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Advanced Algorithms under External Shock

Case Nordic Airline

Juho Nikulainen

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Abstract

Organizations increasingly utilize advanced algorithms and digital technology to gain a competitive advantage. Studies predict that by 2030 the use of Artificial Intelligence alone would increase the global GDP by 10-20%. Moreover, by this time, approximately 70% of companies would have adopted these technologies. Although some fear that machines replace humans, consensus exists, both in the corporate world and academia, that future work will entail synergistic work between humans and machines, i.e., human-machine collaboration.

This thesis illustrates how a Nordic airline changed its advanced algorithms and digitization resources during the coronavirus pandemic. This sudden external shock caused some of the company's advanced tools to fail due to used data becoming unsuitable. Moreover, the interdependencies between tools caused otherwise well-functioning tools to fail. What saved the day was finding non-traditional data sources, going back to the basics, and employing simpler models and tools to replace the failed complex ones. Then again, in other parts of the company, more automation was implemented to match the unforeseen and staggering rise of required work.

This study is among the first ones to show that when implementing new advanced tools to gain a competitive advantage, companies should also be prepared for the eventual failure of the tools. To do this, companies should know how the tools can break and proactively invest in their employees' skills which will be the single lifeboat out of the crisis. Moreover, the synergistic learning between the human users and the advanced tools have shown to provide the best overall results. Thus, investing in employees' learning related to the tools, increases not only the data resiliency but also the competitive advantage of the company.

Keywords Advanced algorithms, AI, Human-machine collaboration, dynamic capabilities.

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Tiivistelmä

Kehittyneiden mallien ja algoritmien sekä digitalisaation käyttö organisaatioissa kasvaa jatkuvasti. Tutkimusten mukaan vuonna 2030 pelkästään tekoälyn lisääntyvä käyttö lisää globaalia bruttokansantuotetta 10-20 prosenttia. Lisäksi vuoteen 2030 mennessä noin 70% organisaatioista olisi ottanut käyttöönsä näitä teknologioita. Vaikka osa pelkää, että koneet ja tekoäly korvaavat täysin ihmisen, ovat sekä yritys- että akateeminen maailma yhteneväisiä siitä, että tulevaisuuden työ tulee sisältämään synergististä yhteistyötä ihmisen jo koneen välillä.

Tämä diplomityö näyttää miten Pohjoismaalainen lentoyhtiö muutti komplekseihin malleihin ja digitalisaatioon liittyviä resurssejaan koronapandemian aikana. Tämä yhtäkkinen, ulkopuolinen shokki aiheutti joidenkin yhtiön kehittyneisiin algoritmeihin liittyvien työkalujen pettämisen kun sisään tuleva data muuttui yhtäkkiä turhaksi vallitsevaan tilanteeseen nähden. Myös joidenkin järjestelmien keskinäisriippuvuudet aiheuttivat muuten täysin toimintakykyisten työkalujen pettämisen. Tilanteen pelasti uusien datalähteiden löytäminen, paluu vanhoihin menetelmiin sekä yksinkertaisten mallien käyttöönotto. Toisaalta joissain osissa organisaatiota automaatiota lisättiin vastaamaan ennalta näkemätöntä ja rajusti lisääntynyttä työn määrää.

Tämä diplomityö on ensimmäisiä tutkimuksia, joka osoittaa, että kun organisaatiot implementoivat uusia kehittyneitä työkaluja parantaakseen kilpailukykyään, tulee näiden olla myös valmistautuneita työkalujen pettämiseen. Organisaatioiden tulisikin tietää miten työkalut voivat pettää sekä proaktiivisesti investoida työntekijöidensä taitoihin, jotta he ovat kykeneviä selvitäkseen näistä tilanteista. Lisäksi synergistinen oppiminen ihmisten ja kehittyneiden työkalujen välillä on soittanut tuottavansa parhaan kokonaistuloksen. Täten organisaatioiden investointi työntekijöidensä oppimiseen ei ainoastaan lisää organisaatioiden data-resilienssiä mutta myös niiden kilpailukykyä.

Avainsanat Advanced algorithms, AI, Human-machine collaboration, dynamic capabilities.

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Preface

I want to thank Assistant Professor Jukka Luoma and Professor Henri Schildt for providing me the possibility for this master's thesis assignment. Interviewing this many people and gathering all the data was an exhilarating experience. I also want to thank Professors Luoma and Schildt for the great discussions we had and their expert guidance helping me to write this thesis.

Helsinki, 25 June 2021

Juho Nikulainen

Abbreviations

AA	Advanced Algorithms
AI	Artificial Intelligence
GDP	Gross Domestic Product
HCI	Human-computer interaction
HMC	Human-machine collaboration
PwC	PricewaterhouseCoopers
RBV	Resource-based view
RM	Revenue Management
RMP	Revenue Management and Pricing
UAV	Unmanned Aerial Vehicle

1 Introduction

The magnitude of change the world is facing is greater than during the previous eras of technological revolutions (Schwab, 2017). Many factors are affecting this, but probably the most important ones are digitization and advanced algorithms. Digitization transforms the physical objects and analog information into a digital format (Yoo, Henfridsson, & Lyytinen, 2010). Then, advanced algorithms utilize the digital format to solve problems such as optimizing, directing actions, predicting future states, and automating decision making (Bose, 2009). Indeed, advanced algorithms is more of a general term that contains various technologies such as data mining, data visualization, statistical analysis, machine learning, and artificial intelligence (AI) (Bose, 2009).

In addition to new insights, this enables ever-increasing leverage of the human work effort and sometimes, replacing the human altogether. Thus, digitization and advanced algorithms complement and often replace the human in the loop. To understand better how this collaboration happens, scholars have created various frameworks for different levels of human-machine (or human-AI) collaboration. For example, Shrestha *et al.* (2019) present four ways humans and AI can make decisions in an organization, and Murray *et al.* (2020) "categorize four forms of conjoined agency between humans and technologies.".

Some organizations are better at renewing themselves when facing external changes. The dynamic capabilities theory aims to answer why some organizations fare better while others fail when facing a changing environment. In their seminal article, Teece *et al.* (1997) defined dynamic capabilities as the organization's "ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments.". Eisenhardt and Martin (2000) continued by stating that organizations can change their resources by leveraging existing resources, creating new resources, accessing external resources, or releasing resources. Danneels (2010) has complemented this by adding that the organization's available resources must be identified and understood to benefit from them (i.e., "resource cognition").

The coronavirus pandemic that started at the beginning of the year 2020, and continues when I am writing this thesis, acts as a case example of a rapid environmental change. This enables us to study how organizations respond when facing a large-scale external shock. The airline industry is arguably one of the industries most affected by the global pandemic and, thus, serves as an exemplary research subject for this study.

With the increasing amount of available data and utilization of advanced algorithms within organizations, I argue that identifying and understanding human-machine collaboration as the main instrument between organizations' digital and human resources is essential for organizations to succeed. When the managers understand the different human-machine collaboration levels and their effect on human expert work, the resources related to advanced algorithms can be better utilized and developed. Moreover, I argue that organizations should be cognisant of how the implementation of new advanced algorithms tools and the evident tool breakdowns affect the required employee skills and, thus, the organization's capability to operate.

To gather the data for this thesis, I conducted 30 interviews around the case company (a Nordic airline) and completed a desktop study on academic articles and airline system providers. I present the results from these data sources and data analysis; the goal is to show how the advanced algorithms tools of the case company performed under the external shock of the global pandemic and answer the research questions presented in chapter 1.2.

1.1 Airline industry and the coronavirus pandemic

The first lines in the 2020 Annual Report of one legacy airline illustrate what kind of external shock the global pandemic was to the airline industry in general: “The year 2020 will go down in history as the most difficult peacetime year in commercial aviation’s 100 years of existence” (Annual Report, 2020). During the end of March 2020, revenues of many airlines dropped more than 90% in only a few days as government after government started closing their borders (Eurocontrol, 2020).

Liquidity was also an issue; airlines had prepaid flight tickets in their balance sheet – money, which the customers wanted back as their flights were canceled. Indeed, airlines were bleeding vast amounts of cash. For example, Lufthansa stated that it is losing *each hour* a staggering 1 million EUR (Reuters, 2021). Still, when I am writing this thesis over a year after the pandemic started, the number of flights in Europe is down approximately -60% from the year 2019 levels (Eurocontrol, 2020). However, as the vaccination campaigns progress, the airlines are now hoping to see a way out of the crisis.

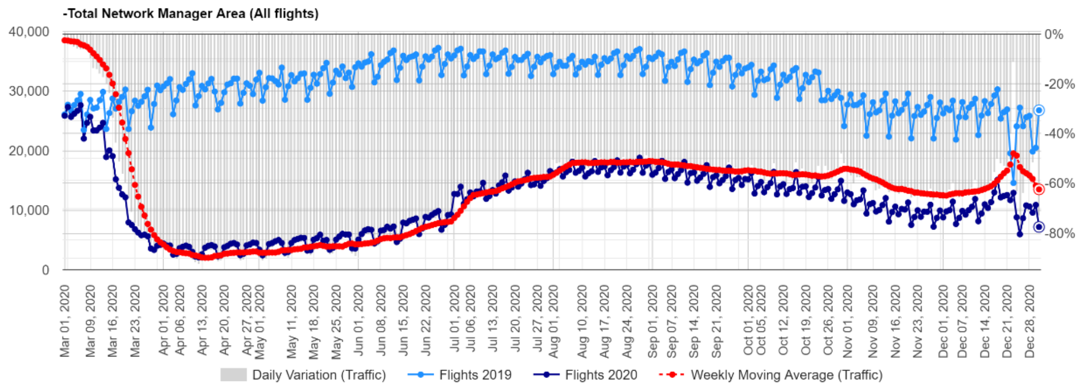

Figure 1. Eurocontrol statistics about the number of flights within Europe between 1st of March 2020 and end of the year 2020 (Eurocontrol, 2020).
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1.2 Research goals and questions

This thesis is based on previous, ongoing research that studies how data and advanced algorithms are changing organizations. However, this thesis is a stand-alone study and does not directly continue or answer any questions posed by this other research. Still, one research goal is to contribute to this ongoing research by providing data in the form of interviews.

During this research, I studied how the digitization and advanced algorithms resources employed by the case company under the external shock of the global corona pandemic were affected. Thus, the goal of the thesis is to answer the following research questions:

> **RQ1** How were the organization's resources related to digitization and advanced algorithms changed under the external shock of the global pandemic?
>
> **RQ2** How did the change affect the human-machine collaboration and the usage of advanced algorithms tools?
>
> **RQ3** How did the change affect the individual employee skill requirements related to advanced algorithms?

Answering these, this study aims to help companies going through similar (or less dramatic) changes by presenting practical examples of what occurred within the case company. Moreover, this study aims to be among the first studies to show that understanding the interdependencies of the tools and the required skills of employees is beneficial when thinking about implementing the new advanced tools – but even more so when the tools eventually fail.

1.3 Structure of the thesis

The thesis consists of six chapters plus an appendix that describes the interview questions. After this introduction, chapter 2 presents the theoretical background related to dynamic capabilities, digitization, advanced algorithms, and human-machine collaboration. Chapter 3 presents the research methodology as well as the data gathering and data analysis methods. In chapter 4, I present the findings from the interviews. In chapter 5, I present the emerged model from the findings. Finally, in chapter 6, I answer to the research questions and discuss about the limitations of the study, contributions to the literature and practice, and suggestions for further research.

2 Literature research

In this chapter, I present the theoretical background for the research. First, I discuss the dynamic capabilities theory and how it is related to other strategic paradigms. Second, I go through what digitization is and how advanced algorithms complement it in organizations. Finally, I review different views on human-machine collaboration.

2.1 Dynamic capabilities theory

Teece, Pisano, and Shuen (1997) first introduced the dynamic capabilities framework (or theory) in their seminal article "Dynamic Capabilities and Strategic Management". To present their framework, they compare it to three other prevalent frameworks on strategic management which purpose is to gain competitive advantage. First, the competitive forces framework (otherwise known as the five-forces framework) developed by Porter (1980) relates a company to its environment via five industry-level forces (see Figure 2): the power of suppliers, power of customers, potential substitutes to company products, potential entrants to the company's markets and competition within the industry incumbents. The competitive forces framework enables companies to systematically define the overall industry structure in which the company operates or wishes to operate (Porter M. E., 1997).

Second, the Strategic Conflict framework introduced by Shapiro (1989) approaches strategy as the competitive interaction between companies that can be analyzed with the tools of game theory (Teece, Pisano, & Shuen, 1997). The Strategic Conflict framework focuses on how companies can influence rival companies to behave or act in specific ways. Moreover, by influencing the rivals like this, also the entire market environment can be influenced. These first two strategy frameworks emphasize the effect of the surroundings, or the environment, on the company.

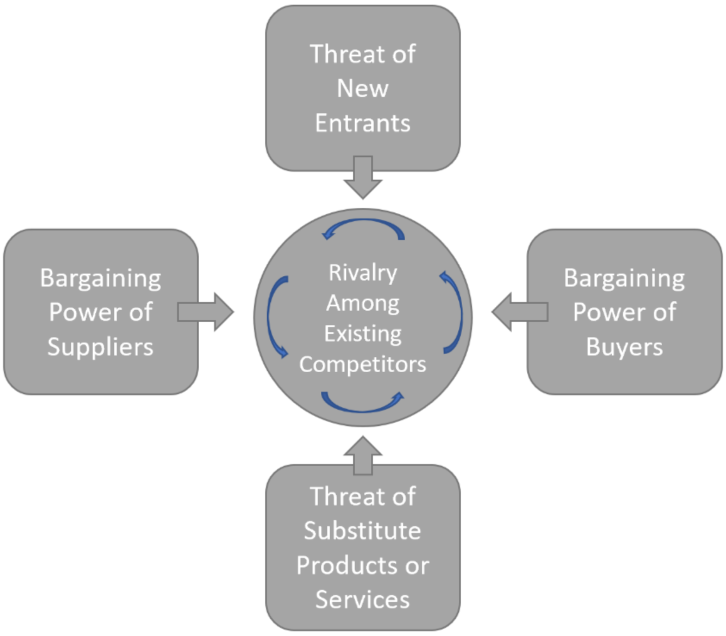

Figure 2. Porter's five forces that shape industry competition, reproduced from (Porter M. E., 2008).

Thirdly, competitive advantage over rivals can be approached via studying the internal organization of the company's resources (Barney, 1991; Eisenhardt & Martin, 2000). This resource-based view (RBV) complements the first two frameworks by introducing the company-specific internal factors rather than its position and influence on rivals (Teece, Pisano, & Shuen, 1997; Eisenhardt & Martin, 2000). According to RBV, companies can be thought of as a mixed combination of resources, different companies possess a different combination of resources, and these differences are stable over time (Barney, 1991; Eisenhardt & Martin, 2000; Teece, Pisano, & Shuen, 1997). Resources themselves are the company's physical (e.g., manufacturing plant), human (e.g., specific subject matter expertise), or organizational (e.g., operational excellence) assets (Eisenhardt & Martin, 2000). When these resources are valuable, inimitable, rare, and non-substitutable (i.e., the VRIN attributes), the company can achieve sustained competitive advantage over rivals (Barney, 1991). The critical point to note here is that in RBV, the resources are sticky, i.e., companies are stuck with the resources they have or lack, at least in the short run (Teece, Pisano, & Shuen, 1997).

