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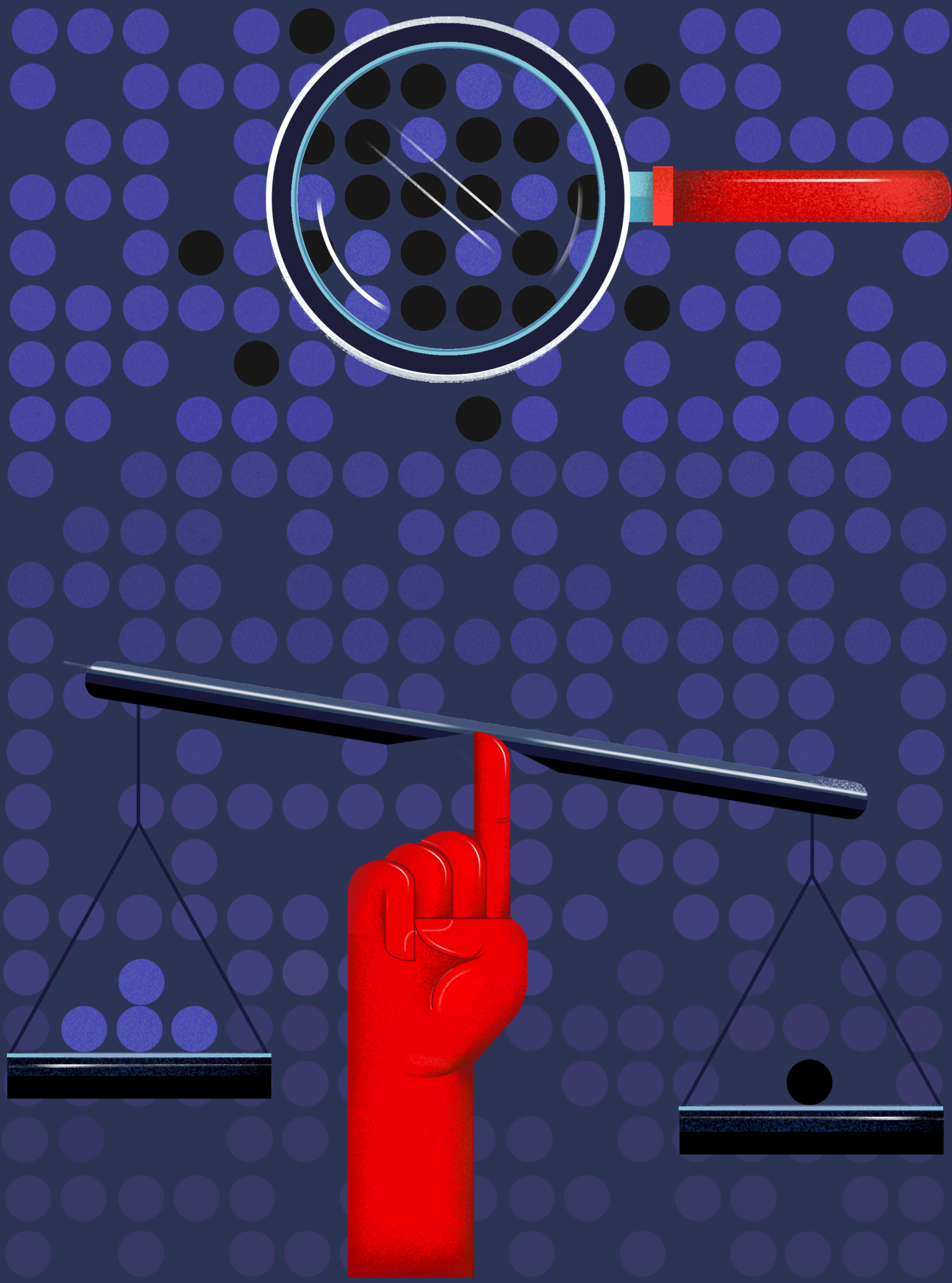
BIAS AND DEBIASING IN DATA-DRIVEN CRISIS DECISION-MAKING

David Paulus



Bias and debiasing in data-driven crisis decision-making

Dissertation

for the purpose of obtaining the degree of doctor

at Delft University of Technology

by the authority of the Rector Magnificus, Prof. dr. ir. T. H. J. J. van der Hagen,

chair of the Board for Doctorates

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Tuesday 30 May 2023 at 12:30 o'clock

by

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Contents

Summary

The United Nations estimates that hundreds of millions of people worldwide are affected by complex crises. Examples are the protracted conflict in Yemen, climate change-induced displacement, and the COVID-19 pandemic. These crises have severe implications for societies. To mitigate crises' effects, crisis response organizations strive to make data-driven decisions. However, these crises are complex: they involve many actors with different mandates and objectives that face uncertain information as well as decision urgencies. These issues can lead to systematic errors within collected crisis data, i.e., data bias, and challenge decision-makers cognitive information processing capacities by inducing cognitive bias.

Data bias is the systematic deviation of a dataset from the real-world phenomenon the data is supposed to represent. Cognitive bias is a judgmental fallacy through which decision-makers are diverted from rational reasoning. Both forms of bias can negatively affect crisis response.

