Crisis management in hospitals – an operations management perspective Learnings from the Covid-19 pandemic in Norway

Krisehåndtering i sykehus - et driftsledelsesperspektiv
Lærdom fra Covid-19-pandemien i Norge

Philosophiae Doctor (PhD) Thesis

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Ås, 2024

Thesis number 2025:2
ISSN 1894-6402
ISBN 978-82-575-2211-7

“Plans are worthless, but planning is everything.”

(Dwight Eisenhower ,1957)

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Acknowledgements

While writing the following section, I feel grateful for being given the possibility to support the healthcare sector and provide additional insights, which I am convinced will improve hospital operations in times of future crises. Be it another global pandemic, the rising shortage of skilled workers – examples are numerous. This PhD thesis would not have been possible without the support from many important persons.

Firstly, I would like to express my gratitude to my supervisor Joachim Scholderer for his support throughout my entire PhD journey, both personally and academically. Our discussions have provided me with food for thought and allowed me to grow as a researcher. I am deeply thankful for the many opportunities you have given me to learn as well as your advice during challenging periods. During times when I felt overwhelmed, you always managed to help me regain focus. Vielen lieben Dank, Joachim.

Next, I would like to thank my co-supervisor Tor Kristian Stevik, who introduced me to the Norwegian healthcare sector and our case hospital. I really enjoyed our cooperation and the discussions we had. I am grateful for your patience when I was initially limited in my Norwegian language skills. Tusen takk, Tor Kristian.

Moreover, I would also like to express my gratitude to my co-supervisor Jens Bengtsson for his support and critical questions on my code and my optimization models. These questions helped me to continuously improve and learn from my mistakes. Tack så mycket, Jens.

A special thanks goes to Katrine. Thanks for your support in establishing connections with the informants. I appreciate your dedication and willingness to devote time to clarify the healthcare context underlying my PhD thesis. Your contributions were essential in shaping this research. Tusen takk, Katrine.

Furthermore, I would like to thank all informants that took their time for the interviews in one of the most challenging periods at the hospital. Tusen takk!

In addition, I would like to thank the School of Economics and Business at the Norwegian University of Life Sciences for the opportunity to pursue a PhD and the possibility of interacting with master students in both teaching and thesis supervision. These experiences are invaluable for my future endeavors.

My deepest gratitude goes to my partner, Julia: You have encouraged me to apply for a PhD position when we were in Bangkok, Thailand on our round-the-world trip. Without you I would not have seized this opportunity. I am grateful for your unconditional support especially in times when I needed it the most. The Covid-19 pandemic made it difficult for us to see each other as often as we would have liked.

Lastly, I would like to thank my family and friends who supported me during this PhD journey.

Winterthur, October 2024

Hendrik Winzer

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Abstract

The Covid-19 pandemic of the years 2019 to 2021 can be characterized as a “creeping” crisis – evolving over time and space, resisting comprehensive and coordinated response – that challenged the global healthcare sector in unprecedented ways. Hospitals had to adapt their operations to respond to the crisis, including the postponement or cancellation of elective appointments to increase capacity for treating Covid-19 patients. As yet, there is only little systematic understanding of how hospitals should respond to creeping crises such as the Covid-19 pandemic, and how crisis mitigation will influence a hospital’s capacity and operational performance. The four articles in this PhD thesis address this problem from different angles. In the first paper, I investigate hospitals’ crisis response in a comparative two-case design. The two case hospitals had very different crisis response strategies. Although no causal conclusions can be drawn from the design, an interesting result was that the case hospital that followed a more data-driven approach to crisis decision-making had fewer days with higher preparedness levels and also higher operational performance. In the second paper, I investigate internal crisis communication, specifically how the choice of communication channels affects communication effectiveness, based on a social network analysis conducted at a tertiary public hospital. Use of communication channels with speed and bandwidth limits significantly increased perceived cooperation problems. Since internal communication is essential for crisis response, crisis managers should decide carefully which communication channels to use. In the third paper, I conduct an in-depth analysis of capacity limitations at a tertiary public hospital to understand the nature of capacity limitations during the early crisis response phase. Limitations were perceived differently across hierarchical levels and organizational functions in the organization. The most serious capacity limitations were related to staff (in terms of quantity and skill levels) and information. Middle management and organizational functions providing specialized treatment felt most affected. The fourth paper follows a more quantitative approach and applies methods from operations research. I develop a two-stage stochastic programming model to create a decision-support tool for crisis managers when cross-training decisions are required and uncertainty in both demand and absenteeism must be incorporated. In three simulation experiments, I investigate how the relation between cost for non-treatment, cost for cross-training and the initial number of nurses affects the cross-training decision and patient service levels. The results indicate that the value of additionally employed nurses decreases with a larger number of initially employed nurses. Taken together, this PhD thesis contributes to the literature on crisis management in the healthcare sector by offering detailed insights into hospital operations during the first wave of the Covid-19 pandemic in Norway. The findings offer a basis for standardization of crisis response and have the potential to enhance crisis

response during similar crisis. More research is needed how crisis response develops during the crisis phases and how crisis response affects treatment quality and patient safety.

Norsk sammendrag

Covid-19-pandemien kan karakteriseres som en «creeping» krise og forårsaket en betydelig utfordring for helsesektoren over hele verden. Sykehusene måtte tilpasse driften for å respondere på krisen, noe som innebar bl.a. utsettelse eller kansellering av planlagte operasjoner for å skape ekstra beredskapskapasitet for behandling av Covid-19-pasienter. Det er lite kunnskap om hvordan sykehus skal agere på en stor krise, som Covid-19-pandemien, og hvilke tiltak som bør iverksettes for å redusere krisens virkning på sykehusets operative ytelse, og dermed sykehusets kapasitet. I mitt arbeid undersøker jeg to sykehus-case, i en sammenlignende casestudie, og finner at det ikke kan identifiseres en standardstrategi i krisehåndtering. Imidlertid hadde ett sykehus en mer datadrevet tilnærming til krisebeslutninger relatert til færre dager på høyere beredskapsnivåer sammenlignet med en mer naturalistisk beslutningstilnærming. Videre finner jeg at jo lenger fasen med høyere beredskapsnivåer er, jo lavere er den operative ytelsen. I denne studien gjennomfører jeg også en inngående analyse av kapasitetsbegrensninger ved et av sykehus, under den tidlige fasen av kriseresponsen. Jeg finner at både antall og ferdighetsnivåer hos personalet, samt informasjon, forårsaket de største kapasitetsbegrensningene, på tvers av hierarkiske nivåer og organisatoriske funksjoner innen organisasjonen. Mellomledelse og organisatoriske funksjoner som gir spesialisert behandling, var mer utsatt for disse begrensningene. Analyser viser at egenskapene til kommunikasjonskanaler er relatert til kapasitetsbegrensninger. Bruk av kommunikasjonskanaler med hastighets- og båndbreddebegrensninger øker betydelig de oppfattede kapasitetsbegrensningene. Siden intern krisekommunikasjon er viktig for krisehåndtering, bør kriseledere velge effektive kommunikasjonskanaler. Den fjerde studien følger en mer kvantitativ tilnærming og bruker metoder fra driftsforskningen. Jeg bygger en to-trinns stokastisk programmeringsmodell for å lage et beslutningsstøtteverktøy for kriseledere når det er nødvendig med opplæring på tvers av fagområder, og når usikkerhet i både etterspørsel og fravær må inkluderes. I tre simuleringseksperimenter visualiserer jeg forholdet mellom kostnadene for ikke-behandling, kostnadene for opplæring på tvers av fagområder og det opprinnelige antallet sykepleiere påvirker opplæringsbeslutningen og pasienttjenestenivåene. Jeg identifiserer at verdien av ytterligere ansatte sykepleiere avtar med en større sykepleierbase. Min doktorgradsavhandling bidrar til litteraturen om kriseledelse i helsevesenet ved å gi innsikt i sykehusets drift under den første bølgen av Covid-19-pandemien, samt at det er utviklet et beslutningsverktøy for rekrutering av sykepleiere i krisesituasjoner. Disse funnene gir et grunnlag for standardisering i krisehåndtering og har potensial til å forbedre krisehåndteringen under lignende kriser. Mer forskning er nødvendig for å forstå hvordan kriseresponsen utvikler seg under krisefasene, og hvordan kriserespons påvirker behandlingskvalitet og pasientsikkerhet.

List of papers

Paper I

Winzer, H., Stevik, T.K., Scholderer, J. (2024a). Crisis decision-making in hospitals - An analysis of the Covid-19 pandemic. Manuscript submitted to *Management Decision*

Paper II

Winzer, H., Stevik, T.K. and Scholderer, J. (2024b). Internal crisis communication in hospitals -The choice of communication channels and its impact on effectiveness. Manuscript accepted with minor revision by the *Journal of Contingencies and Crisis Management*

Paper III

Winzer, H., Stevik, T.K., Lilja, K.A., Seljevold, T. and Scholderer, J. (2024). Tactical capacity planning under uncertainty – A capacity limitation analysis. Published in *Journal of Health Organization and Management*. Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/JHOM-01-2024-0011

Paper IV

Winzer, H. and Bengtsson, J. (2024). Cross-training of nurses during a global pandemic: A two-stage stochastic programming approach – Manuscript submitted to *Journal of Healthcare Management Science*

1. Introduction

1.1. Problem statement

The recent global Covid-19 pandemic has presented unprecedent challenges for the healthcare sector worldwide. Covid-19 as a novel respiratory disease caused by the SARS-CoV-2 virus, was first discovered in China in December 2019 (Lupu & Tiganasu, 2022). From its initial discovery, the virus quickly spread due to interconnected global economies, achieving a widespread prevalence in Europe in spring 2020. Therefore, Covid-19 resulted in a crisis for European hospitals since there was no to little knowledge about treatment methodologies for Covid-19 patients or epidemiological patterns of Covid-19. Compared to other respiratory diseases caused by coronaviruses, patients infected by Covid-19 developed cough, fever and other pneumonia-associated symptoms as well (Weng et al., 2021). Consequently, Covid-19 was the main driver for numerous deaths among older people above the age of sixty in many countries (OECD, 2021). Compared to the Spanish flu, which killed patients by a secondary bacterial infection, Covid-19 spread to twice as many countries (Liang et al., 2021). While the global Covid-19 pandemic is exceptional, it had also predecessors on a smaller scale: Zika virus in 2016 and Ebola in 2018 (Hannan et al., 2021). However, these diseases did not influence all health systems worldwide as Covid-19 did.

Unlike mass accidents, terrorist attacks or earthquakes, the global Covid-19 pandemic can be characterized as a creeping crisis (Boin et al., 2020). Defining the beginning of a creeping crisis by a discrete event is challenging due its spatial and temporal dimension and long incubation periods. These characteristics of a creeping crisis result in uncertainty and impose challenges on crisis response. Furthermore, the global Covid-19 pandemic created shortages for both medical staff and medical equipment such as personal protective equipment or respirators globally. Therefore, sourcing of these supplies became challenging. Considering the temporal perspective, the global Covid-19 pandemic had a long term development based on a wavelike epidemiology, which made existing surge capacities at hospitals ineffective (Winkelmann et al., 2022). In addition, infections among the workforce put additional pressure on the hospitals. As crisis response, hospitals postponed or canceled elective appointments to keep spare capacity for a potential influx of Covid-19 patients. This mitigation action resulted in longer waiting times and increasing backlogs for non-Covid-19 patients. Especially in Western countries these indirect effects of the global Covid-19 pandemic should not be neglected where there is already an increasing demand in healthcare services due an aging society and an increase in chronic diseases (Busse et al., 2010). This inability to flexibly match hospital capacity to incoming patient demand and adapt to changing externalities was one of the top challenges in the healthcare sector next to supply chain resilience (PWC, 2021).

The situation of the global Covid-19 pandemic as a black swan event provides me with the unique possibility to perform an empirical study on crisis management from an operations management perspective in Norwegian hospitals. As there is little systematic understanding about crisis response in creeping crises, my goal is to analyze the effects on the hospital's operation when the hospital needs to effectively respond to externalities.

1.2. Research setting

The foundations of my PhD thesis are rooted in the principles and frameworks of operations management. Although initially formulated in the context of production and manufacturing, the methodologies and constructs of operations management have been successfully adapted for use in the healthcare sector (Keskinocak & Savva, 2020). Operations refer to a sequence or interrelated activities that convert inputs into outputs, which can either be goods or services (Karlsson, 2016). An example in the healthcare sector could be the series of tasks necessary for treating a patient such as scheduling the appointment, planning the required workforce and procuring necessary medical equipment. Research in operations management, therefore, focuses on the analysis of processes both intra-organizational and inter-organizational, providing insights and decision support how these processes can be improved.

In the context of a hospital, there exist two primary strategies to balance patient influx and hospital capacity: 1) demand management and 2) capacity management (Slack et al., 2016). First, hospitals could regulate patient demand through dynamic pricing options and optimized scheduling of elective appointments to mitigate peak times and over-utilization of their capacity. However, this strategy can be employed only under certain conditions and types of hospitals, such as in private hospitals that predominantly offer elective treatments. In situations where hospitals cannot control patient influx, as seen during the global Covid-19 pandemic, capacity management becomes crucial for effective crisis response (Jack & Powers, 2006). Therefore, effective capacity management requires prediction of patient demand and proactive staffing of medical personnel to adequately respond to crises. Given the scarce resources in hospitals, it is crucial to utilize the hospitals capacity as efficiently and effectively as possible. It is important to mention that capacity management involves not just planning patient treatments, but also scheduling cross-training activities for upskilling medical staff. Thus, the research in operations management, as evident in my PhD thesis, embodies a blend of interdisciplinarity and a range of research methodologies tailored to my research questions.

1.3. Research questions and contribution

To address the underlying problem, I define the following three research questions as guidance for my PhD thesis:

How did hospitals in Norway respond to the global Covid-19 pandemic?

How did mitigation actions for crisis response affect the hospital's operation and its performance?

How could crisis response of hospital during a pandemic be improved?

My PhD thesis contributes to the existing body of healthcare crisis management literature by offering one of the few empirical studies in this domain. Unlike prior studies, I study a global pandemic in a real-world setting from a retrospective. This approach offers an enhanced understanding of how the hospital operation was affected. Rather than focusing on single process types like value chain processes such as patient treatment, I adopt a comprehensive perspective on different hospital processes. Therefore, I also analyze the impact on both support and management processes since they also influence crisis response. Consequently, I provide a holistic understanding of the complex relationships in a hospital instead of concentrating on single departments. This approach gains increasing relevance since Covid-19 patients may have an interdisciplinary patient pathway due to comorbidities.

Consequently, my PhD thesis contributes to both theory and practice. First, it provides additional insights to crisis response and complements the crisis management literature that mainly focuses on both contingency and proactive mitigation action planning. While I acknowledge that proactive actions are an important part for crisis management, the operationalization of these plans is equally crucial and has, so far, received little attention from researchers. Given that global pandemics will occur more often due to an increasing globalization, operations managers in healthcare can utilize the findings from my thesis to enhance crisis response (K. F. Smith et al., 2014). Moreover, my work not only analyzes the situation retrospectively but also provides practitioners with a decision-support tool to manage uncertainty, rather than merely improving existing pandemic plans. The contributions to theory and practice of each of the four studies can be found in the synopsis.

2. Theories and previous research

2.1. Crisis management

Hermann (1963) characterizes a crisis by three distinct features: 1) threatens high-priority assets or critical processes, 2) provides only a short period for response and 3) happens unexpectedly. While the global Covid-19 pandemic as a creeping crisis fulfills the requirements to be characterized as a crisis, the response time is relatively long due to its long incubation period (Boin et al., 2020). Compared to disasters like mass accidents or earthquakes, a crisis does not offer a standardized solution for effective crisis response since it is unique in its development (Al-Dahash et al., 2016). Generally, a crisis can be regarded as an event or a process (Williams et al., 2017) (see Figure 1). When analyzing a crisis as an event, the focus of analysis is the trigger event. Contrarily when seeing a crisis as a process, the evolution becomes the focal point of interest. The development of a crisis can be divided into three different phases: 1) pre-crisis, 2) acute crisis 3) post-crisis (D. Smith, 1990). During the pre-crisis, organizations operate normally while monitoring potential crisis events to proactively plan crisis response. Upon the occurrence of a trigger event for a crisis, the pressure on the organization increases. In the acute crisis, the organization needs to effectively respond to the crisis, a phase when it experiences the highest pressure. After the crisis during the post-crisis, the organization can learn from experiences to be better prepared for a similar crisis in the future. This three stage framework of a crisis is sometimes extended by an additional phase between the acute crisis and post-crisis, called end-crisis (Brecher & Wilkenfeld, 2022). This additional phase describes the stage when time pressure and stress level decrease.

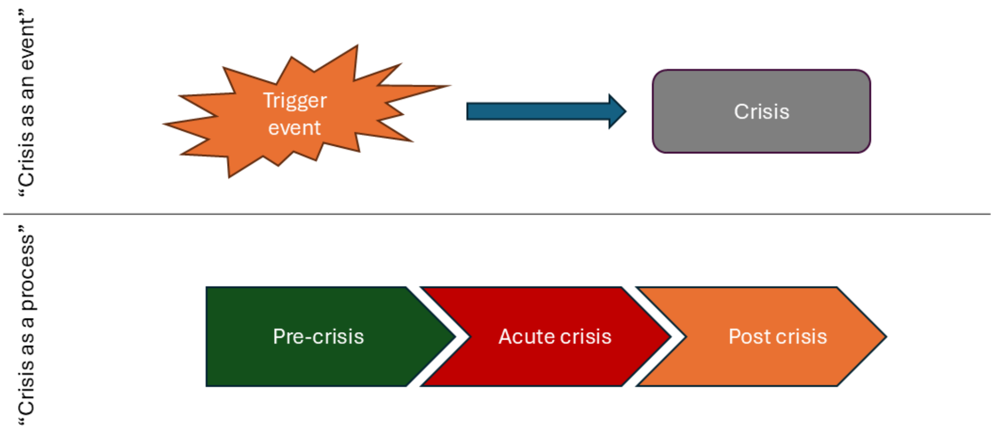

Figure 1: Crisis as an event or process (own illustration)

Crisis management, encompassing both proactive and reactive strategies, covers activities during both the pre-crisis and the acute crisis (Boin, 2008; Mitroff et al., 1987). The objective of crisis management during the pre-crisis is to minimize the risk of trigger events to occur and to formulate blueprints for crisis response, for instance in the form of pandemic plans. Crisis management during the acute crisis deals with the operationalization of pre-existing plans and provision of individual mitigation actions with the aim of enhancing recovery from the crisis and coping with associated challenges. Mitroff et al. (1987) argue that there is a need to follow a systematic approach to effectively manage crises since it is impossible to either predict or prevent all details of crises.

Comfort (2007) introduces a general framework for crisis management that consists of four pillars: 1) cognition, 2) communication, 3) coordination and 4) control. First, cognition of a crisis involves recognizing the emerging risk by having a clear mental model how the hospital should operate and understanding the characteristics of different types of crises to quickly respond to the crisis (Comfort, 2007; Wolbers & Boersma, 2018). Cognition is not only important during the pre-crisis but also during the acute crisis when for instance changes in externalities need to be detected. Hence, cognition triggers the subsequent processes of crisis management. Second, communication is crucial to create a shared understanding of the crisis since it is experienced differently within the organization (Netten & Someren, 2011). Third, coordination ensures that crisis response is aligned and serves an overall goal. This is crucial as preparedness plans cannot cover every possible details for crisis response (Mitroff et al., 1987; Wolbers & Boersma, 2018). Moreover, effective coordination is necessary to avoid redundancies or conflicting mitigation actions. Fourth, given that crises can escalate, there is a need for crisis responders to manage and control the situation. As uncertainty or the number of affected persons can increase, there is a need to retain flexibility and foster de-centralized decision making on the operational level (Wolbers & Boersma, 2018).

The healthcare sector possesses unique characteristics in relation to crisis management, as failures in crisis response and preparedness invariably pose a risk to human life, making monetary losses less pertinent. Given that the health system in Norway is publicly funded, a health crisis has a societal impact as well. With these considerations in mind, let us now turn to crisis management in healthcare. The global Covid-19 pandemic has presented me with the opportunity to reflect on crisis management in hospitals. Bressan et al. (2020) discover that about one out of three hospitals did not have preparedness plans for affected departments during the Covid-19 pandemic, leading to significant variations in crisis preparedness and response. Michenka & Marx (2023) agree with these findings, arguing that crisis management is not only preparing plans but also operationalizing and adapting them after the crisis. These findings are not exclusive for the global Covid-19 pandemic but also for other health crises such as pandemic influenza and dengue epidemics (Dewar et al., 2014; Rathnayake et al., 2021). The primary focus of these studies is on the pre-crisis. Consequently, research on the operationalization of pandemic plans remains fragmented (Verheul & Dückers, 2020). Most attention is paid to the structure of pandemic plans and the process for utilizing them during crisis response. As Mitroff et al. (1987) note, not all types of crisis can be predicted. Therefore, I argue that crisis response, particularly triggered by unknown – unknown events should receive more attention by scholars. Unknown-unknown events are the ones we are neither aware of nor do we understand them. Finally, crisis response is divided into three different types such as 1) effective leadership, 2) rapid resource allocation and 3) multiagency network response (Donelli et al., 2022).

2.2. Internal crisis communication

Crisis communication is an integral part of crisis management. Berlo's (1960) linear concept provides a framework for the communication process which consists of four elements: 1) source, 2) message, 3) channel and 4) receiver. While this concept explains the one-way transfer of information between two actors, it neglects the possibility for immediate feedback. Nevertheless, it shows potential sources of communication challenges, which is essential for my PhD thesis. Consequently, limitations can reside not only from the sender and receiver but also from other aspects like channels characteristics or the information content. For instance, asynchronous communication channels such as email can result in delayed reception by the receiver.

Research on crisis communication has mostly concentrated on the interaction between an organization and external stakeholders such as customers or the press. Protecting the reputation of an organization is a central objective when communicating with externals during a crisis. However, internal stakeholders also need to be continuously updated about the crisis for effective crisis response. Therefore, the stream of literature on internal crisis communication (hereafter named as ICC) has emerged to analyze crisis communication with internal stakeholders like employees. Frandsen & Johansen (2011) are among the pioneers in ICC research and propose a framework for crisis communication along the crisis phases (see Table 1). While they differentiate between vertical and horizontal communication, the interplay between top-down and bottom-up communication is included as well. This communication construct needs to be actively managed for effective crisis response since needs for information evolve with the crisis. While the focus in the pre-crisis is on prevention and preparation for a future crisis, the post-crisis aims to communicate potential lessons learned to the organization. Moreover, the communication strategy needs to be customized to internal or external stakeholders since these two types of audiences might have different needs (Liu et al., 2018; Strandberg & Vigsø, 2016)

Table 1: Internal crisis communication framework (own table adapted from Frandsen & Johansen (2011))

	Pre-crisis	**Acute crisis**	**Post-crisis**
Focal point	*To prepare*	*To manage the crisis*	*To continuously improve*
Employees as receivers Management or taskforce as senders	• Communication of risks and issues • Communication to strengthen crisis preparedness • Communication of the crisis response plan	• Communication of relevant instructions • Handling of reactions to the crisis and sensemaking • Protection of trust and confidence among employees	• Communication of new knowledge and lessons learned • Communication of post-crisis changes
Horizontal communication among managers and among employees			
Employees as senders Management or taskforce as receivers	• Negative upward communication (whistleblowers)	• Communication of reactions to the crisis • Positive and negative organizational “Ambassadors”	• Organizational storytelling

2.3. Operations management in hospitals

Operations managers in hospitals are challenged to maintain a match between the hospital's capacity and the patient influx despite uncertainty and variability during a crisis. A mismatch results in cost-intensive over-capacities or in the worst case poses a risk to human life if the hospital is unable to meet patient demand. Recognizing this problem, scholars have adapted methods from the operations management domain and operations research for application within the healthcare sector to improve capacity management in hospitals.

There are three different interrelated definitions of capacity: design capacity, effective capacity and actual capacity (Lantz & Rosén, 2016; Slack et al., 2016). The design capacity of a hospital is the theoretical maximum available capacity. It symbolizes the available capacity without any planned or unplanned operational performance reductions. Effective capacity, on the other hand, is the design capacity reduced by all expected capacity reductions such as the maintenance of medical equipment, cleaning of operating theatres or absence of personnel due to holidays. Lastly, the actual capacity includes all potential capacity losses due to both unforeseen operational disruptions and all planned down-times. This form of capacity is decisive how many patients can be treated in the hospital.

Furthermore, capacity planning can happen in different time horizons and managerial areas (Hans et al., 2011) (see Figure 2). Four managerial areas can be differentiated: 1) technical equipment and supply, 2) workforce planning, 3) financial planning and 4) medical planning. Depending on the temporal aggregation, the planning subjects of each managerial area change. For instance, short-term planning of materials involves ad-hoc ordering and purchasing, while in the long-term the entire supply chain design for the hospital needs to be established. Tactical capacity planning is essential when the hospital's capacity has to be set temporarily to patient demand (Larsson & Fredriksson, 2019), which also applies for a crisis like the global Covid-19 pandemic.

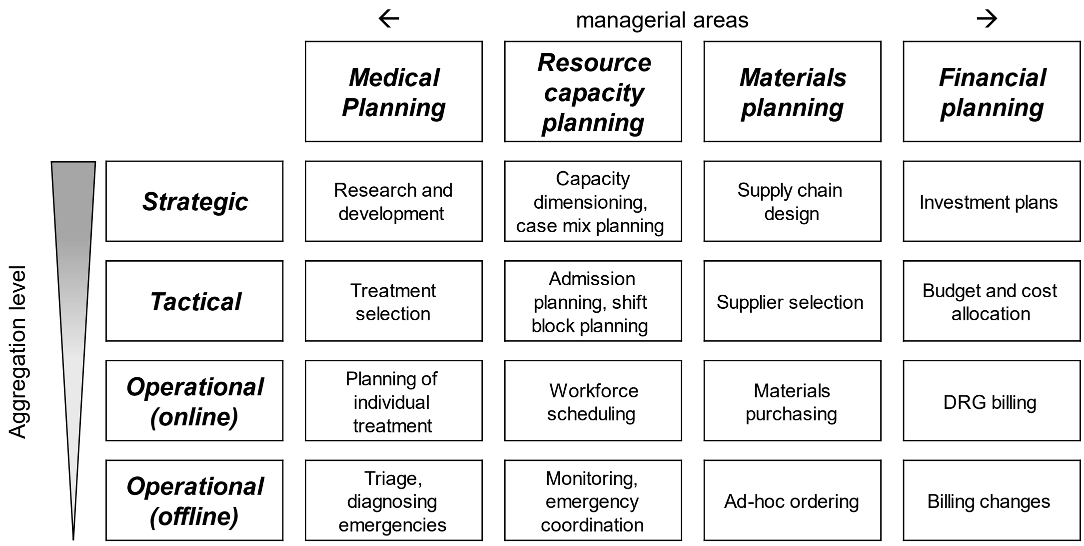

Figure 2: Capacity planning framework (own illustration adapted from Hans et al. (2011))

In capacity planning, there are widely accepted parameters such as the average utilization rate, which is defined as the division between occupied and number of available beds (Green, 2002, 2005; Terwiesch et al., 2011). As a rule of thumb, the hospital should reach an average utilization rate of around 85% (Green, 2002). However, due to the variation in patient demand, this does not per se result in a 100% patient service level. Therefore, hospitals keep "surge capacity" (meaning additional resources) to respond to variation, which is an important part of capacity management in hospitals (Hick et al., 2009).

The global Covid-19 pandemic attracted attention by scholars in operations management and Leite et al. (2020) suggest that lean practices could be utilized to manage capacity and improving crisis response. Marin-Garcia et al. (2020) follow the call for more research from the operations management domain and analyze the Covid-19 patient pathway to predict the patient demand in different departments in the hospital. These forecasts would allow hospitals to adapt preparedness plans even before reaching the capacity limit. Applying methods from operations research aimed to optimize the capacity utilization during the global Covid-19 pandemic and several models have been generated (Bekker et al., 2023; Heins et al., 2022). These studies show that an interdisciplinary approach can provide additional insights and that methods from the operations management domain possess the potential to support crisis response in healthcare.

3. Empirical setting

3.1. The Norwegian healthcare system

The healthcare system in Norway operates on a tax-based model, with shared responsibility by the state and the municipalities for health service delivery and planning. The state is responsible for specialized healthcare provision and hospitals whereas municipalities are responsible for primary care and general practitioners. All legal residents in Norway are entitled to free universal healthcare. The healthcare system is managed through four regional health authorities, which oversee specialist treatments provided by hospital trusts.

In 2021, Norway allocated 12.9% of GDP Mainland Norway in health expenditure, which is among the highest expenditures for healthcare per inhabitant in Europe (OECD/European Observatory on Health Systems and Policies, 2023; Statistik sentralbyrå, 2023). Only Germany had a higher spending per inhabitant on healthcare in 2021. Moreover, Norway also leads in the density of doctors and nurses. In 2021, there were 5.2 practicing doctors and around 18 practicing nurses per 1,000 inhabitants (OECD/European Observatory on Health Systems and Policies, 2023). The doctor density is almost 27% above the European average. With respect to the Covid-19 pandemic, Norway registered only 414 deaths attributable to Covid-19 during 2020, which is significantly lower than the European average (Folkehelseinstituttet, 2022).

3.2. Governance in preparedness planning in Norway

The national law on health and social preparedness in Norway mandates that all actors in the healthcare system like hospitals develop internal preparedness plans how to respond to a crisis and maintain operational in their area of responsibility (Lov om helsemessig og sosial beredskap (helseberedskapsloven), 2023). There may be additional requirements about the content of these plans in terms of operations, supply chain and training of personnel. Consequently, preparedness planning for health crisis is guided by directive from the national health authority and hierarchically organized. Thus, directives are cascaded down to the regional health authorities in the form of regional preparedness plans (Helse- og omsorgsdepartementet, 2018; Helse Sør-Øst, 2023). These regional preparedness plans provide more granular information compared to the national directives and describe strategies for crisis response for several types of crises such as pandemics, shortages in medicine or technological issues. Furthermore, these preparedness plans include the formation of a regional task force as an intermediary function between the national and hospital level.