When the thought behind RBV is extended to rapidly changing market conditions, we arrive at the dynamic capabilities framework by Teece *et al.* (1997). Indeed, Teece *et al.* (1997, p. 516) define dynamic capabilities “as the firm’s ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments.”. However, Eisenhardt and Martin (2000) have taken a differing view to Teece (1997; 2014) when they state that dynamic capabilities have significant commonalities (or ‘best practices’) between companies and, thus, are more substitutable. Moreover, in contrast to Teece *et al.* (1997), they state that in high-velocity markets, dynamic capabilities are likely to break down and cannot be the source of sustained competitive advantage.

To bridge the gap between these two scholarly clusters, Peteraf *et al.* (2013) and Teece (2014) propose that some of the capabilities mentioned by Eisenhardt and Martin are, in fact, *ordinary* capabilities and not *dynamic* capabilities. Winter (2003) defines these ordinary capabilities as the “zero-level” capabilities, those capabilities that the company employs to make a living in a stationary world, where it is selling the same products to the same customers over and over again. Helfat and Winter (2011) denote ordinary capabilities as operational capabilities. They state that the line between these is often quite blurry, as change constantly occurs at some level, and some capabilities can be used for both purposes. In his follow-on article, Teece (2014, p. 328) continue by defining the ordinary capabilities as the “administrative, operational, and governance-related functions that are (technically) necessary to accomplish tasks” and dynamic capabilities involving “higher-level activities that can enable an enterprise to direct its ordinary activities toward high-payoff endeavours.”.

In their view of dynamic capabilities, Eisenhardt and Martin (2000, p. 1107) emphasize the *processes* (e.g., product development) when they define dynamic capabilities as the “firm’s processes that use resources – to match and even create market change”. They continue to discuss that the changes in the company’s resources can be achieved by leveraging, creating, accessing, and releasing (Eisenhardt & Martin, 2000; Danneels, 2010).

Danneels (2010) elaborates more on the abovementioned four ways to change the company’s resource base. First, leveraging the existing resources means finding new ways to use them (Danneels, 2002). However, some existing resources are easier to find new uses when others are harder; the resources vary in their level of fungibility (Teece, 1984). For example, a company with a strong brand might benefit from this when entering some new product segments but find it utterly useless in other segments. Second, if the existing resources cannot be leveraged, new resources might be built or modified from the existing ones to create a new ability to do new things (Danneels, 2010). This process of creating new resources most likely includes some form of explorative learning (Levinthal & March, 1993; Danneels, 2010). One example is prototyping and early testing to create quick learning through immediate feedback (Eisenhardt & Martin, 2000).

Third, the company can change or extend its resource base by accessing external resources outside the company (Danneels, 2010), for example, by alliancing, outsourcing, acquisition, and partnering (Eisenhardt & Martin, 2000). Finally, the company can exercise its dynamic capability by releasing or dropping its current resources when they no longer provide a competitive advantage (Eisenhardt & Martin, 2000). For example, the company may shed off its loss-making product line.

Moreover, Winter (2003) states that the company can change without utilizing its dynamic capabilities. The change may occur by *force majeure* caused by the environment, which companies must then respond by finding a satisfactory alternative action. The nature of this change is novel, unpredictable, and rapid, requiring *ad hoc* problem solving or engaging the organizational ‘firefighting’ mode. Indeed, to have “more” dynamic capabilities than necessary compared to the change the organization faces regularly would mean carrying an unnecessary cost burden (Winter, 2003). Still, micropatterns might exist in all this firefighting, denoting that this, as well, might be part of the dynamic capabilities of the company (Eisenhardt & Martin, 2000; Winter, 2003).

The slight fuzziness of understanding the organization's dynamic capabilities highlights the importance of identifying, locating, and understanding the resources in the first place. Danneels (2010) complements the dynamic capabilities theory by defining "resource cognition" as an essential managerial element to identify resources and understand their fungibility to better exercise dynamic capabilities. Taking this further, Helfat and Peteraf (2015) define "managerial cognitive capability" to highlight the resource cognition's managerial nature and inclusion to the dynamic capabilities. They classify the managerial cognitive capabilities in relation to the three disaggregated dynamic capabilities presented by Teece (2007): sensing, seizing, and reconfiguring. First, the role of manager's capabilities in attention and perception relate to sensing opportunities and threats. Second, his/her problem-solving and reasoning skills relate to seizing opportunities. Thirdly, language, communication, and social cognition relate to reconfiguring the organization's tangible and intangible resources and capabilities.

Dynamic capabilities framework has evolved since Teece *et al.* presented it in 1997. Although the original authors noted that there is not only one strategic framework that suits every situation, they still presented their dynamic capabilities framework at least partly competitive against the three other paradigms presented at the beginning of this chapter. However, as stated later by Teece himself (2014), dynamic capabilities, *together with* good strategy, VRIN resources, strong ordinary capabilities, and scale, enable companies to thrive in the long term. Finally, the dynamic capability framework has its weaknesses: the concept itself can remain ambivalent (Wang & Ahmed, 2007), and companies might find it hard to identify what are the dynamic capabilities and how to operationalize them (Lawson & Samson, 2001).

2.2 Digitization

Digitization converges the real and virtual worlds (Kagermann, 2014). It transforms the physical objects and analog information into a digital format (Yoo, Henfridsson, & Lyytinen, 2010). Yoo (2010) explains seven critical aspects of digitization. First, this makes the physical, real-world, non-digital artifacts *programmable*: they become malleable and able to perform multiple functions. Second, they become *addressable* as each artifact can be uniquely identified (e.g., bar codes and RFID chips) and included in global or local information infrastructure. Third, they become *senseable*: able to collect information from their surroundings. Fourth, digital *communicability* enables sharing of information between the artifacts. Fifth, they become *memorizeable*, able to memorize previous locations, users, interactions, and commands. Sixth, the senseable and memorizeable artifacts make them *traceable* in time and space. Finally, as the digitized artifacts can be identified and related with other objects (e.g., location, humans, other artifacts) based on some common characteristics, they become *associable*.

The number of digitized artifacts and the amount of data is growing at rates never seen before. For example, it is estimated that during the year 2020, every day there were 500 million tweets, 65 billion WhatsApp messages, and 300 billion emails sent and that the entire digital universe reached 44 zettabytes – which is 40 times more bytes than there are stars in the observable universe (Desjardins, 2019). Furthermore, this staggering amount of data is expected to grow to 175 zettabytes by 2025 (Reinsel, Gantz, & Rydning, 2018).

2.3 Advanced algorithms

In this thesis, I take the same terminology stand as Schildt (2020) when I define advanced algorithms as a “catch-all for various technologies” using data. These technologies utilize data from digitized artifacts and apply some sort of advanced algorithms technique to solve problems. The problems are, for example, understanding the past, optimizing, directing, or automating actions, predicting future states, and (automating) decision making (Bose, 2009). The number of different advanced algorithms technologies continues to grow. Some higher-level examples are smart automation, data mining, data visualization, statistical analysis, optimization, machine learning, and AI (Bose, 2009; Schildt, 2020). Going deeper into the advanced algorithms techniques is out of the scope of this thesis. See, for example, the book on Data Analytics by Runkler (2020) to get started. Moreover, multiple online courses exist to learn more about AI specifically.

Companies increasingly utilize advanced algorithms. McKinsey Global Institute (2018) predicts that by 2030, AI alone could boost global GDP each year by 1.2% and that approximately 70% of the companies in the world will have adopted at least one type of AI technology. PricewaterhouseCoopers (PwC) (2018) expects that the global GDP could be 14% higher in 2030 because of AI. The most significant gains would happen to the services industry (21% industry GDP gain due to AI), with the transport and logistics sector also gaining a hefty 10% increase in its GDP by 2030.

2.4 Digitization and advanced algorithms in airlines

It is not surprising that the use of advanced algorithms in airlines is also gaining increased interest. The product airlines are selling is perishable: when the aircraft departs, the airline cannot sell tickets to that flight anymore. In fact, this has created an advanced algorithms research area originating from the airline industry already in the 1970s: revenue management (Pak & Nanda, 2002). Its goal is to maximize the airline's total revenues by forecasting demand for each origin-destination flight leg and using this (among other) information to decide what ticket prices will be available to potential customers at any given time (Pak & Nanda, 2002).

Moreover, airlines are starting to optimize the pricing part of the revenue management problem by introducing dynamic and continuous pricing. Most of the current revenue management systems work with booking classes (ticket prices bonded together with the decided service level) which are fixed in advance (Juhasz, 2021), for example, for a six-month flying season at a time. When the potential customer makes a flight ticket search, only some of these predefined booking classes are shown to maximize revenues. In dynamic pricing, the booking classes offered by the airline can be dynamically decided for that particular customer ticket search enabling faster response to market conditions (Juhasz, 2021). Furthermore, in continuous pricing, the predefined booking classes are not used, but the ticket prices can take any (optimal) value (Juhasz, 2021). The most modern systems utilize both dynamic and continuous pricing.

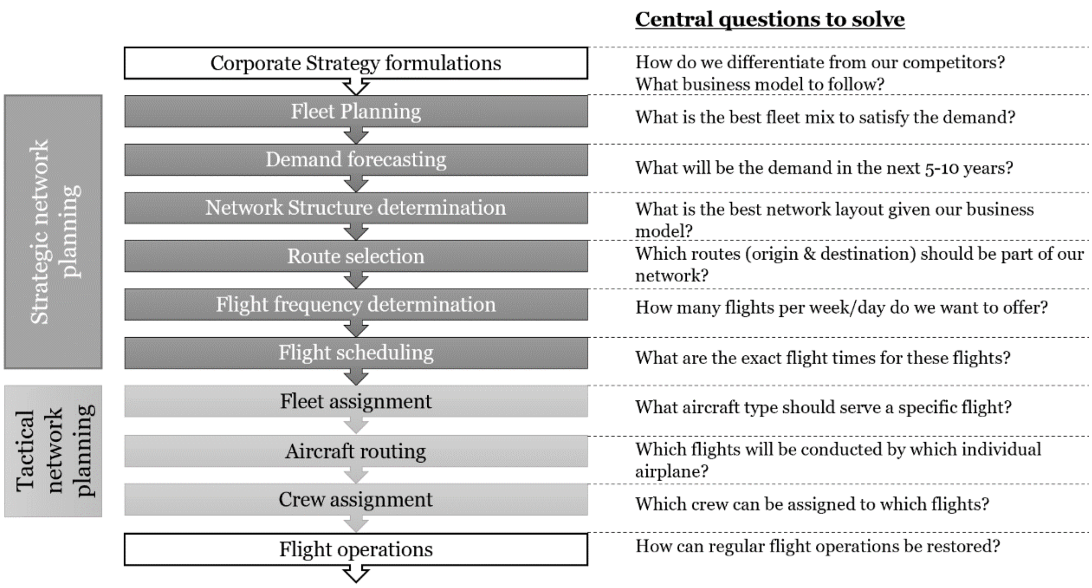

Figure 3. Generic airline network planning process (Hausladen & Schosser, 2020).

Revenue management is not the only place airlines are utilizing digitization and advanced algorithms. Figure 3 illustrates the general planning process of an airline. This includes a multitude of optimization parameters such as the network structure, fleet size and type, route selection, flight frequencies, scheduling, competitor offerings, and customer demand forecasts (Hausladen & Schosser, 2020). Then, operating the network effectively includes optimal fleet assignment, optimized flight planning, optimized turnaround process, crew roster optimization, and predictive maintenance (Hausladen & Schosser, 2020; Daily & Peterson, 2017; Kärhä, 2021). Moreover, in the customer side of the airline business, increasing focus is put on personalization, digital journeys, app development, AI interfaces (e.g., chatbots and corona restriction maps) as well as automating the handling of irregularities and customer processes (FlightGlobal, 2021; Lihavainen & Toivanen, 2020; Finnair, 2020).

Many large airlines make their own digitization and advanced algorithms products either in-house or by using consultants. However, various advanced algorithms system providers for airlines exist. Some of the largest ones are Amadeus IT Group S.A. and Lufthansa Systems GmbH & Co. In 2019, Amadeus had a revenue of 6.2 billion US dollars, employed 16550 workers, spent over 1 billion USD in research and development, and made a profit of 1.2 billion USD (MarketLine, 2021). It operates globally and offers its products to many travel industry companies such as airlines, airport operators, hotels, cruise and ferry lines, travel agencies, and corporations requiring travel (Amadeus, 2020). Lufthansa Systems is part of the Lufthansa Group, has 2400 employees worldwide, and offers airline products to "increase process efficiency and optimizing the use of resources" (Lufthansa Systems, 2021). Other providers include, for example, Boeing/Jeppesen, PROS Holdings Inc, Sabre Corporation, and Leon Software. These companies offer dynamic pricing, revenue management, crew optimization, flight planning/optimization, fleet allocation optimization, booking and inventory handling, automated customer notification, etc.

2.5 Human-machine collaboration

First, no commonly agreed exact definition for the term Human-machine collaboration (HMC) seems to exist. However, it does share some similarities with the Human-computer interaction (HCI). HCI deals mainly with the usability side of how humans *interact* with computers and has been around since the late 1970s when computers became more available (Harper, Rodden, Rogers, & Sellen, 2008). HCI combines computer science, human factors engineering, and cognitive science (Interaction Design Foundation, 2021). It focuses on designing the interface of, for example, a computer or a mobile phone to increase its usability and productivity (Norman & Kirakowski, 2018). For example, the computer mouse and graphical interfaces are products of HCI research (Norman & Kirakowski, 2018).

HMC takes a broader stance compared to HCI. First, *collaboration* is a more general term than interaction, denoting mutual goal understanding, managing tasks together, and sharing progress tracking (Wang & al., 2020). Indeed, Dillenbourg *et al.* (1996) define collaboration in general as "mutual engagement of participants in a coordinated effort to solve a problem together". Wilson and Daugherty (2018) emphasize participants' complementation and augmentation of each other in their view on HMC. Malasky *et al.* (2005) assert that the limitations of humans and machines alone can be triumphed by integrating "a human with the algorithms so that they can become partners". Second, the term *machine* can represent a multitude of systems and not only computer tools or mobile applications. These are, for example, manufacturing robots or cobots, chatbots, wearable devices, or even multiple unmanned aerial vehicles (UAVs) (Wilson & Daugherty, 2018; Malasky, Forest, Kahn, & Key, 2005). Furthermore, the term Human-AI collaboration is often used interchangeably with HMC to highlight the artificial intelligence capabilities of the machine in question.