Understanding the causes and consequences of data and cognitive bias in crisis response is still underdeveloped in the literature, which represents the main knowledge gap this dissertation addresses. For example, studies so far described mostly information management challenges, such as in-access, organizational procedures or political influence. But studies fell short of connecting such challenges to actual biases that emerge in datasets and influence the response system. Therefore, this dissertation's first research is: **RQ1:** *What factors lead to data bias in crisis response?*

Similarly, while some studies investigated cognitive biases in crisis scenarios, evidence of comparing cognitive information processing biases between different decision-maker groups is still lacking. This dissertation addresses the problem through the second research question: **RQ2:** *How are crisis decision-maker groups affected by cognitive bias?*

Considering the scattered evidence base for RQ1 and RQ2, even less is known about the potential reinforcing effect that might arise between data and cognitive bias in crisis response. This dissertation studies the interaction between the two forms of bias by addressing the third research question: **RQ 3:** *Does confirmation bias lead crisis decision-makers to rely on biased data?*

Finally, data and cognitive biases that significantly influence crisis analysis and decision-making need to be mitigated. Because crisis response deals with resource and time-constraints, debias interventions need to be found that reduce implementation and operationalization effort, e.g., based on nudging theory. What bias mitigation strategies are effective is the subject of the fourth research question in this dissertation: **RQ4:** *What are effective nudging interventions to reduce bias in crisis response?*

To address all four questions, this dissertation utilizes a mixed-method approach consisting of interviews, document analysis, as well as online and workshop experiments.

To address **RQ1**, this dissertation employed an interview (n=25) and document analysis (n=47), using the conflict in Yemen as a case study. Previous studies on crisis information management challenges have not described the concrete systematic deviations datasets can show because of biases in data collection efforts. This dissertation contributes an in-depth understanding of how political, accessibility, topical, and sampling biases emerge in crisis information and systematically skew datasets used and shared in the coordinated response system. In a further contribution to crisis management literature, this dissertation shows how operational and strategic levels of the response system rely on biased data for their decision-making and that data-decision-interdependencies between actors lead to cycles of bias reinforcement.

Not only biases in datasets can influence crisis response but also biases in the cognitive information processing of responders and affected people. This dissertation contributes to understanding cognitive bias effects on different decision-maker groups. To address **RQ2**, a series of online experiments (n=471) was conducted with lay people, government and non-profit workers as well as crisis experts. The experiments were based on fictional crisis scenarios. They included established measures to assess the strength of four common cognitive biases in information processing: confirmation bias, anchoring bias, framing effect and bias blind spot. The findings contribute to the literature that different crisis decision-maker groups are differently strong affected by cognitive biases. Overall, crisis experts showed the least susceptibility toward all four tested cognitive biases. Government and non-profit workers showed moderate susceptibility, while the sample of crisis-affected people from the general public showed the most robust susceptibility. All groups were significantly affected by framing and bias blind spot. The findings imply that experience is a moderator for bias mitigation, and debias interventions need to be designed differently for crisis experts than lay people.

The existence of data and cognitive bias begs the question of how they interact in crises. Crisis management literature has argued for adaptive management and dynamic capacities to support crisis response. However, whether adaptive approaches are effective in mitigating bias, and the potential reinforcement effects between data and cognitive bias, has not been investigated. To address **RQ3**, this dissertation conducted a workshop experiment with experienced crisis analysts and decision-makers (n=22) to observe how they handle accessibility bias in data and whether confirmation bias would reinforce their reliance on biased data. The results show that even when biases are detected, correcting them is undervalued because of time pressure, i.e., analysts' are urged to provide actionable information to decision-makers quickly. In addition, confirmation bias leads analysts and decision-makers to try to substantiate assumptions they formed on biased data. Therefore, this dissertation introduces a critical perspective on adaptive approaches in crisis management, because these can fall prey to the same problems they try to solve.

Finally, based on the findings regarding data and cognitive bias and their interaction, the question arises, what bias mitigation strategies are effective in crisis response? The urgent and resource-scarce environments of crises require debias interventions that are quick and easy to implement. Interventions can be, for example, implemented into crisis information systems to make users aware of biases in data as well as in users' selection of information. Information system studies found confirmation bias mitigation strategies to be successful when they were based on nudging theory. Therefore, to address **RQ4**, this dissertation conducted an online experiment (n=606) with a fictional crisis scenario and information selection task. Two forms of nudges, a default and a warning nudge, were compared regarding their effectiveness in reducing confirmation bias. The contribution of this dissertation is that a default nudge effectively reduces confirmation bias in crisis response, while a warning is not. This difference can be explained by the decreased mental effort default nudges require, making it easier for responders to gauge information value, compared to the increased mental efforts in case of warnings.

The overall scientific contribution of this dissertation is that (a) political, accessibility, topical, and sampling biases systematically distort crisis information and are reinforced through data-decision-interdependencies of strategic and operational actors, (b) lay people, government-and non-profit workers and crisis experts have different levels of susceptibility to anchoring, framing, confirmation bias and bias blind spot (c) confirmation bias reinforces the reliance on biased data, and (d) default nudges are more effective than warning nudges to reduce confirmation bias in crisis response.

These findings have implications for crisis response practice. Policymakers and practitioners in the crisis response domain, but also designers and developers of crisis information systems, need to be (a) aware of potential biases in the data they create, share and rely on, and (b) recognize potential cognitive biases in their own analysis and decision-making approaches.

Future research could focus on validating the findings of this dissertation in various crisis response contexts, expand on the assessment of effects caused by data and cognitive biases, further investigate and observe in real crisis scenarios how different data biases interact with cognitive biases, and experimentally test new bias mitigation strategies.

Samenvatting

De Verenigde Naties schatten dat honderden miljoenen mensen wereldwijd worden getroffen door complexe crises. Voorbeelden zijn het aanslepende conflict in Jemen, de door klimaatverandering veroorzaakte ontheemding en de COVID-19-pandemie. Deze crises hebben ernstige gevolgen voor de samenleving. Om de effecten van crises te verzachten, streven organisaties voor crisisrespons ernaar datagestuurde beslissingen te nemen. Deze crises zijn echter complex: er zijn veel actoren bij betrokken met verschillende mandaten en doelstellingen die te maken krijgen met onzekere informatie en beslissingsdrang. Deze problemen kunnen leiden tot systematische fouten in verzamelde crisisgegevens, d.w.z. gegevensbias, en kunnen de cognitieve informatieverwerkingscapaciteiten van besluitvormers uitdagen door cognitieve vooroordelen te induceren.