When the global Covid-19 pandemic hit Norway in Spring 2020, specifically designed pandemic plans were activated and the regional health authorities required hospitals to provide plans for crisis response how to increase capacity in response to a potential surge in Covid-19 patient influx (Folkehelseinstituttet, 2020). While hospitals had access to templates for pandemic plans, these needed to be adapted to the unique situation of the global Covid-19 pandemic. Hospitals defined steps to increase capacity especially in the emergency department and the intensive care unit (hereafter as ICU), based on an epidemiological scenario analysis by the Norwegian Institute of Public Health (Folkehelseinstituttet).

4. Research design and methodology

The first three papers for this thesis are guided by a qualitative case study research design, which allow me to study the selected case hospitals with rich information in their real setting (Yin, 2009). I follow the proposed case study research process by Eisenhardt (1989), which act as a guidance during the entire research process and supports building theories. Before selecting a case hospital for each study, the research goal has been defined. My aim is to enhance the understanding on the operationalization of pandemic plans for crisis response during the global Covid-19 pandemic. The two case hospitals are selected from the same region in Norway, the Oslo region. Hence, they did face similar challenges both in availability of medical personnel and patient demand. Moreover, I decide to conduct interviews with informants that were either involved in crisis response planning or actively participated in crisis decision-making. When creating data collection protocols, I reflect on particularities of the healthcare domain. This approach is in line with the notion, that research should adapt research procedures to the field setting (Welch & Piekkari, 2017). For instance, I decide not to record the interviews, but rather having more than one researcher present to take instant notes. Moreover, qualitative information is richer and more extensive compared to quantitative data, hence allows me to answer my research questions more in details with almost complete knowledge (Karlsson, 2016). Additionally, I triangulate the information from the interviews with documents such as pandemic plans, tertial reports and annual reports whenever possible. When reporting the research findings, I adhere to the COREQ-checklist (Tong et al., 2007) and conduct pilot interviews to check if the questions in the interview guide are understandable for the informants and that medical terms are used unequivocal.

The fourth paper in my PhD thesis aims to develop a decision-support tool for cross-training of nurses under uncertain patient demand and absenteeism among nurses. Given the complex interplay of internal stakeholders within a hospital, a quantitative axiomatic approach could be used to make relationships explicit. While this research design does not capture the entire complexity of the problem, it enables the researcher to run simulation experiments and to understand scenarios when variables like the cross-training cost change.

The recent global Covid-19 pandemic is considered as a black swan event. As previous research is limited, this PhD thesis follows an inductive approach. Traditional deductive methods are often not accessible to extreme cases (Eisenhardt et al., 2016). This characteristic requires a purposive selection as opposed to a random sampling as I need to define the case that is best to illuminate the problem to be studied.

Related fields of research such as health economics or operations research in healthcare study the effects of the global Covid-19 pandemic based on quantitative research designs. Health economics analyzes the effects of the global Covid-19 pandemic on a national wide level and investigates the effects of public health interventions and the incidence rates of Covid-19 within society (Ayouni et al., 2021; Rathnayaka et al., 2023). These studies on health economics and public health are often based on census data. Other than my approach, these studies contribute to adapt policies how to respond as a society to a crisis like a global pandemic. This allows to benchmark different countries in terms of crisis response to the global Covid-19 pandemic (Lupu & Tiganasu, 2022). Moreover, operations research is often theoretically oriented and aims to support decision-making within the healthcare sector to cope with uncertainty in the acute crisis. These models are often based on the organizational level and optimize supply for Covid-19 patients detection or simulating the effect of considered interventions in health services (Lampariello & Sagratella, 2021; Murch et al., 2021). Not only does it consider the effects during the acute crisis but also on the post crisis when there is a need to reduce the backlog of elective appointments (Nehme et al., 2022). These studies are based on quantitative information from hospitals or networks of hospitals. However, the complex relationship of a hospital is not fully captured in this data. While a reduction in complexity offers the possibility to define optimal decisions, it also creates a loss in understanding of the problem's complexity. I apply the methodologies of operations research in the fourth paper for providing a decision support tool that supports the cross-training decision for nurses.

4.1. Methodological reflections

In this section, I would like to reflect upon the methodological choices I made in my PhD project. While the initial idea was to collect quantitative process data to analyze crisis response in hospitals, access to this type of data was not possible. Nevertheless, I was able to collect extensive data from informants who participated in either crisis decision making or crisis response planning during the first wave of the global Covid-19 pandemic (March/April 2020). However, we conducted the interviews a year later in the period between February and April 2021, which could potentially have affected data quality due to recollection bias. One advantage of the timing was that it allowed the informants to reflect on their experiences and contextualize them. I would argue that the advantages of a retrospective approach outweigh its weaknesses.

Furthermore, the selection of informants was not representative for the entire organization but served the purpose of my PhD thesis. Therefore, I informed our main contact persons at the two involved hospitals about the study's purpose to ensure a suitable selection for this purpose. I note that even though I include two cases in the study on crisis decision-making (hereafter named as CDM), the data basis for the Hospital B is smaller compared to the data Hospital A. More cases would have allowed me to generalize the findings. Furthermore, I decided not to record the interviews, which might pose a risk to data quality. However, recent studies have shown that not recording the interviews does not have a significant effect on data quality (Rutakumwa et al., 2020). Since I addressed a delicate topic with the operationalization of pandemic plans in a hospital, which might be related to lower quality in patient treatment, the informants may not want to be recorded to speak more freely. Therefore, my choice of not recording the interviews in this situation shows the awareness of keeping the integrity of the informants.

Compared to related fields as health economics and operations research, I decided to collect qualitative information to analyze the underlying problem. Other methods such as surveys would have been expedient if I would have had access to the information from different case hospitals. I have used simulation as a method to provide insights into the relationships of decisions and their consequences. Another possibility is agent-based simulation to predict patient pathways, which has been applied by research colleagues on the same dataset. Furthermore, my PhD thesis does not use timeseries data, which limits our analysis to a single point in time. Longitudinal prospective methods would have been interesting to enhance the understanding of crisis management during the crisis phases.

Transforming qualitative interview data into quantitative information in the form of binary variables or scores may reduce information richness. However, quantitative information allowed me to visualize the study's results in a more compact format. This underlines the mixed-method approach of my PhD thesis, which contrasts to some degree with the methodology of related fields such as health economics or operations research. However, it allowed me to capture information also from processes that are not administered in information systems or documented.

4.2. Ethical considerations

The qualitative data collected for my PhD thesis does not contain personal data since the information was instantly anonymized during the interviews. This was achieved through the presence of at least more than one researcher who took instantly notes during the interviews. The informants were informed about the purpose of the data collection. Furthermore, participation was voluntary, and the informants were informed that they could withdraw from the study at any time without any consequences. The quantitative information for paper one and paper four was collected from publicly available sources such as the websites of the respective hospitals as well as the Norwegian Institute of Public Health (Folkehelseinstituttet).

5. Synopsis

In this section I will provide reasoning how the four papers in my PhD thesis are connected to each other. The overarching framework for this thesis (see Figure 3) is the 4Cs in crisis management, which are 1) cognition, 2) communication, 3) coordination and 4) control (Comfort, 2007). A detailed description was already given in the literature review on crisis management.

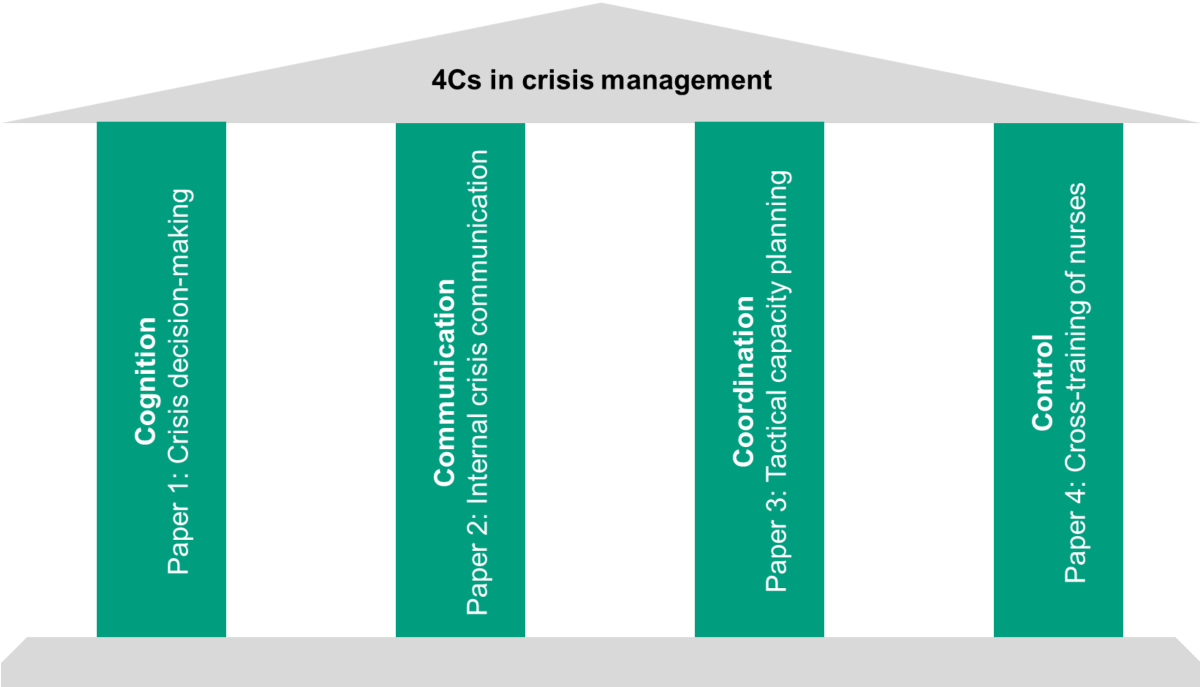

Figure 3: 4Cs in crisis management (own illustration)

Each of the four papers has a distinct focus on one of the Cs. The first paper concentrates on cognition of a crisis when comparing different approaches to CDM. This pillar is further relevant for adequate communication and coordination as crisis managers need to recognize the severity of an emerging crisis. This could be performed by a data-driven or more experience-based strategy. The second paper analyzes the relation between utilized communication channels for internal crisis communication and its effect on operational performance. Crisis communication does not only concern external but also internal stakeholders since crisis managers need to build a shared understanding of the situation. The third paper deals with coordination and explores the limitations to capacity during tactical capacity planning. These insights shed light on the relationship of capacity limitations and hierarchal levels respectively capacity limitations and organizational functions. Tracking the most limiting factors can also improve the effectiveness of crisis response and improves coordination of crisis response. Lastly, the fourth paper offers a decision-support tool for optimal cross-training of nurses, which allows to control and revise the decisions particularly on tactical workforce planning. Therefore, I run three distinct simulation experiments to provide insights into the relationship between decisions and outcomes based on changing variables. The papers are presented in the same order in the following sections.

Overview

Paper	Research question	Theory	Data	Empirical methods
I	1.1. What CDM strategy is followed by hospitals? 1.2. What is the relation between CDM strategies and crisis response including effects on operational performance?	Decision science theory, crisis decision making processes	Primary data, collected 2021 (in-depth interviews in a regional and a tertiary hospital), pandemic plans, tertial and annual reports	Comparative qualitative two-case design, document analysis
II	2.1. What is the communicative relationship between internal stakeholders, the communication channels used and the information being shared? 2.2. What impact does the chosen communication channel have on the effectiveness of crisis communication?	Organizational sensemaking theory, ICC, communication channel characteristics and capabilities	Primary data, collected 2021 (in-depth interviews)	Qualitative case study, document analysis, social network analysis with Markov chain Monte Carlo simulation
III	3.1. Which types of limitations influence the actual hospital's capacity of a hospital during a pandemic? 3.2. How do limitations differ across hierarchical and functional levels?	Tactical capacity planning, capacity limitations	Primary data, collected 2021 (in-depth interviews)	Qualitative case study
IV	4.1. How many nurses need be cross-trained and temporarily hired during a pandemic while minimizing the total cost? 4.2. How do parameters such as cost for non-treating patients, cross-training cost, the initial number of employed nurses and the patient-to-nurse ratio influence the total cost, the performance in terms service levels?	Nurse staffing, cross-training	Covid-19 data from Akershus University hospital, Covid-19 data from the Norwegian Institute of Public Health (both publicly available)	Two-stage stochastic programming, Simulation experiment

I: Crisis decision-making in hospitals - An analysis of the Covid-19 pandemic

The goal of this study is to explore and analyze CDM strategies employed during the early phase of the Covid-19 pandemic when hospitals recognized the need for crisis response based on the spread of Covid-19 in other countries. Furthermore, we investigate the relationship between their CDM strategies and the hospital's crisis response in terms of days in higher preparedness level including the effects on operational performance.

We conduct interviews with informants from a public regional and a public tertiary hospital in the Oslo region. The selected informants actively participated in CDM during the early phase of the Covid-19 pandemic in spring 2020. We code the interview data according to a CDM framework, the OODA cycle (observe, orient, decide and act). In addition, we review initial crisis response plans for each hospital dealing with how to increase capacity as well as the annual reports for the period 2019 to 2021. The annual reports provide us with performance indicators such as DRG (diagnosis-related group)-activity and the average waiting time per patient until commencement of standard treatment. These numbers are standardized across hospitals in Norway in reporting the performance to the authorities. In addition, we retrieve the number of days in higher preparedness level from publicly available reports.

The public regional hospital followed a more naturalistic CDM strategy compared to the public tertiary hospital. We discover that an increased emphasis on naturalistic respectively experienced-based CDM is related to longer periods of higher preparedness levels. Furthermore, this results in a reduced operational performance as evidenced by a decrease in DRG-activity and longer waiting times before standard treatment initiation. Our findings are consistent with the notion from previous research that naturalistic decision making can be influenced by anchoring effects. However, the negative influence of anchoring effects may be mitigated by a combination of CDM strategies like a de-centralized approach or the triangulation of information.

We recommend that crisis managers adopt a mix between different CDM strategies, allowing the advantages of each strategy to complement each other. However, adopting a hybrid CDM strategy would necessitate a shift in the composition of the hospital's crisis management team to include additional data science competencies along with medical expertise. Moreover, we advise future research on CDM to take an empirical approach as we do in our study. Furthermore, this study should be replicated with cases in other countries and different health systems to increase the generalizability of our findings.

II: Internal crisis communication in hospitals -The choice of communication channels and its impact on effectiveness

The goal of this study is to analyze the ICC process during the acute crisis in a public tertiary hospital. We focus on the relationship between the choice of communication channels and the limitations perceived by the involved internal stakeholders. Information about the pandemic situation, updated work instructions, availability of personal protective equipment (PPE), and personnel reallocation are addressed in this study, all essential for internal stakeholders to make sense of the situation.

We visualize the communication lines including the communication channels in a subject interaction diagram to describe the relationship between internal stakeholders in the case hospital. This method offers the possibility to focus on the communication between different stakeholders in a network. Using these social network data, we perform a dyadic analysis to assess the relationships between the chosen communication channels and the capacity limitations perceived by the internal stakeholder groups.

We find that the ICC changed when the preparedness level of the hospital was raised. A Covid-19 taskforce was established as an intermediary body. The intention was to shorten vertical ICC between the top management and the operational level, which also increased complexity. However, we identify that not all vertical communication happened via the Covid-19 taskforce, since redundant ICC processes are identified. Moreover, we discover that communication channels with speed and bandwidth limits led to challenges for the receivers in terms of being able to make sense of the situation. In contrast, communication channels that could transmit contextualized information facilitated sensemaking by receivers.

Overall, we conclude that crisis managers should carefully select their ICC channels to effectively respond to a crisis. Communication channels with high capability to transmit contextualized information should be preferred over channels with speed and bandwidth limits. While the focus was mostly on vertical communication during the acute crisis, we argue that horizontal ICC is not less important and could be studied in future studies. Furthermore, the impact of novel communication channels such as social media should not be neglected by ICC research.

III: Tactical capacity planning under uncertainty – A capacity limitation analysis

In this study the objective is to explore limitations to capacity when the hospital needs to temporarily set capacity to patient demand through tactical capacity planning. Therefore, we report a detailed capacity limitation analysis in a public tertiary hospital to provide insight into the relationships between factors limiting capacity during the early phase of the Covid-19 pandemic. We argue that our findings are generalizable to other tertiary public hospitals since our case possesses common characteristics of this type of hospitals such as professional silos and fragmentation of responsibilities along interdisciplinary patient pathways.

We conduct twenty-two in-depth interviews with informants who engaged in the capacity planning and crisis response during the first wave of the Covid-19 pandemic in spring 2020. We group the collected interview data into categories of capacity limitations and provide additional insights into the effect of hierarchical or functional levels through a correspondence analysis.

We find that the most serious types of capacity limitations were either related to staff or information. The staff dimensions included both a lack in number of employees but also insufficient skill levels due to lack in training. Capacity limitations due to information-related aspects included unavailability, incorrectness, delay and incompleteness. Middle management and the organizational functions providing specialized treatment felt most exposed to these capacity limitations. Furthermore, we find that capacity limitations were dynamic and were perceived differently across the hierarchical levels and organizational functions in the hospital.

Future research on tactical capacity planning should take interdisciplinary patient pathways better into account as capacity limitations are dynamic and systematically different for organizational functions and hierarchical levels. We recommend operations managers in hospitals to focus more on intra-organizational information flows to increase the agility of their organization and optimize their workforce planning with a tactical planning horizon.

IV: Cross-training of nurses during a global pandemic: A two-stage stochastic programming approach

The goal for paper four is to provide a decision-support tool for cross-training of nurses during a crisis with uncertain patient demand and increased risk for absenteeism among nurses. Since nurses are the largest employee group of a hospital and are crucial for effective crisis response, it is essential for hospitals to avoid situations of understaffing both in number of nurses and the nurses' skill set. Understaffing is associated with reduced patient safety levels.

We address this problem by formulating a two-stage stochastic programming model for tactical nurse staffing. Our model divides patient demand into three severity levels of Covid-19 and their required skill level of nurses. We model two staffing decision for the hospital: 1) the tactical decision that defines the number of nurses to be cross-trained and 2) the operational decision that covers the number of nurses to be temporarily hired.

We apply our stochastic programming model to the Akershus university hospital's case during the global Covid-19 pandemic. Our results confirm the understaffing in the ICU that could have been mitigated by cross-training. The simulation experiments show that the value of additionally qualified nurses decreases with a larger nurse base. Moreover, we highlight the effects of cross-training cost and non-treatment cost on the service level.

This study offers valuable insights into operational and tactical nurse staffing decisions under uncertain patient demand and increased risk for absenteeism. While we focus on a single patient pathway and chose one employee group only, the results provide interesting insights into the relationships between cross-training, service levels and total cost. To the best of our knowledge, this is the first study that models cross-training as a tactical staffing decision and its consequences on workforce unavailability during the cross-training period.

6. Discussion

The findings of my PhD thesis align well with similar studies conducted in other European countries during the global Covid-19 pandemic. Although the number of Covid-19 patients varied across Europe, many hospitals responded to the Covid-19 pandemic by cancelling and postponing elective appointments (Berger et al., 2022; Winkelmann et al., 2022). Furthermore, it was common to reorganize the hospital by launching a Covid-19 taskforce as well as increasing the ICU capacity. The ICU was a bottleneck in hospital operation in many countries, and it turned out to be decisive at which point in time crisis response was initiated (Berger et al., 2022). Not only was it the number of beds but also the number of medical staff qualified for working on the ICU. At hospitals in Southeastern Norway, the shortage in medical staff became even worse when Norway closed its borders and cross-border workers from Sweden were not able to come to work any longer. Moreover, these hospitals decided to reallocate medical staff internally but not hire additional external staff such as freelancers or medical students, like many hospitals in the United States did (McNicholas et al., 2021). Furthermore, internal reallocation of medical staff could also be observed in other health systems with public funding (Bieńkowska et al., 2021). Some countries, like the Netherlands, not only adopted capacity management, but also implemented a demand management approach, redistributing patients among a regional network of hospitals (De Koning et al., 2022). Demand management was especially effective in balancing ICU demand. However, due to the geographical uniqueness of Norway, demand management would not have been as feasible as in other Central European countries, given the longer distances between hospitals. From my perspective, the only region that could have benefited from demand management would have been the Oslo region where hospital density is relatively high.

Empirical findings from other studies show that hospitals responded differently to the Covid-19 pandemic depending on the time when the first Covid-19 patients arrived at the hospital and how the number of Covid-19 patients developed over time (Bieńkowska et al., 2021; De Koning et al., 2022; McNicholas et al., 2021). While there are similarities such as the reorganization of hospitals, no standard strategy could be identified nationally or internationally (Winkelmann et al., 2022). Many hospitals established a Covid-19 taskforce, while its competencies as well as the background profiles of their respective members differed. In Norway, the stock of medical equipment was continuously monitored, and the regional health authority rationed and centrally managed the medical equipment. Interestingly, my own empirical research does not identify supply chain challenges related to personal protective equipment or infrastructure as a limitation to crisis response, although I had expected to find this a priori. However, Norway has been one of the few countries in Europe that did not recommend the use of masks in public transportation or closed environments, which influenced the overall consumption (OECD, 2020).

Unlike "normal" disasters (which are often short-term and require quick decision making), the global Covid-19 pandemic required a crisis response that exceeded the available surge capacity. Pandemic plans provided a framework how crisis response should be performed (Helsedirektoratet, 2019). While the uncertainty in availability of medical equipment and changes in the infrastructure was well documented and managed, the operationalization of staffing decisions from pandemic plans could be improved. For instance, due to travel restrictions by the government, some medical staff were prevented to work, which had not been expected in the pandemic plans. These unique developments put additional pressure on Norwegian hospitals, especially those close to the Swedish border, and increased the need for updating the plans. This shows that the staff dimension should receive more attention in crisis management; in the present case it turned out to be the critical factor in responding to the crisis. Furthermore, crisis management measures by the government, such as travel bans and closure, of schools should not decide in isolation but should be better aligned with the requirements by the affected health organizations. Therefore, I would argue that coordination is required not only with internal stakeholders but also externally with authorities and other affected organizations. Since a hospital is a pluralistic organization (with diverging interests and many local decisions) that fosters autonomy but risks fragmentation, it is essential to facilitate coordinate corporate crisis response. It might be that during a global pandemic also staff needs to be centrally managed, which would require standardization of a hospital's processes. A first step could be for hospitals to standardize processes across departments to facilitate internal mobility of medical staff.

Moreover, I would argue that crisis management research should consider empirical insights from the Covid-19 pandemic to update existing models and frameworks. While current frameworks define a crisis as a linear process, I argue that a cyclical perspective is necessary since hospitals need to continuously improve their crisis response during future crises. Pandemic planning should be performed on experiences from similar situations and not only on request by regulatory authorities. Therefore, it is important to analyze the Covid-19 pandemic from a retrospective during the post-crisis and identify the lessons learned. These insights could also support crisis managers in future pandemics to better respond to a creeping crisis. However, one has to find an adequate balance between preparing for crisis and staying flexible to respond to crisis (McKenna et al., 2023). For instance, Norwegian pandemic plans do not explicitly state how stakeholders both internally and externally should be informed (Helsedirektoratet, 2019). Due to digitalization, access to information becomes easier and more convenient, which should be considered in crisis communication (Tuckermann et al., 2012). Therefore, I argue that crisis response frameworks should be adapted to technological advancements as the hunger for information during a crisis appears to grow with easier access to information. Therefore, hospitals are required to adapt and make information access easier while maintaining their leading role in providing information about the crisis. If not, stakeholders may consult sources that provide instant information but with a lower quality. This contradicting information can create confusion among its recipients.

Another approach that the literature offers are decision support tools and training for crisis response (Cesta et al., 2014; Yigitcanlar et al., 2022). Compared to a crisis response framework, decision support tools can enable flexible adaptation during a crisis and offer the possibility for crisis decision makers to link decisions to their consequences. Especially during a pandemic when the consequences of decision may become only effective after days or weeks, these tools can support crisis managers. For instance, hospitals' resource planning decisions can be enhanced by running simulations with several developments of the spread of Covid-19 within the catchment area (Bartz-Beielstein et al., 2020) However, the input data or information for the models or simulations needs to be available or assumed a priori. However, these approaches require a simplification of reality as otherwise, they would take too long to provide a practical solution. Therefore, the purpose of the decision support tool needs to be defined beforehand. Moreover, simulating crises and train for them like in the military or with firefighters. Other than decision support tools that increase decision quality, I would argue that training increases decision speed due to familiar situation in naturalistic decision making (Klein et al., 1986). Furthermore, I would argue that internal communication becomes less relevant as everybody can easier make sense of the situation and unavailable team members can easily be replaced as everybody understands the roles, which are standardized like in the military. Therefore, I argue that during crisis response in hospitals we need to break up silos and think crisis response from a more functional perspective, where resources can be shared between departments and divisions.

7. Conclusion and contribution

My PhD thesis contributes to the body of literature on healthcare crisis management during a pandemic in three distinct ways. First, it presents one of the few empirical studies on the impact of creeping crises such as the Covid-19 pandemic on hospital processes. Applying concepts from operations management, this PhD thesis proposes an integrated approach to crisis response. Instead of solely focusing on a single type of process, I include management and support processes. For instance, the necessity to separate infectious and non-infectious patients for the containment of the Covid-19 required CDM, tactical capacity planning and crisis communication. This methodological approach allows me to shed light into sources of capacity limitations and their relationship between each other. Understanding the most limiting factors to capacity provides a basis for improved crisis response. Since I study an extreme case, inefficiencies exacerbated compared to a normal operation. Consequently, the identification of limiting factors become more distinct and apparent.

Second, applying methods from the operations research domain such as stochastic programming to the field of crisis management offers a structured and analytical approach. The two-stage stochastic programming model could serve as a decision support tool for workforce planning, providing a more robust mechanism for coping with uncertainty. In the study on CDM, I discover that a hybrid strategy combining normative decision-making and naturalistic decision-making is superior compared to a pure experience-based strategy. However, the effectiveness of analytical strategies to crisis response is contingent upon the type of crisis. For instance, a mass casualty incident may occur without any forewarning, while an outbreak of an infectious disease or extreme weather events can often be predicted. The latter type of crises offers an opportunity to use analytical tools. Consequently, this PhD thesis underscores the value and applicability of methods from the operations management and operations research domain in healthcare, with the potential to enhance crisis response effectiveness.

Third, this PhD thesis exemplifies a shift in the research focus in crisis management from crisis preparedness to crisis response. While crisis preparedness in the form of pandemic plans on various levels of the health system are available, the operationalization of these plans should not be overlooked. In turn, the findings of my PhD thesis may provide insights on the development of pandemic plans, which need to be coordinated between granularity levels. I take an intra-organizational perspective on tactical capacity planning, which supports effective crisis response. Since interdisciplinary patient pathways become more common in the future, this approach is expedient than individually managing capacity in single departments. Therefore, integral capacity management should also be applied during crises.

Besides the theoretical contribution, I would like to highlight the value for practitioners. Operations managers in hospitals can use the findings to enhance crisis response. Understanding the relationships between different process types, mitigation actions for crisis response can be coordinated. Furthermore, monitoring the most capacity-limiting factors is essential for the effectiveness of crisis response. Even optimal workforce planning does not lead to maximum effectiveness when internal crisis communication is insufficient. For instance, when staff are reallocated to affected departments but neither trained for nor informed about their new roles. Therefore, the 4Cs in crisis management should be regarded as interrelated and should be evenly managed. At the same time, effective crisis response is individual for each crisis, and pandemic plans should be regarded as guidelines, which can be iteratively updated rather than blueprints.

8. Reflections and future research

Having presented the main contribution both practical and theoretical of this thesis, I would like to reflect upon the findings and provide directions for future research. Since the studies are based on data from up to two case hospitals, the generalizability of the findings might be somewhat limited. Furthermore, I choose to study public hospitals in the same region. The effect of different modes of financing and different structures of the health system cannot be captured based on such a design. Most data I use are static, providing a snapshot of the early phase of the Covid-19 pandemic: findings might change if later phases are included. While I analyze relationships of crisis response strategies, choice of communication channels on operational performance, additional research would be required to understand causality between these aspects. Moreover, action research as a suitable research design would be needed to evaluate the proposed decision-support tools for validity and allow to analyze the relationships between the 4Cs in crisis management. Another possibility to capture the temporal perspective would be the analysis of process data such as event logs to better analyze the situation. As we have identified pandemic plans provide more of a framework rather than a blueprint for crisis response, it would be interesting to analyze which parts of the framework are already well operationalized and where there is still room for improvement. Reorganizations, such as the launch of a Covid-19 taskforce, result in process modifications. Therefore, crisis managers need to understand whether employees adhere to the changes to provide support and guidance where needed, especially in a fragmented and complex organizations like hospitals. This approach would not provide reasons for deviation or variation in the processes but would allow benchmarking of processing times and prediction of future capacity utilization.

Future research is required to analyze how new technologies can support hospitals in operationalizing their pandemic plans. For instance, internal crisis communication can be based on chat bots that provide individualized and timely information for hospital staff. Thus, changing from pushing the information top-down, required information can be requested by staff and pulled as a self-service. Tactical resource planning using stochastic programming can be enhanced by reinforcement learning methods. Multi-stage decision models for crisis response can expand current two-stage decision models. In conclusion, there is a pressing need for further research to examine how crisis response strategies influence the quality of treatment and patient safety. While this PhD thesis scrutinizes the crisis response during the Covid-19 pandemic from an operations management viewpoint, it is crucial to comprehend how these findings correlate with levels of patient safety and treatment quality. This understanding is integral to provide hospitals with the necessary support to respond effectively to crises. The inevitability of crises, whether they be in a few months, years, or even decades, underscores the imperative of improved crisis preparedness. These extraordinary situations require extraordinary solutions and a deeper understanding of the dynamic interplay between crisis management strategies, patient safety, and treatment quality.

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Paper 1: Crisis decision-making in hospitals - An analysis of the Covid-19 pandemic in Norway

Crisis decision-making in hospitals

An analysis of the Covid-19 pandemic in Norway

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Acknowledgement

We would like to thank Jørgen Madsø, Kaspar Akilles Lilja, Therese Seljevold and Tilde Midtvedt who contributed to the data collection at the case hospital. Furthermore, we express our gratitude to all informants who were willing to contribute to this study, especially our main contact persons at the case hospitals.