Strategic management and organizational research are more interested in how technology changes organizations and people's work therein than in individual human-machine system development. For example, Wilson and Daugherty (2018) take a practical stand when they state that humans and machines can complement each other's strengths in two ways. First, *humans can assist machines* by training the machines to perform, explaining the behaviour of machines to non-expert machine users, and sustaining the functioning of the machines. Or vice versa, the *machines can assist humans* by amplifying humans' analytic and decision-making capabilities, interacting more effectively with employees and customers, and embodying the intelligence in otherwise "dumb" machines to work alongside humans.

Moreover, Shrestha *et al.* (2019) theorized a framework for organizational decision-making structures when humans and AI collaborate. The researchers specify five decision-making conditions: how specific the problem is, level of interpretability of the process and outcome, number of alternative choices, decision-making speed, and replicability of outcomes. Based on the different level of these conditions, the framework categorizes four organizational decision-making structures: full human to AI delegation; hybrid 1 – AI to human sequential decision-making; hybrid 2 – human to AI sequential decision-making; and aggregated human-AI decision-making (see Table 2 on page 71 in Shrestha *et al.* (2019) for more). The aggregated human-AI decision-making is particularly interesting as it means that humans and AI are given the same tasks, and then their decisions are aggregated together (with equal or some other weights) to form a single decision.

Then again, Murray *et al.* (2020) theorize between action selection and protocol development in their framework: "four forms of conjoined agency between humans and technologies". Figure 4 illustrates the framework, where either humans or machines (technology) select actions and determine the rules for what to do (develop the protocols).

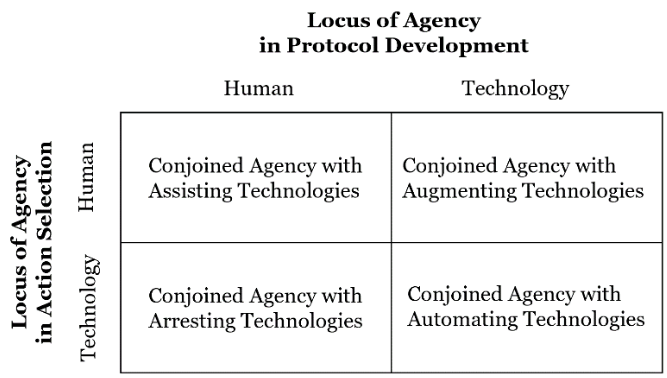

Figure 4. Four forms of conjoined agency, reproduced from (Murray, Rhymer, & Sirmon, 2020).

The human-human element in their 2x2 matrix represents the conjoined agency with *assisting* technologies such as cardiac surgery machines and Excel spreadsheets. Here, the human makes the decision and determines the rules of how things are done, and the machines only assist humans. The next element below this represents the conjoined agency with *arresting* technologies where the human still determines the rules, but the machine now can decide actions over humans. For example, a blockchain-based smart contract or the maneuvering envelope limitations in an aircraft are arresting technologies. The top right corner of the matrix represents the conjoined agency with *augmenting* technologies, in which the machine can determine the rules (develop protocols) but cannot make decisions. For example, a structured machine learning algorithm can identify patterns and recommend humans to act on them. Lastly, when the machine can develop protocols and decide actions (conjoined agency with *automating* technologies), it can fully substitute humans in the process. A classic example is IBM's Deep Blue chess-playing program (an unstructured machine learning program) which defeated the human Chess World Champion for the first time in 1997.

Haesevoets *et al.* (2021) state that, both in the corporate world and academia, a consensus exists that the future of work entails the synergistic work of humans and machines. Wilson and Daugherty (2018) found in their research of over 1000 companies in 12 different industries that organizations gain the most performance improvements the more humans and machines work together. In addition, Gartner (2017) predicts that by 2022, one in five employees who work primarily nonroutine tasks will rely on some form of AI to do their jobs, and it is more likely that the AI assists nonroutine workers than replaces them. PwC (2018) expects that half of the AI-related GDP boost comes from the increased productivity by automating processes and augmenting workers with AI technologies. Almost 80% of Deloitte (2019) survey respondents think that AI augmenting workers will lead to new ways of working. Moreover, the number of inventions related to HMC increases to grow;

between 2009–2018, the number of patents related to HMC grew 32% per annum (IPOS, 2019).

However, implementing HMC in organizations is not always easy. For example, Haesevoets *et al.* (2021) surveyed over 1000 managers and found that 50% of them want a majority vote over machines in managerial decisions. Furthermore, 30% want absolute decision power (and machine have zero power). Only 5% of managers surveyed wish that the machines would have more weight in the decision-making than themselves. Researchers point out that human's lack of trust in machines is one of the main issues when integrating machine agents into human teams (Groom & Nass, 2007; Gillath & al., 2020). Sources for the lack of trust include fear (Dujmovic, 2017), lack of understanding of how machines make decisions (Gillath & al., 2020), and lack of reliability of outcomes (Lee & See, 2004). Moreover, the *automation conundrum* creates challenges, at least in the safety-critical systems: the more automation and reliability is added, the less likely the overseeing human is to be aware of the critical information and take control (Endsley, 2017). See, for example, Gillath *et al.* (2020) and Lee and See (2004) for more about human's trust in machines and Wilson and Daugherty (2018) how to tackle some of these issues.

Although HMC seems to have become more and more important due to the infusion of advanced algorithms into modern organizations, there appears to exist little or no research combining dynamic capabilities and human-machine collaboration. However, few studies can be found merging AI and dynamic capabilities. For example, Mendonca and Andrade (2018a; 2018b) studied dynamic capabilities and their relations to digital transformation in Brazil and Portugal. Furthermore, Hercheui and Ranjith (2020) researched the impact of AI in organizations using the dynamic capabilities theory. They interviewed AI experts to find out how organizations can use AI for enhancing their sensing, seizing, and reconfiguring – the three disaggregated dynamic capabilities presented by Teece (2007).

3 Methodology

In this chapter, I describe the methods and their limitations I used in this research. First, I present the research approach. After this, I explain how I gathered the data for the thesis. Next, I present the data analysis method I used to acquire insights from the collected data. Finally, I briefly talk about the ethical considerations of the study.

3.1 Research approach

I follow loosely the case study research approach by Eisenhardt (1989). I chose this approach because it is used for inducting theory from case studie(s) and also applies to qualitative data. Indeed, the nature of my primary and secondary data is purely qualitative, as I present in the next chapter. Moreover, I studied one case company and its different business units – units, which could each be thought as a single case by themselves. To increase the qualitative rigor, I selectively utilized the Gioia methodology during the data analysis (Gioia, Corley, & Hamilton, 2013). Next, I will explain the steps I took during this research.

First, the Nordic airline that I was about to research was selected based on the ongoing other research, which had already conducted a few interviews at this company. Second, my supervisor, advisor, and I discussed and defined the research questions in very broad terms (Eisenhardt, 1989). Appendix A presents the results of these discussions in the form of interview questions. The company contact person gave me the first 11 interviewees. Then, I had the freedom to select more interviewees in any business units as I progressed in the interviews. I chose these additional informants and units based on theoretical reasons (i.e., not statistical reasons) to extent the emergent theory (Eisenhardt, 1989). Third, I used multiple data collection methods: primary data in the form of interviews and secondary data in the form of desktop study to strengthen the grounding of the theory by triangulation (Eisenhardt, 1989). Moreover, multiple investigators were applied lightly: during two interviews, either the thesis supervisor or advisor was present.

Fourth, the data collection and initial data analysis occurred jointly. For clarity, I discuss more about the data collection and analysis separately in the following chapters. This continuous overlap enabled me to adjust the data collection and its methods based on the themes arising from the preceding data and its analysis (Eisenhardt, 1989). Fifth, the final research questions and four distinctive cases emerged from the joint data collection and analysis (see chapter 5.1). Based on these findings, I conducted further, more rigorous data analysis (Gioia methodology) for the interview data relating to these four cases. Concurrently, I started to search for theories from the extant literature and compare them to the emerging theory (Eisenhardt, 1989). Finally, I reached closure between iterating theory and data when the additional learning became minimal and the thesis schedule dictated so (Eisenhardt, 1989).

3.2 Data collection

The thesis project was started as a kick-off meeting In January 2021 with two contact persons from the Nordic airline, the thesis supervisor, the thesis advisor, and me. The data collection consisted of secondary data in the form of a desktop study and primary data in the form of interviews. I conducted the interviews between January 2021 and April 2021. The desk top study was a continuous process and lasted the entire thesis project between January 2021 and June 2021. The scope of my thesis did not allow me to study all units within the company. Thus, the thesis limits to a few key organization units stated in chapter 3.2.

3.2.1 Desktop study

To collect the secondary data, I used Google Scholar and EBSCO to find the relevant academic articles, the case company's internal and external sources, and the websites of the advanced algorithms system providers. Indeed, many system providers (e.g., Amadeus and Lufthansa Systems) had extensive online brochures about their airline products. I used these to acquire a more profound understanding before and after the interviews. This was quite necessary, as the advanced algorithms tools utilized by the Nordic airline contained confidential information, and the interviewees were not allowed to show me how the tools looked or functioned.

3.2.2 Interviews

To collect the primary data, I conducted 30 interviews around the case company's organization. The interviewees included subject matter experts, (senior) managers, heads of units, Vice Presidents (VP), and Senior VPs. These informants worked in various units within the company: Operations, Network Planning, Traffic Planning, Data and Analytics, Revenue Management and Pricing, Strategic Management, Digital Sales & Marketing, and Cargo. The units within Operations included Operations Control Center, Flight Planning, Resource Planning, and Service Recovery. The informants' work histories varied from a couple of years to over 30 years in the company. The focal period of interest in the interviews was the coronavirus pandemic, meaning from the beginning of 2020 until the interviews were held.

Because one of the research goals was to contribute to the other ongoing research in the form of interview data, my supervisor and I first decided to conduct an interview sweep around the case company organization. By doing this, I would get more familiar with the organization and its units. Moreover, the sweep would produce a broader base for the other researchers to continue their work on.

This first round included a total of 10 interviews given to me by the company contact person. During the first interviews, I used the last few minutes to ask the interviewee about other prominent employees or units to interview. Based on these recommendations and the interview data, I continued to sweep the organization. Concurrently, I started to interview more people in the units found relevant to the research. In addition to the first round of 10 interviews, I completed 9 more general sweeping interviews and 11 second-round interviews (always a new informant).

Table 1. List of interviewees by their position in the organization and interview date.

Informant	Position	Interview date
1	Expert	January 2021
2	Expert	January 2021
3	Manager / Head of	February 2021
4	Manager / Head of	February 2021
5	Manager / Head of	February 2021
6	VP / SVP	February 2021
7	Manager / Head of	February 2021
8	VP / SVP	February 2021
9	Manager / Head of	February 2021
10	Manager / Head of	February 2021
11	Manager / Head of	February 2021
12	Manager / Head of	February 2021
13	Manager / Head of	February 2021
14	Manager / Head of	February 2021
15	Manager / Head of	February 2021
16	Manager / Head of	February 2021
17	Manager / Head of	February 2021
18	Manager / Head of	February 2021
19	VP / SVP	February 2021
20	Manager / Head of	March 2021
21	VP / SVP	March 2021
22	Expert	March 2021
23	Manager / Head of	March 2021
24	Expert	March 2021
25	Manager / Head of	April 2021
26	Manager / Head of	April 2021
27	Expert	April 2021
28	Expert	April 2021
29	Expert	April 2021
30	Manager / Head of	April 2021

I have collected all the interviewees, their generalized title/position, and interview dates in Table 1. Furthermore, to maintain anonymity, I present the quotes of each interviewee with only his/her generalized position. To simplify quoting, I use only "(Manager)" to quote a person who had the role of manager, senior manager, or head of unit.

Due to the ongoing coronavirus pandemic, I conducted all the interviews distantly with Zoom video conferencing software. I recorded every interview and asked permission to do this before the interview started. Before asking permission, I guaranteed the anonymity of the interviews by stating that persons' names will not be shown when quoting informants. Not a single interviewee declined the recording request. Out of the 31 interview email request sent, only one person did not reply (even after several attempts). The interview request email was accompanied by the case company contact person's introductory letter about the research and the researchers' contact information.

I booked 60 minutes for each interview. Some interviews took a bit longer, and a few times, the interview was cut shorter due to the busy schedule of the interviewee. Out of the 30 interviews, 9 were conducted in English and 21 in Finnish, depending on the native language of the interviewee. All but two interviews were conducted one-on-one; during one interview, the thesis supervisor was present, and during one interview, the thesis advisor was present. Both also asked some clarifying questions during the interviews.

I organized the interview questions into four themes with the help of the thesis supervisor and advisor. The interviews were semi-structured to allow improvisation and moving deeper into the more interesting subjects related to that particular interview. The four themes included open-ended questions relating to: 1) work before the corona pandemic; 2) the changes to the work due to the corona pandemic; 3) in-depth questions about the advanced algorithms used; 4) inter-unit cooperation and collaboration.

I always started the interviews by introducing myself, giving a short introduction to the research, and then making a note about the anonymization and asking permission to record the interview. Before the thematic questions, the first opening warm-up question was asking the interviewee about his/her work history in the company. During the interviews, I made personal memos of the answers given by the interviewees. After the interviews, the recordings were transcribed verbatim. See Appendix A for the detailed interview structure and questions.

3.3 Data analysis

I did not use any coding system for the secondary data. However, I did highlight and do short memo-writing to summarize my findings from these information sources. For the primary interview data, I conducted the data analysis in two phases.

First, while conducting the interviews, I analyzed the interview data less systematically. After an interview, I read my own written interview memos and underscored matters of interest. Moreover, after receiving the interview transcriptions, I read them, highlighted the most important factors, and made side notes to the transcribed interview document. When required, I also sent verifying emails to the interviewees to make sure I had understood their views. These were all used in the iterative data collection and analysis process to guide the future interviews as per the case study research approach (Eisenhardt, 1989). Furthermore, I compiled field notes of the main findings in one document to keep the overall picture in mind. Based on these, four cases emerged (see chapter 5.1), each illustrating a different kind of phenomenon.

Second, I conducted a more rigorous data analysis relating to the interviews of these four cases. This consisted of 18 interviews out of the total 30 interviews conducted. I used the Gioia methodology (2013) to line-by-line code the interview transcriptions. For the coding, I utilized the data analysis software ATLAS.ti and Excel. During the first-order analysis, I focused on the factors relevant to the research questions and adhered to the informant terms

(Gioia, Corley, & Hamilton, 2013). A total of 192 first-order concepts emerged.

Then, I started to seek similarities among the first-order concepts. This gave rise to the more theoretical, second-order themes, which could help to explain and describe the observed phenomena (Gioia, Corley, & Hamilton, 2013). After multiple iterative rounds, I was able to distill the 192 first-order concepts into 21 second-order themes. Finally, I grouped these 21 second-order themes into three aggregate dimensions. These topics ended up being also the three final research questions described in chapter 1.2 and the way to present the findings in chapter 4. Figure 5 illustrates the emerged data structure.