Databias is de systematische afwijking van een dataset van het real-world fenomeen dat de data verondersteld wordt te vertegenwoordigen. Cognitieve bias is een denkfout waardoor besluitvormers worden afgeleid van rationeel redeneren. Beide vormen van vooringenomenheid kunnen een negatieve invloed hebben op de crisisrespons.

Het begrijpen van de oorzaken en gevolgen van data en cognitieve bias bij crisisrespons is nog steeds onderontwikkeld in de literatuur, wat de belangrijkste kennislacune vertegenwoordigt die in dit proefschrift wordt aangepakt. Zo beschreven studies tot nu toe voornamelijk uitdagingen op het gebied van informatiebeheer, zoals toegang, organisatorische procedures of politieke invloed. Maar studies slaagden er niet in dergelijke uitdagingen te verbinden met feitelijke vooroordelen die naar voren komen in datasets en het responssysteem beïnvloeden. Daarom is het eerste onderzoek van dit proefschrift: **RQ1:** *Welke factoren leiden tot databias bij crisisrespons?*

Evenzo, terwijl sommige studies cognitieve vooroordelen in crisisscenario's onderzochten, ontbreekt er nog steeds bewijs voor het vergelijken van cognitieve vooroordelen over informatieverwerking tussen verschillende groepen besluitvormers. Dit proefschrift behandelt het probleem door middel van de tweede onderzoeksvraag: **RQ2:** *Hoe worden crisisbeslissersgroepen beïnvloed door cognitieve vooringenomenheid?*

Gezien de versnipperde bewijsbasis voor **RQ1** en **RQ2**, is er zelfs nog minder bekend over het potentiële versterkende effect dat zou kunnen ontstaan tussen gegevens en cognitieve vertekeningen bij crisisrespons. Dit proefschrift bestudeert de interactie tussen de twee vormen van bias door in te gaan op de derde onderzoeksvraag: **RQ 3:** *Zorgt confirmatiebias ervoor dat crisisbeslissers vertrouwen op vertekende data?*

Ten slotte moeten gegevens en cognitieve vooroordelen die een significante invloed hebben op crisisanalyse en besluitvorming worden beperkt. Omdat crisisrespons te maken heeft met beperkte middelen en tijd, moeten debias-interventies worden gevonden die de implementatie- en operationaliseringsinspanning verminderen, bijvoorbeeld op basis van de nudging-theorie. Welke strategieën om bias te verminderen zijn effectief, is het onderwerp van de vierde onderzoeksvraag in dit proefschrift: **RQ4:** *Wat zijn effectieve nudging-interventies om bias in crisisrespons te verminderen?*

Om alle vier de vragen te beantwoorden, maakt dit proefschrift gebruik van een gemengde methode bestaande uit interviews, documentanalyse, evenals online- en workshopexperimenten.

Om **RQ1** aan te pakken, maakte dit proefschrift gebruik van een interview (n=25) en documentanalyse (n=47), waarbij het conflict in Jemen als casestudy werd gebruikt. Eerdere studies over uitdagingen op het gebied van crisisinformatiebeheer hebben niet de concrete systematische afwijkingen beschreven die datasets kunnen vertonen vanwege vooroordelen bij het verzamelen van gegevens. Dit proefschrift draagt bij aan een diepgaand begrip van hoe politieke, toegankelijkheids-, actualiteits- en steekproefbiases ontstaan in crisisinformatie en hoe datasets die worden gebruikt en gedeeld in het gecoördineerde responssysteem systematisch worden scheefgetrokken. In een verdere bijdrage aan de crisisbeheersingsliteratuur laat dit proefschrift zien hoe operationele en strategische niveaus van het responssysteem voor hun besluitvorming afhankelijk zijn van vooringenomen gegevens en dat gegevens-beslissingsafhankelijkheden tussen actoren leiden tot cycli van versterking van vooringenomenheid.

Niet alleen vooroordelen in datasets kunnen de crisisrespons beïnvloeden, maar ook vooroordelen in de cognitieve informatieverwerking van hulpverleners en getroffen mensen. Dit proefschrift draagt bij aan het begrijpen van cognitieve bias-effecten op verschillende groepen besluitvormers. Om **RQ2** aan te pakken, werd een reeks online-experimenten (n=471) uitgevoerd met leken, overheids- en non-profitmedewerkers en crisisexperts. De experimenten waren gebaseerd op fictieve crisisscenario's. Ze omvatten gevestigde maatregelen om de sterkte van vier veelvoorkomende cognitieve vooroordelen bij informatieverwerking te beoordelen: voorkeur voor bevestiging, verankering vooringenomenheid, framing-effect en blinde vlek vooringenomenheid. De bevindingen dragen bij aan de literatuur dat verschillende groepen besluitvormers op verschillende manieren sterk worden beïnvloed door cognitieve vooroordelen. Over het algemeen toonden crisisexperts de minste gevoeligheid voor alle vier de geteste cognitieve vooroordelen. Overheids- en non-profitwerknemers toonden een matige gevoeligheid, terwijl de steekproef van door de crisis getroffen mensen uit het grote publiek de meest robuuste gevoeligheid vertoonde. Alle groepen werden significant beïnvloed door framing en bias blind spot. De bevindingen impliceren dat ervaring een moderator is voor het verminderen van vooringenomenheid, en dat debias-interventies anders moeten worden ontworpen voor crisisexperts dan voor leken.