Declaration of interests

We received no external funding for this study. The authors declare no competing interests of relevance to the content of this article.

Abstract

Purpose: Matching the moving target of patient influx and coping with uncertainty during a creeping crisis such as the Covid-19 pandemic is challenging but crucial for effective crisis response. There is still limited understanding on the nature of crisis decision-making as empirical studies in the field are scarce. Therefore, we investigate crisis decision-making processes and relate them to the crisis response.

Design/methodology/approach: We perform a comparative two-case study, conducting nine interviews with informants actively participating in the crisis decision-making processes during the early phase of the Covid-19 pandemic. In a second step, the interview data is related to information on crisis response and operational performance.

Findings: The findings of our study are twofold. Firstly, we cannot identify a standard between the hospitals in terms of crisis decision-making. Secondly, we can conclude that a more experienced-based approach relates to more days in higher preparedness level. As a result, operational performance might be reduced and the number of patients waiting for treatment increases.

Practical implications: We recommend that crisis managers adopt a mix between different crisis decision-making strategies, allowing the advantages of each strategy to complement each other. However, adopting a hybrid crisis decision-making strategy would necessitate a shift in the composition of the hospital's crisis management team to include additional data competencies along with medical expertise.

Originality/value: Our study represents one of the few empirical studies that investigates crisis decision-making strategies and to the best of our knowledge we are the first who relate the crisis decision-making strategies to crisis response and operational performance.

Keywords: Crisis decision-making, hospital, naturalistic decision-making, healthcare

Paper type: Research paper

1. Introduction

The global Covid-19 pandemic as a creeping crisis put healthcare services under exceptional pressure (Boin *et al.*, 2020; Macnamara, 2021). Particularly in the early phase of the Covid-19 pandemic, crisis managers faced two uncertainties when temporarily setting the hospital's capacity to patient demand: the number of Covid-19 hospitalizations and their length of stay. Matching the moving target of Covid-19 patients required effective tactical capacity planning in hospitals. Both organizational re-structuring and reallocation of medical staff to affected departments like the intensive care unit ensured an effective crisis response (Donelli *et al.*, 2022; Da Ros *et al.*, 2024). Furthermore, mobilizing additional personnel resources by postponing or canceling elective appointments became possible by increasing the hospital's level of preparedness (Helse Sør-Øst, 2023). Therefore, defining the preparedness level played a crucial role in responding to the Covid-19 crisis. Interestingly, there was a need for many ad-hoc decisions despite hospital had pandemic plans or more general disaster plans in place (McKenna *et al.*, 2023). However, these plans tended not to provide ready-made blueprints. Consequently, crisis managers lacked experience in crisis decision-making (hereafter named as CDM) strategies to operationalize pandemic plans. Arguably, the Covid-19 experience has shown the need for better integration of CDM into crisis management (Michenka and Marx, 2023).

The decision science literature distinguishes between a normative and a naturalistic "mode" of decision making, which are also applicable to CDM (Cardona *et al.*, 2021; Debnath *et al.*, 2020; Lehto and Nanda, 2021; Okoli and Watt, 2018). While naturalistic decision-making (hereafter named as NDM) is faster than a normative approach, it is also more vulnerable to biases, particularly in clinical settings (Kayman and Logar, 2015; Marino *et al.*, 2020; Martínez-Sanz *et al.*, 2020; Okoli and Watt, 2018). These characteristics create a trade-off between decision speed and decision quality. However, there is yet not consensus among scholars which approach is expedient for crisis managers in hospitals during a creeping crisis like a global pandemic for effective crisis response.

Using the Covid-19 pandemic as a context, our comparative two-case study of hospitals in Norway contributes to the field CDM in a twofold manner. First, we analyze what CDM approach each hospital followed during the early phase of the Covid-19 pandemic and compare them with each other. Second, we investigate the relationship between CDM approaches and crisis response including its effect on operational performance. These insights will support crisis managers to better understand CDM as a crucial aspect for effective crisis response and enhanced tactical capacity planning in a creeping crisis.

2. Literature Review

2.1. Crisis decision making processes

The lack of crisis preparedness during the Covid-19 pandemic showed that crisis management extends beyond the development of pandemic plans. It also demands the definition of CDM approaches to operationalize and adapt existing pandemic or disaster plans (Michenka and Marx, 2023). Crisis decision theory as part of the decision science literature focuses on decision-making during crises. Boin (2008) claims that every organization should have a standard operating procedure in place for CDM. Existing frameworks regard CDM as a linear multi-stage process. For instance, Sweeny (2008) finds that the CDM theory includes a three-stage framework comprising of the following stages: 1) assessment of the crisis severity, 2) determination of a crisis response options and 3) evaluation the decision options. Furthermore, a widely applied framework is the OODA cycle, which was introduced by colonel John Boyd in the mid-1950s (Richards, 2020) and includes four steps for decision-making: **o**bserve the situation and collect available information, **o**rient – contextualize the collected information to the situation, **d**ecide based on the findings from the observation and orientation phase and **a**ct accordingly. This cycle provides a universal strategy for decision-making in uncertain environments and under time pressure, such as crises. While the OODA cycle provides a rational approach to CDM, the role of heuristics should not be neglected, particularly in relation to intuitive decisions (Sayegh *et al.*, 2004). Finally, the OODA cycle provides a universal framework for practitioners but does not specify the cognitive decision process.

Let us now turn to the two approaches of CDM. Unlike normative approaches, which prioritize an optimal and rational decision based on comprehensive information, naturalistic approaches recognize human limitations in decision-making, for instance in processing available information or generating decision options (Lehto and Nanda, 2021). These cognitive limitations may be overcome by heuristics (Tversky and Kahneman, 1974). The concept of NDM can be traced back to the 1980s, when Klein *et al.* (1986) conducted a study on decision-making in a natural setting with firefighters at the scene. They discover that firefighters facing an uncertain and time-critical context rely on their experience rather than engaging in the evaluation of decision options. Based on this finding they propose a recognition primed decision model for CDM (Klein *et al.*, 1986; Nehmet and Klein, 2011). The model is based on the identification of known patterns and perceptual cues of the situation. In a next step, the decision maker chooses the most similar option that is plausible. In contrast, normative approaches assume complete information about the situation such that the decision maker is able to evaluate the consequences of all possible options to reach an optimal decision (Vazsonyi, 1990). Therefore, a normative approach to CDM requires the collection of high quality data to be effective (Comfort *et al.*, 2020). We would like to stress that there is an ambidexterity between these two CDM approaches. Neither NDM nor normative approaches should be regarded in isolation but more as opposites on a decision continuum (Klein, 2008).

While a normative approach NDM facilitates quick decision-making it is not without deficiencies. Falzer (2018) argues that following a naturalistic approach helps to reduce the problem's complexity, but might lead to suboptimal decisions. Gardell (2024) notes that an exclusive focus on experiences without triangulation might increase the risk for biases. Moreover, cognitive biases are strengthened and become more visible during crises (Norris *et al.*, 2020). These disadvantages of NDM can be overcome by providing feedback on decision-making or training of crisis situations. Disclosing decision outcome variables as feedback allows crisis decision makers to adapt crisis response and adjust (Yigitcanlar *et al.*, 2022). Another approach to increase CDM performance next to decision support tools is the training and preparation of crisis decision makers for new crises. Cesta *et al.* (2014) provide a training tool that replicates crisis situations and focuses on timely decision-making when adaption of existing pandemic or disaster plans becomes necessary. Based on these insights, crisis decision makers can accumulate relevant experiences in CDM that may improve decision quality as the training set-up can simulate several crisis scenarios.

2.2. CDM in hospitals during the Covid-19 pandemic

In relation to the recent global Covid-19 pandemic, research on CDM within hospital environments has gained momentum. Temporarily setting the hospital's capacity to accommodate an increased influx of Covid-19 patients was a critical component for effective crisis response. Cardona *et al.* (2021) conducted a review of guidelines concerning the allocation of staff to the intensive care unit and the triage of patients. They examined eighty protocols from hospitals in different countries, finding a lack of consensus in these treatment guidelines. In addition, existing pandemic plans proved challenging to operationalize, requiring the implementation of command control structures (McKenna *et al.*, 2023). Such organizational re-structuring shifted decision power to a single decision maker and facilitated quicker crisis response compared to a consensus approach when stakeholders would have been involved into CDM. Further evidence of the need to shift toward centralized CDM was identified by Donelli *et al.* (2022) within an Italian hospital setting. These perspectives are contrasted by Joniaková *et al.*

(2021) who posit that cognitive diversity can enhance both the speed of CDM and overall team CDM performance. Therefore, CDM does not necessarily need to be centralized but persons with different skills and backgrounds should reach a shared decision. However, Joniaková *et al.* (2021) asked the heads of each department to measure team performance using a score, which might be individually dependent. Furthermore, Joniaková *et al.* (2021) suggested that particularly in the absence of quantitative information, cognitive diversity may reduce cognitive biases. The rationale behind this organizational re-structuring and shifts in power of CDM remains somewhat unclear as well as the impact on operational performance. Da Ros *et al.* (2024) supplemented existing research on CDM by providing a hierarchical perspective. In a single case study conducted within an Italian healthcare organization, they concluded that CDM processes are hierarchically dependent, with decisions made on the macro level significantly influencing CDM on the meso and micro levels. Unlike previous studies on CDM that relied on a single source of information, Da Ros *et al.* (2024) utilized patient pathway data to triangulate whether the decision to cancel or postpone elective appointments was adhered to. As quantitative information became available during the Covid-19 pandemic, normative CDM strategies were enabled. Therefore, Debnath *et al.* (2020) created an emergency machine learning algorithm to improve decision-making for medical staff in managing hospital capacity and patient treatment, thus enhancing the quality of CDM. Another aspect that needs to be considered when measuring the performance of CDM is the unique organizational structure within the healthcare sector. Hospitals are pluralistic and internal stakeholders enjoy a high degree of autonomy, which hinders organization-wide CDM (Tuckermann *et al.*, 2012). This may result in contradicting or redundant crisis responses due to distinct CDM strategies even if each decision-making process itself is performative.

2.3. Aims of the study

The Covid-19 pandemic offers scholars the possibility to empirically analyze CDM, often in single case studies. However, there is yet little understanding of the relationship between CDM strategies in hospitals and its impact on the effectiveness of crisis response. Therefore, our study contributes to the literature of CDM by comparing the CDM strategies of two hospitals and relates these results to crisis response in terms of duration in higher preparedness level and operational performance indicators. These insights will enhance the understanding of CDM during a creeping crisis and support crisis decision maker in hospitals to improve crisis response and resilience.

3. Methodology

3.1. Case description

The underlying two case hospitals for our study are both located in the Oslo region. Hospital A, a tertiary public hospital with approximately 10,500 employees and Hospital B, a regional hospital with around 1,200 employees. Hospital B is part of a regional healthcare network encompassing other hospitals as well. When the global Covid-19 pandemic reached Norway in March 2020, the regional health authority for Southeastern Norway (Helse Sør-Øst) requested that the two case hospitals submit plans outlining how to increase capacity and respond to a potential increased influx of Covid-19 patients based on epidemiological scenario analyses (Folkehelseinstituttet, 2020). Due to their geographical vicinity, the hospitals faced similar challenges in terms of the number of hospitalized Covid-19 patients. Thereupon, the two case hospitals for our study composed the necessary plans and transitioned into an emergency organization by raising their preparedness levels.

Preparedness levels are standardized by the regional health authority of Southeastern Norway and can be categorized into three distinct levels: green, yellow and red. The lowest level, green, indicates the establishment of a task force and signifies that necessary support can be received. The yellow level empowers the hospital to mobilize additional resources including reallocation and demanding extra work from employees. Red as the highest level is characterized by a substantial modification in the hospital's operations with significant human resources mobilized to cope with the situation. Notably, the red level is only viable for a short period (i.e. few days) following events such as mass accidents (Helse Sør-Øst, 2023).

Hospital A increased the preparedness level on 9th of March 2020 and established a tactical Covid-19 taskforce, which consisted of six doctors. This mitigation action was aimed at enhancing crisis response by streamlining information flow and chains of command. This tactical Covid-19 taskforce was supported by an operations committee, while all strategic decisions remained in the top management's competence. Furthermore, Hospital B set up a local tactical Covid-19 taskforce on 3rd of March 2020, which consisted of up to twenty-five persons having both an administrative and medical background. The strategic decisions for Hospital B were made on the network level in a strategic Covid-19 taskforce. To conclude both hospitals shifted the decision power to a specifically established Covid-19 taskforce to increase agility and better respond to the crisis within an interval of only six days. However, the composition of this Covid-19 taskforce differed in the number of persons, professions and backgrounds.

3.2. Data collection

We decided to collect data from two different sources: 1) qualitative information from semi-structured interviews with informants who actively participated in CDM and 2) selected financial data from the annual reports (2019-2021) of each hospital. Furthermore, we triangulated the information from the interviews with the preliminary plans from the hospitals describing their strategy to increase capacity for an increased influx of Covid-19 patients (created in April 2020). These plans encompassed a description of mitigation actions to cope with the pandemic situation, such as the adapting the hospital's operation and scheduling trainings for accumulating necessary Covid-19 competencies among medical staff.

At each case hospital a main contact person supported us in the purposive sampling process, helping us identify key informants. We defined active participation in the CDM process during the initial phase of the global pandemic in March/April 2020 as inclusion criteria. In total, we interviewed nine informants: seven from hospital A and two from hospital B. The underlying interview guide was pilot tested with two informants from hospital A to assure the adequate use of medical terminology and concepts. The one-hour interviews were conducted in February and March 2021 and informants were asked to recollect the Covid-19 situation during March/April 2020. Due to Covid-19 measures, all interviews were conducted virtually, and we allowed the informants to choose their preferred communication platform (either Zoom, MS Teams, Skype or telephone). Furthermore, we decided not to record the interviews, trying to encourage the informants to answer more freely. Instead, we ensured that at least two other researchers were present during the interview to take notes. Rutakumwa *et al.* (2020) argue that this method does not negatively impact data quality compared to a recorded interview. Prior to each interview, we informed all participants about the study's purpose and obtained their consent. Ethical approval was not necessary as the collected information was immediately anonymized to protect the informant's privacy.

Second, we extracted data from annual reports spanning a three-year period from 2019 to 2021. The data for 2019 defines the baseline followed by two years during the Covid-19 pandemic, which ended in 2021 when Norway returned to a normal life again (Norwegian Government, 2021). We selected the number of days in higher preparedness level and operational performance indicators from the annual reports like activity in DRG (diagnostic-related groups) -points, average patient waiting times for standard treatment (as a measure for the backlog). The standardized framework of DRG provides a basis for categorizing different patient groups and allows benchmarking performance of patient clusters in terms of use and cost of hospitals (Fetter, 1991).

3.3. Data analysis

After we had conducted the nine interviews, we merged the transcripts created by the different researchers who had taken notes during the interviews, thereby enhancing the completeness and quality of the collected information. In cases of disagreement, we recontacted the respective informant and asked for clarification. This strategy allowed us to further increase the quality of the data. The data were analyzed in two steps:

- Qualitative content analysis and quantification,
- Descriptive comparative analysis of both qualitative and quantitative information

In the qualitative content analysis step, we coded the transcripts along the OODA cycle for CDM (Richards, 2020). Hereby, we categorized the data into a naturalistic or a normative CDM strategy as follows. To collect information and observe the situation, the decision-maker can either seek available data or consult explicit (e.g., pandemic plans) or tacit knowledge of previous experiences. During the orientation phase to contextualize, the decision-makers may either rely on their experiences or perform scenario analyses as a normative approach. Lastly, CDM can happen centrally by an experienced expert or a group of decision makers or dispersed when guidelines for CDM are provided.

In the quantification step, we constructed a matrix with binary variables for each informant to indicate whether a CDM strategy for the selected three phases was or was not mentioned. Based on this matrix, we calculated the share of informants per CDM strategy, which serves as an indicator for the balance of normative and naturalistic CDM each hospital follows along the phases observe, orient and decide. We chose to visualize the shares of informants in radar charts, a suitable visualization method for comparative studies (Rubinson, 2019). Finally, we related the characteristics of CDM strategies per hospital to their outcomes in terms of number of days in higher preparedness level, DRG-points and average waiting times.

4. Results

4.1. Comparison of CDM strategies.

Overall, we observe that Hospital A and Hospital B adhere to different CDM strategies (see Figure 1). We would like to note that the dimensions for the “observe” and “orient” phase should be regarded as characteristics of the respective CDM strategies since an informant might mention both data-driven and existing pandemic plans as a basis during these phases. Nevertheless, we identify a clear distinction of the decision phase. Informants portrayed it as either centralized or dispersed, but never both.

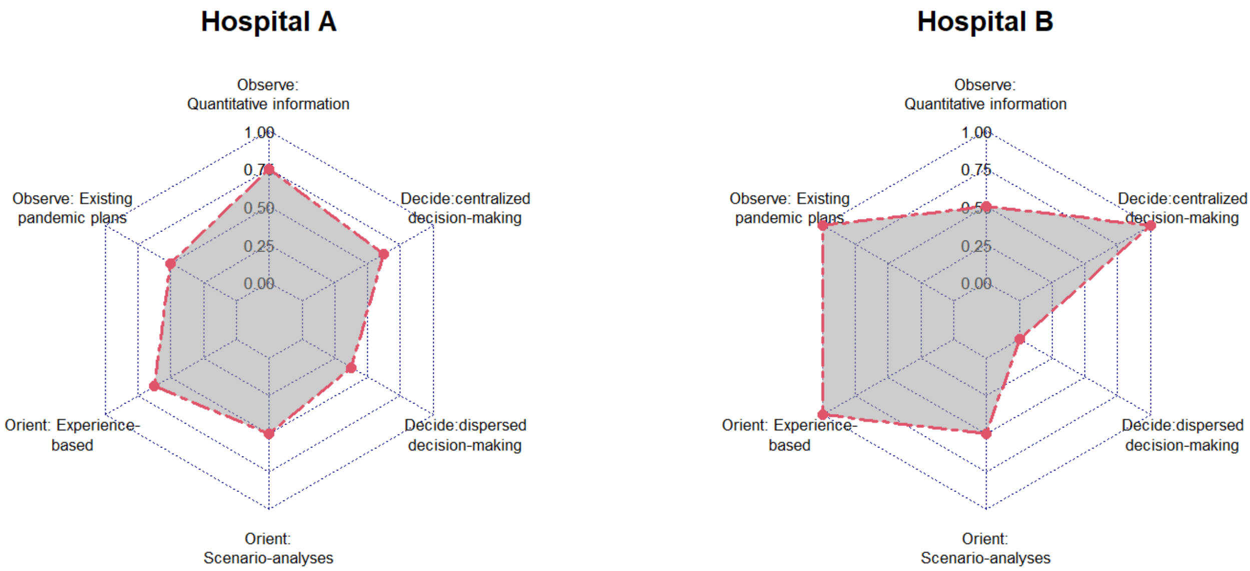

Figure 1: Characteristics of CDM strategies per hospital in the share of informants along the decision phases: "observe", "orient" and "decide".

First, 75% of informants from Hospital A said that they followed a data-driven approach to observe the situation in contrast to Hospital B (50% data-driven), which placed a greater emphasis on existing pandemic plans. These plans outlined potential mitigation actions and provided a framework for CDM. Differently, Hospital A created a Covid-19 dashboard containing relevant information such as the number of hospitalized Covid-19 patients or the number of medical staff in quarantine. These numbers supported crisis management by indicating the urgency for crisis response. Second, half of the informants in both hospitals noted that they utilized scenario analyses. Moreover, more informants from Hospital B adopted a more experienced-based approach during the "orient"-phase. One of the reasons for this CDM strategy is found in the composition of its taskforce. It included medical personnel who had experienced a pandemic situation (Ebola outbreak in Africa) before, enabling the Covid-19 taskforce to draw upon past experiences in crisis response. Interestingly, CDM was more centralized at Hospital B compared to Hospital A. While informants at Hospital B reported that decisions were made by the Covid-19 taskforce only, informants from Hospital A used trigger-based action plans that were self-explaining. Consequently, decisions could be made by each individual employee as it was possible to make informed decisions based on relevant information (triggers) and guidelines.

Let us now compare the crisis response resp. the "act"-phase of Hospitals A and B. Using the information from our interviews and documentation on existing pandemic plans of each hospital, we describe their crisis response actions and highlight both similarities and unique features for each hospital.

Four decisions for crisis response were common in both hospitals. First, crisis managers determined additional departments to be re-functioned for treatment of Covid-19 patients. Second, the inventory of medical equipment, such as respirators and personal protective equipment, was made transparent and monitored. Third, training plans were established to ensure that the medical staff had sufficient expertise in treating Covid-19 patients. Fourth, a possible cooperation with partner hospitals was being considered and broadly outlined.

Hospital A, being a tertiary public hospital, was supposed to treat more severe cases of Covid-19 patients compared to Hospital B. Therefore, Hospital A faced limitations in transferring patients to partner hospitals without compromising the treatment quality. Moreover, Hospital A differentiated between a strategic and a tactical Covid-19 taskforce to define the areas of responsibility within the organization, but we identified a collaboration between them. The increase in medical staff in the most affected departments in Hospital A was achieved by reallocation, rather than recruiting external medical staff on an ad-hoc basis. For Hospital B we identify two unique aspects of crisis response. Hospital B performed a qualitative risk management by developing a matrix that considered both the probability of occurrence and the impact of undesired events. This matrix assisted decision-makers to prioritize crisis response. Moreover, Hospital B considered a reduction in nurse-to-patient ratio to cope with a potential high influx of Covid-19 patients. The plan was to reduce the nurse-to-patient ratio from one to 0.5 in the intensive care unit when necessary.

Another measure for crisis response is the duration each hospital decided to operate in a higher preparedness level. Table I shows the share of days per year in green and yellow preparedness level per hospital during the years 2020 and 2021 amidst the Covid-19 pandemic. Overall, Hospital B deviated from normal operation for a longer period than Hospital A in both years and stayed longer in preparedness level “yellow”. As mentioned already, higher preparedness levels had significantly impact on the hospital’s processes, hence on operational performance.

Table I: Percentage of days in higher preparedness levels for each hospital per calendar year 2020/21

	Hospital A		Hospital B	
	2020	2021	2020	2021
Level «green»	*15.3%*	*5.5%*	*72.1%*	*36.2%*
Level «yellow»	*9.6 %*	*17.5%*	*10.4%*	*21.4%*
Total	*24.9%*	*23.0%*	*82.5%*	*57.6%*

4.2. Crisis response in relation to operational performance

Figure 2 illustrates the activity level in DRG-points per hospital and the average patient waiting time until standard treatment between 2019 and 2021. We designate 2019, the year prior to the Covid-19 pandemic, as the baseline for our comparative analysis. Therefore, all subsequent data for the years 2020 and 2021 are referenced against this baseline, set as 100.

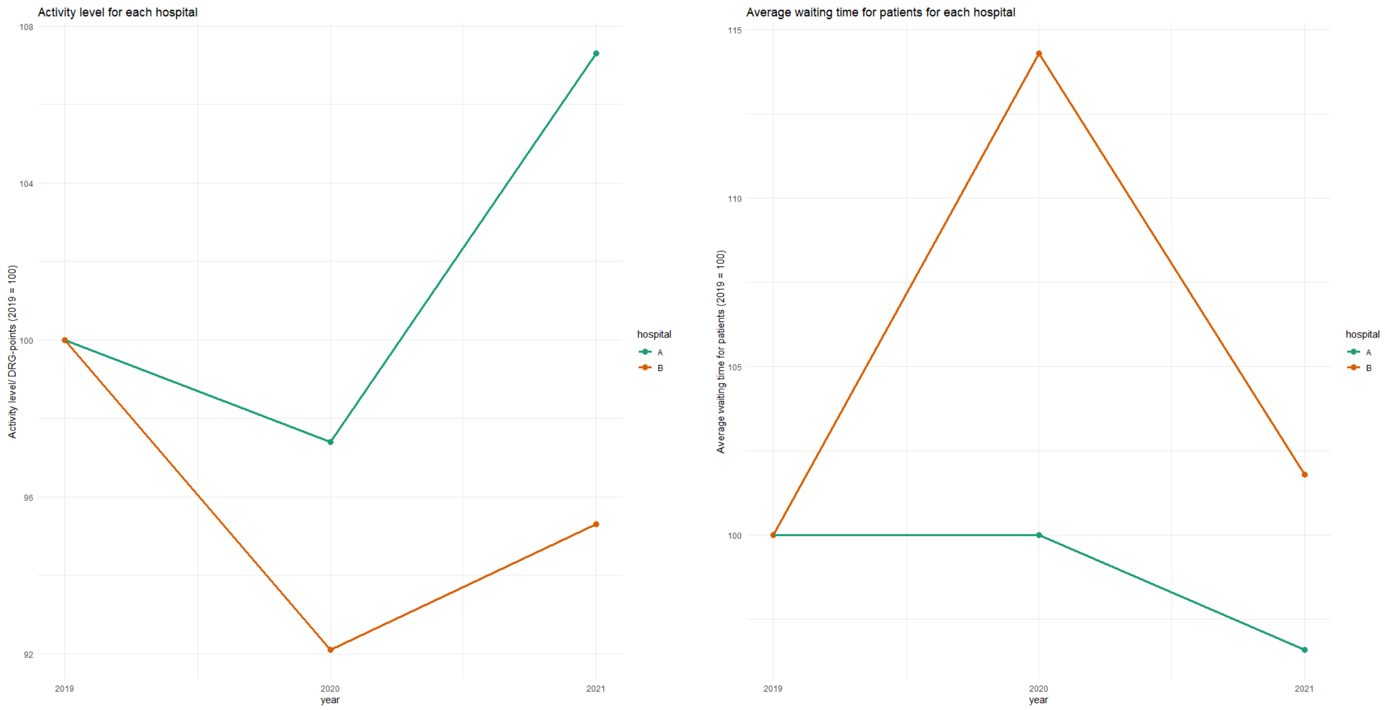

Figure 2: (1) Activity level registered in DRG-points and (2) average waiting time for patients until beginning of standard treatments for each hospital

Hospital B exhibited an approximately 8% reduction in DRG-activity from 2019 to 2021 and failed to recover to pre-Covid-19 levels until 2021. Differently, Hospital A experienced a smaller reduction (3%) in DRG-activity during 2020 compared to Hospital B. By 2021 activity levels at

Hospital A were 7% above pre-Covid-19 figures. Another metric for operational performance is the average waiting time since it indicates the backlog for each hospital. Hospital A successfully maintained the average waiting time during the Covid-19 pandemic whereas Hospital B faced a 14% increase. In 2021, both hospitals managed to reduce their average waiting times, which is aligned with higher activity levels. Hospital A even achieved a lower average waiting compared to pre-Covid-19 levels. These selected performance indicators illustrate the relationship between DRG-activity and average patient waiting times. When the hospitals were able to increase activity above arrival rates, their backlog could be reduced. Interestingly, Hospital B faced lower patient demand in 2021 compared to 2019 as the average waiting time could be reduced despite a lower activity.

5. Discussion

Our research reveals a divergence in CDM strategies employed by hospitals in Norway during the early phase of the Covid-19 pandemic. Even though both hospitals received identical information about the epidemiological development from the regional healthcare authority of Southeastern Norway, the types of additional information they gathered to support their CDM varied. Hospital A adopted a comprehensive approach that took various perspectives into consideration such as data, pandemic plans, scenario analyses and previous experiences. Conversely, Hospital B mostly relied on pandemic plans and experience. Other than hospital A, Hospital B fostered centralized decision-making by the Covid-19 taskforce. We find that a the CDM strategy by hospital B with a more naturalistic character was associated with longer periods of sustaining a higher preparedness level. This higher preparedness level directly impacted the hospital's operation due to the mobilization of additional personnel resources, causing a decrease in DRG-activity. Consequently, the average waiting time per patient for treatment increased when activity felt below the average arrival rate of patients. Therefore, we can conclude that a more naturalistic CDM strategy relates to reduced operational performance.

Other than previous studies on crisis response, which predominantly focus on leadership styles for CDM, our analysis extends to the CDM process itself (Donelli *et al.*, 2022; McKenna *et al.*, 2023). This approach augments our understanding of the relation between CDM strategies and crisis response. We find that a more naturalistic CDM strategy is associated with reduced operational performance during crisis response as opposed to a more normative CDM strategy. This finding is aligned with previous studies on NDM, which suggest that a naturalistic CDM strategy may be influenced by anchoring effects and biases (Gardell, 2024; Kayman and Logar, 2015; Martínez-Sanz *et al.*, 2020). It is imperative to understand that the CDM strategy should not be perceived as static throughout the crisis phase. Instead, it should be regarded as an iterative process that continuously improves CDM (Hugelius *et al.*, 2021; Michenka and Marx, 2023). During the initial phase of a crisis, a naturalistic CDM strategy might prove advantageous when immediate crisis response is required. However, as the crisis progresses and more information becomes available, a more data-driven and optimization CDM strategy may prove more expedient. Katsikopoulos *et al.* (2022) propose a combination of both approaches by creating an optimization model that incorporates intuition into the optimization algorithm. However, both the availability and the quality of information, which form the basis for a normative CDM strategy, must be sufficiently high. Lack of information could render a normative CDM strategy ineffective. In circumstances where information is either unavailable or of insufficient quality, crisis managers tend to sacrifice, which means that they decide even when not all information is available (MacDonald *et al.*, 2011).

In a creeping crisis like a global pandemic, the advantage of quick decision-making inherent in a more naturalistic CDM strategy might not be as beneficial compared to other types of crises like mass accidents or natural disasters (Kayman and Logar, 2015). Unlike mass accidents, the number of individuals affected by a global pandemic can fluctuate over longer time, thereby introducing a dimension of temporal uncertainty to a crisis. This unique crisis characteristic makes our case study unique to contribute to the existing literature. One of the few empirical studies on CDM identifies in total three additional factors – organization, context and personal, that influence the decision-making process (Hugelius *et al.*, 2021). Therefore, we argue that research on CDM should consider these three influential factors of a crisis when following an empirical research design, an approach we have integrated in our study as well.