3.4 Ethical considerations

To protect the privacy of the case company, I am not presenting the name of the company in this publication. Moreover, I guaranteed anonymity for all informants before the interviews started. The interview invites shortly explained what kind of study I am conducting to aid the employees to decide themselves if they want to participate in the research. Finally, to quote the interviews, I present only the very generalized title of the informant.

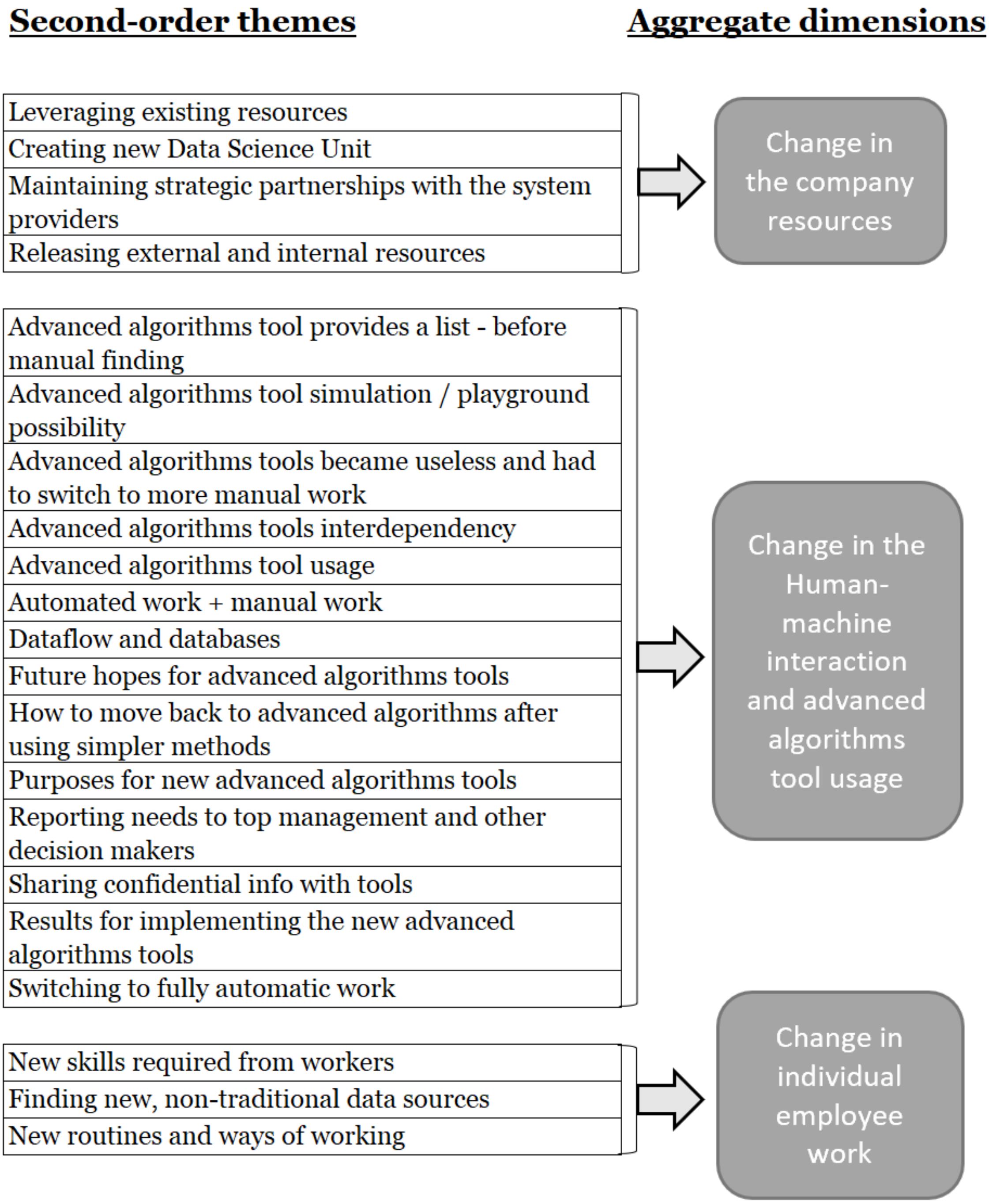

Figure 5. Data structure with the second-order themes and the aggregate dimensions.

4 Findings

In this chapter, I present the findings from the interviews. These are divided into three subsections according to the three research questions. First, I go through how the organization resources related to digitization and advanced algorithms tools were changed during the corona pandemic. Next, I present the findings related to the following change in the human-machine collaboration and usage of the tools. Finally, I go through how the above changes affected the required individual employee skills.

Because some of the interviews were held in Finnish, I have translated the quotations related to these interviews into English. Moreover, some quotations have been altered slightly to increase readability (for example, removing repetitions). However, the content of the quotations remains unchanged.

4.1 How were the organization's resources related to digitization and advanced algorithms changed?

Luckily, not many companies face external disruption comparable to what the global coronavirus pandemic had on the airline industry. As mentioned in the introduction, most airlines saw a sudden decrease of their revenues to only one-tenth of normal levels. Moreover, this happened in a matter of days as nations started closing their borders. Understandably, this affected how airlines utilize their resources in this highly dynamic situation. In this chapter, I present how this external shock affected the utilization of digitization and advanced algorithms resources in the Nordic airline I studied. This subsection is divided into four subsubsections according to the second-order themes found during the data analysis process. The data presented limits itself to the business units stated in chapter 3.2.2.

4.1.1 Creating the new Data and Analytics unit

Already before the crisis, the company had decided that data and analytics are one of its core competencies. Previously, it had data scientists and engineers scattered around and supporting the different business units:

> "It is a strategic competence. So, we must strengthen the abilities related to that. Generally, the journey of analytics in companies goes like that at some point, centralizing the abilities together enhances the abilities more than if staying in decentralized, business unit based (data analytics) teams. Corona hastened this transformation." (Manager)

The Data and Analytics unit was finally created after approximately half a year into the crisis, during the autumn of 2020. The role of this newly formed unit is not to answer many ad hoc questions arising from various business units it supports, but to increase the company data knowledge and produce new advanced algorithms tools:

> "One of the most important things in my scope is to drive the usage of data and analytics within the company. So, we have quite good capabilities to do things. But the business units who are using our products do not necessarily know what are the actual data and analytics products that they need – they only have problems and no solutions. And then they try to solve the problems in their own way." (Manager)

> "We produce data science products. Not so much ad hoc tasks anymore." (Manager)

> "A lot of these ad hoc tasks are fetching data from databases using SQL. So, I think that using a data scientist for these tasks is a bit of misusing resources." (Manager)

Moreover, one strategic goal of the Data and Analytics unit is to increase the self-service analytics within the company:

> "Our strategic goal in Data and Analytics team is to increase self-service analytics. If we have a repetitive request, then there should be a place where the person who made the request could see the answers by himself. This also requires that he is capable to use those tools and, of course, he has work time to go and check it out. And he should be able to trust what he sees." (Manager)

Finally, the unit strives to bring data and analytics already to the design phase of various projects which are not necessarily directly data and analytics related:

> "It is not yet in the mainstream in our company that if a project is started, we will ask also the data and analytics expert to be present." (Manager)

4.1.2 Maintaining strategic partnerships with system providers

The airline uses various advanced algorithms tools provided by external companies (see chapter 2.4 for more information about the tools used in airlines). During the crisis, many projects were cut due to cost reductions. However, the company kept close contact with many of its advanced algorithms tool/system providers:

> "[The system provider name] has these kinds of communities in which different airlines participate. Two of my colleagues and I participate in this champion community where we together with the system provider develop their systems, at a very concrete level." (Expert)

> "We also used the learnings to drive some developments at [system provider name] and this is something that I would say works our relatively well with them ... we can also basically place questions which go very into detail on the market share models or whatever and how this is calibrated and at least the senior people have a very good understanding of what's actually happening in the tools." (VP)

Indeed, some system providers are considered as strategic partners:

> "This system provider is our strategic partner and we have their inventory, revenue management system, and DCS and merchandising and what not." (VP)

Still, the partnerships do not mean that airlines can dictate what the system provider will exactly do:

> "Of course, you know, [name of the system provider] is a huge company and they have their own priorities, and they very often don't listen very much to what we are telling them. At the very least, with for example dynamic pricing, this is a new product. So at least they are listening very much. Hopefully, they not only listen but also... how to say, heed our advice and warnings about what to do and what not to do. But yeah. We are involved." (Manager)

One essential advanced algorithms tool used by network airlines is the revenue management (RM) system. Its goal is to maximize the overall revenues within the airline. During the corona pandemic, this tool had some significant issues to cope with the change:

> "Because now with COVID, behaviour is completely different now. People don't really book far away from departure, they only book very close. And... the forecaster in the RM software needs to learn this new behaviour, that now bookings come very close to departure. And this kind of quick adaptation is a new feature that [system provider] is now testing in the software. It's not yet live, it's not in production yet, but... but yeah, this is something that we also had discussions with them already last year [2020]. Nowadays, they are still, I think, collecting data about this. So that the software can learn." (Manager)

Moreover, many system providers update their products regularly, and even though most of the projects within the airline were cut, some of these updates were considered necessary to complete even if they cost money:

> "Last June [2020] we did this major update to [advanced algorithms tool although corona happened. These updates happen every now and then, and we don't have to participate in all of them, but these major upgrades bring additional features and enhancements." (Manager)

4.1.3 Releasing internal and external resources

When a company faces a sudden -90% decrease in its revenues, some cost-cutting can be expected.

> "We have lower resources; this is fair to say as well. It has to be said we've been as the department, the unit, we've been decreased heavily so there wouldn't be enough people to actually make sure that the [Revenue Management] forecast is correct if we would still use the forecast." (Manager)

> "Due to these corona related issues, we laid off 22 people from our department. At this moment there are only 20 people left." (Manager)

> "Everyone from around me are basically furloughed and huge amounts of people have been laid off. So, of course the environment you work in is very different as well." (Manager)

The reduction of employees created some issues as well:

> "It has been challenging, that now that people were let go, you don't necessarily know where and how things are done. Furthermore, as people are also furloughed, it is not easy to put things forwards as you don't know who to contact, and even if you know, that person might not be at work right now." (Manager)

In addition to internal employees, also external consultants' and other external workers' contracts were ended:

> "Before COVID, we had external expensive consultants, we had working on these things [developing new advanced algorithms tools], and those were quite quickly decided that we cannot keep them." (Expert)

> "Well in the beginning [spring 2020] when nobody knew what is going to happen there was a small pause [on using external consultants to develop tools], but then we continued during the summer [2020]. But we had set a goal to move this work as purely inhouse development. So, in the autumn the use of these external consultants was basically banned [when the new Data and Analytics unit was formed]."

Moreover, more than one department had outsourced certain routine tasks abroad. These tasks could have been fully automated, but as the outsourcing was cheap and changing this would have required work, it was not done at first:

> "It is one of those funny areas that there is now reason to use humans, some of the processes are quite complicated, but then again all of these are rule-based, so no one is making any decisions here, but there is a rule list to follow. So, this should be easily automated, but it has been just cheap to do it [abroad]." (VP)

> "When we talk about refunds, it may seem that it's a really easy thing to do. Easy thing to calculate. People think that it's mostly automated. But it's not. Because it's a small process somewhere behind, not that important, and it's not really useful maybe to automate it, at first." (Expert)

Then, when the corona pandemic hit, the environment changed rapidly, mandating more automation on these routine tasks:

> "In total, during this crisis, we've had almost eight years workload. But then, different teams started to help. And then we just started to

communicate to customers that sorry, it will take time and so on. And also this automation was built then." (Expert)

Furthermore, one business unit continuously updated the procured advanced algorithms tool with its dedicated system provider. This development led to the release of external work abroad during the crisis:

> "We had a service provider in India helping in stuff that was not that time sensitive. But now because of corona – and the development we did at the systems side and automating and getting new tools, the need for this slow, manual work has dramatically dropped. And then we realized that we don't have any bulk-work to give to India." (Manager)

> "They did a lot of manual work, just handling reservations and so forth. Then, we got this new tool, and the need for this manual work disappeared. Now we can handle many flights at a time with this tool and the system basically does all the work. And the India was more like a back up for us. So, then little by little there were no work to give to India." (Expert)

4.1.4 Leveraging existing resources

In addition to creating the new Data and Analytics unit within the company, many employees who did not get laid off had to work harder than before:

> "This is a bit exaggerated but before, if you had a 70% workload so that you had 30% time for development ... you can use this 30% of your capacity to think about all funny requests to the data and analytics team. But now that you suddenly have 150% workload, naturally you have to prioritize the 50% off from that ... and you don't have possibilities to ask stuff just to make it sure or what if." (Manager)

Furthermore, the company started to make savings also in facilities. However, this had some positive effects when some teams were now physically located closer to each other:

> "Everything went quite well. Quite quickly it was decided that we relocate, it took probably only three months and now we are there … There is also the technical unit and crew control … from our side it is good to have stakeholders closer together … but flight operations management is not there anymore, and that bad. That we lose." (Manager)

When some business units lost almost all their work, other units' workload dramatically increased. Thus, the company shifted employees between units to put out fires where they lit up:

> "Actually, our [team name] sized up also to, beforehand we had fifteen persons, but during the corona we had... I think up to thirty five. So here I have forty... sixty... sixty five, seventy, eighty, one hundred... One hundred plus persons in total during this time. And this also includes those COVID first months, I think, March and April, when we did not have the these two teams helping us. So we had all the different sales units, airport staff, different teams around the company helping us. So I think a hundred, up to a hundred and fifty persons … ten times more people than normally." (Expert)

The employees in the units needing help were also amazed how fast the employees from the other units learned to help: "They learned basically refund handling within two weeks. They were so fast." (expert). However, this learning did not include the use of any advanced tools:

> "We have always used Excel quite a lot. But it increased because at first, we had helpers from, for example airports and all different kinds of people who didn't have the access to the system. So, it was easy and reasonable to have one SharePoint team, and upload Excels there with tickets or document numbers which need to be refunded. So, we took [PNR

number] from Salesforce, we had the reason, we had the document number, case number, if there was case number. And everything was uploaded there. So, we added some columns that... refunded amount, currency and comments area. So, basically our helpers filled in those Excels then, and worked at first with those only."

4.2 How did the change affect the usage of advanced algorithms tools?

The airline I studied utilizes digitization and advanced algorithms tools at various levels. In some units, the basic tools are MS Office products when other units use highly complex products procured from external system providers and customized for the company. Then again, some tools are built in-house, and some routines have been automated partly or fully. In this subsection, I present how the external shock of the corona pandemic affected some of these systems and tools in different ways. The following sections are based loosely on the second-order themes found during the data analysis process.