Het bestaan van gegevens en cognitieve vooringenomenheid roept de vraag op hoe ze op elkaar inwerken in crises. In de literatuur over crisisbeheersing wordt gepleit voor adaptief beheer en dynamische capaciteiten om crisisrespons te ondersteunen. Of adaptieve benaderingen effectief zijn in het verminderen van vooringenomenheid en de mogelijke versterkende effecten tussen gegevens en cognitieve vooringenomenheid, is echter niet onderzocht. Om **RQ3** aan te pakken, voerde dit proefschrift een workshop-experiment uit met ervaren crisisanalisten en besluitvormers (n=22) om te observeren hoe zij omgaan met toegankelijkheidsbias in data en of voorkeur voor bevestiging hun afhankelijkheid van vertekende data zou versterken. De resultaten laten zien dat zelfs wanneer vooroordelen worden gedetecteerd, het corrigeren ervan ondergewaardeerd wordt vanwege de tijdsdruk, d.w.z. dat analisten worden aangespoord om snel bruikbare informatie te verstrekken aan besluitvormers. Bovendien leidt voorkeur voor bevestiging ertoe dat analisten en besluitvormers proberen de aannames die ze op basis van vooringenomen gegevens hebben gemaakt, te onderbouwen. Daarom introduceert dit proefschrift een kritisch perspectief op adaptieve benaderingen in crisisbeheersing, omdat deze ten prooi kunnen vallen aan dezelfde problemen die ze proberen op te lossen.

Tot slot, op basis van de bevindingen met betrekking tot data en cognitieve bias en hun interactie, rijst de vraag welke strategieën om bias te verminderen effectief zijn bij crisisrespons? De urgente en schaarse omgevingen van crises vereisen debias-interventies die snel en gemakkelijk te implementeren zijn. Interventies kunnen bijvoorbeeld worden geïmplementeerd in crisisinformatiesystemen om gebruikers bewust te maken van vooroordelen in gegevens en in de selectie van informatie door gebruikers. Onderzoek naar informatiesystemen wees uit dat strategieën voor het verminderen van voorkeur voor bevestiging succesvol waren als ze waren gebaseerd op de nudging-theorie. Daarom voerde dit proefschrift, om **RQ4** aan te pakken, een online experiment uit (n=606) met een fictief crisisscenario en informatieselectietaak. Twee vormen van nudges, een default en een warning nudge, werden vergeleken met betrekking tot hun effectiviteit bij het verminderen van voorkeur voor bevestiging. De bijdrage van dit proefschrift is dat een default nudge de voorkeur voor bevestiging bij crisisrespons effectief vermindert, terwijl een waarschuwing dat niet is. Dit verschil kan worden verklaard door de verminderde mentale inspanning die standaard nudges vereisen, waardoor het voor responders gemakkelijker wordt om de informatiewaarde te meten, in vergelijking met de verhoogde mentale inspanning in het geval van waarschuwingen.

De algemene wetenschappelijke bijdrage van dit proefschrift is dat (a) politieke, toegankelijkheids-, actualiteits- en steekproefvooroordelen systematisch crisisinformatie vervormen en worden versterkt door data-beslissingsafhankelijkheden van strategische en operationele actoren, (b) leken, overheids- en - Profitwerknemers en crisisexperts hebben verschillende niveaus van gevoeligheid voor verankering, framing, voorkeur voor bevestiging en vooringenomenheid blinde vlek (c) voorkeur voor bevestiging versterkt de afhankelijkheid van vooringenomen gegevens, en (d) default nudges zijn effectiever dan waarschuwende nudges om bevestigingsbias te verminderen bij crisisopvang.

Deze bevindingen hebben implicaties voor de praktijk van crisisrespons. Beleidsmakers en praktijkmensen in het crisisresponsdomein, maar ook ontwerpers en ontwikkelaars van crisisinformatiesystemen, moeten (a) zich bewust zijn van mogelijke vooroordelen in de gegevens die ze creëren, delen en waarop ze vertrouwen, en (b) mogelijke cognitieve vooroordelen herkennen in hun eigen analyse- en besluitvormingsbenaderingen.

Toekomstig onderzoek zou zich kunnen richten op het valideren van de bevindingen van dit proefschrift in verschillende crisisresponscontexten, de beoordeling van effecten veroorzaakt door data en cognitieve biases uitbreiden, verder onderzoeken en observeren in echte crisisscenario's hoe verschillende databiasen interageren met cognitieve biases, en experimenteel testen nieuwe strategieën om bias te verminderen.

1 Introduction

1.1 Biased data-driven decision-making in complex crisis response

The United Nations estimated that over 230 million people needed humanitarian assistance in 2021, many due to complex crises (United Nations, 2021a). The main drivers of humanitarian needs, e.g., protection, shelter, food and education, have been ongoing conflicts such as in Yemen and Syria, but also climate change-induced displacement, the outbreak of the COVID-19 pandemic as well as the war on Ukraine (Dellmuth, Bender, Jönsson, Rosvold, & von Uexkull, 2021; Devi, 2022). In contrast to disasters and emergencies that are short-term and location-specific (e.g., earthquakes, wildfires, floods), complex crises have pro-longed adverse effects on societies, often with no clear boundaries (Gralla, Goentzel, & Fine, 2016). These humanitarian crises are complex because of the following:

(a) the dynamic interaction of a multitude of diverse actors, including the affected population, local and international non-governmental organizations, UN and governmental agencies (Clarke & Campbell, 2018),

(b) the different mandates, values, objectives, standards, capacities and resources of the actors involved (Zwitter, 2011),

(c) the uncertainty about the current situation and future trends (Charles, Lauras, & van Wassenhove, 2010), and

(d) the decision urgencies for effective aid delivery (Bartel Van de Walle, Brugghemans, & Comes, 2016).