Given that our two cases are not different from other hospitals in various countries, our study contributes to a more comprehensive understanding of the relationships between CDM processes and crisis response/operational performance (Donelli *et al.*, 2022). Contrary to the findings by Donelli *et al.* (2022), we posit that decentralized CDM might be expedient, particularly when sufficient information is available to make sense of the situation. For instance, Hospital A initiated a trigger-based training of medical staff with action plans, serving as a decision support tool for CDM. Another advantage of decentralized CDM lies in the distribution of responsibilities, which can encourage shared CDM (Simpson *et al.*, 2020). Nonetheless, we agree with Donelli *et al.* (2022) regarding the necessity of a coordinating role for CDM, which could, for instance, be realized through a Covid-19 taskforce.

In addition to providing insights into the CDM process, our study links the type of CDM strategy to crisis response and operational performance indicators. These indicators are widely accepted and standardized in hospitals' financial reporting in Norway. Analogous to the reference document for triage proposed by Cardona *et al.* (2021), we recommend creating a document for outcome variables (resp. operational performance indicators) when studying CDM. Such a set of outcome variables would facilitate benchmarking among hospitals and increase comparability. However, we acknowledge the existence of other relevant factors that influence the outcome of CDM. Therefore, this set of variables should be regarded as a starting point for future research.

We agree with Da Ros *et al.* (2024) who argue that triangulation of healthcare data is crucial for increasing internal validity. Collecting data from interviews, official documentation and annual reports allowed us to increase internal validity. Furthermore. this variety of information sources allows us to draw conclusions and offer recommendations for a more effective and efficient CDM within the healthcare sector.

The findings from our study are based on two specific cases only, which may potentially limit their generalizability to other hospitals. However, we argue that our case hospitals are representative of other hospitals, given the similarity of their organizational structure. Furthermore, the operational consequences of higher preparedness levels are standardized at a national level. Setting up a task force for crisis response is also widely adopted in other hospitals (Donelli *et al.*, 2022). Since we solely focus on one type of crisis, the findings may not be applicable to other contexts like mass accidents or natural disasters. A global pandemic, as a creeping crisis, allows crisis managers to collect information from other countries even before the hospital faces the influx of Covid-19 patients (Boin *et al.*, 2020). Therefore, we conclude that our findings can primarily be transferred to other creeping crises. Finally, the wealth of experiences each decision-maker incorporates into CDM cannot be fully captured by interviews, nor can it be easily triangulated with other information sources. Nevertheless, we argue that a qualitative research design is suitable for collecting such information.

As a direction for future research, we suggest studying the types of information required for effective CDM. Moreover, it would be interesting to analyze whether CDM strategies change during the phases of a crisis and how this relates to crisis response and operational performance. These insights could further to improve crisis response and provide additional practical value to healthcare organizations.

6. Conclusion and practical implications

Our study represents one of the few empirical studies that investigates CDM strategies in relation to crisis response and operational performance indicators during a global pandemic. Based on our comparative two case study, we provide a comprehensive understanding of CDM and conclude that a more naturalistic CDM strategy relates to more days in higher preparedness level. Consequently, the operational performance may be reduced due to mobilizing additional medical staff. Therefore, we recommend that crisis managers follow a blend of both naturalistic and normative CDM strategies, allowing the advantages of each strategy to complement each other. This approach can help mitigate deficiencies such as biases, anchoring effects and tedious decision-making processes. Adopting a hybrid strategy would necessitate a shift in the composition of the hospital's taskforce to include additional data competencies along with medical expertise.

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Paper 2: Internal crisis communication in hospitals -The choice of communication channels and its impact on effectiveness

Internal crisis communication in hospitals

The choice of communication channels and its impact on effectiveness

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Acknowledgement

We would like to thank Jørgen Madsø, Kaspar Akilles Lilja, Therese Seljevold and Tilde Midtvedt who contributed to the data collection at the case hospital. Furthermore, we express our gratitude to all informants who were willing to contribute to this study, especially our main contact person.

Declaration of interests

We received no external funding for this study. The authors declare no competing interests of relevance to the content of this article.

Data availability statement

The data that support the findings are available from the corresponding author upon reasonable request.

Abstract

The Covid-19 pandemic has highlighted the need for effective internal crisis communication (ICC) in hospitals. However, only little is known about how the choice of communication channels influences the effectiveness of ICC. Our case study offers novel insights into this relationship. We performed an in-depth analysis of ICC during the Covid-19 pandemic at a Norwegian tertiary public hospital. We conducted twenty-two in-depth interviews with stakeholders from various hierarchical levels who actively participated in ICC. We mapped the relationships of the actors involved in ICC and performed a social network analysis. The emergency reorganization of the hospital made ICC processes more complex compared to the ordinary line structure of communication, and on lower hierarchical levels several redundant (and not necessarily officially approved) communication channels were used. Moreover, we found that the effectiveness of ICC was reduced by communication channels with speed and bandwidth limits. In contrast, communication channels with a high capability to transmit contextualized information improved the effectiveness of ICC. Since our case hospital shares common characteristics with many other tertiary public hospitals, including fragmentation of responsibilities during crisis response, we use our results as a basis for recommending appropriate communication channels and avoiding a decoupling of ICC between hierarchical levels and professions.

1. Introduction

The global Covid-19 pandemic caused by coronavirus SARS-CoV-2 resulted in the largest health crisis since mid-20th century (Macnamara, 2021). Due to the long incubation period, the Covid-19 pandemic was a creeping crisis with a slow onset (Boin et al., 2020; Ndlela, 2019). Especially in the early phase, marked by high levels of uncertainty, ambiguity and complexity, there was a strong need for crisis communication with the internal and external stakeholders of hospitals. Medical staff had to be informed about changed work instructions for treating Covid-19 patients and the use of personal protective equipment such as masks, but also had to be provided with situational updates on the spread of Covid-19 in society. Effective crisis communication was essential for providing the required psychological support and guidance from superiors (Ruck & Men, 2021). The Covid-19 crisis revealed, and exacerbated, problems with incomplete, poor and inefficient information flow (Blumenthal et al., 2020; Boin, 2008; Leite et al., 2020). In hospitals, deficiencies in crisis communication can have serious consequences, for example when work instructions for treating Covid-19 patients are not sufficiently updated.

In the past, research on crisis communication has focused on communication with external stakeholders. ICC has only recently received attention (Frandsen & Johansen, 2011; Kim et al., 2023; Ruck & Men, 2021). Studies on ICC typically focus on communication strategy, including information content and receiver perspectives (Kim et al., 2023; Madsen et al., 2023). However, crisis management in hospitals can be rather different from crisis management in business organizations or public administration: the hospital's organization is often restructured, and new roles such as crisis communicators are implemented (Boin, 2008; Deverell, 2021). So far, there is only little research on the organization of ICC in hospitals, the choice of communication channels, and the impact of these factors on the effectiveness of ICC.

Experiences gathered during the Covid-19 pandemic offer the opportunity to address this gap. We report a case study at a tertiary public hospital in Norway. Our study aims to contribute to the ICC literature in two ways. First, we investigate the communication network between internal stakeholders in the hospital, including the information shared and the communication channel chosen for this. Second, we analyze what effect the chosen communication channel has on the effectiveness of ICC. Our study aims to provide support for crisis communicators in effectively communicating with internal stakeholders during the acute crisis phase and improve operational resilience.

2. Crisis communication

Berlo's (1960) linear model of communication is also applicable to crisis communication. This model comprises four elements: source, message, channel, and receiver. The responsibility for defining information content, communication channel and receiver lies with the crisis communicator who must tailor messages to the receiver's needs. Organizational structure and culture must be considered to achieve a mutual understanding between crisis communicator and receiver. Crisis communication with internal stakeholders is more intuitive as the crisis communicator already shares their organizational identity (Ma, 2019). This results in different strategies for internal and external crisis communication (Liu et al., 2018; Strandberg & Vigsø, 2016).

The content of crisis communication can be broken down into three categories: instructing information, adjusting information and internalizing information (Kim et al., 2023; Sturges, 1994). Instructing information tells stakeholders how they should respond to a crisis. For instance, changes in work instructions or protective measures for patients need to be shared to align crisis response and precautions. Adjusting information allows crisis communicators to offer psychological support. It is important to make the threat transparent without inciting fear or panic (Noar & Austin, 2020). The intention is to develop a sense of urgency among stakeholders and change the perspective of the organization. Internalizing information allows to maintain the reputation of the organization. Sharing achievements like successful mitigation actions can secure the organization's reputation among society and employees. Since stakeholders may change during the crisis, it is beneficial to provide internalizing information to current and prospective stakeholders, whereas the latter helps to build a crisis-detection network (Ndlela, 2019). While crisis communication during the acute crisis phase is crucial, it is important to note that crisis phases are interconnected, and communication efforts before a crisis can yield tangible or intangible benefits during subsequent crisis phases (Mazzei & Ravazzani, 2011).

2.1. The role of communication channels in crisis communication

The effectiveness of crisis communication is not only dependent on the content but also on the choice of communication channel. Communication channels can be categorized into two types. First, asynchronous channels such as email or documents can convey complex content despite their inability to offer immediate interaction between the sender and receiver. Second, synchronous channels like telephone or face-to-face meetings offer the receiver an opportunity to provide instant feedback. We should note that no communication channel holds superiority over the other (Diwanji et al., 2020). Contrary to health campaigns, which can be effectively managed through a single communication channel, crisis communicators should leverage both asynchronous and synchronous communication channels to reach all stakeholders effectively (Jang & Park, 2018). However, employing different channels either simultaneously or sequentially is not without its challenges. It necessitates strategic planning and maintaining the consistency of the information content becomes imperative (Diwanji et al., 2020; Warren & Lofstedt, 2021).

Dennis et al. (2008) base their model for communication channel characteristics and capabilities on the media synchronicity theory. They highlight conveyance and convergence as the primary communication performance measures, both dependent on the communication channel. While conveyance defines the volume of information being transmitted within a specific time period, convergence describes the information depth to achieve a mutual understanding between the sender and receiver.

Table I: Communication channel characteristics and capabilities (developed from Dennis et al. (2008))

	Dimensions							
Communication channel	Transmission velocity	Parallelism	Symbol sets	Rehears-ability	Reprocess-ability	Information Transmission	Information processing	Synchronicity
Face-to-face	+++	++	+ - +++	+	+	+++	+	+++
Video conference	+++	++	+ - ++	+	+	+++	+	+++
Telephone	+++	+	+	+	+	+++	+	++
Synchronous instant messaging	++ - +++	+ - ++	+ - ++	++	++ - +++	++	+ - ++	++
Synchronous electronic conferencing	++ - +++	+++	+ - ++	++	+++	++	++	+ - ++
Asynchronous Electronic Mail	+ - ++	+++	+ - ++	+++	+++	+	+++	+
Voice Mail	+ - ++	+	+	+ - ++	+++	+	++	+
Fax	+ - ++	+	+ - ++	+++	+++	+	+++	+
Documents	+	+++	+ - ++	+++	+++	+	+++	+

Legend: +: low; ++: medium, +++: high

Table I shows the characteristics and capabilities of selected communication channels. Capabilities include information processing, information transmission and synchronicity, indicating how well a communication channel can achieve a given objective. All other dimensions are classified as characteristics that distinguish a given communication channel from others. Dennis et al. (2008) derive three of their characteristics from Shannon & Weaver's (1964) capacity concept: transmission velocity, parallelism, and symbol sets. Transmission velocity refers to the speed at which a communication channel can deliver information to designated receivers. Parallelism is indicative of the communication channel's width, which is the number of simultaneous transmissions that can take place (e.g., asynchronous email allows multiple senders to transmit information concurrently, while telephone requires serial communication with more than one sender). Symbol sets refer to multiple ways in which information can be encoded on a channel (e.g., face-to-face meeting can utilize gestures and language, while telephone calls are limited to speech only).

Rehearsability and reprocessability are similar characteristics at different stages of the communication process. Rehearsability allows the sender to fine-tune and iteratively refine information content during encoding before its transmitted to receivers. Reprocessability, however, is indicative of the possibility for the receiver to re-evaluate the information after the communication process has been completed. Dennis et al. (2008) claim that convergence requires more information transmission capabilities than information processing capabilities. The opposite applies for conveyance. When multiple receivers are involved, it is beneficial to employ more than one communication channel.

The advent of digitalization, particularly the rise of social media use in organizations, presents novel opportunities for crisis communication including instant feedback loops or message forwarding (Veil et al., 2011). Liu et al. (2018) emphasize that organizations should actively participate in conversations on social media during crises. Otherwise, stakeholders may initiate separate dialogues within these channels, which an organization cannot control. Moreover, new technologies, like chatbots, should be used to enhance crisis communication (Liu et al., 2018; Veil et al., 2011), which is part of the best-practice checklist for crisis communication. These novel communication channels allow for a more timely and transparent information sharing (Barsasella et al., 2022). However, social media channels can lead to decentralized control over information, allowing dialogue and thereby blurring the conceptual line between sender and receiver (Olsson, 2014). While decentralized communication systems often conflict with hierarchical structures, they ensure the inclusion of relevant stakeholders (Olsson, 2014). Additionally, they offer space for improvisation and dialogues to better cope with uncertainty through horizontal listening (Madsen et al., 2023).

2.2. Internal crisis communication

To the best of our knowledge, Frandsen & Johansen (2011) were the first who create a framework for ICC recommending that crisis communication strategies should be contingent upon the crisis phase. Furthermore, they suggest that ICC should incorporate the internal stakeholders' needs to enhance sensemaking of the situation and promote active participation. Therefore, ICC should not only be regarded as a tool to convey instructing information but also adjusting information as an integral part of crisis management. Four communication directions can be distinguished: 1) top-down, 2) bottom-up, 3) horizontal and 4) inside-out. This somewhat reductionist concept of communication directions may not be entirely applicable in complex organizations like hospitals, where the control of information is decentralized and the lines between affiliations and hierarchical roles are fluid (Olsson, 2014). Despite these limitations, formalizing ICC can support crisis response and lay the groundwork for continuous improvement.

Heide & Simonsson (2015) report a case study at a Swedish hospital, identifying five bipolar dimensions that can characterize ICC in a situation: 1) centralized vs. decentralized, 2) pre-planned vs. improvised, 3) internal vs. external, 4) professional vs. organizational and 5) episodic vs. emergent. However, these do neither provide a blueprint for effective ICC nor a possibility to measure the quality of ICC. To address this shortcoming, Adamu & Mohamad (2019) suggest a set of eleven indicators for ICC quality. However, the indicators are based on sender's or receiver's perception and may therefore be misleading if perceptions are misaligned (Mazzei & Ravazzani, 2011). For instance, while employees may criticize the lack of clarity and inappropriate choice of communication channels for instructing information, crisis communicators may have a contrasting view, leading to the impression that crisis communicators are behaving opportunistically even when ICC is well planned. Strandberg & Vigsø (2016), on the other hand, highlight the challenge of information incompleteness for employees, particularly when crisis communicators withhold relevant information. This could potentially hinder sensemaking, giving rise to a dysfunctional culture and rumors.

2.3. Internal crisis communication in healthcare during the Covid-19 pandemic

The global Covid-19 pandemic has shown the need for effective communication with internal stakeholders in hospitals. Nurses required timely and accurate information, which leaders needed to process and internalize. This task was time consuming and challenging since information differed between different communication channels during the first phase of the Covid-19 pandemic (Ahlqvist et al., 2023). For instance, when information through email reached employees, it might have already been outdated. Kämäräinen et al. (2022) identify that most nurses perceive timeliness of information as the most crucial factor in ICC. Interestingly, this finding is not homogenous for all nurses. Specialized nurses at the intensive care unit and the emergency department value accurate information even over timely information. Furthermore, instructing information related to work instructions is positively correlated with the perceived quality of ICC, whereas general information about Covid-19 is not (Kim et al., 2023). Therefore, communication skills by leaders may foster the employee's empowerment. Other studies on ICC during the Covid-19 pandemic link ICC to crisis leadership. For instance, Heide & Simonsson (2021) agree that leadership is essential for ICC and conclude in a case study that crisis leadership and hence ICC is more democratic than previously assumed. For leaders it is essential to have effective ICC within the organization as it may improve crisis response when timely and accurate information is available. However, ICC is not only about instructing information that flows top-down, but also horizontal communication when employees on the same hierarchical levels can share their experiences with each other (Madsen et al., 2023).

2.4. Aims of the study

Existing research on ICC during the Covid-19 pandemic has mostly been nurse-oriented and focused on top-down communication by leaders, while the role of communication channels on the effectiveness of ICC has been neglected. ICC challenges due to contrasting information have been described in the literature, but there is only little understanding whether these stem from inadequate choice of communication channels or insufficient communication skills by the sender. The aim of this study is to address this gap by mapping the relationships between internal stakeholders during the Covid-19 pandemic and investigating which effect the choice of communication channels had for ICC effectiveness.

3. Methodology

3.1. Case description

The underlying case for our study is a tertiary public hospital in the southeast of Norway. The organizational structure follows a function-based line organization. The highest level is the top management, which the division leaders and central administration functions (e.g., HR, finance, or communication) directly report to. Each division is subdivided into departments that are subdivided into sections. The lowest level symbolizes the operational level. When the Covid-19 crisis hit the hospital during spring 2020, the preparedness level was raised. Consequently, a Covid-19 taskforce was launched, who received significant decision power, and the hospital transformed into an emergency organization. The Covid-19 taskforce consisted of six doctors and internal communication processes were shortened since the line communication processes were broken up. Furthermore, the higher preparedness level resulted in postponing or cancelling of all elective appointments to keep spare capacity for Covid-19 patients. During this period there has been a high need for all internal stakeholders for instructing and adjusting information especially when staff needed to be reallocated.

3.2. Data collection

We followed a purposive sampling approach, identifying informants in the case hospital who actively participated in crisis response and crisis communication. Of the twenty-nine persons identified, seven declined participation or failed to respond to the invitation. We conducted semi-structured interviews with the remaining twenty-two informants. Table II shows the hierarchical positions of our informants.

Table II: Number of informants by hierarchical level

Hierarchical level	***Number of informants***
Central administration	4
Covid-19 taskforce	1
Division leader	2
Department leader	4
Section leader	8
Operational level	3
Total	22

We conducted the interviews in February and March 2021, during which the informants were asked to recollect the Covid-19 situation in March/April 2020 from an ICC perspective. The interview guide focused on who the informants communicated with, which channels they used, and which information flow problems they experienced. Due to the Covid-19 measures in force at the time, the interviews were conducted virtually (MS Teams, Skype or Zoom) and lasted approximately one hour per informant. The informants were allowed to choose their preferred virtual communication platform and received the interview guide beforehand. The interviews were not recorded, however in addition to the interviewer, two additional researchers were present during each interview, taking notes in real time. The collected information was immediately anonymized to protect the informants' privacy.

3.3. Data analysis

The transcripts were coded according to Berlo's (1960) communication model, resulting in a network representation of internal communications during the focal period, including senders, receivers, communication channels, and type of information shared. Furthermore, we coded the problems informants reported with the information flow in terms of perceived limitations. These limitations were either information quality issues (incomplete information or incorrect understanding) or communication process issues (unavailable information or delayed reception of information). To quantify these limitations, we utilized a binary variable as a limitation score. This variable served to indicate whether the information limitation was mentioned or not. The data were then analyzed in two steps.

3.3.1. Descriptive analysis of the internal crisis communication process

For our descriptive analysis of the ICC processes at the case of the hospital we used a process visualization approach, subject-oriented business process management (S-BPM) (Fleischmann et al., 2012; Moattar et al., 2022). Information about sender, receiver, type of information and chosen channel is represented in the same diagram. We defined the hierarchical levels in the hospital plus the Covid-19 taskforce as actors and analyzed their roles as senders and receivers of information: for each dyad of actors, either no communication at all, one-way communication from one actor to the other, or exchange of information in both ways. Based on our interview data, we exploratively analyzed the type of information shared in each dyad of actors and the communication channel used. Using these inputs, we created a subject-interaction diagrams (SID) for the acute crisis phase.

3.3.2. Social network analysis

The dyadic relations identified in the descriptive analysis also provided the adjacency matrix for the social network analysis we performed in the next step. For this, we used the Bayesian mixed-model version of the social relations model (Hoff, 2009; Warner et al., 1979), appropriate for situations when a dependent relationship dimension Y and one or more independent relationship dimensions $X_1, X_2, \dots X_P$ have been measured for the same social network. The value y_{sr} of a "dependent" edge linking the sth sender to the rth receiver in the network is predicted by the model:

$$y_{sr} = \boldsymbol{\beta}^{\mathrm{T}}\mathbf{x}_{sr} + a_s + b_r + \gamma_{sr} + \mathbf{u}_s\mathbf{D}\mathbf{v}_r^{\mathrm{T}} \qquad (1)$$

Where $\boldsymbol{\beta}$ is the vector of regression coefficients to be estimated and $\mathbf{x}_{sr}$ is the vector of values on the P "independent" edges linking that sender to that receiver. The data used for estimating the model are stacked in such a way that every cell in the adjacency matrix becomes a row in the data table. To account for the dependencies caused by the fact that the same senders, the same receivers and the same dyads occur multiple times in the data table, we include random effects a_s for each sender, b_r for each receiver, and γ_{sr} for each dyad. The last term $\mathbf{u}_s\mathbf{D}\mathbf{v}_r^{\mathrm{T}}$ is a singular value decomposition of higher order dependencies into multiplicative sender and receiver random effects. The model is estimated using Bayesian techniques with Markov-chain Monte Carlo sampling (MCMC); the point estimates $\widehat{\boldsymbol{\beta}}$ of the regression coefficients are the posterior means of the MCMC estimates of $\boldsymbol{\beta}$, and the standard errors are the posterior standard deviations. We used the R package amen, with 1,000 burn-in iterations and 1,000 MCMC iterations per model.

In our study, the dependent relationships are information limitations perceived by a given dyad of actors. As values, we assigned the logit-transformed limitation scores from our qualitative interview analysis, which we evenly distributed across all receiving dyads per hierarchical level. The independent relationships in our study are the characteristics and capabilities of the communication channels of a given dyad used. To quantify these, we assigned scores (ranging from one to three) to each channel and characteristic, using Table 1 (see above). Whenever a dyad had used more than one channel, we calculated the average across the channels used by that dyad. Since the eight channel characteristics were highly correlated, we decided to reduce the number of dimensions using principal component analysis. The results indicated that two components were sufficient, explaining 98.57% of the variation in the data. We interpret these components as 1) speed and bandwidth limits and 2) capability to transmit contextualized information.

4. Results

4.1. Internal crisis communication analysis

Six distinct hierarchical levels in the case hospital actively participated in ICC (see Figure 1). The diagram's upper part illustrates an ordinary hierarchical line structure, from division leader (left) down to the operational level (right). A feature in this diagram is the Covid-19 taskforce, which communicated with all internal stakeholders regardless of their hierarchical level, transcending hierarchical boundaries. This unique position allowed the Covid-19 taskforce to streamline ICC processes during the acute crisis phase. The central administration played a somewhat similar role but focused on communication with middle management. This configuration implies that the ICC network is more complex and fostered direct communication between hierarchical levels. While we see vertical communication lines (top-down), there is also lateral communication among section and department leaders who engage in horizontal information exchange.

We could identify two types of information communicated during the acute crisis phase: adjusting and instructing information. Adjusting information in the form of situational updates played a crucial role to support internal stakeholders to make sense of the situation. This information encompassed details such as Covid-19 prevalence and incidence, the availability of medical equipment such as personal protective equipment and respirators, and the utilization rates of the intensive care unit and other wards. Given the high need for information, crisis communicators were unable to meet the information needs fully. Medical staff contacted colleagues from other countries such as Italy who were ahead in the epidemiological trajectory of Covid-19 to gain insights based on their experiences. Second, instructing information was necessary to reallocate medical staff to departments affected by the influx of Covid-19 patients. The intensive care unit was the primary recipient of additional staff. Moreover, due to both regulatory changes and increasing experience with Covid-19 treatments, work instructions required constant updating and dissemination to the operational level.

Four distinct communication channels were used: face-to-face meetings, email, synchronous instant messaging, and phone/text messaging. Communication within a given dyad of actors was not limited to a single communication channel. Interestingly, the relevance of email decreased down the organizational hierarchy. Middle management, including department and section leaders, received and sent information through four different communication channels. The Covid-19 taskforce's communication primarily relied on two communication channels btu had a clear focus on effective face-to-face communication in daily meetings with internal stakeholders. Informants both from the operational level and among section leaders suggested the need for additional communication channels: staff needed timely updates, but those from lower hierarchical levels had limited access to internal communication tools when they were out of the office. Hence, face-to-face meetings and emails were only useful for groups of actors physically present at the hospital.

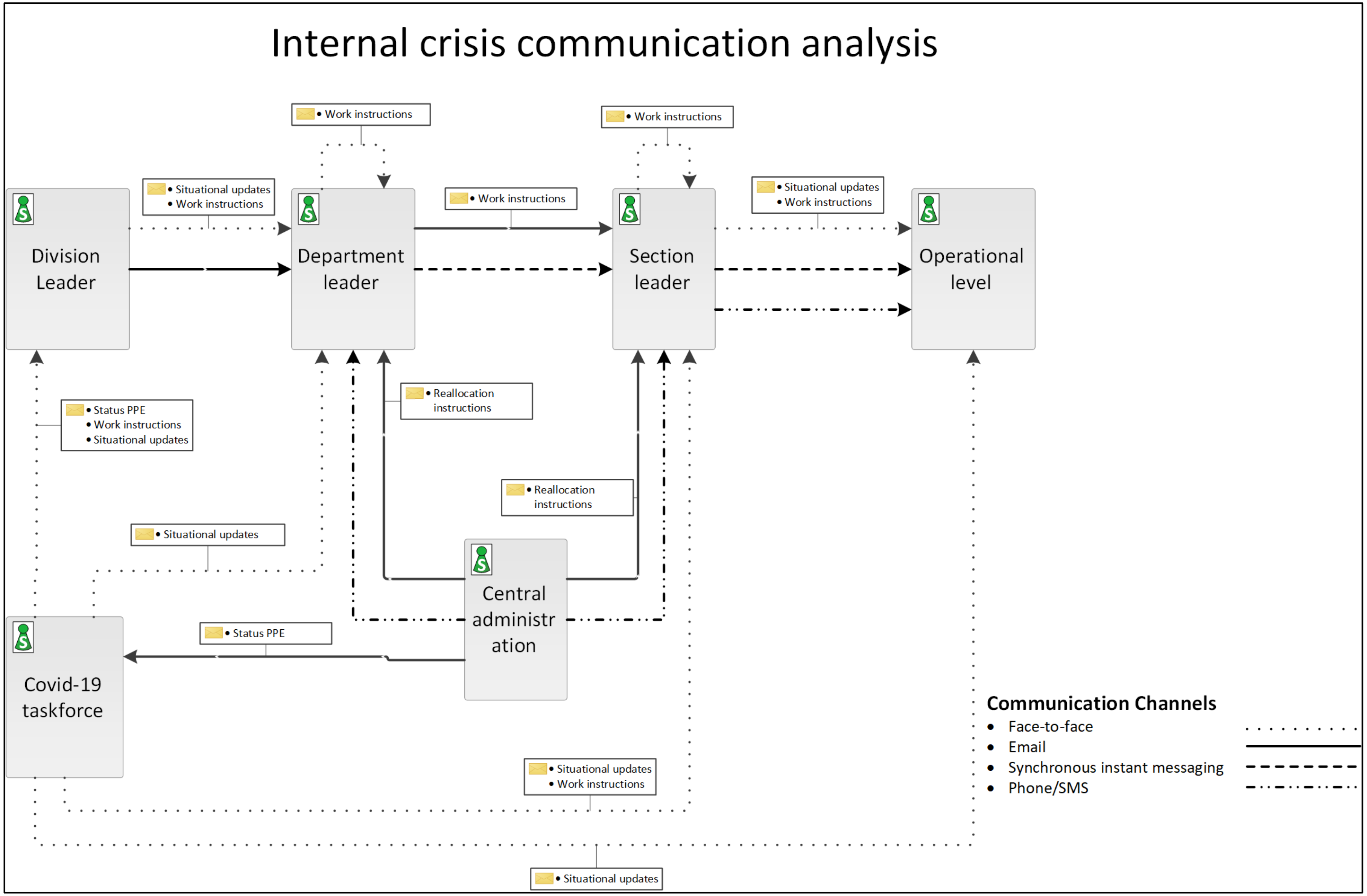

Figure 1: Subject interaction diagram of ICC during the acute crisis including information content and communication channels.

4.2. Overall information limitation per dyad of actors

The contribution to the overall information limitation of each dyad between hierarchical levels in the hospital is visualized in a directed Fruchterman-Reingold plot (see Figure 2). We assume that the perceived information limitation only applies to receivers and is evenly distributed over all incoming communication channels. The orientation of the edges indicates the direction of information flow, while the width of the edges is proportional to the overall information limitation. The connections between central administration and Covid-19 taskforce as well as between division leaders and Covid-19 taskforce contributed most to cooperation problems due to information limitations, hence the effectiveness of ICC. One informant highlighted the challenge of a parallel communication structure, where line functions received information from both the central administration and the Covid-19 taskforce. A member of the Covid-19 taskforce noticed that they were not involved in the decision-making process led by the central administration, which emphasizes the findings from the Fruchterman-Reingold plot. From a communication perspective, division leaders were often bypassed when the Covid-19 taskforce prioritized effective communication with lower hierarchical levels (section leaders and operational level) to expedite ICC. The vertex sizes in Figure 2 are proportional to the indegree. As we have already seen in the SID, the department leaders and the section leaders were crucial actors in the ICC process and received information from three other internal stakeholders.