4.2.1 Fully automating tasks

As I mentioned in chapter 4.1.3, certain routine tasks were outsourced abroad before the crisis. During the interviews, I found two distinct ways how the full automation of certain processes was achieved. First, during the start of the pandemic, the refunds unit was overwhelmed with work as customers started to claim their money back from the canceled flights. Indeed, the amount of work increased dramatically: "During March [2020], we had an average 3.5 years' workload." (Expert). Hence, they decided to complete a full software robotic automation on certain parts of their process:

> "End of March [2020] when we started to think about and develop our first robot. And it was actually automation to close Salesforce cases." (Expert)

> “I think it was Sunday evening when we got the request and on Monday morning, we had the draft and go live was within two weeks. And so, basically my team, one person from there, she had previous experience with automation. So, she completely took that one over. And we had quite a small team developing those robots.” (Expert)

> “Salesforce automation was live, then we started to create this [name of the system provider] automation, which is actually processing refunds, monetary refunds. So... we set the kind of rules that it’s only credit card refunds that... PNR is cancelled, that it had this corona remark line, so we defined those rules and I think that took about four weeks. And we were live in May with that one … May until September [2020], forty percent of the refund volume was handled by automation robot.” (Expert)

Moreover, now that the refunds team had started utilizing automation, new bottle necks started to emerge in different departments under the same process:

> “We had a third automation team in Autumn [2020]. It’s not by our department, but by finance department, to get these refund payments to banking system … Because when we basically had our refund backlog under control, more or less, then we had the next bottleneck in the finance. So, then you basically manage that bottleneck, even though it was not our process or our team anymore.” (Expert)

The second automation that has helped the company through the crisis was completed only shortly before the crisis started.

> “Just before corona I was heavily involved in [implementing the tool]. So, we automated the notifications to customers … Before it was heavily manual work … When we had cancelled a flight, we had to go and look for all the passengers [on that flight] and search for correct notification layout … Now this is fully automated … About 80% of all disruption notifications are sent automatically.” (Expert)

> “We just published June traffic and there are thousands and thousands of cancellations and before this was done manually, this notification sending. It is amazing how much time and effort we spare because it is automated.” (Expert)

Naturally, the automation also decreased customer contacts to the airline, and thus, the need for some customer care employees:

> “[The automated customer notification system] significantly decreased customer contacts to our contact centers. There was less confusion that [my flight is cancelled] and I don’t have any information about it. Also, the transfer desks at airports were abolished due to this system. Before, we were fighting against time; so, if our ‘work order’ comes when the plane touches down and the next ones leave in 50 minutes, there just was not much time to work on the problems.” (Manager)

4.2.2 Implementing new advanced algorithms tools

Because the company created the Data and Analytics unit in the autumn of 2020 (see chapter 4.1.1), it was now well suited for creating inhouse digitization and advanced algorithms tools without outside aid. One tool was an evolution of previous work completed by the external consultants. The Operations Control Center uses the tool to help to decide if an airplane should be switched to a smaller one when there are fewer passengers than previously planned. For example, a 150 seater jet could be switched to a 72 seater turboprop only a few days before the departure. As the direct costs of operating the smaller turboprop are significantly less, the company could save on each of these tail switches (in airlines, a “tail” stands for an aircraft individual). In normal times, it is not possible to switch the tails this close to departure as all airplanes are entirely in use.

> “We are [downsizing] the aircrafts to save some money to company.” (Expert)

> “There was an external developer who had been working on this. But then this was ended, and we developed this only internally. [The tool] has been very useful. Before we did the same work but manually, so it took considerably more time. And now, especially the latest version, it gathers data from so many sources. It makes work a lot easier.” (Expert)

Indeed, the tool gathers data from various sources to help in faster, data-based decision-making:

> “It bases on number of passengers and what each airplane can carry and which destinations the airplane can fly to. And there is a lot of more information like cargo, cargo revenues … special baggage, special passengers and all this sort of stuff which before required huge amount of work if you wanted to go through all of those [from different systems]. Now we see right away, for example, that if there is 3 tons of cargo, we should not downsize to turboprop aircraft [it cannot carry that much].” (Expert)

> “[Especially when there are more flights,] there is not just enough time to go through all the flights and find all the data from all the different sources.” (Expert)

The tool works by providing a list of all near future flights and a filter option to show the flights the system recommends downsizing:

> “[The tool] gives a list. It has different views and you can check all the flights. And it can also filter only the flights that it calculates that could be downsized.” (Expert)

> “We press this down gauge button and then it recommends us which flights could be downsized … and to which aircraft type … and this is how we go through the list … and we can also put a marker or a comment if for some reason I don’t downsize … and we can also leave it pending … to be checked again the next day, for example.” (Expert)

In addition to aiding in faster decision-making, the tool has made the work quality among the employees more constant:

> "We have had data but it has not been in a form that is easy and simple for the end user to utilize. And because of that, only the most progressive and motivated employees have used that data to back them up. Now we have made this visually and practically in form that everyone can use with very little training ... so the quality of work is more even, I now know that every day certain things are done because we have good systems and tools which support the work ... we have made huge savings with this tool." (Manager)

However, the employees using the tool highlight that it is still just a tool with often also unnecessary recommendations:

> "We have been doing this a long time and the tool is just helping in this. We do not trust is blindly ... it is not like that that if there is a flight on the list that could be downsized, it must be downsized. It is just for us to start thinking about it." (Expert)

Another tool has been helping the Operations Control Center to maintain the airline's network and flight connections. If a flight arrives late and has connecting passengers onboard, the tool helps to decide which of the connecting flights should wait and how many minutes:

> "[The tool] is calculating if flights are delayed, what [other] flights we should [then] delay. There is a 10, 20, 30, 40, 60, 90, 180 minutes, it calculates the cost of those delayed minutes. If a flight is delayed for example 20 minutes, what is the cost for [aircraft's] rotational and passenger related costs, and it's calculating the passenger rerouting and also EU 261 compensation fees. And also, it's calculating if ... we have to cancel the flight. We are choosing the best one for us the passengers. And we have to also monitor the crew duty hours [which] are complex." (Expert)

The tool was initially developed already before the corona pandemic and has now been continuously finetuned. During the crisis, the number of flights has been very low, and the tool has not been under heavy use. However, it has enabled confidential data sharing, which was not done before. Indeed, before this data sharing, the employees did not have all the necessary data to make the best decisions for the company:

> "Our sold flight ticket prices have always been a guarded secret … in part I understand this, in part I don't … because this information heavily affects [our] decision making … and before we have not been able to make cost effective decisions." (Manager)

> "This is a big change to everything. Now we have the euros there. Before we had all sorts of indexes and other systems, it was hard [to understand]. (Expert)

Furthermore, the company has a separate tool to optimally reroute the passengers if their purchased flight has some issues (or their connecting flight is late, as mentioned above). This tool was also implemented just before the corona pandemic and is provided by an external system provider. However, due to a low number of flights, the tool has not been used extensively during the crisis.

> "Now probably 15 airlines use this tool … but when we started using this, we were among the first five airlines to have it." (Expert)

> "Before this it was more or less manual work … [for example,] if a flight was cancelled or these passengers will lose their connecting flight. Then, I will go and reserve from the system … that looks like a good flight for that passenger, I will book it … Now with this tool, we have saved all the rules what our company wants in [almost all] situations … it is not based on individual employee making a decision anymore … but the tool finds optimal solutions." (Expert)

In addition to optimizing and having common rules, the tool sped up the process significantly:

> It used to take us long time to figure the available seats on different flights … and now this tool does almost all for us … it looks that ok, there are 300 passengers to be rerouted, it can see availabilities for all airlines and scatter the passengers to those [optimal] flights; 3 goes that way, five goes there … and then, it also changes the flight tickets for the passengers and everything." (Expert)

> "For example, before, if one long haul flight was delayed, it could take 7-8 hours of total work before all the passenger connections had been solved … now we can do this within minutes." (Manager)

Still, the tool user will make the final decision based on the tool's recommendations:

> "So, if I have three flights and one has to be cancelled, I can enter these separately to the system and look the overall key figures for each option. Like how many passengers can actually be rerouted, how many passengers have to stay for a night – it costs money and is not good for customer experience … how large is the average delay per passenger … what is the cargo … based on these key figures I will make the decision which flight to cancel." (Expert)

Finally, this tool works together with the automated customer notification system mentioned in chapter 4.2.1. Thus, when the passengers are optimally distributed to flights, the notification system automatically informs the affected passengers and gives them options if the selected solution does not suit them.

> "If a flight is canceled and we make the reroutings, then the messages are sent [automatically with the customer notification system] to passengers" (Expert)

> “And if the solution does not suit the passenger, the message gives instructions what to do then.” (Manager)

4.2.3 Interdependencies between tools creating problems

The tools mentioned in the previous section can be considered as fine-tuning operations (downsizing planes) or handling irregularities well enough (flight delay, optimal passenger rerouting, and customer notification tools). However, the backbone of an airline is its network/traffic planning and revenue management systems. The network planning systems help to decide which routes to operate in the long run. The traffic planning systems optimize aircraft fleet utilization and follow the cost structure. The revenue management system aims to maximize the total revenues by forecasting the demand based on historical data and deciding which ticket prices to offer. The demand forecast is required by the Traffic Planning’s tool to function:

> “The Fleet Assigner tool is our most important in optimizing, and we need the demand and revenue forecast from Revenue Management … Then we have cost structure inside [the tool] which calculates how much it costs to fly this route with that aircraft … there are turnaround times, maintenance slots and other hard limits … the tool calculates for each day and each flight and each aircraft type what the profits are … and then combines these as optimal rotations [for the entire network] … and we always manually check that this is reasonable.” (Manager)

> “[The Fleet Assigner tool] is actually managing your sub fleets to optimize the revenue … along with the forecasting which is coming from revenue management. So, if the revenue management system which is basically predicting for each flight … the demand one year [out], if we notice some demands spikes, specific routes, specific days, actually the fleet assignment is taking care that we create room for this demand so we fly then with [a bigger aircraft], I don't know, Rome.” (VP)

Now, during the corona pandemic, the historical data required for the demand forecast became almost useless as the market changed completely:

> “The time frame of business has dramatically decreased. Our booking curves have shifted so much closer to the [flight] departure. And we know that all of our [demand] forecasts are totally nonsense if we look any further.” (VP)

> “We [, the Revenue Management] are feeding some forecasted demand revenue numbers ... so that [Traffic Planning] can allocate the planes optimally. But of course, during COVID, that’s just rubbish” (Manager)

> “Currently, we cannot use [the Traffic Planning’s Fleet Assigner] tool simply due to the fact that the forecasting from the revenue management system does not work at all.” (VP)

However, the entire demand forecast did not become useless. It can still be cautiously utilized to some degree:

> “There are some things which are as true after corona as they are before corona. For example, variation in demand for different weekdays and seasonality within a calendar year and this sort of stuff.” (VP).

Still, the result was that the tool used by Traffic Planning to optimally assign aircraft to routes became suddenly useless. The causal link was the sudden loss of suitable data for the Revenue Management’s demand forecast tool and the data interdependency between the Revenue Management tool’s outputs and the Traffic Planning tool’s inputs. It is noteworthy to highlight here just how advanced the Revenue Management tool is:

> “Some people in the company might not realize how complex [the revenue management system] is ... we have about 50 000 origin destination pairs ... multiple different fare families ... and all these are forecasted 362 days into the future ... the data feed which we get is about 9 billion

forecast every week ... only about 10% of that can be validated by the tool users." (VP)

> "You have a system where you have the couple of billion forecasts and then it solves the Bellman equation, to get the right decisions, so that you can get to the optimal solution ... and many kinds of fancy machine learning in the background ... pretty cool systems." (VP)

Furthermore, the tools used in the Network Planning department were similarly affected by the sudden loss of reasonable (historical) data. The Network Planning department and their tool focus on the longer-term planning of how the company network should look (which aircraft to own and which destinations to fly, etc.). An additional problem for the Network Planning department was that the competitor airlines were having similar issues:

> "But the problem is that all the tools the [Network Planning] use are virtually redundant now. It works on a market share kind of model to try and model all the flows that impact the [airline] network based on competitive schedules and historic data ... So you know, the methodology we've been taking is essentially, 2019 is the base ... So we take percentages of 2019 to try and figure out a market share or passenger flow volumes. The problem is, we don't have any reliable competitive schedules. There's none out there, no-one's looking in that far advance at this stage for us to use the model, what the potential impacts would be, and now without that kind of effective modelling it's very hard for us to dictate kind of, what kind of frequencies we require and what kind of aircraft types we require. So, the traditional tools as such are virtually been made redundant." (Manager)

Finally, switching and mixing between different external system providers is difficult due to highly integrated system architectures:

> "Basically, there are no data standards within airlines. So, switching components, so that you mix up different vendors is a bit hard as these

> systems don't know how to share data automatically … and often these vendors are competitors and so its always funny to get these vendors to sign Non-Disclosure Agreements together." (VP)

For example, in the Revenue Management and Traffic Planning interdependency problem, both departments use a different system provider for their tools; the tools are procured from competing, large system providers and highly customized for the airline in question.