The following real-life case exemplifies the complexity of humanitarian crises. The United Nations World Food Programme (WFP) is mandated to provide emergency food assistance to millions of food-insecure people in Yemen. The complexity of its operation is manifested by competing political parties that govern different parts of Yemen and pose conflicting requirements to humanitarian organizations to conduct their work (Orkaby, 2017). At the same time, dozens of humanitarian organizations operate in the country and need to coordinate their response efforts (Dureab, Al-Awlaqi, & Jahn, 2020; Mena & Hilhorst, 2021; Spiegel et al., 2019). The situation in

Yemen remains uncertain because food security assessments were restricted, leading to data gaps and outdated information that blur the actual extent of the crisis (Maxwell, Hailey, Spainhour Baker, & Janet Kim, 2018). Nevertheless, WFP had to make critical decisions, and falling short on the delivery of emergency food assistance would mean that malnutrition rates increase up to the threat of famine (Baldauf, 2021; Eshaq, Fothan, Jensen, Khan, & AlAmodi, 2017).

Making good decisions, i.e., allocating scarce aid resources to the most-in-need population, depends on having accurate information in-time. More reliance on data is seen by many humanitarian organizations as a strategy to deal with the crisis complexities they deal with. Thus, humanitarian organizations strive to become more data-driven in their decision-making. For example, this is reflected in the novel United Nations Data Strategy (United Nations, 2020b). The strategy lays out how the United Nations and its agencies want to invest in and use more sophisticated data collection and analytics methods to inform their crisis response efforts (Franklinos et al., 2020). Effective crisis information management (CIM) is necessary to support data-driven decision-making under circumstances of crisis complexity (Lentz, Michelson, Baylis, & Zhou, 2019). CIM is the central component that facilitates data collection, processing, analysis and sharing between actors who are part of the multi-level crisis response system (Iannella & Henricksen, 2007).

The literature describes crisis response actors on the strategic, operational, and intermediate strategic/operational levels (Muhren & Van de Walle, 2010; Thapa, Budhathoki, & Munkvold, 2017). Actors on the strategic level are mostly governmental agencies that make allocation decisions on funding to response organizations (Narang, 2016). The intermediate strategic/operational level, mainly response organizations' headquarters, decide how to distribute the received funding within their organizations (Knox Clarke & Campbell, 2020). From there, the operational level receives funding to conduct the actual aid implementation in the crisis environment (ibid.).

Each level relies on data that describes the crisis situation. The most important data comes directly from the crisis environment. Organizations implementing humanitarian aid, collect data through surveying crisis-affected populations and conducting situation assessments (Patel, King, Phelps, & Sanderson, 2017). The objective is to establish the extent of the crisis severity, understand the affected people's needs and assess current response capacities (Chan, Bateman, &

Olafsson, 2016). Therefore, the data are analyzed into information products (e.g., reports, fact sheets, datasets, dashboards) that represent the basis for decision-making. Examples of major humanitarian information products are the Humanitarian Needs Overview (HNO) and the Humanitarian Response Plan (HRP). The former synthesizes the collected data for all categories of humanitarian need. The latter specifies what resources are required to respond to the identified needs. Both reports are created through the joint crisis information management process of the responding organizations, and act as the main evidence-base and decision-support information. The operational level uses the data to inform the logistics of on-the-ground activities.

Not only do response organizations rely on these information products on an operational level, but they are also further shared with and used by organizations' management and donor agencies for strategic decisions (Campbell & Clarke, 2018). The primary decision type of both operational and strategic levels is allocation problems (Fink & Redaelli, 2011; Juric & Shamoug, 2017). Governmental donors provide the majority of funding for humanitarian response (Development Initiatives, 2018). These strategic levels must decide what budget to allocate to different crises worldwide. The management of the organizations receiving the funds needs to determine how to allocate staff and resources to their operational foci.

This multi-level approach to crisis response reveals the data-decision-dependencies between operational and strategic actors. Crisis response can only function efficiently when the different actors can rely on accurate data and objective decision-making. In practice, however, the factors of crisis complexity can induce biases, both in the data created (Fast, 2017), as well as in the cognitive decision-making processes (Comes, 2016).

Data bias is defined as a systematic deviation of a dataset from the real-world phenomena the data is supposed to represent (Jo & Gebru, 2020; Taylor, 1997). An example of data bias, or more specifically, availability or accessibility bias, in crisis information is the systematic underrepresentation of a geographic region. Because of ongoing access impediments, e.g., caused by ongoing conflict, districts within active conflict zones will be represented with less data than easier-to-access areas (Maxwell & Hailey, 2021). This dissertation defines cognitive bias as a systematic deviation in people's estimation, judgment and information evaluation from what could be expected rationally. In crisis decision-making, an example of cognitive bias, or more specifically, information processing bias, is the systematic undervaluation of contradictory information. Confirmation bias literature suggests that crisis responders overly rely on information that supports previous decisions, even though opposing information is of equal value and could potentially correct wrong decisions made earlier (Jonas, Traut-Mattausch, Frey, & Greenberg, 2008).

Effective crisis response is at risk of failing to address humanitarian needs adequately when data and cognitive challenges systematically influence, i.e., *bias*, available information and decisions. Biased data can skew key variables in crisis information, and cognitive biases can misguide crisis decision-making.

Previous literature has not directly linked systematic challenges in crisis information management to actual bias in datasets and reports. Similarly, there is a lack of evidence on how cognitive biases influence crisis decision-makers' information processing capabilities. Further, the interplay of data and cognitive bias in crisis response is not well understood. Finally, previous literature does not provide evidence of the effectiveness of bias mitigation strategies in crisis response.