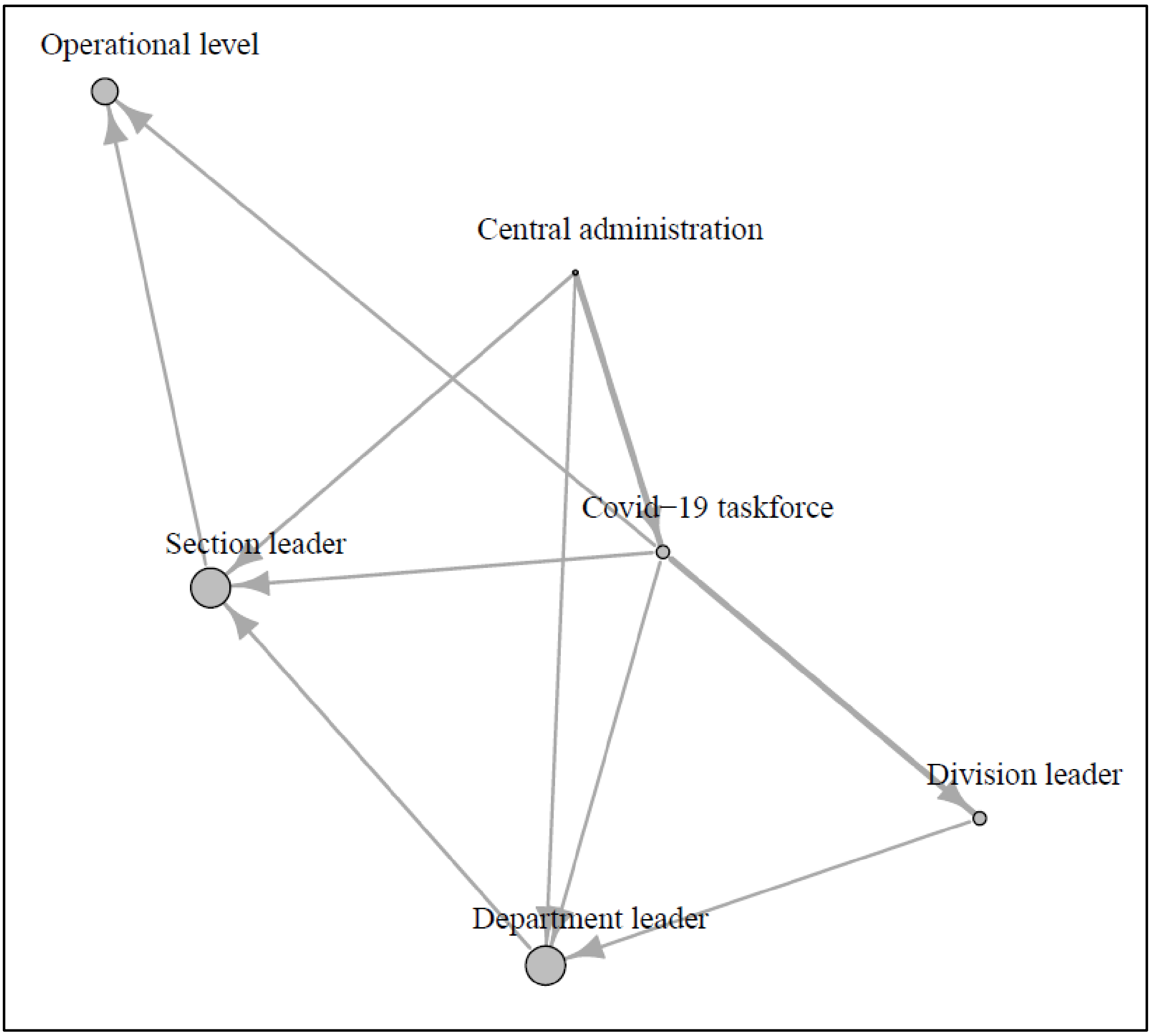

Figure 2: Fruchterman-Reingold plot of communicating actors and their perceived contribution to the overall information limitation (arrow width proportional to the edge weight, circle size proportional to the indegree)

4.3. Relationship between communication channel characteristics/capabilities and information quality limitations

Our quantitative social network analysis addressed the relationship between the dyadic relationships and cooperation problems due the information quality limitations. We sub-categorize these limitations on the receiver side into two dimensions: incomplete information (the receiver requires or expects more information on a topic for cooperation) and incorrect understanding of information (the receiver wrongly understands incoming information or the information later turns out to have been incorrect).

Table III shows the parameter estimates. Overall, we see that both limitations in speed and bandwidth as well as the capability to transmit contextualized information are significantly related to the information quality limitations. The first dyad-level predictor is positively correlated while the second one is negatively correlated with the information quality limitations. In the model predicting challenges due to incorrect understanding, the absolute value of the coefficient of capability to transmit contextualized information is twice as high as the coefficient of limitations in speed and bandwidth. In the model predicting challenges due to incomplete information, the two coefficients have roughly equal absolute size.

Table III: Effect of dyadic communication channels characteristics/capabilities on perceived information incompleteness and incorrectness

	Dependent variable	Dyad-level predictors	Beta	*S.E.*	*Z*	*p*
Cooperation problems due to	Incomplete information	Intercept	-2.23	1.40	-1.60	.11
		Speed and bandwidth limits	**8.55**	**1.34**	**6.36**	**.00**
		Capability to transmit contextualized information	**-9.91**	**2.81**	**-3.53**	**.00**
	Incorrect understanding of information	Intercept	.87	2.22	0.39	.70
		Speed and bandwidth limits	**6.79**	**2.09**	**3.25**	**.00**
		Capability to transmit contextualized information	**-13.79**	**4.23**	**-3.26**	**.00**

Middle management (department and section leaders) followed a hybrid ICC strategy and utilized both synchronous and asynchronous communication channels for communication. Although this made it possible to document essential information, it also created a bottleneck in the ICC process. One informant mentioned that they had not been able to share all required information with internal stakeholders before they already received updated information. Consequently, the receiver did not possess the necessary context information when the sender decided to no longer share information because it was outdated, and the risk of incorrect understanding increased. Another informant noted that the work instructions for treating Covid-19 patients were not correctly understood. Since the ICC process itself often failed to deliver the required information, internal stakeholders would refer to other information that was publicly available (e.g., from the national institute of public health) but not actually relevant to the case hospital. This led to a perception of incorrect information when various sources contradicted each other.

Besides speed and bandwidth limits of the chosen communication channel, we found that limited capability to transmit contextualized information was associated with perceptions of incompleteness of information and incorrect understanding. Particularly communication channels that allow more than one option to encode information reduce the risk of errors or incomplete information. One informant reported that they used everyday communication channels where they could send images, videos and text (instant synchronous messaging). These channels had two advantages: the receiver can choose the method for encoding and thus maximize the information intake, and the receiver can triangulate the information and reduce the risk for errors when text is combined with images or videos.

4.4. Relationship between communication channel characteristics/capabilities and communication process limitations

In this section we present cooperation problems due to delayed reception of information and unavailable information. These two dimensions are interrelated since information unavailability often results in a delay. We present the results in the same way as for the information quality limitation.

Table IV shows the parameter estimates. In the same ways as for the information quality limitation, we detect a significant relationship between the communication characteristics/capabilities and the communication process limitation. Speed and bandwidth limits of the chosen channel are again positively associated with delayed reception and unavailable information while the capability to transmit contextualized information is negatively associated with both dimensions. In both models, the absolute value of the coefficient of contextualized information is approximately twice as high as the coefficient of speed and bandwidth limits.

Table IV: Effect of dyadic communication channels characteristics/capabilities on perceived delayed reception of information and unavailability

	Dependent variable	Dyad-level predictors	Beta	*S.E.*	*Z*	*p*
Cooperation problems due to	Delayed reception of information	Intercept	.87	2.05	.43	.67
		Speed and bandwidth limits	**7.24**	**1.70**	**4.25**	**.00**
		Capability to transmit contextualized information	**-14.38**	**4.03**	**-3.57**	**.00**
	Unavailable information	Intercept	.82	2.30	.36	.72
		Speed and bandwidth limits	**6.99**	**2.16**	**3.24**	**.00**
		Capability to transmit contextualized information	**-13.87**	**4.19**	**-3.31**	**.00**

Speed and bandwidth limits of the chosen communication channel are associated with information being unavailable or delayed. These limitations occur both on the sender and receiver side. Informants frequently reported that information regarding work instructions was received late. Particularly the top-down information flow from middle management was hindered by the choice of communication channels. Work instructions were disseminated via email. Although email facilitates documentation and transparency, it also caused delays and unavailability. Due to parallel communication structures with synchronous communication channels, top-down barriers became visible to section leaders.

While speed and bandwidth limits increase communication process limitations, the capability to transmit contextualized information can reduce these limitations. Since communication channels such as email were not available to section leaders and the operational level who were outside the hospital, section leaders became creative in finding new ways of communicating (e.g., synchronous instant messaging tools such as WhatsApp). This higher convergence in communicating between section leaders and the operational level reduced delays and problems of information unavailability.

5. Discussion

Our first key result is that the increased preparedness level of the hospital resulted in increased complexity compared to ordinary line communication processes. Vertical ICC was shortened by the launch of a Covid-19 taskforce as a central crisis communicator. However, some stakeholders were reluctant to accept the ICC processes, which resulted in parallel communication processes. Lower hierarchical levels received instructing and adjusting information from more than one sender. Not only the complexity of the network was decisive for the effectiveness of ICC, but also the existence of redundant communication channels between hierarchical levels. Except for the Covid-19 taskforce, communicators used more than one communication channel to convey information to other hierarchical levels.

Our second key result is the effect of the communication channel choice on the effectiveness of ICC. We find that communication channels with speed and bandwidth limits can create challenges for the receiver, limiting information quality and decreasing efficiency of the ICC process. Choosing communication channels that can transmit contextualized information, on the other hand, facilitates ICC. Note that the effect of a channel's capability to transmit contextualized information was twice as high as the effect of speed and bandwidth limits. Moreover, the impact of the communication channel characteristics and capabilities is similar for the information quality and ICC process limitation.

Although our study was based on a single case at a tertiary public hospital during the early phase Covid-19 pandemic, our findings may generalize to other hospitals in a comparable situation. Two studies with nurses during Covid-19 found that redundant communication channels led to contradicting instructions (Ahlqvist et al., 2023; Cha & Park, 2021). And while the choice of communication channels for ICC in hospitals may be profession-dependent (Cha & Park, 2021; Falkheimer et al., 2022), our results indicate that the choice is also related to hierarchical level: section leaders and the Covid-19 taskforce communicated through channels with a high capability to transmit contextualized information, while the central administration and division leaders chose email as their preferred channel. These findings are in line with the argument by Kämäräinen et al. (2022) that the ICC needs depend the organizational function. Furthermore, crisis communicators who are closer to the operational level foster collaborative crisis management (Deverell, 2021). We find that such crisis communicators, like the Covid-19 taskforce in our case hospital (which was closer to the operational level than division leaders or central administration, communicated through channels with both a high transmission velocity and a high capability to transmit contextualized information.

Other studies on ICC during the Covid-19 pandemic focused on nurses, defining ICC as a leadership skill (Ahlqvist et al., 2023; Kämäräinen et al., 2022; Kim et al., 2023). To complement this literature, we analyzed the effectiveness of ICC in terms of communication channels used by, and between, different hierarchical levels in the hospital organization—we included stakeholders from different professions and backgrounds.

We argue that the choice of communication channels should not be neglected when defining the effectiveness of ICC. An interesting result of our case study was that inadequate choice of communication channels (with speed and bandwidth limits) result in unequally informed stakeholder groups. This weakness became apparent when not only vertical but also horizontal ICC occurred in our case hospital. Madsen et al. (2023) agree that a hospital should provide a forum to facilitate horizontal communication among the lower hierarchical levels. Especially the listening process allows employees to find other peers with similar thoughts and beliefs. Social media would be a suitable communication channel for horizontal communication as it allows the internal stakeholders to actively participate in the ICC process, which can be considered favorable (Heide & Simonsson, 2021). Future research is required to enhance the understanding how new communication technologies such as chatbots or voicebots can improve the effectiveness of ICC. Moreover, it would be interesting to perform a longitudinal study and describe the temporal development of ICC during a crisis.

6. Conclusion and practical implications

The global Covid-19 pandemic has shown the need for effective ICC in hospitals. We show that the complexity of internal communication processes increased, and several redundant communication channels were used, including channels that were not officially sanctioned. Moreover, we found that the effectiveness of ICC was reduced by communication channels with speed and bandwidth limits and increased by communication channels with a high capability to transmit contextualized information.

Our study highlights the importance of selecting appropriate communication channels for ICC. We suggest that crisis communicators should find a balance between the capability to transmit contextualized information and the level of synchronicity of each communication channel, especially during the acute crisis phase when need for information is high. Moreover, choice of communication channels should be tailored to the receivers' needs and preferences, which might change over time. For instance, internal stakeholders who are not physically present at the workplace (e.g., home office or on sick leave) need to be included in ICC. It is not sufficient to share information exclusively in face-to-face meetings; at least one additional channel (such as email) must be used that is remotely accessible. Finally, we recommend that crisis communicators should avoid a decoupling of ICC between the medical professions and the administration. Flexible and accessible communication channels are needed to facilitate effective communication across all levels of the organization.

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Paper 3: Tactical capacity planning under uncertainty – A capacity limitation analysis

Tactical capacity planning under uncertainty

A capacity limitation analysis

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Acknowledgement

We would like to thank Jørgen Madsø and Tilde Midtvedt for contributing to the data collection at the case hospital and the fruitful discussions on the results. Furthermore, we are grateful for the support we received from all the experts at the case hospital, especially our main contact person.

Declaration of interests

We received no external funding for this study. The authors declare no competing interests of relevance to the content of this article.

Ethics statement

In accordance with the policies of the authors' institutions, an ethics approval by a review board was not needed for this work.

Keywords	healthcare, hospital, tactical capacity planning, capacity management, capacity limitations
Paper type	Research paper

Abstract

Purpose: Tactical capacity planning is crucial when hospitals must cope with substantial changes in patient requirements, as recently experienced during the Covid-19 pandemic. However, there is only little understanding of the nature of capacity limitations in a hospital, which is essential for effective tactical capacity planning.

Design/methodology/approach: We report a detailed analysis of capacity limitations at a Norwegian tertiary public hospital and conducted twenty-two in-depth interviews. The informants participated in capacity planning and decision-making during the Covid-19 pandemic. Data is clustered into categories of capacity limitations and a correspondence analysis provides additional insights.

Findings: Personnel and information were the most mentioned types of capacity limitations, and middle management and organizational functions providing specialized treatment felt most exposed to capacity limitations. Further analysis reveals that capacity limitations are dynamic and vary across hierarchical levels and organizational functions.

Research implications: Future research on tactical capacity planning should take interdisciplinary patient pathways better into account as capacity limitations are dynamic and systematically different for organizational functions and hierarchical levels.

Practical implications: We argue that our study possesses common characteristics of tertiary public hospitals, including professional silos and fragmentation of responsibilities along patient pathways. Therefore, we recommend operations managers in hospitals to focus more on intra-organizational information flows to increase the agility of their organization.

Originality/value: Our detailed capacity limitation analysis at a tertiary public hospital in Norway during the Covid-19 pandemic provides novel insights into the nature of capacity limitations, which may enhance tactical capacity planning.

Keywords: healthcare, hospital, tactical capacity planning, capacity management, capacity limitations

Paper type: Research paper

1. Introduction

Healthcare organizations in Western countries are facing the challenge of an ageing society, expecting more patients with chronic diseases who require more complex treatments (Busse *et al.*, 2010). Infectious disease outbreaks have caused additional short-term pressure in a more globalized world (EU Expert Group on Health Systems Performance Assessment (HSPA), 2020; Smith *et al.*, 2014). As a result, level and volatility of demand for healthcare services have increased, and operations managers in the healthcare sector—whose task is to ensure alignment between demand and supply—have increasing difficulty with their short and medium-term ("tactical") capacity planning (Meites *et al.*, 2011). This is a particular problem in hospitals due to scarcity of resources, variation in processes, and system complexity (Green, 2005; Terwiesch *et al.*, 2011).

A growing body of healthcare research recognizes the importance of tactical capacity planning for coping with temporary fluctuations in patient demand (Leeftink *et al.*, 2020). Modifying organizational structures and processes can help hospitals increase operational flexibility and thereby (at least temporarily) match capacity to patient demand. However, this can also reduce performance, for example when information flow and decision-making structures are decentralized, which might create redundancies or separation (Coyle *et al.*, 2021).

Up until now, many studies on tactical capacity planning have avoided this problem by focusing on key performance indicators that do not take demand variability into account. The average hospital bed utilization rate is such an indicator (often used in queuing models; see (Bittencourt *et al.*, 2018; Lantz and Rosén, 2016, 2017)). One problem is that demand variability either naturally or artificially occurring together with high average utilization increases the risk of resource unavailability during peak times (Green, 2002; Otten *et al.*, 2021; Proudlove, 2020). And simply increasing the number of beds will not lead to a higher number of treated patients unless more personnel become available, too. These examples demonstrate that tactical capacity planning needs to identify the drivers of capacity limitations, assess their importance and their relationships to each other, and monitor their dynamics. Even Larsson and Fredriksson (2019), who were to the best of our knowledge the first (and as yet only ones) to create a framework for tactical capacity planning in the healthcare sector, do not specify how operational limitations should be identified.

We follow the call by Kumar and Singh (2020) for more research on the dynamics of flexibility, often referred to as agility, in healthcare operations. Using the setting of a tertiary hospital in the southeast of Norway as a case, our contribution is twofold. First, we explore which types of limitations influence the actual treatment capacity of a hospital in a situation in which the hospital needs to be agile and adapt its capacity to deal with changing patient requirements: the Covid-19 pandemic. Since external pressure can exacerbate operational inefficiencies and thereby make them more visible (Blumenthal *et al.*, 2020; Leite *et al.*, 2020), the situation of a global pandemic offers the unique possibility to study the capacity limitations of a hospital in depth. Therefore, we refine the framework by Larsson and Fredriksson (2019) by exploring additional capacity limitations categories. Second, we analyze the moderating influence of organizational structure: how limitations differ across hierarchical levels and functions within the organization. Taken together, our study provides novel insights into the tactical capacity planning process in a hospital, with a specific focus on inter-departmental capacity limitations.

1.1. Capacity planning in healthcare organizations

The healthcare sector has received significant attention from scholars in the field of operations management (OM) as healthcare organizations have striven for more efficient processes due to either steadily increasing financial pressure or increasing patient demand. Effective capacity planning is necessary to ensure an equilibrium between available supply and patient demand as otherwise consequences are either unsatisfied patients or cost-intensive overcapacity ("surge capacity"). In the worst case, not being able to serve the incoming patient demand might pose a risk to human life.

In studies on capacity limitations and operational bottlenecks in the healthcare operation, researchers reach a consensus that there are five main different categories of capacity limitation (Souza *et al.*, 2020; Thompson *et al.*, 2013):

- An insufficient number of rooms or beds limits the capacity of a hospital from a physical perspective;
- Inappropriate scheduling strategies of either patient demand or resources result in bottlenecks;
- The available workforce is either too small in quantity or does not have the necessary competences;
- Unavailability of supplies, such as medication or medical equipment, hinders the execution of effective treatment;
- Information shortage leads to operational constraints (e.g., when medical personnel must wait for laboratory test results).

Even though Souza *et al.* (2020) and Thompson *et al.* (2013) provide a thorough overview of constraints in the hospital's operation, the interrelation between the presented categories remains unclear.

Hans *et al.* (2011) create a framework for capacity planning in healthcare organizations and include four capacity planning categories: 1) medical planning, 2) resource capacity planning, 3) material planning and 4) financial planning. In addition, they distinguish four planning levels (longest to shortest planning horizon): strategic, tactical, operational-reactive (online), and operational-proactive (offline) (Hans *et al.*, 2011). The longer the planning horizon, the lower the granularity of the planning. Strategic capacity planning often considers the entire healthcare organization and its external stakeholders. The tactical level addresses both the design and organization of value chain and supply chain processes (Hulshof *et al.*, 2012). Tactical planning aims to increase the effectiveness of a given process, hence improving the effective capacity, while operational planning aims to increase efficiency (Karuppan *et al.*, 2016; Vissers *et al.*, 2001). Moreover, tactical capacity planning plays a crucial role when temporarily setting capacity to patient demand when the organization is viewed as a set of business processes that can be modified. Hence, blueprints for processes can be generated that support ad-hoc decisions. Therefore, these four capacity planning levels are not isolated but more as hierarchically interrelated.

Process flexibility as a type of agility is dependent on the ability to change of human resources, technology and facilities (Karuppan *et al.*, 2016). The concept of agility does not have a strong theoretical grounding in healthcare yet (Patri and Suresh, 2019). Therefore, we refer to more mature streams of research on agility like the supply chain literature for a framework. There is a common understanding that agile supply chains have four distinct characteristics that may exist to different extents (Harrison and van Hoek, 2008):

- Transparent information sharing,
- Coordinated processes across the supply chain,
- Centralized planning,
- Capacity is adjusted according to customer needs rather than based on forecasts.

These characteristics are interconnected. For instance, the sharing of information enables all units in the chain to have a mutual understanding, which in turn facilitates the alignment of process and capacity planning. In hospitals, the term for collaborative capacity planning is integral capacity planning, i.e. when departments in a hospital coordinate capacity planning with an end-to-end perspective that enables capacity to become agile (Schneider, 2020). In another study, Simwita and Helgheim (2016) find that resource flexibility can improve agility to better respond to increasing patient demand and used as a strategy for process improvement.

1.2. Tactical capacity planning

We now focus on the tactical capacity planning level according to the framework by Hans *et al.* (2011). Especially during situations when a hospital needs to adjust its capacity to changing patient requirements, active tactical capacity planning is essential for becoming agile.

Larsson and Fredriksson (2019) were the first who create a framework for tactical capacity planning in healthcare organizations, which includes components such as future demand, available capacity, restrictions, targets, and tolerance levels. Larsson and Fredriksson (2019) report an explorative cross-departmental case study at a Swedish university hospital and conclude that active tactical capacity planning results in lower costs and higher flexibility. Their study involved three departments that had different priorities for tactical capacity planning, for example focusing on consistency or flexibility. A shortcoming of this study is its exclusive focus on tactical capacity planning processes within departments; interdepartmental patient pathways are not considered.

Since tactical capacity planning problems tend to be complex, other researchers try to reduce the complexity by focusing on single indicators from the OM domain. We can identify three distinct methodologies. First, queuing theory offers the possibility to objectively measure the hospital's capacity and structures the tactical capacity planning process to maximize outcomes (Boulton *et al.*, 2016; Lantz and Rosén, 2016, 2017). This method is based on probabilistic distributions for arrival rates and processing times, normally from historic data. Thus, assumption about the underlying distribution need to be made a priori but queuing models can enhance forecasting or provide insights how to optimize bed and nurse utilization rates (Baas *et al.*, 2021; Bittencourt *et al.*, 2018). However, tactical capacity planning should rather regard utilization rates as outcomes and not as targets as variability and uncertainty in patient demand might result in refusals of admission (Green, 2002; Proudlove, 2020). Curry *et al.* (2021) overcome the shortcoming of traditional queuing models by creating a serial queuing network that consists of transition probability for patient to sequentially move between departments. This model could function as a basis for informed tactical capacity planning decisions especially in cases of interdisciplinary patient pathways. Second, mathematical optimization is another method to support tactical capacity planning for hospitals. Aslani *et al.* (2021) create a model for an outpatient setting that is robust against uncertainty and ensures a feasible allocation of physicians in different demand scenarios. Third, simulation can support tactical decision making for instance through scenario analyses. Marin-Garcia *et al.* (2020) propose a discrete event simulation during global pandemic situation in order to predict the number of patients in need of hospitalization and the required resources based on the epidemiological development.

1.3. Aims of the study

In summary, studies on tactical capacity planning in the healthcare sector often incorporate uncertainty and support resource allocation and scheduling. However, quantitative decision support tools require a reduction in the problem's complexity and assumptions need to be made when translating the data to the model. Therefore, the relationship between capacity limitation categories is not completely addressed. Recent studies on tactical capacity planning are fragmented since they focus on single capacity limitation categories mostly resource oriented such as beds, physicians, nurses and personal protective equipment (PPE) (Aslani *et al.*, 2021; Bittencourt *et al.*, 2018; Furman *et al.*, 2021; Lantz and Rosén, 2016). As the relationship between resource input (e.g., nurses) and actual output is divergent, it would be interesting to find additional capacity limitations (Lantz and Rosén, 2016). Consequently, our study aims to enhance the understanding of the relationship between different capacity limitations. Therefore, we map existing bottlenecks at the hospital as they will limit the actual capacity (Anupindi *et al.*, 2012). In addition, as patient pathways are getting more interdisciplinary, there is a need to shift the focus from single departments towards inter-departmental analyzes or even on a regional level in a cluster of hospitals (KC *et al.*, 2020). As the dynamics of flexibility are not yet widely understood, temporary capacity changes through tactical capacity planning should receive more attention (Kumar and Singh, 2020).

2. Method

The COREQ (COnsolidated criteria for REporting Qualitative research) checklist was adhered to in the reporting of this study (Tong *et al.*, 2007) (see Appendix A)

2.1. The case hospital

The underlying case for this study is a tertiary public hospital in the southeast of Norway. Its organizational structure is characterized by a function-based line organization. The topmost level is the top management, which the division leaders and central administration functions (e.g., HR, finance, or communication) directly report to. Each division is then subdivided into departments that are subdivided into sections. The lowest level symbolizes the operational level. Overall, the hospital management consists of sixteen directors (top management plus division leaders), eighty department leaders and 245 section leaders. During the start of the Covid-19 pandemic in Spring 2020, the hospital was challenged by a sudden influx of Covid-19 patients that medical personnel had little or no experience with. Severe cases required close monitoring and respirator treatment in the intensive care unit (ICU), with significantly longer stays compared to other ICU patients (Klein *et al.*, 2020). The top management raised the level of preparedness, changing the function-based structure to an emergency organization governed by a task force, which received significant decision-making power to increase responsiveness and flexibility. Vertical communication and decision processes along the functional line structure were broken up, and horizontal/cross-functional communication and decision processes became the norm. Moreover, elective appointments were postponed or canceled, which allowed the hospital to re-disposition medical personnel to the most affected departments, like the emergency department (ED) and the ICU. In a nutshell, the hospital was transformed into a full acute hospital.

2.2. Data collection and analysis

As research on tactical capacity planning in hospitals is still scarce, a qualitative case study is best suited for knowledge creation. The findings both across hierarchical levels and functions aim to enhance the understanding of capacity limitations within a hospital during tactical capacity planning. A single case can be conclusive to explore a complex problem and supplement the literature according to Remenyi *et al.* (1998).

We selected informants who experienced the pandemic situation in Spring 2020. A contact person at the case hospital supported us in the purposive sampling process, Inclusion criteria were active participation in the tactical capacity planning process and/or involvement in the taskforce's decision-making processes during the Covid-19 pandemic in Spring 2020. The initial sample consisted of twenty-nine informants (of which sixteen had a medical education). After an initial invitation by email, we followed up with reminders via email or telephone. Twenty-two off these agreed to participate in the interviews, yielding in a participation rate of 80%. We group the informants from a hierarchical perspective and according to their organizational function We chose to include the following organizational functions: the ED, the general ward, the intermediate care unit, the ICU and support units.

The development of the interview guide (see Appendix B) followed established guidelines (Kallio *et al.*, 2016). After checking the prerequisites for conducting semi-structured interview, we reviewed the literature on capacity limitations. We found a suitable framework by Thompson *et al.* (2013) that distinguishes five categories of capacity limitation in healthcare operations. We used these categories to structure the interview guide: physical, scheduling, personnel, supply and information.

We conducted pilot interviews with two persons working at the case hospital, of which one was a doctor and one was part of the administration. These interviews helped us to improve the comprehensibility of interview questions and standardized the use of terminology (i.e., medical concepts). We conducted twenty-two one-hour interviews in February and March 2021. The informants were allowed to choose their preferred virtual communication platform and received the interview guide in advance. We decided not to record the interviews, trying to motivate the informants to answer more freely. Instead, we ensured that two additional researchers participated in each interview taking notes. Rutakumwa *et al.* (2020) argue that this method does not have a negative effect on the data quality compared to a recorded interview. While the majority of researchers generally record interviews, it should be noted that informants might also become more cautious in providing answers (Swain and King, 2022). Prior to each interview, we informed all participants about the study's purpose and obtained their consent. The collected information was immediately anonymized to protect the informants' privacy. Therefore, ethical review was not required as no sensitive information was included.

In a next step, we merged the transcripts made by the different researchers who had taken notes during the interviews, improving the completeness and quality of the collected information. Furthermore, we discussed data saturation and found that themes were recurring in the last interviews and no new information was revealed. The data were analyzed in three steps:

- Qualitative content analysis to identify subgroups of capacity limitations,
- Quantification of the qualitative information,
- Multivariate analysis (correspondence and cluster analysis) to identify patterns in the quantified data.

In the qualitative content analysis step, we coded the transcripts with the intention to extend the granularity of capacity limitations categories by adding subcategories. In the quantification step, we created a matrix with binary variables per capacity limitation subcategory and informant to indicate whether the respective limitation was or was not mentioned. Hence, we can quantify the qualitative material into a capacity limitation score per capacity limitation category. We decide to calculate the weighted arithmetic mean to normalize the limitation score because the number of capacity limitation subcategories per capacity limitation category varied. Thus, the limitation scores range between zero and one. We will analyze the limitation scores between hierarchical levels and between the organizational functions in the hospital, using tabulations as well as correspondence analysis (Greenacre, 2007) and cluster analysis.

3. Results

3.1. Categories of capacity limitations

In a first step, we identified the sources of capacity limitations. The amount of differentiation our informants showed in the interviews defines the granularity level respectively the number of subcategories. In the following, we present the identified subcategories for each of the five capacity limitation categories: (1) physical, (2) scheduling, (3) personnel, (4) supply and (5) information.

In the category of physical capacity limitations, we could not identify any differentiation between subcategories. Informants associated this category with the available infrastructure, while they interchangeably used the beds or rooms depending on their background. Three subcategories of scheduling as a capacity limitation could be identified: supply uncertainty, demand-supply mismatch, and demand uncertainty. Effective scheduling of both patient demand and resources was challenging as the hospital was exposed to exceptional exogenous uncertainty. In addition, there was a higher risk of absenteeism and scheduling could not fully cope with these levels of uncertainty, resulting in a mismatch between demand and supply. In the personnel category, we could identify two subcategories: number of available personnel, and their competency. Medical personnel were required to possess additional skills when treating Covid-19 patients and the risk for absenteeism increased. In the category of supply as a capacity limitation, we identified two subcategories: technical equipment and medical equipment. Initially, technical equipment such as respirators but also medical equipment in the sense of consumable supplies like PPE was limited due to disrupted supply chains. Information as a capacity limitation was more diverse since we could identify four subcategories: completeness, timeliness, quality, and availability of information. Incomplete information hindered operationalization of updated treatment procedures. The timeliness of information decreased since existing top-down communication processes were unable to cope with the sheer load of information. At the same time, information quality was low due to a lack of knowledge about the novel disease. The risk of information unavailability increased due to missing standardized communication channels.