4.2.4 Falling back to simpler models and tools

The company tackled the problem of suddenly losing some of its most crucial forecasting and optimizing tools by falling back to simpler methods and ad hoc problem-solving. In the Revenue Management department, they were still able to use their advanced algorithms tool but with a lot of tweaking and tuning:

> "What is happening now … this [tool], it's still producing forecast … Normally, the forecast is based on the last twelve months of departures, but now it's changed. Now it's based on 2019 departures, so it's kind of frozen in the [past] … [so the demand is] way too high [because the number of flights is down almost -90% compared to 2019]." (Manager)

In addition to freezing the forecast into the past, the company top management provided their view on the traffic that will happen – and the forecast was then partly scaled down to match this:

> "To have something meaningful out, we kind of scaled the forecast down on a monthly basis and lots of, like… kind of region-to-region adjustments we made based on, well… party based on, so there are some revenue targets each month for the company, that how much should be done. Or how much the higher management thinks the revenue for June or July or May or whatever [should be]. And then… we adjusted our forecast such, that with this adjustment forecast, demand forecast and thus

> revenue forecast kind of matches this higher-level forecast from the management.” (Manager)

However, doing this matchup is no easy task:

> “We have basically very, very detailed demand forecasts ... And our RM is on origin destination pairs, while the higher-level forecast is not that detailed, it’s more on traffic category levels so there is forecast for domestic and Europe and Asia and Atlantic. And so, we have to allocate our forecast with the revenue to these different traffic categories and scales, so it’s a bit complicated, it’s also kind of optimization problem. But it’s doable, so that’s what we did, basically.” (Manager)

Moreover, the Revenue Management department’s more sophisticated flight ticket pricing methods used during normal times fell back to simpler rules to decide which prices to offer:

> “Now, during COVID, we threw everything out of the window. All this nice optimization based on demand forecast. And instead, we just use simple rules. Rule-based availabilities, you know, if the flight is 70 percent full and this and this booking class, it should be closed and whatnot. It’s very primitive. And certainly not optimal, but this was a quick and dirty solution to implement ... our demand forecast is basically not used for [flight ticket pricing].” (Manager)

The Network planning is also making use of the old school methods and traditional approaches to obtain more clarity for the future network structure for the airline:

> “I'm overdoing it now but it's like 15 years ago when you simply didn't have the tools ... [The network planning tool] is a super complex tool, it's a very sophisticated one and actually really well proven ... but of course if it doesn't work you need to go back to much more genuine research, also kind of market research ... the research really focuses now

on what drives or holds back demands … restrictions are a very decisive factors for the time being … what we are currently basically doing is trying to come up with a simplified model where we say, we know the certain segments, passenger segments, corporate groups, we basically build scenarios how the recovery speed for those segments will be playing out" (VP)

> "The tool was just spitting out rubbish … So, it very much came down to … putting in very simple models in Excel to try and predict what we would need, and then kind of formulating what the network would look like." (Manager)

> "The work has changed from optimizing work to planning an entire network of a small airline, in a very short time-span." (Manager)

In doing this, the management highlights the importance to understand the new models:

> "For the medium term, take some assumptions and do it as sophisticated as possible but also as simple as possible to keep it transparent and trackable." (VP)

However, in Network Planning, like in Revenue Management, they can still utilize their complex tool for some scenarios:

> "We are using it very cautiously, basically to optimise within our own network and being very cautious in taking too many conclusions in terms of optimising something versus the competition because it's simply not possible … But we are using it to simulate certain impacts. It's not the kind of traditional use of really creating the best possible result for [the company] on a season basis, it's more like really testing what are the differences in terms of [how many aircraft we have] and how basically the network effects play-out, how much of transfer volume are being lost with less frequency with certain connectivities compromised

> … But it's definitely a big challenge now to read the output of the tools, it's not as reliable, it's more like a reference than a guidance.” (VP)

In Traffic Planning, the entire complex advanced algorithms tool to optimize the fleet usage and cost structure was replaced by an Excel model. This Excel is developed mainly by a single person within the company. This Excel model utilizes the scaled-down and simplified demand forecast from Revenue Management:

> “What [our demand forecast] is used … [we] give this data after a lot of data manipulation to our traffic planning colleagues, who are then using this to decide, you know, which flights look profitable and which not, and so which flight might need to be cancelled and whatnot … this is the kind of most important use of this … demand forecast data. And for that purpose, it certainly helps a lot to have a demand forecast which is scaled down from 2019 levels to a more believable level.” (Manager)

Traffic Planning then utilizes this demand forecast data along with a multitude of other data to follow the profitability of all flights operated:

> “We virtually built some sort of our own logic and models. Unfortunately we really rely here just on Excel which is a pain … but when we started [we believed] it's something that will go just for few, for handful of month and not for a year or even longer … we need to collect still data, try to forecast with kind of manually shaped booking curves, we are scanning the market for trends … from social media to google searches and all this stuff to be ready if there is some pop demand.” (VP)

> “We've got hundreds different kind of elements, 938 to be exact, kind of different data types that I can actually pull out of the system to do what I need to do … my weekly modelling of the entire network is done from this … It gives me all the information I need, which is the flight number, where it's coming from, what date it's departing, you know, it's a return leg so, you know, the aircraft type, service type, how many seats, the

> block hours, ASKs. So, this particular report is kind of running all the profitability for the entire network right now in through Excel." (Manager)

The reason for using Excel was that the focal employees were used to utilize it, and it was a relatively quick solution to implement:

> "My bread and butter is still Excel, primarily because it's versatile in what we need and it's quick to get actions going and it's controllable." (Manager)

> "We were relatively quickly able to produce manual forecast which we could use to ... manage finance and [to brief Executive Board] ... we have created relatively quickly an alternative way to create the forecast and to have virtually a tool to simulate ... the profit contribution on direct operating cost for different kind of capacity levels ... we can actively manage capacity on the basis of data. I think still that the data itself can be improved and the forecasting needs to be potentially a little bit more sophisticated with kind of new [data] sources." (VP)

> "Excel allowed in this development phase quite a lot of agile testing really from different people ... if I would have more data scientist and I would be more comfortable with Python, then it might be simply wiser in the meantime to do it because it would run in a more efficient way." (VP)

Moreover, the scale of flight operations is so low that the more manual, simpler models can work:

> "Because kind of the network is so small that we can actually do this." (Manager)

> "Lower amount of flights and production volume this kind of manual work is more possible than in the normal amount of production volume." (VP)

4.2.5 How to move back to advanced algorithms after using simpler methods?

Now that some departments have had to fall back into using simpler models and methods, they must start thinking about how to get back using the more advanced methods when the amount of traffic increases:

> "Sometimes simpler is good enough, but there will be organizational challenges, because [using simpler methods] is easier, so you have to conscientiously move away from them back to the more advanced decision processes after the situation is over." (VP)

> "I'm a bit afraid, yeah, how the forecast will look like ... one thing we can do is, continue applying these high-level forecast adjustments, kind of like blanket rules, a few blanket rules over the whole network, just to have at least on a network level, have a correct forecast. And then the analyst can individually adjust the different traffic flows." (Manager)

Moreover, using the Network and Traffic Planning's simpler Excel models will not fit the scope of the normal number of operations:

> "At some point we need to switch, at least the Tactical Fleet Assigner ON again because it simply gets too complicated ... you are starting to optimize across the entire network and you virtually would get crazy if you really do this manually." (VP)

> "Whether this process sticks I don't know, but it would have to move out of Excel if it was to be a permanent thing because the Excel just can't handle the scope of what it is. But it is a new concept to have that live profitability going." (Manager)

4.3 How did the change affect the individual employee skill requirements?

Changing the resources (chapter 4.1) and, thus, how the advanced algorithms tools are used (chapter 4.2) has also altered some of the employee skill requirements within the airline. In this subsection, I present how the external shock of the corona pandemic affected the required employee skills related to the advanced algorithms tools. The following sections are based on the second-order themes found during the data analysis process.

4.3.1 Finding new, non-traditional data sources

As the traditional data sources, such as historical flight data and competitors' schedules cannot be trusted (see chapters 4.2.3 and 4.2.4), the employees and managers had to search for other, non-traditional data sources to base their decisions on. Such sources are, for example, Google and social media:

> "Now we have tried to dig deeper into Google-data, etc. There, we could find something that we have not yet seen in our network … we have two kinds of Google data: search data and Google Analytics' Google Flights data … We are trying to find we ways to find demand … our own website traffic, our Instagram and Facebook data." (Manager)

> "The biggest change is kind of relying less on historical data and trying to find new data that we can feed, not necessarily into our systems but even into new models that finds new opportunities for us. And that's why kind of the likes of Google Trends and Google Analysis is coming in. I'm gonna start trying to be looking kind of at social media data. How do we use that to feed into some of our Network Planning. How do we use kind of mobility data, you know, mass people's movements? How can we use to find pockets of demand and feed that into our systems?" (Manager)

> "Getting hold of demand data … from google searches, down to social media, trending staff and observations, and mobility gains." (VP)

Moreover, Google already has prediction capabilities to predict flight delays. Knowledge of this has given the company incentive to look more into building prediction models themselves. Indeed, airlines are in a position to obtain more data from their own operations and, thus, should be able to make better predictions about their own flights:

> "Google has this, it can predict [flight delays], but however good Google is, if you think about the probabilities for the delays of our own flights, then we should have more information what Google can get from anywhere ... we should be able to build a better [model]." (Manager)

4.3.2 New skills required from employees and managers

The coronavirus pandemic created an unstable environment in which many of the normal proactive actions became less effective:

> "Because of the changing environment, there is so much more ad hoc tasks, reactive tasks ... there is not that much stability. A good example is last weekend; on Thursday Norway shut its borders, on Friday Czech announced the same, Saturday France, Sunday Sweden ... then we make these decisions ... and follow do these cause any change, do we have to do something ... very reactive in a way." (VP)

> "Just now during the covid time there's more emphasis for those really ad hoc and short-term decisions to be made." (Manager)

> "What is harder is that we don't have any visibility. Normally, we have a stable visibility, and some things might change, but most of them stay within a certain curve ... Now, it cannot be super proactive so that you go forwards with decisions locked but you must react to everything, all the time. (Manager)

The more volatile environment added to the fact that the company had to lay off people, changed the work of many managers and VPs to much more operational:

> "[My work] has changed heavily. I would say most of my time, it could be 60-70% is scattered somewhat around the short-term ad hoc topics. So basically, we need to react very quickly different restrictions around the world and so on. It's way more operational stuff." (Manager)

This meant that the operative digital skills and advanced algorithms tool knowledge of some managers and VPs became even more beneficial:

> "I don't have any subordinates anymore who can help me in the actual operative planning … concretely, I do the changes to the systems … in this abnormal situation, I do so much more manual tasks." (Manager)

> "Because of resources, my work is much more operative, and also because of my background [history of routinely using the tools and systems], I can also do the manual work … I can use the systems." (VP)

Then again, the managers and VPs wished that their employees have creativity and agility in this volatile situation:

> "[To have] people who enjoy developing new things and agile problem solving, often even slightly cutting the corners … [more] than people who enjoy building the analytics stone house for years with polished nuances and interdependencies and accuracies." (VP)

> "But I think in terms of the skills in the team, I think this kind of creativity of … figuring out what can determine air traffic demand … that you have the people around which are sufficiently creative." (VP)

> "Now we have there this small, agile team of 2-3 persons … and the idea is that the team does everything agile." (VP)

Moreover, the result of this employee creativity and agility could be the simpler solutions and models to replace the complex tools normally in use:

> "We had standard ways we did things and now everything really relies also up to a certain degree on the creativity of people to find work around to replace actually very, very complex tools with much simpler solutions which we still can use to steer our capacity. I think that basically this kind of, the skill of being able to come up with let's say simplified solutions, simplified models, is currently the, I would say highest valued feature." (VP)

Furthermore, the changing environment called for more flexible and resilient workers who can handle the ever-changing situation:

> "You need to build up relatively flexible staff so that you're coming up each week with a completely different [plan], you need to also build up something which you can track and where you can say okay, yea this works, give me something which makes sense, this doesn't work, let's keep … a little bit of trial and error exercise in this regard." (VP)

Finally, some amount of time, especially in the new Data and Analytics department, was spent on learning to use new common tools and methods:

> "We have now people from three different teams … to get them working with the same methods." (Manager)

> "Now we have team members who really knows that stuff and that I can learn from, so that's a really good thing." (Expert)

> "I'm learning at the same time how to use those systems … [And] I've just used R for most of my work but now I'm learning to use Python … we decided that our main tool should [be] Python." (Expert)

4.3.3 New routines and ways of working

Resource changes did not only affect the individual skillsets of employees. Also, some of the old ways of working had to give way to new routines and methods to do work. For example, the Data and Analytics unit that was set up in the Autumn of 2020 started to utilize agile ways of working:

> ”Now that we have this organization change, also at the same time, or maybe slightly after it, we started to think about our methods and develop them more towards Agile-way. So, that we do two-week scrams, and we have a backlog for the entire team. This has just started so there is work to do still.” (Expert)

One interviewee noted that the agile way of working is also used in other departments, not only in the Data and Analytics unit:

> “Now we have moved a lot more towards this agile way to work, so we don’t have projects anymore, but it is daily development.” (Expert)

Moreover, the creation of advanced algorithms tools by the Data and Analytics unit goes now through a prioritization funnel when previously it was done in a less systematic way:

> “If I would be some person from a business unit and I need [new data and analytics tools], I then have to take this request to higher level in my business unit … then it goes all the way to the leadership team of that unit where they decide what is important for that unit and what is the prioritization order of these requests … Then these requests come to this prioritization forum where are all the units leadership teams … and [Data and Analytics unit] representatives … and then they prioritize all these requests [from different units].” (Manager)

> “We did not have this before corona … we have had now two prioritization forums … feedback has been that this is good … but not everyone knows this exists or what it is yet.” (Manager)

5 Model of advanced algorithms-centric organizational change to external shocks

In this chapter, I first present the summary of findings as a model. Then, I utilize this model to illustrate four distinct cases which emerged during the interview process.

5.1 Summary of findings as a model

In this thesis, I studied how the external shock of the global corona pandemic affected the digitization and advanced algorithms (AA) resources employed by a Nordic airline. To gather the data, I conducted 30 interviews around the company during the spring of 2021. I have compiled the summary of findings as a *model of advanced algorithms-centric organizational change to external shocks*, which is presented in Figure 6.

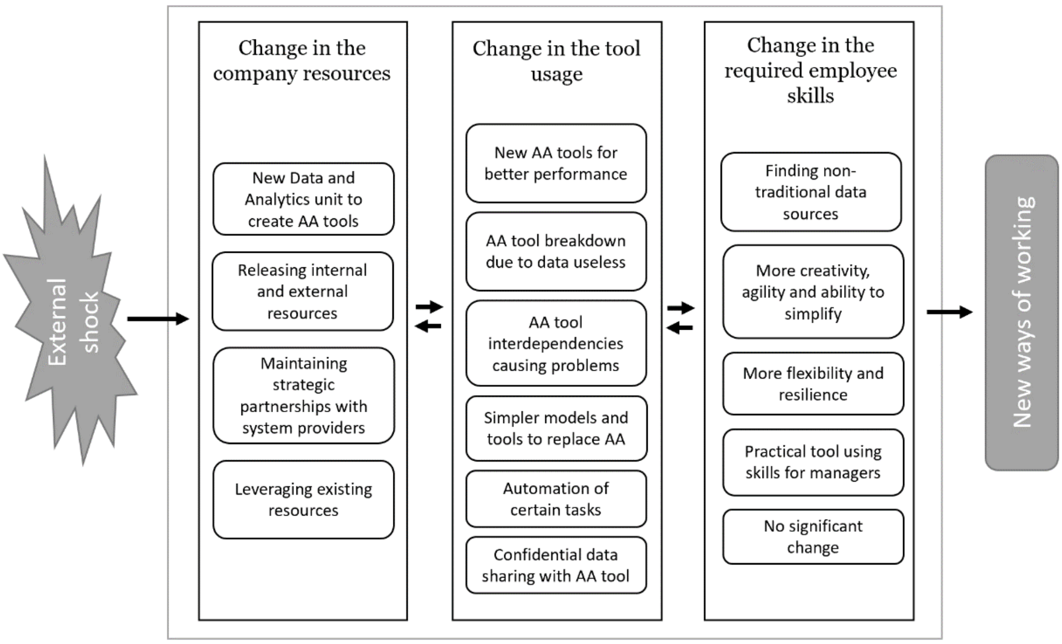

Figure 6. Summary of findings: Model of advanced algorithms-centric organizational change to external shocks. [AA = advanced algorithms]

The model illustrates how the external shock caused a change in the company digitization and advanced algorithms resources. Furthermore, this change affected how employees used the digitization and AA tools; there was a distinct change in the human-machine collaboration levels in many cases. Finally, this change in how the tools are used caused an alteration in the desired skillset of some employees and managers. Next, I will go through the four cases that emerged during the interview process. These cases give practical examples of what happened.