This dissertation provides a deeper understanding of systematic causes that lead to different types of data bias in crisis response. It compares different crisis decision-maker groups regarding their susceptibility toward cognitive biases, examines the reinforcement effects between data and cognitive bias, and assesses bias mitigation strategies. The scope of this research is depicted in Figure 1.1.

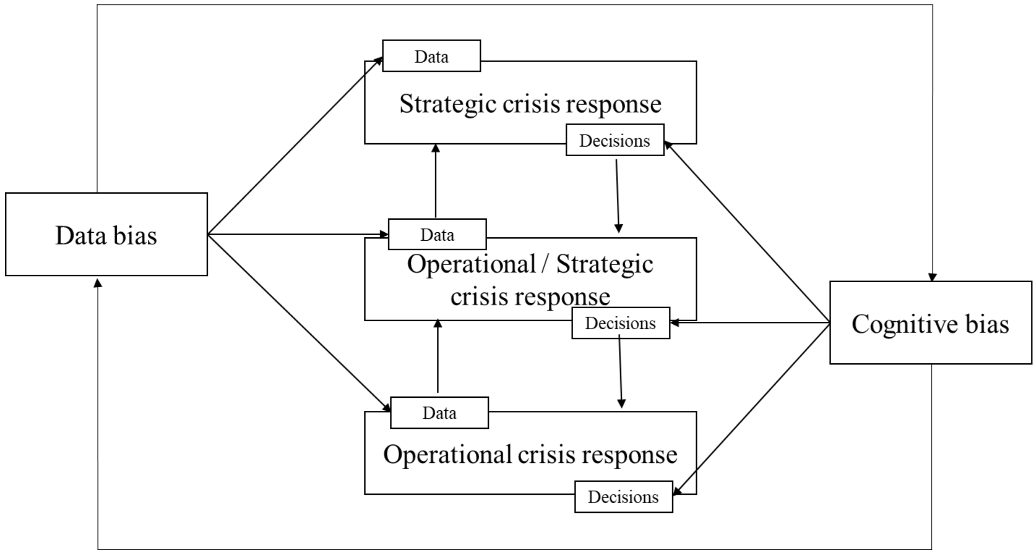


Figure 1.1. Data-decision-interdependencies within the multi-actor system of humanitarian crisis response and the potential points of interference of data and cognitive bias.

1.2 Literature review, research gaps and questions

The following sub-chapters 1.2.1 to 1.2.4 review the current state of the literature on data and cognitive bias, their interplay and possible mitigation strategies, to synthesize what is known and what the knowledge gaps are. Each sub-chapter concludes with a research question. Sub-chapters 1.3.1 to 1.3.4 describe how this thesis addresses each research question, i.e., the selected research methods.

1.2.1 Data bias in crisis response

In 2021, almost 50% of the information needed across worldwide humanitarian operations was either incomplete or unavailable, where incompleteness refers to datasets lacking geographic or demographic coverage, timeliness, or a standard format (United Nations, 2021c). For crisis responders, the relevant information is often unavailable or inaccessible (Altay & Labonte, 2014; Day, Junglas, & Silva, 2009), while irrelevant information is abundant (Van de Walle & Dugdale, 2012).

Primary data is created by response organizations that implement operational activities in crisis-affected areas, i.e., in the field. Organizations collect data through situation assessments, household surveys, focus-group discussions, key-informant interviews, and observations. The collected information consists, therefore, of qualitative (e.g., interviews, observations) and quantitative (e.g., surveys) data (Finn & Oreglia, 2016). Represented in the data are crisis-affected people, households, communities, geographic districts and social groups, together with their capacities (e.g., income, savings, qualifications) and humanitarian needs (e.g., protection, nutrition, shelter, education). Biases in these datasets might take the form of systematic underrepresentation of specific geographic regions or demographic and social groups.

The creation of these datasets happens within the complex crisis environment that is characterized by a multitude of actors with different mandates, as well as time pressure and uncertainty. For example, in conflicts, humanitarian response organizations must acquire permits from authorities to access and collect data in certain areas (Maxwell, Hailey, Spainhour Baker, et al., 2018). While responding to COVID-19, researchers, response organizations, and policymakers have had difficulties agreeing on the critical variables for decision-making (Hale et al., 2021).

Generally, two forms of disturbances can distort crisis data: random non-systematic error and non-random systematic error, i.e., bias. The distinction is important because the first form happens unpredictably and is caused by dynamic changes in the data collection environment, e.g., random noise or human error during measurement. This form of data error can often be mitigated through repeated measures following the same procedures (Taylor, 1997). The second form, bias, is rooted in structural, mid- to long-term issues within the data collection environment (Birhane, 2021), e.g., pro-longed in-access to certain geographic areas. This second form of data error can usually not be mitigated through repeated measures as the structural cause remains unaddressed. Biased datasets can misguide crisis decision-making in ways that disproportionately negatively affect certain social groups and geographic areas.

When geographic areas that are the most affected become inaccessible for data collection, this will result in *biased* data availability or accessibility (Rahman, Comes, & Majchrzak, 2017). For example, response organizations might not be permitted to access and assess an active conflict zone. While data is being collected from areas with no active conflict, more data will be available from these regions and less from active conflict zones where access is hindered. If not identified and mitigated, biases could cascade into information for decision-support and misguide the decision-making process.

When biases systematically skew the understanding of the crisis, decisions will become negatively affected, and the humanitarian objective to deliver aid in a neutral way will be missed.