Informants mentioned personnel most often and physical least often when we interviewed them about the capacity limitations. Almost the same limitation score was reached in the information category, followed by scheduling and supply. The categories and subcategories of capacity limitations identified here, we would like to stress that these are interrelated and should not be regarded in isolation. For instance, improper handling of technical equipment may lead to inefficiencies in the treatment process, irrespective of whether this was due to inaccurate information or to insufficient competence.

3.2. Effect of hierarchical level

Table I shows how capacity limitations were perceived on different hierarchical levels in the hospital. In general, we can identify differences of the limitation score between hierarchical levels irrespective of the level of analysis. While the overall limitations score for the leadership levels was higher than for the operational level and the central administration, their absolute difference across all capacity limitation categories was lower. Therefore, we identify a negative relationship between the overall limitation score and the variation across the category's limitation scores. We could identify the highest overall limitations scores in this category among the division and department leaders, which reflect the demanding role as being responsible for the tactical capacity planning process.

Table I: Limitation score per main category of capacity limitation, shown by hierarchical level

Hierarchical levels	Number of informants	Physical	Scheduling	Personnel	Supply	Information	Overall
Central administration	4	0.38	0.75	0.88	0.50	0.75	0.68
Division leader	2	1.00	1.00	0.75	1.00	1.00	0.95
Department leader	5	0.50	0.67	1.00	0.60	0.80	0.77
Section leader	8	0.38	0.79	0.94	0.75	0.94	0.78
Operational level	3	0.17	0.78	0.33	0.50	0.58	0.51

The biplot in Figure 1 shows the results from a correspondence analysis to obtain further insight into the relationship between capacity limitation categories and hierarchical levels. Taken together, the first two dimensions accounted for 77% of the variability in the results, suggesting that the two dimensions were sufficient to represent the underlying contingency table. Dots that are located close to each other tend to co-occur, whereas dots which are located far from each other tend not to co-occur. Perceptions of supply uncertainty and information incompleteness as constraints differed least between hierarchical levels. Although close to each other in the organization chart, there were clear differences between central administration and division leaders.

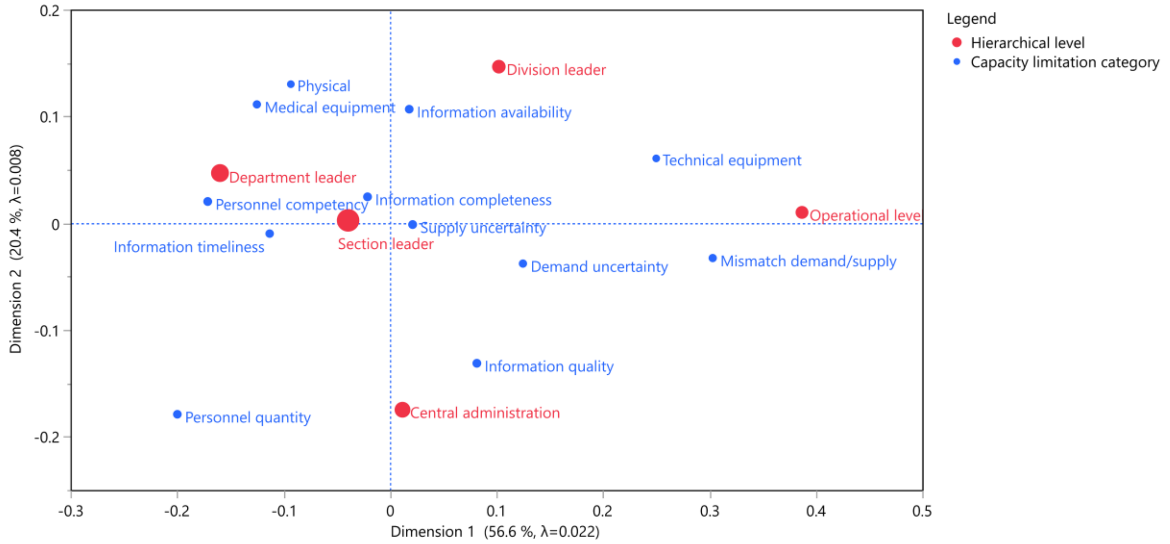

Figure 1: Correspondence analysis biplot of categories and subcategories of capacity limitations (blue dots) against hierarchical levels in the organization (red dots)

To better structure the results of the correspondence analysis, we performed a cluster analysis (Ward's method) over the joined set of coordinates of the capacity limitation categories and the hierarchical levels. We identify four clusters that we find most interpretable. The central administration was most concerned about demand uncertainty and information quality as capacity limitations. Section leaders were most concerned about information availability, information timeliness, supply uncertainty, personnel competency, and medical equipment. Department leaders were most concerned about information completeness, physical and personnel quantity. Division leaders and employees on the operational level were most concerned with demand-supply mismatches and technical equipment.

3.3. Effect of organizational function

In a next step, we analyzed the relationship between capacity limitations and the organizational functions that are related to Covid-19 patient treatment (see Table II).

Table II: Limitation score per main category of capacity limitation, shown per organizational function

Function	Number of informants	Physical	Scheduling	Personnel	Supply	Information	Overall
ED	1	0.50	1.00	1.00	0.50	0.50	0.80
Ward	5	0.80	0.93	0.80	0.70	0.90	0.83
Intermediate Care	2	0.75	0.67	1.00	1.00	1.00	0.93
ICU	4	0.38	1.00	1.00	0.88	0.94	0.91
Support	10	0.20	0.60	0.75	0.50	0.75	0.58

The overall limitation score was lowest for the supporting functions and highest for intermediate care. ICU had the second-largest overall limitation score, followed by ward and ED. Compared to the analysis by hierarchy (see above), the analysis by function clearly shows that these groups are more homogenous in terms of what they perceive as capacity limitations. Informants from ED were least likely to see information as a capacity limitation. ED and ICU also had the highest overall limitation scores for the scheduling dimension. Taken together, this suggests that the beginning and the end of the intrahospital Covid-19 patient pathway suffer from scheduling bottlenecks, while all intermediate steps are much less affected. Supply limitations, however, appear to increase along the patient pathway. This is consistent with the notion that patients in intermediate care and ICU require more resources.

We conducted another correspondence analysis, this time with capacity limitation subcategories by organizational functions (see Figure 2). The dots representing intermediate care and ICU are close to the origin, indicating that they had the least distinctive views of capacity limitations. The ED, on the other hand, is a clear outlier, neither associated with any limitation subcategories nor close to any other organizational function.

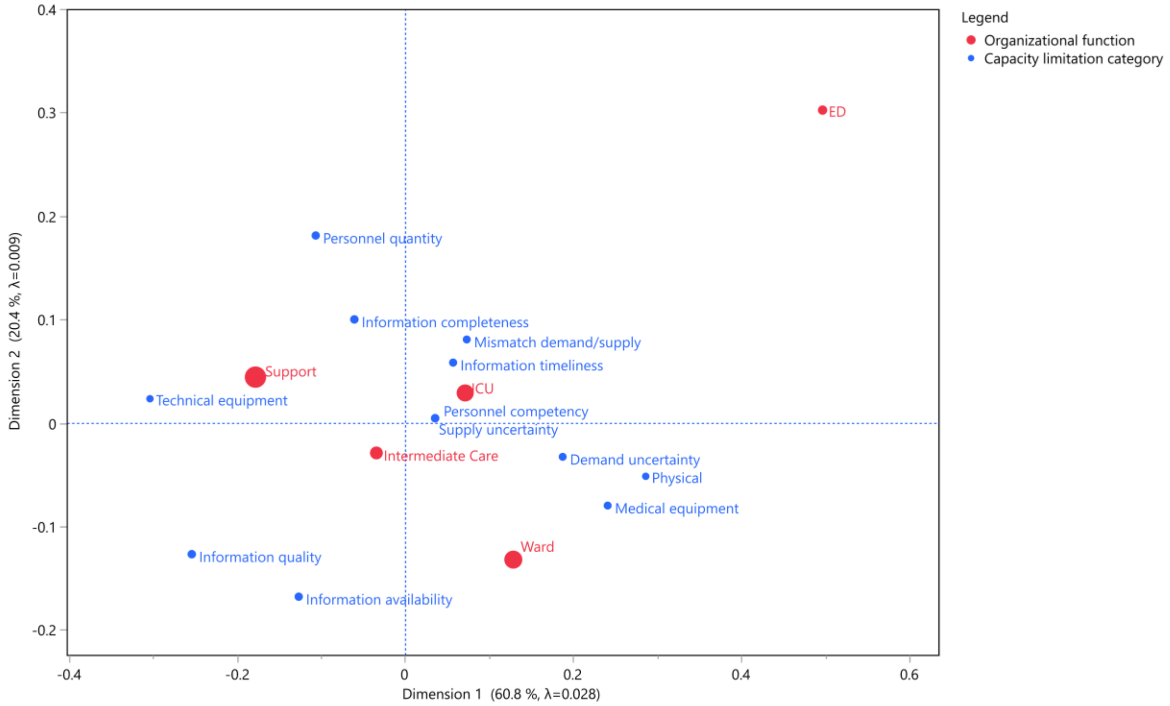

Figure 2: Correspondence analysis biplot of categories and subcategories of capacity limitations (blue dots) against organizational functions (red dots)

The ward and support functions are located at some distance from each other, indicating that they had distinct views of what constrained their respective capacity. Again, we performed a hierarchical cluster analysis to better structure the correspondence analysis results. As could be expected from the correspondence analysis biplot, the ED formed a cluster of its own. Physical capacity limitations and limitations in terms of medical equipment clustered together, but not with any function, indicating that these types of limitations were perceived in an equivalent manner across organizational functions. One of the two larger clusters included ward and ICU, together with all scheduling subcategories and with information timeliness and personnel competency. The other of the two larger clusters included cluster intermediate care and support, together with the remaining information subcategories and with personnel quantity and technical equipment.

4. Discussion

Our first key result is qualitative, concerning the nature of capacity limitations. Eleven capacity limitation subcategories can be added to the broad categories suggested by Thompson *et al.* (2013) and Souza *et al.* (2020) for the healthcare sector. For example, our results indicate that information as a capacity limitation can be broken down into four subcategories: availability, completeness, quality, and timeliness of information. The higher level of granularity achieved by the analysis should allow more specific planning of mitigating measures to overcome the respective capacity limitations. Other types of capacity limitations which we had expected a priori – such as minimum for treatment quality requirements (e.g., in terms of nurse-to-patient ratio) or stock-out of medicines – could not empirically be identified, at least not in the present case.

Our second key result is that the nature of what is perceived as a capacity limitation varies systematically between the hierarchical levels and organizational functions in a hospital. This allows us to refine the tactical capacity planning framework originally suggested by Larsson and Fredriksson (2019). While Larsson and Fredriksson (2019) acknowledge contextual diversity between departments, they assume that limitations are static and equally distributed across departments. In contrast, we find that capacity limitations are dynamic and differ between hierarchical levels and organizational functions.

Informants mentioned personnel and information the most when being asked about capacity limitations. This suggests that, to become tactically agile, a hospital must primarily overcome resource scarcity and fragmented information. In terms of functions, the strongest capacity limitations were felt by ICU and intermediate care. In terms of hierarchical level, it was middle management who felt most limitations. Almost all types of capacity limitations in our analysis were perceived by specific hierarchical levels in the hospital organization. There were two exceptions: limitations in terms of technical equipment and mismatches between demand and supply; these were prominent among middle management as well as on the operational level.

Other studies conducted in Swedish and Czech hospitals during the Covid-19 pandemic identified similar challenges as the ones observed in our study, such as personnel shortages in the ICU or limitations of workforce re-dispositioning (Michenka and Marx, 2023; Rosenbäck and Svensson, 2023). Another aspect is the hospital's partner ecosystem, which can support in pandemic response. For instance, private clinics whose elective appointments are postponed or cancelled can provide personnel or technical equipment to public hospitals. These private-public partnerships allow to complement required competencies for effective pandemic response (Abbas *et al.*, 2023).

We chose a qualitative research design for this study since research on tactical capacity planning during the Covid-19 pandemic is still scarce. Our interview strategy was to ask informants about limiting factors and challenges, rather than positive experiences. We chose this strategy because the smoothness of operations in a hospital depends on the interplay of more factors than a single informant can be expected to identify. This strategy also reduces the recollection bias as it is easier for an informant to report workplace experiences where problems and deviations occurred.

However, one should keep in mind that intangible capacity limitations (i.e., unknown unknowns) have not been captured by the interviews. It was not the objective of this study to identify the root causes of the distinct types of capacity limitations; informants' knowledge is likely to be limited when root causes are outside their area of responsibility. Still, we tried to minimize this threat to validity by selecting key informants based on the criterion that they had been involved in capacity planning and/or taskforce's decision-making processes during the Covid-19 pandemic.

Another, related challenge is the natural variability of patient pathways (Otten *et al.*, 2021). Bittencourt *et al.* (2018) conclude that the natural variability of patient pathways and processes has a negative impact on actual capacity. However, it may be difficult for informants to define whether capacity limitations stem from intended process changes or from "normal" responses due to the diversity of the patient population.

The data sources accessible to us were not sufficiently detailed to allow us to quantify the capacity losses (Blumenthal *et al.*, 2020; Leite *et al.*, 2020) that occurred during the Covid-19 pandemic. Since operations managers could not predict changes in patient requirements from historical data, the focus of capacity planning shifted towards operational flexibility. Process monitoring and control were neglected, including the collection of relevant process data. More research is required here; we hope that other hospitals were able to maintain better process monitoring during the Covid-19 pandemic so that light may be shed on this.

A shortcoming of our study is the sole focus on one hospital during the global Covid-19 pandemic. While the organizational structure in other hospitals might be different, the dominance of strong medical professions that result in silos is similar (Frandsen and Johansen, 2020). Our findings show that these professional silos hampered tactical agility; personnel reallocation was limited because of the strict but disparate qualification requirements in the different organizational functions.

One recommendation that can be based on our analysis is that future tactical capacity planning must take interdisciplinary patient pathways (KC *et al.*, 2020) better into account. Although an organization-wide approach is challenging, effective tactical capacity planning should take a global view, as we did in our study, since simply managing the capacity of one hospital department will not be sufficient when the patient pathways change (Anupindi *et al.*, 2012). One can even take this approach one step further. Balancing patient demand, especially for the ICU within a cluster of hospitals in a region proves to be effective in pandemic response (De Koning *et al.*, 2022).

It should be noted that some types of capacity limitations can be alleviated if there is slack capacity in others. For instance, problems with peak hours caused by ineffective scheduling can be reduced if there is spare workforce capacity. However, not all types of limitations have a compensatory relationship with each other. For instance, too little physical capacity cannot be balanced by additional stocks of medical equipment. Therefore, our results should be regarded as relative than hard values as the ability to compensate for a capacity limitation category differs. Still, our findings contribute to the literature and have the potential to help hospital managers better understand how to adapt treatment capacity when patient requirements change, which is not yet widely understood (Kumar and Singh, 2020).

In terms of theory, our recommendation to adapt to interdisciplinary patient pathways (which requires an organization-wide view) blurs the distinction between strategic and tactical capacity planning. While existing models of the capacity planning process see case mix planning and capacity dimensioning as strategic tasks (Hans *et al.*, 2011), our study shows that strict top-down planning may impose constraints on the agility of the process as a whole. One could even argue that during a global pandemic, hospitals are not in control of case mix planning (which depends on referrals) and capacity dimensioning (which depends on past data about capacity utilization), since all functions are affected. Therefore, we propose that tactical capacity planning during pandemic situations should not only consider a shorter planning horizon than strategic planning (which is often the only difference between the two planning levels) but also consider compensatory relationships between different resources at various stages in relevant patient pathways. Unfortunately, optimization models that can enhance tactical capacity planning tend to focus on a single resource such as the number of beds, nurses, or doctors (Aslani *et al.*, 2021; Bittencourt *et al.*, 2018). A way to overcome this challenge could be to utilize serial queuing networks, a method that considers when the hospital is able to adjust capacities (Curry *et al.*, 2021).

As a direction of future research, we would suggest comparative analyses of capacity limitation in other tertiary public hospitals under a global pandemic. This would offer the possibility to identify common patterns in tactical capacity planning and the capacity limitations resulting from it, and how they develop over time. Moreover, we propose that the information flow—one of the major types of capacity limitations and an integral part of tactical agility—should receive more attention during the analysis. A recent study pinpoints this challenge and concludes that even low hurdles in the information-gathering process could impair effective capacity planning (Kim *et al.*, 2020). It would be important to study which strategies can improve information flow inside the hospital and with external stakeholders.

5. Conclusion and implications for practice

Effective tactical capacity planning in hospitals is crucial when patient requirements substantially change as experienced during the Covid-19 pandemic. To the best of our knowledge, our study is the first which analyzes capacity limitations across different hierarchical levels and organizational functions. Our findings highlight that capacity limitations are dynamic and systematically different. As a result, we propose that future research on tactical capacity planning should take interdisciplinary patient pathways better into account.

Operations managers in hospitals can leverage the study's findings to prioritize tactical capacity planning efforts more effectively during pandemic situations. Our case study reveals common characteristics of tertiary public hospitals, like professional silos and fragmentation along patient pathways. Therefore, we argue that our insights are transferrable and can be applied to other tertiary public hospitals during similar situations. We recommend that operation managers should focus more on the personnel dimension and the intra-organizational information flow to increase the agility of the hospital.

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Appendix A

Consolidated criteria for reporting qualitative studies (COREQ) Checklist

Developed from:
Tong A, Sainsbury P, Craig J. Consolidated criteria for reporting qualitative research (COREQ): a 32-item checklist for interviews and focus groups. *International Journal for Quality in Health Care*. 2007. Volume 19, Number 6: pp. 349 – 357

Domain 1: Research team and reflexivity	**Reported in section #**
Personal Characteristics	
1. Interviewer/facilitator	Author list
2. Credentials (e.g. PhD)	NA
3. Occupation/Affiliation	Author list
4. Gender	NA
5. Experience and training	NA
Relationship with participants	
6. Relationship established	2.2
7. Participant knowledge of the interviewer	2.2
8. Interviewer characteristics	2.2
Domain 2: study design	
Theoretical framework	
9. Methodological orientation and Theory	2.2
Participant selection	
10. Sampling	2.2
11. Method of approach	2.2
12. Sample size	2.2
13. Non-participation	2.2
Setting	
14. Setting of data collection	2.2
15. Presence of non-participants	2.2
16. Description of sample	2.2
Data collection	
17. Interview guide	Appendix B
18. Repetition of interviews	NA
19. Audio/visual recording	2.2
20. Field notes	NA
21. Interview duration	2.2
22. Data saturation	2.2
23. Returning transcripts	NA
Domain 3: analysis and findings	
Data analysis	
24. Number of data coders	2.2
25. Description of the coding tree	NA
26. Derivation of themes	2.2
27. Software	NA
28. Checking by participants	NA
Reporting	
29. Presentation of quotations	NA
30. Consistency of data and findings	3
31. Clarity of major themes	3
32. Clarity of minor themes	3

Appendix B

Interview guide

Introduction:
• What is your profession and role? • How much work experience this year do you have in your current role? ☐ Less than a year ☐ 1-2 years ☐ 3-5 years ☐ 5-10 years ☐ More than 10 years • How many departments have you worked in at the hospital? • What is your educational background?
Challenges, decisions and information flow
The hospital was in yellow preparedness level from March 12 to April 16, 2020. Let's limit the interview to this time. • How did the yellow preparedness level affect the work in your department and what was challenging? • How dependent is your department on the activities happening outside your department? Has that changed during the COVID-19 situation? • How do you communicate with the mentioned departments (dependencies)? • Does the communication between you work well? Why and why not? • Has it changed during the COVID-19 situation? • Based on what information do you make decisions in your department? What information is missing? • How was this information collected? • How are conflicts/irritation/challenges across departments handled? • What kind of information did you share with the Covid-19 taskforce about your department/area of responsibility? • How should/was the pandemic plan operationalized in your department
Limitations

• How do you know you are working efficiently or how do you know if you are working well? Is there any parameter or key figure? Do you record it in any way?
• What are the biggest constraints for your department in the time from March 12 to April 16 (yellow preparedness level)?
    o Category:
        ▪ Physical (e.g. infrastructure)
        ▪ Scheduling (Are there times of day when it's more stressful?)
        ▪ Staffing
        ▪ Equipment and supplies
        ▪ Information
• Did these limitations/challenges change due to the pandemic situation? If yes, how? (become less or even increased).

Future work
What are your suggestions for improvement? Can we contact you again if we have any more questions?

Paper 4: Cross-training of nurses during a global pandemic: A two-stage stochastic programming approach

Cross-training of nurses during a global pandemic

A two-stage stochastic programming approach

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Declaration of interests

We received no external funding for this study. The authors declare no competing interests of relevance to the content of this article.

Ethics statement

In accordance with the policies of the authors' institutions, an ethics approval by a review board was not needed for this work.

Data availability statement

The data that support the findings is available from the corresponding author upon reasonable request.

Keywords: two-stage stochastic programming, nurse staffing, cross-training, absenteeism, healthcare, hospital, tactical staffing decisions

Paper type: Research paper

Abstract

Uncertain patient demand during a global pandemic and increased risk for absenteeism among nurses are negatively associated with patient safety levels. Maintaining an adequate patient safety level, requires effective nurse staffing to avoid understaffing. To address this problem, we formulate a two-stage stochastic programming model for tactical nurse staffing that incorporates stochasticity in patient demand and nurse absenteeism. Our model supports two nurse staffing decisions: first, the tactical decision regarding the quantity of nurses to be cross-trained and second, the operational decision concerning the number of temporary nurses to be hired. Utilizing data from a Norwegian university hospital during the Covid-19 pandemic, our model reveals a bottleneck of nurses in the intensive care unit. Our simulation experiments show that the value of additionally qualified nurses decreases with a larger nurse base. Moreover, we highlight the effects of cross-training cost and non-treatment cost on the service level. Despite the study's limited focus on a singular patient pathway and the exclusive consideration of nurses, this study provides invaluable insights into tactical nurse staffing decisions. To the best of our knowledge, this is the first study that models cross-training as a tactical staffing decision and its consequences on workforce availability during the cross-training period.

Highlights

- To the best of our knowledge, this is the first two-stage stochastic programming model that models the unavailability for treatment during the cross-training period.
- Our results enhance the understanding of the interplay between service levels and the cross-training as well as the temporary hiring decision.
- The value of additional qualified nurses decreases with a larger nurse base.
- The proposed model can support operations managers in hospitals to make informed nurse staffing decisions and leverage cross-training as a tactical nurse staffing strategy.

1. Introduction

Rapid changes in patient demand pose a risk of disruption to the operations of hospitals as the recent shock caused by the Covid-19 pandemic has demonstrated. According to the World Health Organization (WHO), the most common cause of such disruptions is workforce-related, like unusual rates of absenteeism among medical personnel and lack of required competency [1]. These factors can adversely affect patient safety and, in the worst case, may even pose a risk to human life. Therefore, it is imperative that the workforce in a hospital, both in terms of quantity and skill mix, matches with the patient demand. During periods characterized by volatile patient demand and uncertain workforce availability, hospitals need to deploy mitigation strategies. Hiring temporary medical personnel can help to maintain an adequate patient safety level, but this approach is expected to lose its effectiveness in the future, as the WHO predicts a shortage of 1.4 million healthcare workers by 2030 in Europe alone, the majority of whom will be nurses [2]. Given this forecast, hospitals are required to plan their existing medical personnel resources, particularly nurses, more flexibly to better adapt to changing patient demand and evolving disease profiles. An increase in the operational flexibility of nurses can be achieved by cross-training, a process that involves educating nurses to work in more than one role. This allows cross-trained nurses to be assigned to different functions or departments in the hospital, enabling more effective utilization of available nurses. However, healthcare operations managers need to find the balance between flexibility and cost effectiveness. Nurses being cross-trained are not available for patient care during either classroom teaching/e-learning and require additional resources during on-the-job training [3,4]. Moreover, the cross-training decision is irreversible. Therefore, it would not be prudent to cross-train every nurse since the costs would be immense despite the potential increase in flexibility.

The problem of nurse staffing has already received attention by scholars in the early 20th century [5] as nurses play a pivotal role due to their intermediary function between doctors and patients. With the rising number of multi-disciplinary patient pathways and the increasing specialization of departments, incorporating the skill dimension into staffing decisions has become increasingly crucial [6]. Consequently, specialized treatment is confined to nurses with specific skills [7]. We define skills as the competency to perform an assigned task without errors while ensuring an adequate patient safety level. In addition, uncertainty is omnipresent in hospitals, both exogenous (i.e., arising from externalities) and endogenous (i.e., depending on decisions) [8]. To cope with uncertainty, methods from operations research have been applied to nurse staffing problems. In particular, stochastic programming offers the potential to model uncertainty in nurse staffing problems [9-11]. To the best of our knowledge, there is yet no study that has addressed nurses' cross-training activities in relation to both uncertain demand and nurse absenteeism, while pursuing a two-stage stochastic programming approach for a tactical cross-training decision and an operational temporary hiring decision. Therefore, we extend the model by Maass et al. [10] by incorporating an internal process perspective on cross-training and determining the number of nurses to be cross-trained and temporarily hired while minimizing the total cost. Furthermore, we analyze how parameters such as cost for non-treating patients, cross-training cost, the initial number of qualified nurses influence the total cost, the service level (SL) and the two decisions.

2. Literature Review

2.1. Nurse staffing

The nurse staffing literature traces back to the early 1920s and has since gathered attention by scholars. Lewinski-Corwin [5] was the first to tackle the problem of determining an adequate nurse level required to meet a given patient demand. The nurse staffing decision aims maintaining an adequate patient safety level and is not trivial in practice due to the complexity of influential factors such as the patients' disease mix and their acuity levels [11]. Nevertheless, many operations managers make use of static patient-to-nurse ratios when determining the required number of nurses [12]. An alternative approach to achieving a match between nurses and patient demand is to shift decision-making power to patients, for instance, by disclosing nurse staffing levels and allowing patient to decide which hospital to go to [13]. However, this option mostly applies for elective appointments. Patient-to-nurse ratios are not yet standardized across regions/countries and vary across disciplines, while nursing workload is not adequately captured [14,15]. Although there is no standardization, a consensus among scholars suggests that patient outcomes are positively correlated with an increasing number of available medical personnel [12,16]. One disadvantage of static patient-to-nurse ratios is the inability to accommodate every patient demand scenario. Therefore, hospitals need to find mitigation strategies to cope with uncertainty. Such strategies may include working overtime, temporary hiring or re-dispositioning nurses within the hospital to ensure an adequate nurse staffing level in every department [17]. However, these mitigation actions cannot be sustained in the long term as they may lead to higher stress levels among nurses, potentially resulting in an increased employee turnover rate or increased financial expenses. Therefore, many studies on nurse staffing aim to find a balance between defining adequate nurse staff levels, ensuring sustainable patient outcomes and maintaining costs low.

Kao and Queyranne [18] highlight the risk for understaffing when uncertainty or variability is not incorporated into nurse staffing decisions. We observe efforts from the academic society to create decision support tools, capable of managing uncertainty and variability in patient demand. For instance, Fagerström et al. [19] question the use of static patient-to-nurse ratios, proposing a resource-centered approach that respects the individuality of patients and nurses. Their RAFAELA workforce planning system bases decisions on the nurse intensity index and the patients' care needs. Another tool is the "Safer Nursing Care Tool" widely used in the United Kingdom, assists in defining optimal nurse staffing levels and provides metrics for benchmarking [20]. While this tool includes patient demand uncertainty and nurse absenteeism, it does not provide solutions for demand scenarios outside the 90%-percentile. Therefore, the tool requires satisfactory baseline estimates for permanently employed nurses a priori to avoid understaffing scenarios [21]. Moreover, its underlying simulation is based on historical data, hence the period of data collection time is decisive for the tool's accuracy [21]. While these presented decision support tools offer a data-driven approach to tackle the challenge of determining adequate nurse staffing levels, they overlook the required skill levels to meet the patient demand and its variability beyond seasonal changes.

2.2. Cross-training of nurses

In addition to demand uncertainty, the required nurse skill mix needs to be considered when determining nurse staffing levels [10,11,22]. Both the incoming disease mix and individual patient pathways (or their acuity levels) are decisive for determining the necessary nurses' skills [23]. Workforce planning literature distinguishes between two different categories of skills: 1) hierarchical and 2) categorical skills [7]. First, hierarchical skills are universal and can be arranged in an order such that nurses with higher skill levels can perform more tasks than those with lower skill levels. Furthermore, high skilled nurses can substitute for lower skilled nurses at a higher cost [7]. Second, categorical skills cannot be hierarchically ordered and are often usable only in unique settings. As a result, additional training becomes necessary when external conditions change. The acquisition of additional categorical competencies is called cross-training. Within the healthcare domain, cross-trained nurses are sometimes referred to as pool nurses [24]. These nurses can be allocated to different departments enabling a flexible allocation of resources. In contrast, specialized nurses are limited to one department but can perform complex tasks or treatments within their domain.

Overall, there is a consensus that cross-training increases the operational flexibility, since it can better adapt to changes in demand, while reducing the overall cost [25-28]. Paul and Mac Donald [29] even argue that cross-training could serve as a mitigation strategy to overcome future nurse shortages. However, cross-training incurs additional cost and cross-trained nurses are often less efficient than their specialist peers [27,30]. Consequently, the hospital faces a dilemma between the positive effect on operational flexibility and the negative impact on operational efficiency. Maenhout and Vanhoucke [24] conduct a case study at a Belgian university hospital and conclude that the cross-training decision for nurses should be centrally coordinated across departments to achieve higher operational flexibility. Ahmadi-Javid and Ramshe [31] demonstrate through their queuing model for a primary healthcare network that coordinated cross-training could diversify the offer for health services and reduce network costs. However, Davis et al. [12] note that cost reduction is dependent on context characteristics. In complex environments like the intensive care unit (ICU), it is more cost-effective to employ additional skilled nurses than to cross-train existing nurses.