5.1.1 Case 1: new inhouse tool enabled large cost savings through faster and more consistent performance from employees

The airline's Operations Control Center handles all the flights within a seven-day time window (-7 days until the flight returns to home base). They are, for example, responsible for deciding which flights to cancel or delay to keep the entire network of the airline functioning. To help in this continuous balancing act, they received a new AA tool to help in their decision-making during the coronavirus pandemic.

The tool was quickly created in-house by the company's new Data and Analytics unit (see chapter 4.1.1) based on previous work done by external consultants. The tool continues to be developed with a lot of feedback from the users in two-week Agile sprints. The tool's purpose is to help downsize aircraft to save costs, as presented in chapter 4.2.2. To do this, it gathers information from various data sources automatically. Then, the user can press a button to show a list of recommended aircraft to downsize. Before, it was more up to the employees to go through various systems if aircraft could and should be downsized.

Now, the tool gives more structure to the employees' work as they have agreed on a specific schedule to use it within shifts; for example, the morning shift goes through the flights for tomorrow. Moreover, the easy interface of providing a list of recommendations means that the work is a lot faster (than going through many data sources manually), and employees perform more evenly (it is less up to the motivation and skills of the employee to find the flights). The results are better cost savings by downsizing more aircraft than without the tool. However, the employees using the tool emphasized that they still must know what they are doing and that the tool "is just for us to start thinking about [downsizing the aircraft]". Thus, the required core skills of the employees did not change. Figure 7 illustrates how this played out in the summary data frame.

Moreover, the unit has another tool in use to enhance decision-making to keep the network running optimally when flights get delayed. Previously, the unit did not have all the necessary data to make the best decisions due to confidentiality issues. One of the inputs in this AA tool is now the confidential information about the flight ticket prices. Having all the data, the unit has now made huge savings compared to previous times with only part of the necessary data (most of the savings are pre-corona as there are not that many connecting flights during the pandemic).

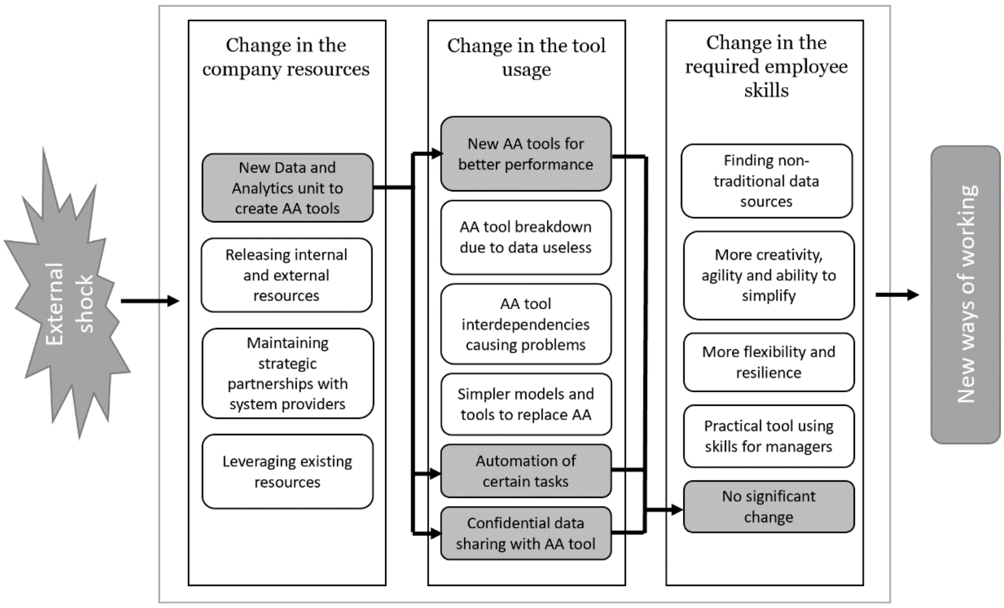

Figure 7. Case 1: new in-house tool enabled significant cost savings through faster and more consistent performance from employees.

5.1.2 Case 2: pre-pandemic investment on new tools, purchased from an external system provider automated and sped up processes significantly

When the Operations Control Center deal with the overall functioning of the airline's network, the Service Recovery unit handles the passenger reconnections and rebookings when changes to their flights are needed. This unit had just implemented new tools and automation before the corona pandemic hit the airline. These were purchased from an external, large system provider and customized to the airline in question. The case company airline stated that the external system provider could be considered as their strategic partner as they develop AA tools at least partly together.

Two tools significantly changed the work done by employees. The first tool was implemented to help optimize the rerouting of passengers to other flights when they have missed their original flight connection (see chapter 4.2.2). This tool searches for availabilities on the company's own flights as well as competitors' flights, considers the overnight costs and average delays for passengers, etc. Before this, all was done manually and, thus, was more subject to individual employee skills and preferences. The tool now follows predefined company rules, and the tool user is left with only a decision to make from a few options. In addition to more consistent results (like in case 1), the tool increased the speed of optimizing and decision-making significantly; before, manually rerouting 300 passengers could take 7-8 hours, and now, this all could be done in a matter of *minutes*. The manual work by the tool user is now almost inexistent, and he/she can now focus on decision-making and communicating with the stakeholders.

The second tool to help in the above situation was the automated notification system to passengers (see chapter 4.2.1). This is used to notify passengers about any changes to their original flight(s). Again, before the system implementation, informing passengers was more of a manual task (even though some systems were in place). Now, the new system was implemented with the external system provider to automate almost all notifications. This again enabled to use of predefined company rules and default notifications (with options for passengers to choose from if they are not happy with the offered solution). It also made the notification process almost instantaneous. The implementation of these tools/systems also decreased the need for experts calculating the reroutings and customer service people at airports. However, due to low number of connecting flights during the pandemic, the usage of the rerouting optimizer tool has been limited. Figure 8 illustrates case 2 in the model.

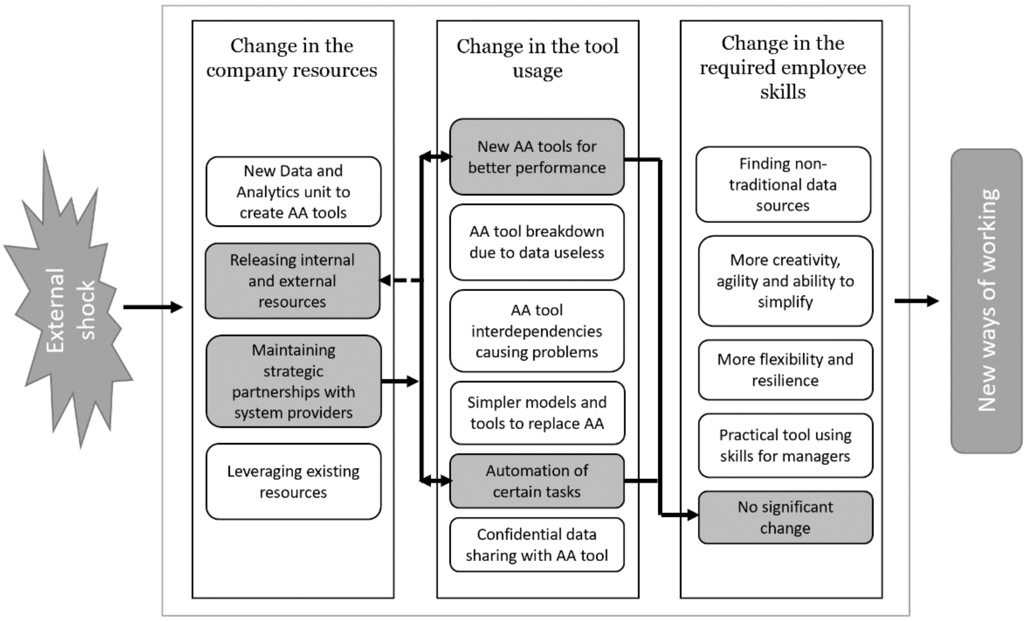

Figure 8. Case 2: new tools to handle irregularities purchased from an external system provider automated and sped up processes by many magnitudes.

5.1.3 Case 3: ad hoc software automation within a business unit

As described in chapter 4.2.1, the number of flight cancellations the company suddenly encountered was staggering; during the start of the pandemic, in March 2020, the company refunds unit was faced with over 40 times the normal workload ("During March [2020], we had an average 3.5 years' workload."). Moreover, all refunds had been handled manually until this. Some of the manual work was outsourced abroad, and the company management was aware that this work could and maybe should be automated at some point. However, no automation was done as there has not been enough incentives to instigate a change.

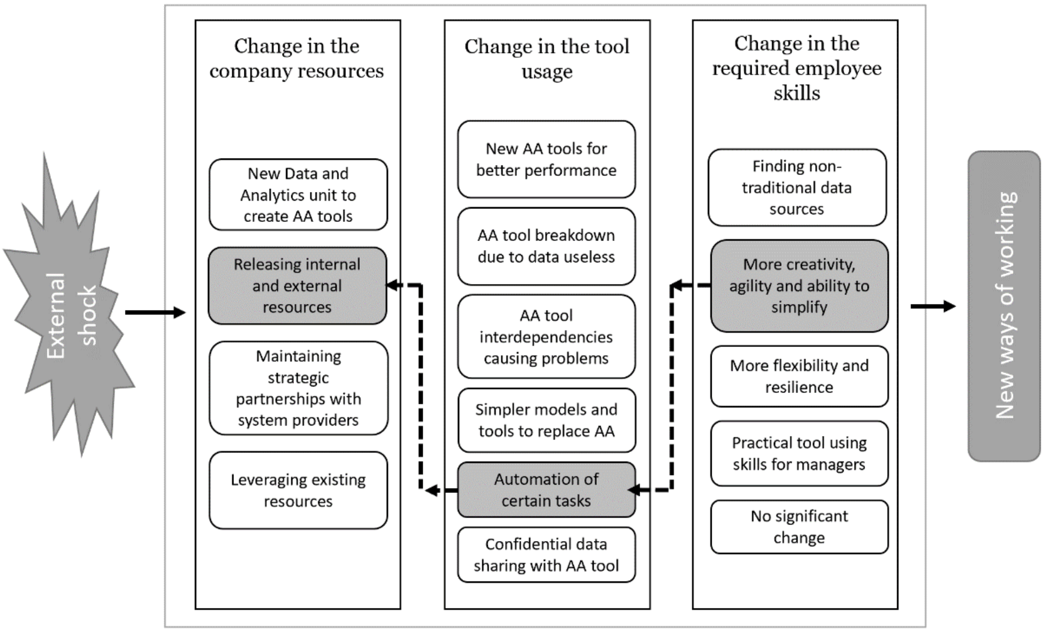

Figure 9. Case 3: ad hoc software automation within a business unit.

Now that the unit was under a heavy workload, it first got help from other parts of the company to help in the required manual work (see chapter 4.1.4). Then, it started creating ad hoc software automation to take the load away from the forty times normal amount of manual work. This development was mainly done inside the unit, with people who happened to have some previous skills to aid in the automation creation. The first software robot was created in two weeks, and the second one in four weeks. The result was that 40% of the refund work could now be handled with automation. Furthermore, the manual labour outsourcing contract was now redundant and could be ended.

The creation of the automation was not due to a certain dynamic capability of the company. It was more of an ad hoc undertaking by a few employees with enough skills, creativity, and agility to instigate and complete the change. Indeed, this case was unlike the first case (5.1.1), where the company's dynamic capabilities handled the external disruption.

5.1.4 Case 4: insufficient data and AA tool interdependencies caused tools to become suddenly useless – simpler, more manual methods saved the day

The revenue management system of an airline produces a demand forecast which other AA tools and systems utilize as input (see chapter 4.2.3). The demand forecast bases heavily on the last twelve months of historical flight data with additional manual tuning by expert workers and managers. Now, the corona pandemic changed the business landscape entirely in a matter of days, and most of the normal ways to forecast demand with the revenue management AA tool could be thrown out of the window.

As the airline business and other systems still require some form of demand forecast, the company had to develop alternative ways to produce it. Now, the historical flight data continues to be used, for example, to capture the weekday variations and seasonality (see chapter 4.2.4). However, these are more like fine-tuning the absolute demand forecast. This more absolute traffic demand is now received from the top management: they provide the Revenue Management unit their forecast based on business goals and general oversight of the market development. As this is a very high-level forecast, the Revenue Management experts and managers must make it more granular to fit it with their AA tool. Thus, the tool now outputs a demand forecast (for other systems to use) which is not purely a data-based product of highly sophisticated AA tool computations but more of a wish or a decision by the top management.

There are several repercussions of this. First, the flight ticket pricing, which relies heavily on the demand forecast, went back to the more old school – and significantly simpler methods. The ticket pricing is now based mainly on the available seat capacity: less availability – higher ticket price and vice versa. This method is very simple to calculate compared to the methods used before.

Second, the AA tool used by traffic planning needs a very high accuracy demand forecast to produce the optimal rotations for the entire fleet of aircraft (see chapter 4.2.3). Now, as the demand forecast is not highly accurate, the tool cannot be used. Still, the aircraft must be assigned to the routes and preferably as optimally as possible to save costs. The result was an Excel model to replace this highly sophisticated AA tool. Partly this was possible because the amount of traffic was very low compared to more normal times. However, this also highlights the need for people who understand the underlying interdependencies of the business and, thus, can simplify and create quickly new, simpler models to replace the unusable complex ones (see chapter 4.3.2).

Furthermore, this case provides an excellent example of how the interdependencies among AA tools can cause a total breakdown of systems when a data source is lost in only one tool. It also illustrates that organizations require people who understand these interdependencies, the core business, and can quickly create new models in the face of external disruption.

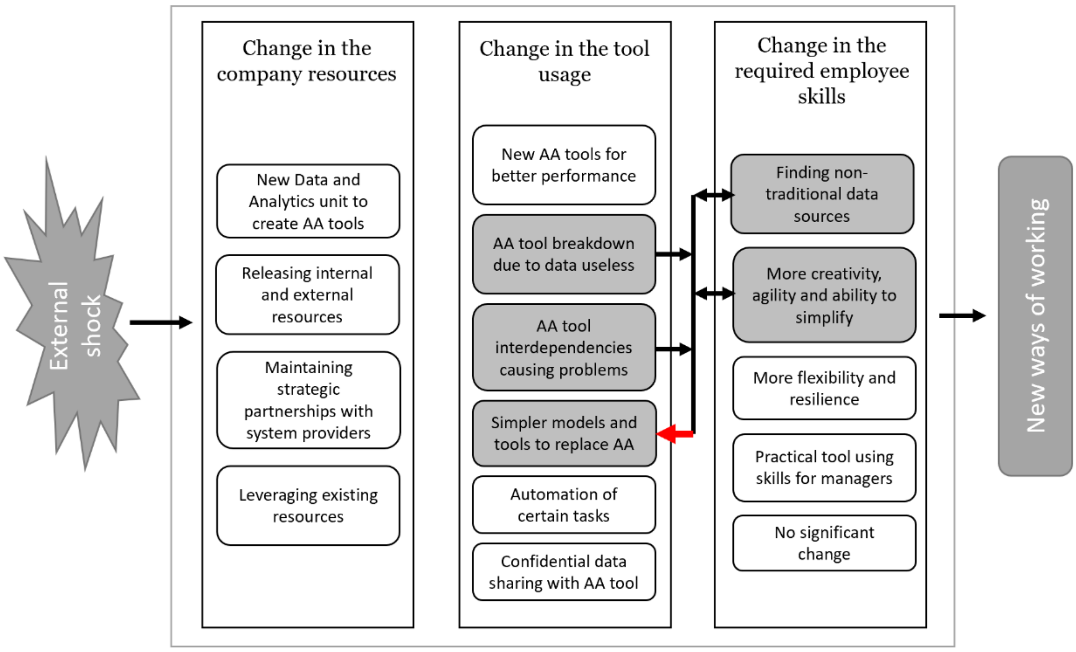

Figure 10. Case 4: insufficient data and AA tool interdependencies caused tools to become suddenly useless – simpler, more manual methods saved the day.

