manage crises with disruptive conditions. Comparative studies across sectors such as healthcare, manufacturing or logistics could provide a deeper understanding of whether the observed challenges and adaptations are universal or context-specific. Similarly, examining organizations in countries with varying levels of digital infrastructure could reveal the influence of technological maturity on the application of analytics during crises.

Second, this research centered on the Covid-19 pandemic, a global and unprecedented crisis. Future studies could explore how analytics tools are used in different types of crises with disruptive conditions. By comparing the approaches taken in various crises, researchers could identify patterns in the deployment of analytics tools and evaluate whether certain strategies are more effective based on the nature of the disruption.

Third, given the rapid evolution of technology, it would be valuable to examine how emerging data analytics tools, such as AI-driven adaptive systems and machine learning are integrated into organizational decision-making. Specifically, future research could explore how real time data contributes and could be utilized in decision-making processes during disruptive events in order to build resilience and respond to volatile conditions, bridging the gap between stability and disruptions.

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