While the aforementioned studies assume a priori knowledge of the learning curve and treat the skill level as a binary variable, Cavagnini et al. [32] develop a two-stage stochastic program for the production environment that models uncertainty in either learning rate or forgetting rate. They conclude that incorporating internal uncertainty in terms of learning rate can further minimize the total cost compared to a model without internal parameters for uncertainty. Bam et al. [9] conduct a case study at a surgical unit and offer a novel approach to the nurse staffing decision. Their optimization model assigns services to nurse teams rather than individual nurses to better balance cross-training time. While they focus extensively on the skill dimension, they overlook the risk of nurse absenteeism.

2.3. Nurse staffing under absenteeism

Another source of uncertainty to be integrated into staffing decisions is absenteeism [33].The reasons for absenteeism are manifold and can be differentiated into endogenous and exogenous absenteeism [34]. While many studies treat absenteeism as an exogenous phenomenon, it is also important to consider endogenous absenteeism, for instance, as a function of expected workloads or nurse staffing levels inadequacy [34-36]. Regardless the type of absenteeism, hospitals need to minimize the risk for understaffing. Easton and Goodale [35] compare various strategies and conclude that overtime work is an effective short-term strategy but requires a legal basis. Otherwise, temporary hiring might become necessary. Another interesting finding is that the mere anticipation of absenteeism positively influences the effectiveness of staffing strategies [35].

Given that absenteeism is only one of many aspects to be incorporated into staffing decisions, we recognize the need to consider absenteeism and skills simultaneously. We note that most studies on staffing models is theoretically driven. For instance, Olivella and Nembhard [37] create a mathematical model that presents an optimal skill matrices and cross-training levels for teams. However, they remark that optimality and a higher chance for infeasibility is less practically valuable than models with suboptimal results but with a larger area of feasibility. In a subsequent paper, they analyze the robustness of the model's solution and conclude that focusing on meeting the incoming demand would increase the training cost and reduce the solution's robustness [38].

As the presented studies address both the absenteeism and employee's skills mix but lack the connection to healthcare specifications, we now review studies in the healthcare domain. Ryu and Jiang [39] use a distributional and robust approach to define the optimal layout for cross-trained nurse pools to meet the incoming demand and variable nurse absenteeism. Their numerical results based on a case study show that the departments with a higher probability of nurse absenteeism should perform centralized workforce planning. Arguably, the most related paper to our study is by Maass et al. [10]. The model's first stage decision is strategic and defines the organizational layout into pools of specialized nurses and float pools, which symbolizes the level of cross-training. During the second stage, extra nurses can be hired to accommodate for absenteeism, which is an operational decision. Experiments show that the additional value of an extra nurse influences the optimal staffing level. Even though this study considers both the nurses' skill mixes and absenteeism, it neglects the possibility for additional cross-training of nurses internally within the decision period and assumes a priori an almost infinite external nurse pool. Thus, the consequences of cross-training such as unavailability and additional resources for on-the-job training are not included.

3. Problem formulation

In the following section, we illustrate the underlying problem. As a case we choose a Norwegian university hospital during the Covid-19 pandemic in March/April 2020. We initially explain the requirements for nurse skills when treating Covid-19 patients. Subsequently, we present the implications of Covid-19 on nurse absenteeism, followed by a comprehensive problem formulation.

Covid-19, a respiratory disease caused by the coronavirus SARS-CoV-2, requires a longer average hospitalization for patients compared to similar respiratory diseases [40]. This characteristic results in increased pressure on the hospital's services both in terms of infrastructure and personnel resources. Furthermore, patients with a severe Covid-19 pathway require admission to the ICU as they need respirator treatment and close monitoring by specialized medical personnel. Reports from hospitals differentiate between three treatment levels of hospitalized Covid-19 patients: hospitalized patients, patient on the ICU without respiration (i.e., intermediate care) and patient on the ICU with respiration [41]. In the early phase of the Covid-19 pandemic, it was expected 4-20% of all individuals who tested positive for Covid-19 were hospitalized of whom 25% admitted to the ICU, staying there on average for 15-17 days [41,42]. However, not only was the length of stay at the hospital uncertain but also the actual number of patients influx as the epidemiological development was difficult to predict as we can already see in the share of hospitalizations in different countries. Furthermore, these ratios are dependent on testing capacities and vaccination coverage. Consequently, hospitals had to adapt their capacity by sourcing additional medical equipment (e.g., respirators), freeing up physical space and upskilling nurses to cope with the increasing number of Covid-19 patients. As there was no possibility to train additional nurses with basic competencies (meaning an education period three years under normal circumstances) or specialize nurses (meaning a specializing education period two years) due to the constraints in time, hospitals decided to cross-train nurses for treating Covid-19 patients. This cross-training provided basic knowledge for essential Covid-19 treatment activities. For instance, ICU cross-trained nurses could operate respirators and perform close monitoring. The cross-training syllabus consisted of either classroom teaching or web-based learning and the on-the-job training. The latter enabled the nurses to familiarize with their new role.

The Covid-19 pandemic resulted in a higher risk for nurses to be absent from work compared to regular situations [43]. The reasons for a higher nurse absenteeism were manifold and we illustrate three possible root causes for a nurse being absent. Firstly, a nurse tests positive for Covid-19 and must isolate to prevent further spread of the virus within the hospital. Secondly, a nurse is considered a close contact of a person that tested positive for Covid-19, necessitating the nurse’s quarantine. The isolation and quarantine regulations may vary across regions/countries. Finally, there may be other personal reasons due to state-enforced containment measures. For instance, a nurse might be absent when childcare is required at home due to school closures or cross-border workers are hindered to reach the hospital by travel bans.

In conclusion, hospitals faced two main challenges during the Covid-19 pandemic. First, there was a need to train nurses to ensure the treatment of Covid-19 patients across all severity levels. Second, absent nurses needed to be replaced, for example by temporarily hiring nurses. These challenges created a dilemma between patient safety and financial resources. For instance, it was not expedient to cross-train every nurse as this decision would be costly. Furthermore, the cross-training process would be lengthy since the number of nurses being cross-trained simultaneously is limited due to a finite number of trainers and the fact that nurses under cross-training are not available for patient treatment. Therefore, there was a need to optimize the number of nurses being cross-trained or temporarily hired to minimize the total cost while maintaining an adequate patient safety level.

4. Methodology

4.1. Two-stage stochastic programming

As previously outlined, our study creates a decision-support tool for nurse staffing in times of uncertain patient demand and nurse absenteeism. We employ methods from the field of operations research as they have the potential to complement and enrich the nurse staffing literature [11]. These methods offer a structured and data-driven approach by providing tools for optimization such as simulation or mathematical algorithms [11]. Given that model parameters, variables and limitations need to be explicitly stated a priori, this methodology enhances transparency. Additionally, stochastic programming offers the possibility to model uncertainty. Traditional optimization techniques have been applied in interdisciplinary studies to solve problems in the healthcare sector, like the definition of optimal layout designs for hospitals [44]. The layout is decisive for the distance traveled by medical personnel and patients, which can improve operational efficiency and patient experience. Another study proposes a model to optimize patient flows thereby reducing costs [45].

We choose a stochastic programming approach since the underlying problem is characterized by uncertainty. The decisions modeled by stochastic programming are robust as they include a distribution of parameters and a possible recourse action allows refining the initial decision [46]. Moreover, this method provides decision support for various scenarios and not only for average scenarios [47]. A deterministic approach that replaces all random variables (e.g., patient demand, absent nurses) by their means would less accurately represent reality and might lead to severe or even fatal consequences. To motivate our choice of method, we illustrate two disadvantages of a deterministic approach.

If the number of absent nurses is higher than its expected value, a deterministic model will not accommodate the increased absenteeism that could result in a shortage of nurses. Hence, patient safety is negatively affected, which may pose a risk to human life. Conversely, if there are fewer absent nurses than the average, a deterministic approach will result in an overuse of financial and human resources, which could be used more profitably elsewhere (e.g., buying personal protective equipment). Particularly, when uncertainty is high in forecasted demand and absenteeism, a deterministic approach would inadequately consider the tails of the distributions. Solving stochastic programming models is often slower than solving deterministic models due to scenario dependent computational resources and offers no guarantee of finding the global optimum. However, the focus of our study is on understanding the relationship between decisions made and outcomes rather than optimality. Therefore, stochastic programming constitutes an adequate method for our study.

We choose a two-stage stochastic programming approach, a specific type of stochastic programming model that includes two sequential decisions. First, we need to determine the number of nurses that should be cross-trained. Second, the number of nurses that need to be temporarily hired needs to be defined to replace absent nurses. While the first-stage decision is irreversible, cost-intensive and tactical, the second stage decision is operational and dependent on the number of nurses being cross-trained. Therefore, our model is inspired by an invest-and-use model, one of the most essential models in stochastic programming [47]. Moreover, the two-stages are mathematically different as decision variables and constraints vary.

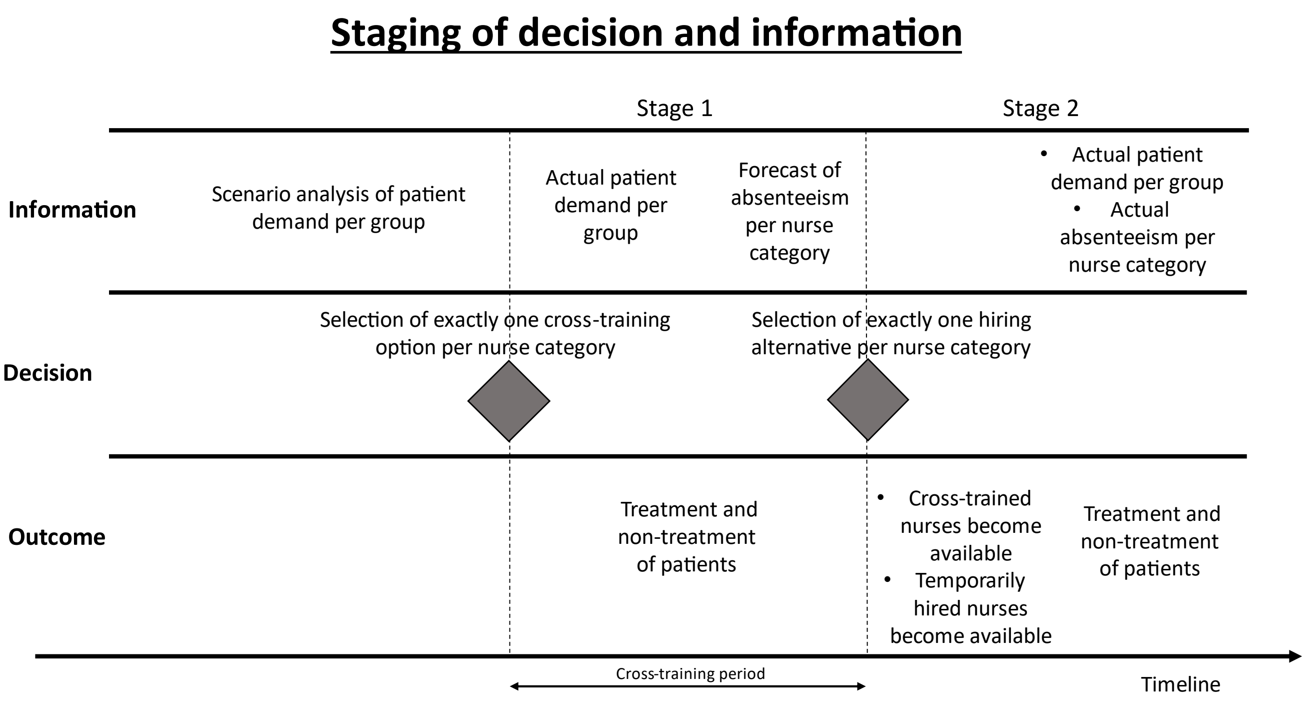

Figure 1: Sequential decision structure and information structure including related outcomes.

We now clarify the information structure of our two-stage sequential decision model. As every decision is made based on the available information at this moment and leads to a specific outcome, we structure our description accordingly (see Figure 1). The cross-training decision, in which exactly one cross-training option per nurse category (normal, intermediate, ICU) is chosen, is based on the scenario analysis for patient demand in 2-4 weeks. The cross-training options are defined a priori and may be dependent on the number of available trainers and/or training infrastructure. Additionally, during the first stage the actual demand for stage one is revealed. Based on this information the model decides how many patients per group should be treated and non-treated during the first stage. The subsequent second decision regarding the number of nurses to be temporarily hired is based on the scenario analysis on patient demand and nurse absenteeism. We assume that absenteeism is only considered during the second stage. At the beginning of the second stage, the additional cross-trained nurses become available for treating Covid-19 patients in their additional functions. Temporarily hired nurses becomes immediately available. Hence, the model can define the number of treated and non-treated patients when the actual demand for the second stage is revealed.

4.2. Data collection

The initial parameters for our two-stage stochastic programming model are publicly accessible by: 1) OECD, 2) Norwegian Directorate for Higher Education and skills and 3) Akershus university hospital, the case hospital. First, we collect the information on average patient-to-nurse ratios and average nurse-doctor ratios for Norway from the OECD [15]. Second, we gather Norwegian data on the share of specialization among the nurses either for the ICU or other specilization including the respective salary [48]. Third, we collect case-related information from reports by Akershus university hospital [41]. These documents contain the number of Covid-19 patients per patient group (normal, ICU w/o respiration, ICU) during March/April 2020. Moreover, they include information about absenteeism among the personnel due to isolation. In addition, the documents contain information about the average cost for temporarily hired nurses as well as the training structure for cross-training. The aggregated number of total hospitalized Covid-19 patients at Akershus university hospital is triangulated with the information from Helsedirektoratet [49].

4.3. Simulation experiments

Our research design follows an experimental approach consisting of two phases. First, we apply our two-stage stochastic programming model on historic data from the first Covid-19 wave at Akershus university hospital, retrospectively determining the optimal number of nurses to be cross-trained and temporarily hired. Additionally, we proceed to run three simulation experiments to enhance the understanding about relationships of modelled parameters. Hence, we choose to alter exactly one of the following parameters in each experiment: 1) the cost for non-treated patients, 2) the average cross-training cost per nurse and 3) the initial number of qualified nurses. Furthermore, we select parameters that affect decisions in either two of the stages or one stage only. Finally, simulation experiments offer insights into complex relationships between decision and dependent variables while supporting practitioners in their decision-making process [52].

5. Formal problem description and model formulation

The formulation of the two-stage stochastic program, for the problem described earlier, is presented in the following section. The notation for five global input parameters is defined as follows:

$\boldsymbol{f}$	Cost for non-treated patient
$\boldsymbol{e}$	Average treatment cost per patient
$\boldsymbol{s_c}$	Salary per nurse in category c
$\boldsymbol{base_c}$	Number of initially qualified nurses per category c
$\boldsymbol{minbase_c}$	Minimum number of qualified nurses per category c

The cost for non-treated patients is set at twice the average actual treatment cost per patient (i.e., 200,000 NOK). This cost includes for instance opportunity costs for lost revenue but also community health cost when transferring patients to a partner hospital within the region. We propose a linear cost for non-treated patients, denoted as $\boldsymbol{e}$, per patient under the assumption administrative activities and loss of revenue do not increase irrespective of the number of non-treated patients. We calculate the average treatment cost per patient based on findings from existing literature. Lindemark et al. [53] report that the average daily cost for an ICU patient is 3,980€ and for the normal patient 640€. Moreover, the median length of stay of Covid-19 patients is five days on the normal ward and seven days on the ICU [54]. As 25% of the hospitalized patient with Covid-19 require treatment on the ICU while the other share solely requires treatment on the normal ward for five days, we can calculate the average cost for a hospitalized Covid-19 patient to be 10,165€ [42]. Nurses are classified into three categories: normal, intermediate and ICU, to account for the varying needs of different patients.

The nurse categories are hierarchically organized with ICU as the highest and normal being the lowest: Each category corresponds to a different nurse salary, denoted as $\boldsymbol{s_c}$. The number of initially qualified nurses is denoted as $\boldsymbol{base_{c}}$. and the minimum of qualified nurses is denoted $\boldsymbol{minbase_{c}}$. Given that we do not distinguish between individual patients or their specific treatment pathways, we utilize minimum nurse-to-patient ratios from the literature [55]. Hence, we assume a minimum patient-to-nurse ratio of 1:1 for intermediate and ICU patients and for the normal ward 4:1.

5.1. Cross-training – first stage decision

In a next step, we define the input parameters for the first stage, the cross-training decision, as follows:

$\boldsymbol{p^{s}}$	Probability of demand scenario *s*
$\boldsymbol{D_{c}^{s}}$	Patient demand in scenario s per nurse category *c*
$\boldsymbol{n}$	Number of available cross-training options
$\boldsymbol{train_{c,\,i}}$	Number of nurses cross-trained per option *i* and nurse category *c*
$\boldsymbol{tc_{c,\,i}}$	Cost per cross-training option *i* and nurse category *c*

Drawing on the hospitalization data from Akershus university hospital over a one-month period during the first wave of Covid-19, we generate demand scenarios $\boldsymbol{D_{c}^{s}}$ each occurring with a probability of $\boldsymbol{p^{s}}$. The patient demand is divided into the respective nurse categories. We derive the daily change of patient demand and fit the distribution. The Shapiro-Will normality test validates that the daily change in patient demand follows a normal distribution. To enrich the empirical distributions, we estimate the mean and standard deviation of a normal distribution [47]. Subsequently, we discretize the normal distribution into twenty-five demand scenarios, which is arbitrarily chosen a priori. The different cross-training options denoted as $\boldsymbol{train_{c,i}}$ are also defined beforehand, simulating the restrictions of finite class sizes of ten trainees. Furthermore, we propose that the cross-training cost denoted as $\boldsymbol{tc_{c,i}}$ comprises a variable component and a fixed component. For instance, the cost of creating training manuals is an initial investment independent on the number of nurses to be cross-trained.

We also define the decision variables for the first stage as follows:

$\boldsymbol{x_{c,i}}$	Cross-training option *i* per nurse category *c* chosen
$\boldsymbol{t1_{c}}$	Number of treated patients per category *c* in the first stage
$\boldsymbol{u1_{c}}$	Number of non-treated patients per category *c* in the first stage

We would like to emphasize that the selection of cross-training options does not necessarily have to be equal across different nurse categories. In situations where the model identifies a shortage of nurses in one category, it can define cross-training exclusively for that category, while the other two categories may not participate in any cross-training activities. Moreover, while a cross-trained nurse can treat Covid-19 patients in a department other than the original department, this is not applicable in context of another disease. Nurses for cross-trained are selected from less affected departments that postponed or cancelled elective appointments. Finally, we introduce the number of non-treated patients to improve comprehension of the extent to which the hospital's capacity is exceeded. This parameter serves as a measure of the pressure on the hospital's resources and the efficacy of the implemented cross-training options.

5.2. Temporary hiring decision – second stage

Let us now turn to the second stage decision, the temporary hiring decision, which is our mitigation action for absenteeism. We define the input parameters as follows:

$\boldsymbol{q^r}$	Probability of absenteeism realization *r*
$\boldsymbol{a_c^{r,s}}$	Nurse absenteeism in realization *r* per demand scenario *s* and category *c*
$\boldsymbol{m}$	Number of hiring alternatives
$\boldsymbol{hire_{c,j}}$	Number of nurses hired per alternative *i* and nurse category *c*
$\boldsymbol{hc_{c,j}}$	Cost per hiring alternative *j* and nurse category *c*

The realizations of nurse absenteeism $\boldsymbol{a_c^{r,s}}$ and their probabilities denoted as $\boldsymbol{q^r}$ are generated from information on absenteeism in similar manner to the demand scenarios, resulting in twenty-five absenteeism realizations. The Shapiro-Will normality test validates a normal distribution for the daily change in absenteeism. While the values for temporarily hired nurses could theoretically take any non-negative integer value, we define hiring alternatives denoted as $\boldsymbol{m}$ a priori to model a finite number of available nurses for temporary hiring. The average cost per temporarily hired nurse is structured to progressively increase to account for the scarcity of available nurses as the need for temporary hiring of nurses escalates. This progressive cost structure is designed to better reflect reality where the cost of hiring increases due to limited supply.

The decision variables for the second stage are analogously defined as for the first stage:

$\boldsymbol{y_{c,j}}$	Hiring alternative *j* per nurse category *c*
$\boldsymbol{t2_c}$	Number of treated patients per category *c* in second stage
$\boldsymbol{u2_c}$	Number of non-treated patients per category c in second stage

The objective function (1), which consists of seven terms, minimizes the total cost that arises both from fixed cost and decision dependent cost. The first term represents the cost of permanently employed nurses while the second presents the cost for cross-training. We note that these two types of costs are scenario independent. The third and fourth term describe the cost for treated and non-treated patients that occur during the first stage. The fifth term displays the cost for temporary hiring of nurses while finally the last two terms represent the cost for treated and non-treated patients during the second stage.

$$\begin{aligned} minimize \sum_{c\in C} s_c base_c &+ \sum_{c\in C}\sum_{i=1}^{n} tc_{c,i}x_{c,i} \\ &+ \sum_{c\in C}\sum_{s\in S} p^s t1_c e + \sum_{c\in C}\sum_{s\in S} p^s u1_c f \\ &+ \sum_{c\in C}\sum_{s\in S}\sum_{j=1}^{m} p^s hc_{c,j} y_{c,j} + \sum_{c\in C}\sum_{s\in S}\sum_{r\in R} p^s q^r t2_c c + \sum_{c\in C}\sum_{s\in S}\sum_{r\in R} p^s q^r u2_c f \end{aligned} \tag{1}$$

$$\text{s.t.} \quad base_c - \sum_{i=1}^{n} train_{c,i}\, x_{c,i} \geq t1_c \quad \forall c \in C \tag{2}$$

$$base_c - \sum_{i=1}^{n} train_{c,i}\, x_{c,i} \geq minbase_c \quad \forall c \in C \tag{3}$$

$$t1_c + u1_c = D_c^s \quad \forall c \in C; \forall s \in S \tag{4}$$

$$base_c + \sum_{i=1}^{n} train_{c,i}\, x_{c,i} + \sum_{j=1}^{m} hire_{c,j}\, y_{c,j} - a_c^{rs} \geq t2_c \quad \forall s \in S; \forall c \in C; r \in R \tag{5}$$

$$t2_c + u2_c = D_c^{rs} \quad \forall c \in C; \forall s \in S, r \in R \tag{6}$$

$$a_c^{rs} \geq 0 \qquad \forall s \in S; r \in R \tag{7}$$

$$D_c^s \geq 0 \qquad \forall c \in C; \forall s \in S \tag{8}$$

$$x_{c,i}, y_{c,j} \in \{0,1\} \quad i = 1, \dots, n \qquad j = 1, \dots, m \tag{9}$$

We decide to formulate our stochastic model using penalty functions respectively soft constraints as they represent real life conditions better than hard constraints. This approach assumes that the hospital would be able to manage the demand by redirecting patient to other hospitals in the vicinity or adjust the capacity by temporary hiring. Previous research claims that cooperation with hospitals in the region to reallocate patients also avoids congestion as well as higher mortality rates [56,57]. We define two distinct mitigation strategies for uncertain demand and absenteeism. Hence, we accommodate for an uncertain demand by cross-training and for absenteeism among nurses by temporarily hiring nurses. Therefore, we are not allowed to temporarily hire nurses to serve the incoming patient demand during the first stage. Modelling of hard constraints would have the effect of pessimistic decision and that the final solution would move towards the worst-case scenario [47].

The four constraints for the first stage decision are formulated in formula (2)-(4) and (8), which we describe in the latter. First, we assume that any cross-trained nurse requires on the job training whereby permanently employed nurses become unavailable for treating patients Therefore, the difference between permanently employed nurses per category $\boldsymbol{base_c}$ and the number of nurses to be cross-trained $\boldsymbol{train_{c,i}}$ must be greater or equal the number of treated patients $\boldsymbol{t1_c}$. Second, we ensure that the patient safety level is maintained such that the minimal nurse-to-patient must always be ensured. Therefore, the difference between qualified nurses and cross-trained nurses must be greater or equal to the minimal required number of nurses $\boldsymbol{minbase_c}$. Third, the number of patients either non-treated $\boldsymbol{u1_c}$ or treated $\boldsymbol{t1_c}$ must be equal to the demand $\mathbf{D_c^s}$. Fourth, the demand is non-negative.

Moreover, we define three constraints for the temporary hiring decision that are defined in formula (5)-(7). First, the sum of permanently employed nurses, cross-trained nurses and temporarily hired nurses minus the number of absent nurses must be at least the number of treated patients $\boldsymbol{t2_c}$ during the second stage. Second, the sum of patients both non-treated $\boldsymbol{u2_c}$. and treated $\boldsymbol{t2_c}$ must be equal to the demand $\boldsymbol{D_c^{r,s}}$ in the second stage. Third, the number of nurses being absent $\boldsymbol{a_c^{r,s}}$ is non-negative.

6. Case study

First, we apply our two-stage stochastic programming model to the context of Akershus university hospital, situated in the southeastern part of Norway and serving a population of approximately 560’000 inhabitants. The first wave of Covid-19 during March/April 2020 offers a unique use case for retrospective analysis. The underlying data spans a period between 11th March 2020 until 15th April 2020. During this phase the hospital faced the challenge of uncertain patient demand and its requirements due to insufficient knowledge about the novel disease. Concurrently, the hospital experienced difficulties in nurse staffing due to both uncertain absenteeism rates and changed requirements to the nurses’ skills. The key metrics per nurse category, including the decision variables per stage and the patient demand parameters for each stage are presented in the following table (see Table I).

Table I: Optimal solution for cross-training decision and temporary hiring decision including the number of treated and non-treated patient per group and stage for Akershus university hospital case

	Category		
	normal	**intermediate**	**ICU**
Decision			
Cross-trained nurses	0	0	70
Temporarily hired nurses	0	0	110
Stage 1			
Treated patients	299	198	22
Non-treated patients	0	0	109
Stage 2			
Treated patients	310	203	109
Non-treated patients	0	0	27

The optimal solution for Akershus university hospital operates at a cost of 908.6 million NOK. What stands out in the table is the distribution of non-treated patients. It appears that the ICU constitutes a bottleneck as it is the only patient group with non-treated patients. During the first stage, 109 ICU patients cannot be treated. Moreover, the hospital can treat all patients in the second stage regardless of their patient group. It is important to highlight that the patient demand increases in total by 21 patients between the first and the second stage from 628 to 649 including a base load operation whose treatments could not be postponed or cancelled as follows: 250 normal, 180 intermediate and 120 ICU patients. The model chooses to cross-train an additional 70 nurses for the ICU. As each nurse undergoing cross-training occupies resources, the ICU-capacity drops in the first stage, but capacity is increased for future stages. This latent capacity increase helps to cope with absenteeism and increases operational flexibility.

7. Simulation experiments

Following the application of our two-stage stochastic program to a case, we now present the outcomes from three simulation experiments: 1) modifying the cost for non-treated patient, 2) modifying the cross-training cost and 3) varying the initial number of qualified nurses. For each simulation experiment we illustrate the relationship between the parameter that has been adjusted and the following aspects: the objective function (i.e., total cost), the overall SL per stage (respectively the share of treated patients) and the number of nurses who are cross-trained or are hired on a temporary basis. Detailed data for each simulation experiment, such as per patient group can be found in the appendix.

7.1. Effect of variable non-treatment cost

The first simulation experiment replicates situations in which the opportunity cost or community health cost fluctuates. For instance, patients may be sent to more distant hospital due to the lack of capacity. We modify cost per non-treated patient from 20,000 NOK up to 4 million NOK.

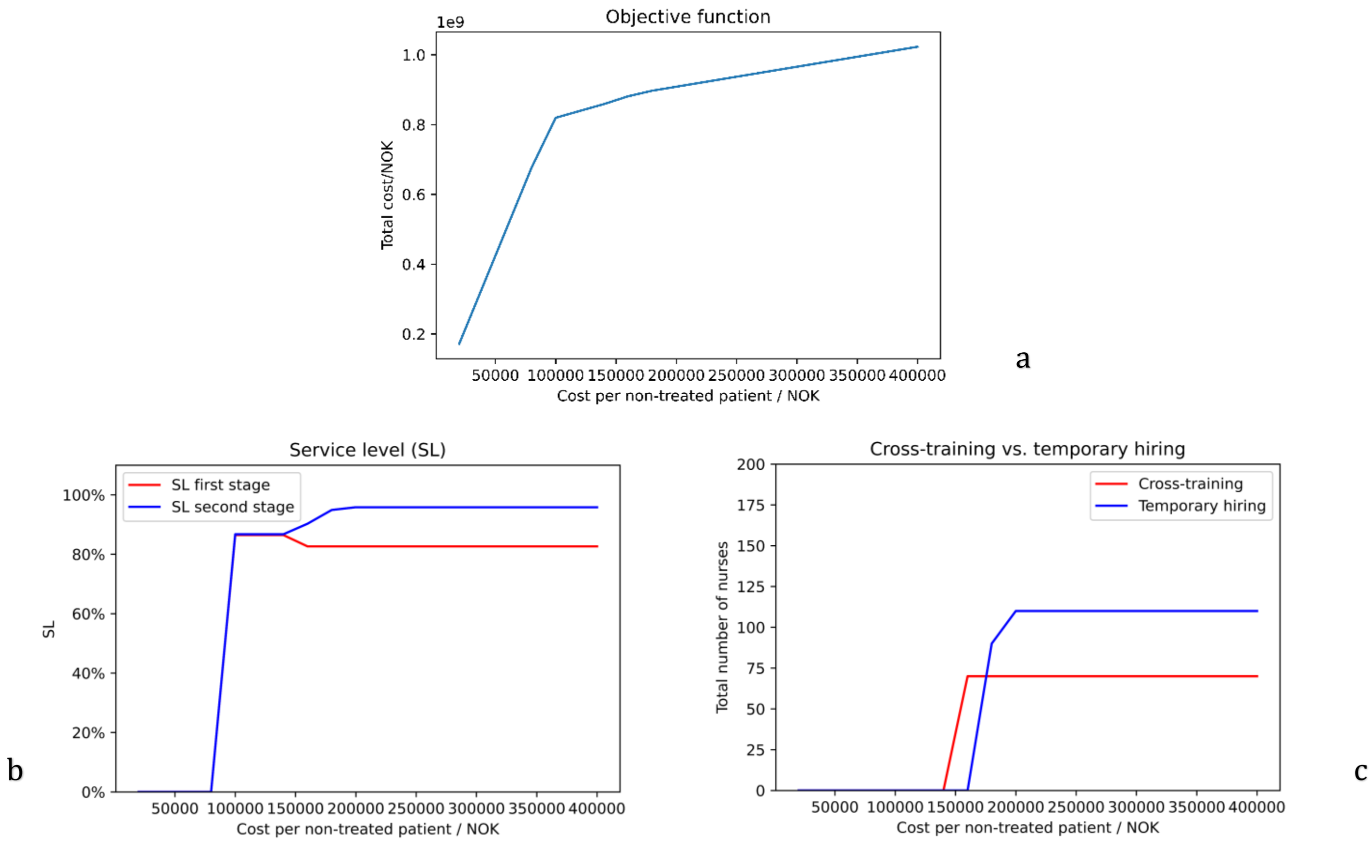

Figure 2: Results in relation to variable cost for non-treatment - a: Objective function - total cost, b: Overall service level (SL) per stage, c: Number of cross-trained vs. temporarily hired nurses.