6 Conclusions and discussion

In this chapter, I first present the concluding answers to the three research questions presented in chapter 1.2. Next, I talk about the limitations of the study and show how these findings contribute to the existing theoretical literature and future practical work within organizations. Finally, I present possible future lines of research.

6.1 Answers to research questions

6.1.1 RQ1 How were the organization's resources related to digitization and advanced algorithms changed under the external shock of the global pandemic?

Arguably the most significant change related to digitization and AA tools resources was creating Data and Analytics unit within the company (see chapter 4.1.1) and ending the external developer contracts. Although the coronavirus pandemic was not the only reason, it significantly sped up the unit's creation. Moreover, the company maintained and leveraged the existing external resources by utilizing the various AA tools provided and customized by the external system providers (see chapter 4.1.2).

Conclusion: This study shows that several resources have aided the company to navigate through the pandemic. First, the pre-pandemic investment into various tools and systems (e.g., case 2) has taken the load from extensive manual work during irregular situations in some parts of the organization. Second, the creation of the Data and Analytics unit has provided an effective and focused way to build in-house tools to decrease operational costs in multiple ways. Finally, the investment into the employees' skills has made it possible to create and effectively use these tools.

6.1.2 RQ2 How did the change affect the human-machine collaboration and the usage of advanced algorithms tools?

Many AA tools either generated in-house or purchased externally decreased manual work and required decision-making time significantly (see chapters 4.2.1 and 4.2.2). Moreover, they made the employees perform more evenly.

Cases 1 and 2 (see chapters 5.1.1 and 5.1.2) illustrate how much of the previous manual work was replaced by the AA tool. In terms of human-machine collaboration by Murray *et al.* (2020), the change happened from Conjoined Agency with Assisting Technologies to Conjoined Agency with Augmenting Technologies (see Figure 4). Indeed, the AA tool provided the protocol, and the human user was left with the decision. Regarding Shrestha *et al.* (2019), cases 1 and 2 present the hybrid 1: AI to human sequential decision-making. However, what is interesting is that these AA tools provided more even employee performance – in contrast to Shrestha *et al.* (2019) asserting that this form of decision-making yields low replicability due to human biases. However, the AA tools of cases 1 and 2 cannot be said to be AI tools (there are no prediction capabilities in them).

Furthermore, case 3 (see chapter 5.1.3) illustrates an example of Shrestha *et al.'s* (2019) full human-to-machine delegation in the form of robotic software automation. However, like above, the developed automation cannot be said to represent AI. In terms of Murray *et al.* (2020), the new location in their matrix would mainly represent the Conjoined Agency with Arresting Technologies: the humans make the rules and protocols, and the technology makes the decisions. What is interesting here is that Murray *et al.* speak about *arresting* technologies that can intervene the human decision-making. However, in this relatively simple software robotic automation, the sides are reversed: the technology makes all the decisions, and humans can intervene if needed by adjusting the protocols.

In the last case, number 4 (see chapter 5.1.4), the hugely complex AA tools were partially or entirely left useless and replaced by simpler Excel models. The revenue management, pricing, and traffic planning tools utilized in more normal times are close to full human to AI delegation (Shrestha *et al.* (2019)). With the simpler models, the new way of working represents more Murray *et al.'s* (2020) Conjoined Agency with Assisting Technologies.

The above changes related to these cases and the results presented in chapter 4 happened under an unprecedented external shock. This could mean that there was not enough time to think about the human-machine collaboration side of the tools. Indeed, the overall driver for the new tools seems to have been quickly to save costs and/or survive. However, when organizations increasingly utilize AA tools that are more complex, they should focus on how humans collaborate with the tools to gain the best results. As the collaborative research by MIT Sloan Management Review and Boston Consulting Group concludes: "Significant financial benefits are likely only when organizations define multiple, effective ways for humans and AI to work and learn together." (Ransbotham, et al., 2020).

Conclusion: Organizations should be cognizant of human-machine collaboration as the main instrument between their digital and human resources. In this way, they can find the most suitable and, thus, the most effective ways of humans working together with the machines. The result of this will be better utilization of company resources. For even greater results, companies should strive for synergistic learning between humans and machines (Ransbotham, et al., 2020).

6.1.3 RQ3 How did the change affect the individual employee skill requirements related to advanced algorithms?

The new AA tools the company adopted did not seem to alter the required skillset of employees (see chapters 4.2.2, 5.1.1, and 5.1.2). The tools were there to speed things up and provide recommendations; the employees still made the final decision taking the overall situation into account. But what changed was that the new tools made the performance of the employees more consistent. This could mean that with the new tools, the less performing workers could now perform as well as the better-performing workers – without additional skills. In contrast to the tool users, the tool developers were learning new skills. This was partly due to creating the Data and Analytics unit and the standardization of methods within it (see chapter 4.3.2).

But when the used AA tools broke down (see chapters 4.2.3, 4.2.4, and 5.1.4), the employees and managers were faced with a sudden lack of decision-making support and increased manual work. Although manual work increased relative to the number of flights, it was still reasonable due to only approx. 1/10 of normal traffic volumes (see chapter 4.2.5). Employees who flourished in this new situation were more creative in finding new non-traditional data sources. They could understand the business interdependencies, simplify and even cut some corners when necessary to create new simpler models to replace the unusable old ones (see chapters 4.3.1 and 4.3.2).

Hence, implementing the new AA tools did not require a change in employee skills. But when the complex AA tools broke down, new kinds of skills were needed. Here an analogy could be drawn to the *automation conundrum*: more automation should mean more (and not less) training to handle the abnormal situations when the tool does not work as designed (Endsley, 2017). Indeed, in the extreme case where a company would purchase all its AA tools from external providers and give minimal training to its employees, the company operations would probably seize when anything abnormal happens.

Conclusion: Findings of this study show that complementing humans with new advanced tools does not mandate employees to learn substantial new skills. However, when these tools break, someone must handle the situation without the help of the tools. Thus, when implementing new tools, organizations should know how these tools can break (e.g., bad data or interdependencies like in case 4). Moreover, when the tools break, the organizations should be prepared by having employees in place who already possess the necessary skills to replace the tools – either manually or by building new tools quickly. For example, in case 4, the employees replacing the highly complex tools used Excel for replacement because it was the most familiar tool to the relevant employees and managers. However, in other kinds of disruptions, more sophisticated programming methods/languages might be required.

6.2 Limitations of the study

Naturally, several limitations to this study exist. First, this was my first qualitative, inductive study. Although I received excellent support from the thesis supervisor and advisor, the distance work made it slightly harder to just pop by to the office and ask silly questions. Moreover, the scope of a master's thesis is limited in time and man-hours. I did most of the interviews and all the data analysis and writing by myself (only during two interviews the thesis supervisor or advisor was present). Thus, more triangulation of the data gathering and analysis might have helped. Also, the fact that the case company employs me might affect how the interviewees responded. However, I noticed almost no holding back of information – most often, the opposite was true.

The study focuses only on one company, and the answers to the research questions would have benefited if more case companies would have been studied. Furthermore, gathering more interview data could have provided even more in-depth knowledge about the results (chapter 4) and cases (chapter 5). However, interviewing people from different levels (employees, managers, VPs) greatly aided in understanding what had happened. When conducting the interviews, I reached a good level of saturation, and no surprising new things popped up anymore during the last interviews.

6.3 Contributions to theory

The dynamic capabilities theory (see chapter 2.1) was selected as one of the theoretical bases of this study. It has gained popularity, illustrated by a large number of citations (Yassien, 2015; Arend & Bromiley, 2009) and aims to theorize "firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (Teece, Pisano, & Shuen, 1997, p. 516).

The results of this study (chapters 4 and 5) indicate that only one dynamic capability of the company was directly related to the resource change. In case 1 (chapter 5.1.1), the creation of the Data and Analytics unit was able to dynamically address the changing environment by providing new, customized tools to maintain competitive advantage. However, it is unclear if the unit's creation can be considered a dynamic capability – or only its functioning after creation. Case 2 (see chapter 5.1.2), where the new tools were purchased externally, would be more of an ordinary capability as defined by Teece in his later article (2014). Moreover, cases 3 and 4 (chapters 5.1.3 and 5.1.4) illustrate more ad hoc problem solving (Winter, 2003) and not the dynamic capabilities. Hence, based on the results of this thesis, dynamic capabilities theory fails to provide a comprehensive theoretical base to study how companies maintain a competitive advantage in highly volatile situations.

Furthermore, focusing more on gaining the competitive advantage, the previous academic and business studies do not discuss what happens when the new advanced tools fail. This thesis is among the first ones to show that when implementing new advanced tools, organizations should also pay attention to the eventual tool breakdowns. The study presents two causalities how this may happen. Firstly, simply losing necessary input data (chapter 5.1.4) can cause the breakdown. Secondly, and arguably more interestingly, the interdependencies between the tools can cause a perfectly functioning tool to become useless (case 4, chapter 5.1.4). Moreover, when these tools fail, it will be down to the current skill set of employees to fix the issues. Thus, one way to increase organizational data resiliency is to invest in these skills before a crisis happens. The best mix of skills might be great core business knowledge combined with the ability to quickly create simpler models to replace the old complex ones.

6.4 Practical implications

Here, I give practical recommendations for companies implementing new advanced tools based on findings from this study.

New tools do not require significant new skills to be learned

The findings of this study show that complementing humans with new digitized or advanced tools decreases manual work and speeds up decision-making. They also enable more predefined business rules to be included in the decision-making process, leaving it less up to the individual employees to decide all the factors. This all makes employees perform more evenly and helps in saving direct operational costs. Still, the introduction of the new tools did not mandate employees to learn substantial new skills.

Know how the tools can fail – and invest in employees' skills before this happens

When the advanced tools break, someone must handle the situation without the help of the tools. Thus, when implementing new tools, companies should understand how the tools can fail (e.g., bad data or interdependencies between the tools) and be prepared by having employees in place who already possess the necessary skills to replace the tools – either manually or by building new tools quickly. Indeed, during a crisis, there is not enough time for extensive learning of new skills. For example, in case 4 (chapter 5.1.4), what saved the day was finding non-traditional data sources, understanding the core business, and going back to simpler, old-school methods – methods and tools the employees and managers were already familiar with (e.g., Excel in case 4).

Indeed, as organizations increasingly utilize advanced algorithms tools, they should also focus on hazard identification and risk mitigation familiar in safety systems engineering and human factors literature (for example, see the book "Engineering a Safer World" by Leveson (2011)). However, these methods might prove too heavy as often only money – and no lives are at stake. They might still function as a guideline to develop more business-friendly ways of increasing organizational data resiliency.

Investing in employees' learning not only increases the organizational data resiliency but also produces the best overall results

Based on the results of this study, to gain and maintain a competitive advantage relating to implementation and usage of advanced algorithms tools, companies are better at consulting the more business-focused studies. For example, Wilson & Daugherty (2018) and Ransbotham *et al.* (2020) provide excellent starting points. Indeed, Ransbotham *et al.* (2020) have shown that the best results are gained when organizations strive for synergistic learning between human users and the new advanced tools. Thus, when implementing new tools, companies should also consider how to enhance employee learning– and not just how to replace them.

Learn what others are doing

Finally, the case company could benefit from this study. During the interview process, it became clear that employees are most familiar with things happening within their own units. Understanding what is happening company-wide could open doors to innovations and new ways of working within the company. The same applies to other companies reading this study.

6.5 Future research

Future research could focus more on how the implementation of new tools affects the required skillsets of employees. This would be beneficial in the recruitment and allocation of employees within the company. Moreover, it would be beneficial to study more about what happens when advanced algorithms tools fail and how these situations can be prevented or handled in the most effective ways. Here, an exciting viewpoint would be finding similarities between human factors and safety systems engineering research to help organizations increase their resilience related to digitization and advanced algorithms tools.

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A. Appendix – Interview Structure

Depending on the native language of the interviewee, the interviews were held either in Finnish or English. The interviews were semi-structured, based on the question presented in this Appendix. Additional questions were asked depending on the answers given by the interviewees.

All the interviews were conducted as distance meetings via Zoom. The interview was started by the interviewer introducing himself as well as the background and motivation for the research. This was followed by highlighting the anonymity of the interview and asking the interviewee the permission to record the interview. The interview questions are presented below.

0. Background

a. Can you briefly tell me about your work history at the company?

1. Before COVID

a. So, let’s first think about the situation before the COVID-19. Could you tell me about your work then? Not just the algorithmic based work but in general about your work at the company.

b. Could you describe me your typical working week back then?

2. Present day with COVID

a. Now let's come back to present day with the COVID-19 situation. Could you tell me how your work has changed in general?

b. And your working week?

c. Are there some work tasks that have been dropped all together? Why?

d. Are there some work tasks that you do now, but did not do before the COVID-19?

3. Complex algorithms / models

a. What kind of tools do you use in your work that include complex models or algorithms? Let's first think about the "normal" situation before COVID-19. (*By complex I mean models that are not easily tractable by human because they are so complicated or have so many interdependencies. E.g. Excel is not complicated because you could do the work by hand but it would just take longer*.)

a. How do these tools complement or help in your decision making?

b. How much time do you spend using these tools per day or week?

c. Would you like to understand more deeply how the algorithms or mathematics behind the tool(s) work? Would your work be more efficient if you would understand these better?

d. How would you improve the tool(s) so that your work would be easier? (e.g. competitors having better tools or more training/education?)

e. Then let's think about the current situation we live in now. How has the use of these tools changed in your work and decision making?

4. Inter-unit cooperation and coordination.

a. Before COVID-19, what units did you cooperate with or share information?

   i. How much time did you spend with these units, e.g. weekly?

   ii. What kind of information is shared with these units?

b. Then, how about now during the COVID-19 situation…

   i. Have you stopped cooperating with any of these units?

   ii. Are there some new units you cooperate with?

   iii. How much time do you spend cooperating with these units now (e.g. weekly)?

   iv. What kind of information is shared with these units… so what info has dropped and what is new?

c. What units would you like to cooperate with more… or less?