So far, literature has discussed challenges to data collection, sharing and use, including time and political pressure, physical access constraints, lack of incentives and interoperability (Altay & Labonte, 2014; Tina Comes, Van de Walle, & Van Wassenhove, 2020; Day et al., 2009; Fast, 2017; Maxwell, Hailey, Kim, Mccloskey, & Wrabel, 2018; Villa, Urrea, Andrés Castañeda, & Larsen, 2019). However, literature has fallen short of explaining how these challenges can lead to systematic data biases in crisis response and how the multi-level response system becomes affected by data bias.

Based on data collection, sharing and analysis challenges previously reported in the crisis information management literature, this dissertation adds an in-depth understanding of how data biases emerge in crisis datasets and how the data-decision-interdependencies within the response system are affected. Addressing this gap is the aim of this dissertation's first research question.

RQ 1: *What factors lead to data bias in crisis response?*

1.2.2 Cognitive bias in crisis response

The classical perspective on decision-making takes a normative stance and sees decision-makers as rational agents following the rules of expected utility (Savage, 1954; von Neumann & Morgenstern, 1944). The concepts of bounded rationality (Simon, 1955, 1956) and prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) contributed to a descriptive perspective on human decision-making. This research builds on the understanding that human reasoning can be described through dual-process models. These models have in common that they describe that reasoning can happen through first, a quick, heuristic intuitive process, or second, through a more elaborate, information-intensive reasoning process (Chaiken, 1980; Kahneman, 2003; Petty & Cacioppo, 1986).

In complex crises, decision-makers are often urged to make quick decisions (Comes, 2016). However, this urgent, non-elaborate approach can lead to cognitive biases and negatively influence decision-making. Under risk, urgency, and uncertainty, cognitive biases are particularly influential. Therefore, crises are particularly suited to induce cognitive biases (ibid.).

Because of limited information, potential future resources need to be estimated (Knox Clarke & Campbell, 2020). For example, a key planning question for a response organization is: *how much funds will be approximately provided by donors?* Based on the estimated answer to this question, decisions need to be made regarding hiring staff and acquiring relief material. However, in these numerical estimations, people can show *anchoring bias*, i.e., they *anchor* their estimation around arbitrary information that is available to them but irrelevant or inaccurate (Yasseri & Reher, 2018). As such, unsuitable pieces of available information might influence crisis responders' assessments. They might rely on estimates that are too close to inaccurate information.

Different actors portray information differently in complex systems like the multi-actor crisis environment (Campbell & Clarke, 2018; de Bruijn & Janssen, 2017). How information is framed can influence decision-makers' choices (Tversky & Kahneman, 1981). For example, managers of response organizations need to decide between response options where the consequences of available options are framed as gains or losses in the form of lives saved or lost. Prospect theory explains why people perceive losses as stronger than gains of the same value (Tversky & Kahneman, 1992). People's loss aversion means they prefer sure gains over probable gains and probable losses of sure losses. In other words, people are risk-seeking when expecting losses and risk-averse when expecting gains. Crisis responders need to be aware of potential *framing effects* on their decision-making.

Available information and datasets in crises can contradict each other, leading to conflicting recommendations for response priorities (Comes, Van de Walle, & Van Wassenhove, 2020). Reasons for contradicting information can be time, resource, and access constraints that make it difficult to reconcile or synthesize information. Crisis decision-makers should base decisions on the best available information. However, people commonly favor information that confirms their previous choices and disregard information that contradicts them (Festinger, 1957). In crises, *confirmation bias* can lead to ill-informed response decisions. A previously chosen priority, e.g., distribution of food items, might be continued, even if better information suggests the priority should be shifted toward shelter item distribution.

The first step to mitigate cognitive biases is that crisis responders must be aware of their own potential biases (Pope, Price, & Wolfers, 2018). The research on the *bias blind spot* shows that people are better at detecting biases in others than in themselves (Scopelliti et al., 2015). Awareness of their own biases can lead decision-makers to act as their devil's advocate, critically examining their own choices, opinions and assessments (Lidén, Gräns, & Juslin, 2019). Being mindful and increasing one's metacognition can lead people to move from a biased heuristic to a more sophisticated reasoning approach.

Finally, as mentioned above, there are three main decision-maker groups in crisis response: (1) crisis-affected people, (2) professional responders (i.e., mostly government and non-profit workers), and (3) crisis experts. However, there is little empirical evidence on the strength of anchoring, framing, confirmation bias and bias blind posts for different stakeholder groups in humanitarian response. This dissertation addresses the issue in the second research question.

RQ 2: *How are crisis decision-maker groups affected by cognitive bias?*

1.2.3 The interplay of data and cognitive bias in crisis response

Chapters 2 and 3 focus on data bias and cognitive bias in crisis response separately. However, because both forms of bias likely emerge in crisis contexts simultaneously, it is essential to study how they interact. For example, accessibility bias in data can misrepresent geographic areas, demographic groups, or issues (Comes et al., 2020; Fast, 2017), and at the same time, confirmation bias can lead crisis responders to overly rely on supportive information rather than opposing information (Comes, 2016). Early assumptions might be formed based on biased data because it is the only data available at first. Confirmation bias might then lead crisis responders to further prefer data that confirms these early biased assumptions, even though opposing and unbiased data might be available.

Crisis information management literature suggests focusing on sensemaking and adaptive capacity to improve information and decision quality (Janssen, Lee, Bharosa, & Cresswell, 2010; Janssen & van der Voort, 2020; Wolbers, 2021). Incorporating additional analysis capacity into the response process means that the new analysts also face the issues of uncertainty and urgency that make crises complex. While they are intended to support the data-driven decision-making process, additional analysts might fail to identify data biases and show the same cognitive biases as the response organizations (Comes, 2016).

So far, the literature does not provide evidence on how far data and cognitive bias interact and affect data-driven decision-making in crisis response. This dissertation studies whether adaptive approaches are sufficient to counter confirmation bias when available crisis information is also biased.