Figure 2a shows the relation between total cost and the cost per non-treated patient. At first sight, it is evident that the total cost steadily increases as the cost per non-treated patient rises. The gradient significantly decreases beyond a cost per non-treated patient of 100,000 NOK, which equates to the treatment cost. This turning point, where the cost per non-treated patient is equal to the treatment cost, is reflected in the overall SL per stage as well (see Figure.2b). Below this threshold, the hospital does not treat patients in either the first stage or the second stage. Between a cost per non-treated patient of 100,000 NOK and 140,000 NOK, the SLs in both stages are compatible. When the cost per non-treated patient continues to rise, the overall SL in the first stage declines to 82.6% while the overall SL in the second stage increases to 95.8%. Let us turn now to the relationship between cross-trained nurses and temporarily hired nurses (see Figure 2c). The model commences the cross-training of nurses at a cost per non-treated patient of 160,000 NOK. We detect a sudden surge in number of cross-trained nurses to 70. The model exclusively cross-trains nurses for the ICU. Furthermore, when the cost per non-treated patient exceeds 180,000 NOK, the model begins to temporarily hire first 90 ICU nurses and further 110 ICU nurses on a temporary basis. The model achieves a steady state at a cost per non-treated patient of 200,000 NOK and the total cost increases in tandem with the increase in cost per non-treated patients.

7.2. Effect of variable cross-training cost

In the second simulation experiment we adjust the cost of cross-training per nurse. Factors for varying cross-training cost include modifications in the cross-training curriculum or the option to conduct cross-training via online learning platforms, which could require fewer trainers. Given that cross-training costs vary across nurse categories, we designate the average cross-training cost per nurse as the mean across all cross-training options and nurse categories. We modify this parameter within a range from 91,850 NOK to 9.185 million NOK.

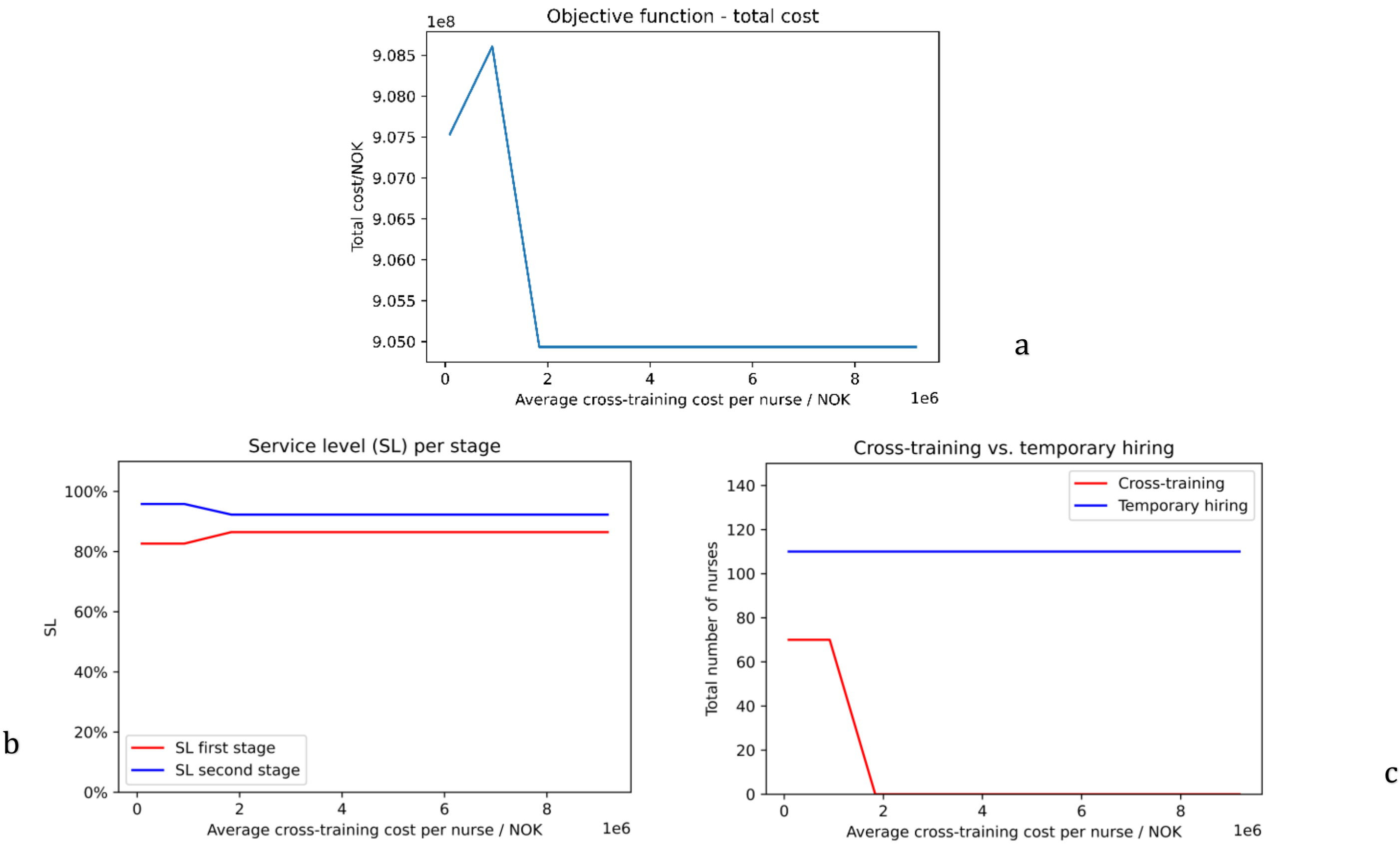

Figure 3: Results in relation to variable cross-training cost - a: Objective function - total cost, b: Overall service level (SL) per stage, c: Number of cross-trained vs. temporarily hired nurses.

Looking at the relationship between the objective function and the average cross-training cost per nurse (see Figure 3a). Up to an average cross-training cost per nurse of 918,500 NOK, the total cost steadily increases by 1.07 million. NOK. As we continue to increase the parameter, the total cost drops to 904.9 million NOK and remains constant when the average cross-training cost per nurse rises further. Observing the overall SL per stage, we detect a shift in overall SLs in the segment where the total cost decreases (see Figure 3b). While the overall SL in the first stage increases from 82.6% to 84.5%, it decreases in the second stage from 95.8% to 92.3%. These changes are the consequences of the decisions to cross-train and hire on a temporary basis (see Figure 3c). As the model ceases to cross-train nurses above an average cross-training cost per nurse of 918,500 NOK, an additional 70 ICU nurses are available for treating patients during the first stage. This results in a higher overall SL. However, fewer cross-trained nurses lead to a reduced workforce during the second stage. Consequently, we observe a lower overall SL in the second stage when the number of cross-trained nurses decreases. The number of hired nurses on a temporary basis is unaffected by the varying cross-training cost per nurses and remains constant at 110 nurses.

7.3. Effect of variable initial number of qualified nurses

In the third simulation experiment, we modify the initial number of qualified nurses to simulate the impact of staffing levels or the competence level of nurses. For instance, a hospital can choose to either cross-train or employ more qualified nurses to effectively manage variability in patient demand by creating surge capacity. We adjust the initial number of qualified nurses from 1,280 to 7,200 and assume the number of nurses simultaneously increases across all nurse categories.

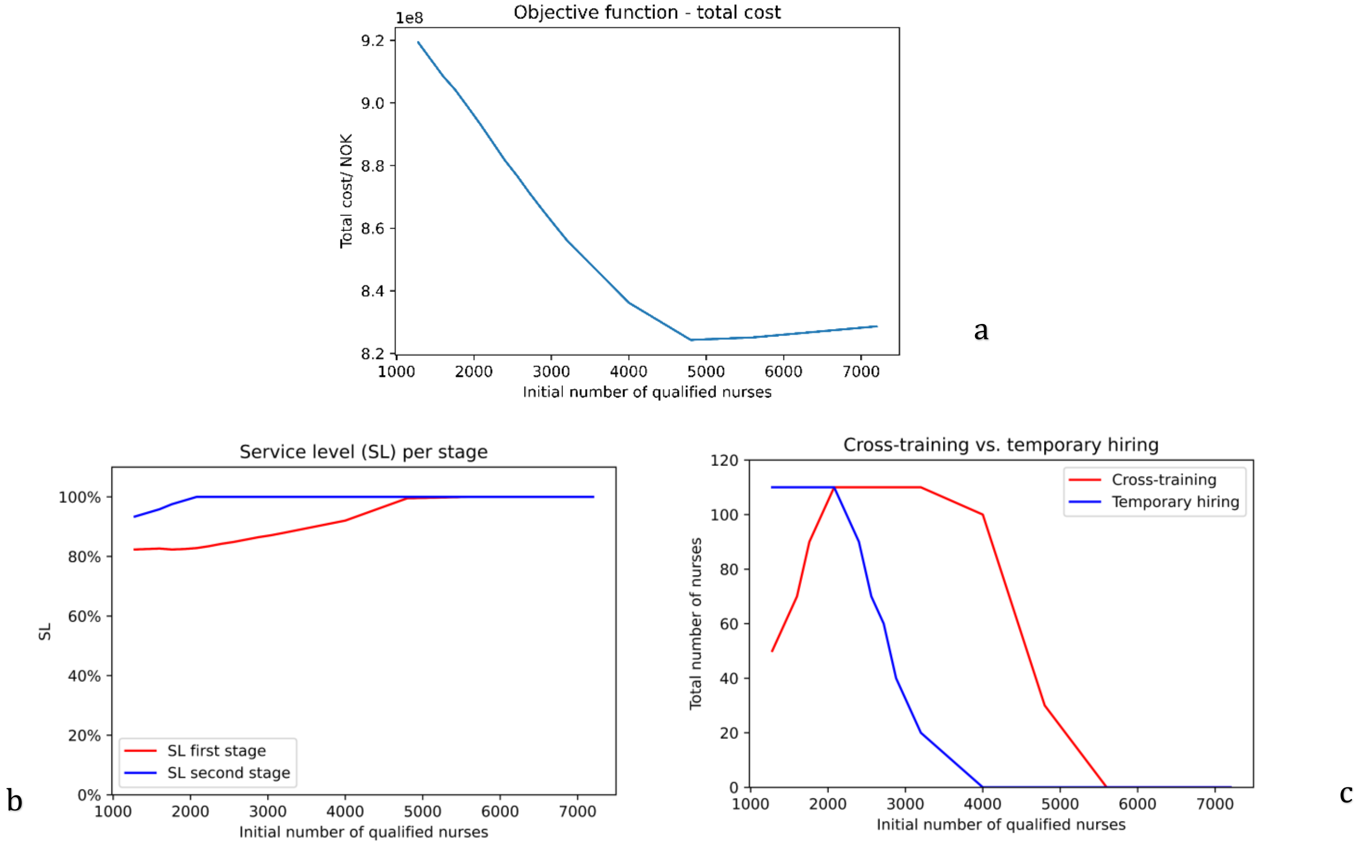

Figure 4: Results in relation to variable initial number of qualified nurses - a: Objective function - total cost, b: Overall service level (SL) per stage, c: Number of cross-trained vs. temporarily hired nurses.

The relationship between the objective function and the initial number of nurses forms a parabolic curve (see Figure 4a). We identify a minimum of total cost when the initial number of nurses is 4,800 amounting to 824.3 million NOK. When the number of nurses is higher than 4,800, the total cost increases. Observing the SL per stage, we note that all patients in both stages can be treated once the initial number of nurses exceeds 4,800 (see Figure 4b). Moreover, we identify that the SL in the second stage is always higher or equal to the SL in the first stage. The overall SL in both stages steadily increases but the second stage already attains a SL of 100% at an initial number of nurses of 2,080. Beyond this threshold, the model consistently reduces the number of temporarily hired nurses in the ICU category (see Figure 4c). The relationship for the number of cross-trained nurses differs. The cross-training activity peaks at 110 ICU nurses between 2,080 and 3,200 initial nurses. Below this range, the model is unable to cross-train more nurses due to the constraint for the minimum number of nurses. Overall, only nurses in the ICU category are cross-trained or temporarily hired as there is always sufficient capacity for the intermediate and normal category for the incoming patient demand.

8. Discussion

In our literature review on nurse staffing, we identify two shortcomings: 1) tactical nurse staffing decisions have received little attention and 2) there is still little knowledge how cross-training can function as a tactical capacity planning strategy to adjust the nurses' skill mix in hospitals. To address these shortcomings, we augment the two-stage stochastic staffing model by Maass et al. [10] with two features. First, we lower the decision-making level of the first stage from a strategic to a tactical level, which covers a period of approximately four days, from the decision to cross-train nurses to their readiness to treat Covid-19 patients. Second, we include the effects of cross-training on the available workforce during either the first or second stage. Thus, we incorporate the primary consequences of cross-training rather instead of predetermining a static nurse pool size. We use data collected over a month during the pandemic situation in March/April 2020 from a university hospital in Norway as a benchmark for the model's inputs. We find an optimal solution at a cost of 908.6 million NOK and an overall SL of 95% with the ICU capacity being increased via cross-trained nurses. Furthermore, we perform three distinct simulation experiments in each of which exactly one parameter (i.e., non-treatment cost, cross-training cost and initial number of employed nurses) is modified. We demonstrate that the SL per stage is influenced by the interplay between the decision to cross-train and temporarily hire. While hiring on a temporary basis is more expensive and short-term oriented, the decision to cross-train, despite cross-training cost and initial lower treatment performance, enhances operational flexibility. It may thus be necessary to include an implicit value of cross-trained nurses. Moreover, we show that the value of additional initially qualified nurses decreases as the relation between the initial nurse base and total cost is divergent. However, we observe that under-staffing costs more than over-staffing. Concisely, while the cross-training strategy serves as a tactical capacity planning tool, the hiring of temporary nurses (e.g., freelancer) offers a more operational solution.

Our study exemplifies how operational research techniques such as stochastic programming can offer innovative and data-driven approaches for nurse staffing [11]. Compared to a deterministic approach, a stochastic programming methodology is superior, allowing for the modelling of exogenous uncertainty [8,47]. Therefore, the solution of a stochastic model holds for more than one patient demand scenario or absenteeism outcome. As the input parameters for the model are census data, neither variability in patient demand throughout the day nor the individual characteristics of the nurses are reflected. Thus, information on patients' pathways is not incorporated. Additionally, we predefine a static average patient-to-nurse ratio per patient group, which overlooks the patient's uniqueness. While studies demonstrate a positive relation between patient safety and the number of available nurses for treatment, it should be noted that standardization across European countries is yet to be achieved [11,16,53]. Furthermore, the classification between defined nurse categories or patient groups is fluent as the spectrum of patients' requirements in each category is variable. Therefore, information about the distribution of nursing time per patient treatment would a better input parameter for making a more informed decision. Another aspect not included in our model is the nurses' learning curve after cross-training. Given that nurses are individuals, we cannot assume identical learning curves or motivation levels, which can influence work performance or efficiency [32]. For instance, a recently cross-trained nurse may still require support from other co-nurses, resulting in a lower efficiency. Moreover, a nurse with previous experience dealing with an infectious disease during a pandemic may better adapt to the required work routines. Hence, we can argue that a nurse's performance is dependent on their work experience and background, which impacts the patient-to-nurse ratio. Another limitation of our model is the focus nurses despite nurses being the most numerous employee group in a hospital. It would be interesting to model team compositions as doctors from less affected departments (e.g., orthopaedical surgery) might perform nursing tasks to handle short-term peaks. This strategy would be another operational capacity planning tools alongside hiring nurses on a temporary basis. Furthermore, our model addresses one disease in isolation and overlooks interdependencies between other departments.

Compared to a previous study our model encompasses the entire patient pathway during hospitalization from admission on the wards towards the ICU [58]. Furthermore, we incorporate three distinct mitigations strategies to manage uncertainty both in patient demand and absenteeism: 1) cross-training, 2) temporary hiring nurses and 3) transfer patients to another hospital. Hence, we integrate approaches from both demand and capacity management. This approach stands in contrast to the stochastic model by Maass et al. [10] who define a set of cross-trained nurses a priori and only permit the hiring of temporary nurses to meet the patient demand. However, optimizing to meet demand would lead to an increased need for cross-trained nurses [38]. Especially during periods with rapidly increasing patient influx, cooperation between hospitals is expedient to balance demand peaks and reduce the average quantity of technical equipment, such as respirator [57,58]. Our model also facilitates cooperation between hospitals since there is an additional cost for non-treated patients who must be diverted to other hospitals. Therefore, we circumvent the challenge of infeasibility due to high patient demand, which can be found in the study by Jiang et al. [57]. While Jiang et al. [57] consider endogenous uncertainty where higher workload increases the risk for absenteeism, our study concentrates exclusively on exogenous aspects.

Turning our attention to the generalizability of our findings, we argue that our two-stage stochastic model can be employed in other hospitals facing in a similar situation when a change in the incoming patient disease mix necessitates the acquisition of additional skills. Other situations not caused by an infectious disease where our model could be applicable are heat waves since they result in an increase in the overall patients' influx acuity [58]. Simultaneously there is a higher risk for absenteeism among nurses due to infections or regulatory containment measurements. Contrary to our study's modeling, absenteeism could be next to the exogenous dimension modelled as an endogenous uncertainty when high workloads increase the risk of absent nurses, which is dependent on individual factors [39]. However, we acknowledge that not every type of hospital has the same capacity to transfer patients in case of insufficient treatment capacity. For example, hospitals, which provide specialized treatments, have limited options to transfer patients due to the scarcity of cooperations at the same treatment specialization. Furthermore, we propose that our model can be applied to other service industries with specialized workers under a sudden change in demand. This is especially relevant when regulations define the required skill set to accommodate incoming demand mix variations. We could think of insurances as exemplary organizations our model can be applied to. For instance, when natural disasters (like flooding) but also pandemics influence the mix of incoming claims that need to be processed and require special skills.

Future work is necessary to enhance our understanding of optimal nurse cross-training strategies in the healthcare context under conditions of absenteeism. There are two prominent issues that are still unanswered while conducting our study. First, it is interesting to expand the model to a multi-stage problem to define the optimal strategy for cross-training and answer the questions regarding the sequence in which nurses should be cross-trained. Especially in a lifelong learning working environment and changing externalities (e.g., technical advancements), hospitals need to devise strategies on how nurses are cross-trained to either increase operational flexibility or ensure the performance of critical tasks. This prospective work would also enhance the understanding of an optimal layout of nurse pools as done by Maass et al. [10]. Moreover, the absenteeism should not be regarded as exogenous uncertain but also endogenous when high workloads result in an increased risk for absenteeism. Second, the impact of other parameters on skill level and performance should be investigated. Therefore, the cross-training variable should not be regarded as binary but as a continuous function. As previously described, the nurse's motivation and background can affect how efficiency increases after cross-training when performing the new tasks. This approach would also raise the question how nurse teams should be composed and what share of nurses per department should be a cross-trained or specialized.

9. Conclusion

The main purpose of our study was to develop a two-stage stochastic programming model as decision support tool for tactical nurse staffing that utilizes cross-training and accounts for absenteeism. The second aim was to investigate the effects of cost for non-treated patients, cross-training cost and number of permanently employed nurses on the nurse staffing decision (e.g., cross-training and temporary hiring), total cost and SLs. The simulation experiments show that the additional value of one permanently employed nurse decreases with increasing nurse base. This new understanding should help to enhance the cross-training decision. However, our study is limited by its singular focus on one patient group and a granularity limit due to the underlying patient census data. Therefore, it is not possible to model a lateral perspective to the selected patient pathway or an organization-wide approach. Moreover, other than presented by our two-stage model, the cross-training and hiring decision is recurring. Despite these limitations, our study offers valuable insights into the tactical nurse staffing decision and how cross-training can be utilized as a mitigation action.

The findings of this study have several practical implications. First, we believe that our model can act as a decision support tool for operations managers in hospitals to make more informed decision and hence improve the patient safety level while minimizing the total cost. Second, we enhance the understanding on the effects of cross-training as a strategy to utilize existing personnel more efficiently to be better prepared for future developments both due to more frequent infectious disease outbreaks and an aging society in Western countries.

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Appendix

Appendix A: Simulation experiment 1: Variable cost for non-treated patients

			Stage 1						Stage 2						Decisions					
			treated			non-treated			treated			non-treated			cross-trained			hired		
Experiment	Objective function	Penalty	normal	intermediate	ICU	normal	intermediate	ICU	normal	intermediate	ICU	normal	intermediate	ICU	normal	intermediate	ICU	normal	intermediate	ICU
1	kr 861,822,584	kr 2,000,000	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
2	kr 836,784,724	kr 1,800,000	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
3	kr 811,746,864	kr 1,600,000	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
4	kr 786,709,004	kr 1,400,000	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
5	kr 761,671,144	kr 1,200,000	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
6	kr 723,550,984	kr 1,000,000	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
7	kr 698,513,124	kr 800,000	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
8	kr 673,475,264	kr 600,000	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
9	kr 648,437,404	kr 400,000	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
10	kr 621,690,332	kr 200,000	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
11	kr 620,049,367	kr 180,000	228	98	23	0	0	38	240	103	62	0	0	4	1	1	70	1	1	1
12	kr 637,618,169	kr 160,000	228	98	39	0	0	22	240	103	46	0	0	20	1	1	20	1	1	1
13	kr 623,147,507	kr 140,000	228	98	39	0	0	22	240	103	46	0	0	20	1	1	20	1	1	1
14	kr 619,160,698	kr 120,000	228	98	43	0	0	18	240	103	42	0	0	24	1	1	10	1	1	1
15	kr 594,304,438	kr 100,000	228	98	46	0	0	15	240	103	39	0	0	27	1	1	1	1	1	1
16	kr 492,572,959	kr 80,000	0	0	0	228	98	61	0	0	0	240	103	66	1	1	1	1	1	1
17	kr 370,282,959	kr 60,000	0	0	0	228	98	61	0	0	0	240	103	66	1	1	1	1	1	1
18	kr 247,992,959	kr 40,000	0	0	0	228	98	61	0	0	0	240	103	66	1	1	1	1	1	1
19	kr 125,702,959	kr 20,000	0	0	0	228	98	61	0	0	0	240	103	66	1	1	1	1	1	1

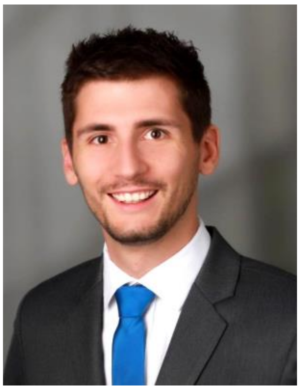
Appendix B: Simulation experiment 2: Variable cross-training cost

			Stage 1						Stage 2						Decisions					
			treated			non-treated			treated			non-treated			cross-trained			hired		
Experiment	Objective function	rage cross-training	normal	intermediate	ICU	normal	intermediate	ICU	normal	intermediate	ICU	normal	intermediate	ICU	normal	intermediate	ICU	normal	intermediate	ICU
1	kr 639,619,930	kr 21,584,750	228	98	46	0	0	15	240	103	39	0	0	27	1	1	1	1	1	1
2	kr 639,569,830	kr 19,426,275	228	98	46	0	0	15	240	103	39	0	0	27	1	1	1	1	1	1
3	kr 639,519,730	kr 17,267,800	228	98	46	0	0	15	240	103	39	0	0	27	1	1	1	1	1	1
4	kr 639,469,630	kr 15,109,325	228	98	46	0	0	15	240	103	39	0	0	27	1	1	1	1	1	1
5	kr 639,419,530	kr 12,950,850	228	98	46	0	0	15	240	103	39	0	0	27	1	1	1	1	1	1
6	kr 639,369,430	kr 10,792,375	228	98	46	0	0	15	240	103	39	0	0	27	1	1	1	1	1	1
7	kr 640,339,041	kr 8,633,900	228	98	43	0	0	18	240	103	42	0	0	24	1	1	10	1	1	1
8	kr 641,141,093	kr 6,475,425	228	98	39	0	0	22	240	103	46	0	0	20	1	1	20	1	1	1
9	kr 640,767,993	kr 4,316,950	228	98	39	0	0	22	240	103	46	0	0	20	1	1	20	1	1	1
10	kr 621,690,332	kr 2,158,475	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
11	kr 621,551,022	kr 1,942,628	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
12	kr 621,411,712	kr 1,726,780	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
13	kr 621,272,402	kr 1,510,933	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
14	kr 621,133,092	kr 1,295,085	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
15	kr 620,993,782	kr 1,079,238	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
16	kr 620,854,472	kr 863,390	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
17	kr 620,715,162	kr 647,543	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
18	kr 620,575,852	kr 431,695	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
19	kr 620,436,542	kr 215,848	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1

Appendix C: Simulation experiment 3: Variable initial number of qualified nurses

			Stage 1						Stage 2						Decisions					
			treated			non-treated			treated			non-treated			cross-trained			hired		
Experiment	Objective function	Nurse base	normal	intermediate	ICU	normal	intermediate	ICU	normal	intermediate	ICU	normal	intermediate	ICU	normal	intermediate	ICU	normal	intermediate	ICU
1	kr 603,005,130	21123	228	98	61	0	0	0	240	103	66	0	0	0	1	1	1	1	1	1
2	kr 601,700,380	18776	228	98	61	0	0	0	240	103	66	0	0	0	1	1	1	1	1	1
3	kr 600,395,630	16429	228	98	61	0	0	0	240	103	66	0	0	0	1	1	1	1	1	1
4	kr 599,090,880	14082	228	98	61	0	0	0	240	103	66	0	0	0	1	1	1	1	1	1
5	kr 597,900,580	11735	228	98	61	0	0	0	240	103	66	0	0	0	1	1	1	1	1	1
6	kr 599,751,530	9388	228	98	61	0	0	0	240	103	66	0	0	0	1	1	1	1	1	1
7	kr 600,116,648	8919	228	98	61	0	0	0	240	103	66	0	0	0	1	1	1	1	1	1
8	kr 602,554,410	8449	228	98	61	0	0	0	240	103	66	0	0	0	1	1	1	1	1	1
9	kr 606,892,293	7980	228	98	61	0	0	0	240	103	66	0	0	0	1	1	1	1	1	1
10	kr 608,964,327	7510	228	98	61	0	0	0	240	103	66	0	0	0	1	1	1	1	1	1
11	kr 610,604,749	7041	228	98	61	0	0	0	240	103	65	0	0	1	1	1	10	1	1	1
12	kr 611,601,846	6572	228	98	58	0	0	3	240	103	64	0	0	2	1	1	20	1	1	1
13	kr 614,047,005	6102	228	98	50	0	0	11	240	103	63	0	0	3	1	1	30	1	1	1
14	kr 617,500,695	5633	228	98	39	0	0	22	240	103	65	0	0	1	1	1	50	1	1	1
15	kr 619,945,854	5163	228	98	31	0	0	30	240	103	64	0	0	2	1	1	60	1	1	1
16	kr 621,690,332	4694	228	98	19	0	0	42	240	103	66	0	0	0	1	1	80	1	1	1
17	kr 627,278,865	4225	228	98	18	0	0	43	240	103	58	0	0	8	1	1	70	1	1	1
18	kr 645,210,038	3755	228	98	17	0	0	44	240	103	50	0	0	16	1	1	60	1	1	1
19	kr 647,412,184	3286	228	98	19	0	0	42	240	103	39	0	0	27	1	1	40	1	1	1
20	kr 684,887,602	2816	228	98	18	0	0	43	240	103	40	0	0	26	1	1	30	1	1	30

Hendrik Winzer



Hendrik Winzer was born in Sonneberg, Germany. He holds a BSc in Aviation with major in operations and management from the Zurich University of Applied Sciences, School of Engineering in Winterthur, Switzerland (2015). Additionally, he has an MSc in Operations Management and Control from the Stockholm Business School, Stockholm University in Sweden (2018).

His PhD thesis contributes to the literature of healthcare crisis management by providing detailed insights in the hospital's operation during the first wave of the Covid-19 pandemic in Norway, as documented in four studies.

Paper one analyzes crisis decision-making strategies in a comparative two-case study. We find that there is no standard strategy in crisis response. However, a more data-driven approach in crisis decision-making was related to fewer days at higher preparedness levels compared to a more naturalistic decision-making approach. Phases of higher preparedness level are further related to lower operational performance.

Paper two investigates capacity limitations at a tertiary public hospital and concludes that medical staff, both in quantity and skills levels, as well as information were perceived as the largest limitations. These limitations differ across hierarchical levels and organizational functions within the organization.

Paper three provides a more detailed analysis of the information dimension concluding that communication channel characteristics and capabilities influence capacity limitations. Using communication channels with speed and bandwidth limits significantly increases the perceived capacity limitations.

Paper four presents a two-stage stochastic programming model to create a decision-support tool for cross-training decisions, incorporating uncertainty in both patient demand and staff absenteeism. In three simulation experiments, the relation between cost for non-treatment, cost for cross-training and the initial number of nurses affects the cross-training decision and patient service levels is visualized.

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Thesis number: 2025:2
ISSN: 1894-6402
ISBN: 978-82-575-2211-7