RQ 3: *Does confirmation bias lead crisis decision-makers to rely on biased data?*

1.2.4 Mitigating bias in crisis response

As explained above, both data and cognitive bias can negatively affect crisis response. When both types of bias come together, their combined effects might be even worse as the biases might reinforce each other. Thus, effective bias mitigation strategies need to be found.

Theoretically, mitigation strategies can be tested for both types of bias. The urgency of crisis response, coupled with the funding gap experienced by response organizations, limits which debias interventions are suitable for implementation. However, as the primary source of data bias are systematic and structural underlying issues within societies and the crisis response context, resolving them requires significant investments in research capacities. Cognitive bias can be mitigated through more subtle, low-cost, and time-saving approaches. Interventions based on *nudging theory* have effectively reduced cognitive bias at low costs. The purpose behind nudging is to gently push decision-makers into making a superior choice (Sunstein & Thaler, 2008).

Nudges are subtle hints within the choice architecture a decision-maker is confronted with (Hummel & Maedche, 2019). In crisis response settings, the choice architecture can be the user interface of an information system or the presentation of different information that provides contradictory decision-making advice. When newly obtained information offers more evidence for a course correction, i.e., opposing an initial decision, a responder should give this information higher importance, especially when some of the information has a data bias that negatively affects the coverage and representativeness of specific geographic regions. However, confirmation bias will act against this by leading responders to rely overly on confirming rather than on opposing information (Jonas, Schulz-Hardt, Frey, & Thelen, 2001). To counter this, a nudge, i.e., a subtle hint for the decision-maker, can help responders to focus on the unbiased opposing information and make a decision that is grounded on the better information.

Previous research found that nudges can effectively reduce cognitive bias, such as confirmation bias (Rieger, Draws, Theune, & Tintarev, 2021). However, there has been no investigation into the effectiveness of different nudges in reducing cognitive bias in complex crisis responses. This dissertation's fourth research question will address this issue.

RQ 4: *What are effective nudging interventions to reduce bias in crisis response?*

1.3 Research method

This dissertation addresses each of the four research questions in a separate Chapter. Chapter **Error! Reference source not found.** addresses **RQ 1**, Chapter 3 addresses **RQ 2**, Chapter 4 addresses **RQ 3**, and Chapter **Error! Reference source not found.** addresses **RQ 4**. Each chapter introduces the relevant theoretical background of the respective research question, presents the research method employed to answer the question, and discusses the results in light of previous knowledge.

The chapters are logically linked together, as depicted in Figure 1.2. Chapter **Error! Reference source not found.** establishes the evidence base for data bias in crisis response. Chapter 3 studies how cognitive biases influence information processing by crisis decision-makers. The results of Chapter **Error! Reference source not found.** and 3 are then used to study reinforcement effects between data and cognitive bias in Chapter 4. Based on the findings of Chapter 4, Chapter **Error! Reference source not found.** tests the effectiveness of bias mitigation strategies in crisis response. Finally, the outcomes of the four chapters are synthesized into the overall scientific contribution of this dissertation in Chapter 6.

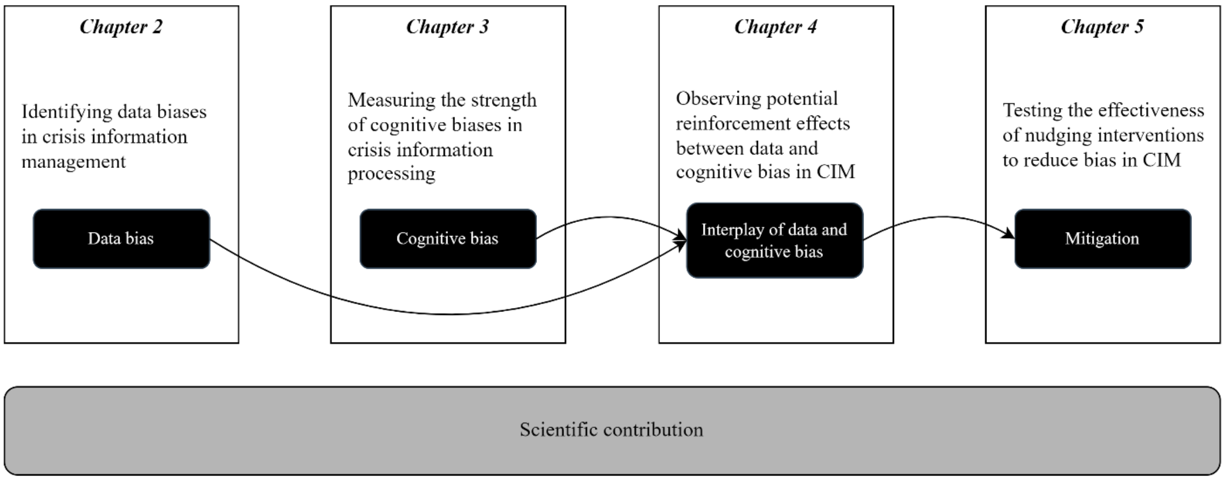


Figure 1.2. Sequence and connection of this dissertation's chapters.

This thesis addresses the research questions through a mixed-methods research approach that combines quantitative and qualitative data collection and analysis. Answering how data biases influence data-driven decision-making in crisis response (**RQ 1**) is achieved through an interview study combined with document analysis. Online experiments assessed how cognitive biases affect data-driven decision-making in crisis response (**RQ 2**). The interplay of data and cognitive biases (**RQ 3**) is studied in a realistic, scenario-based workshop experiment. Finally, nudging strategies to mitigate the negative effects of bias on data-driven decision-making in crisis response (**RQ 4**) are studied through an online experiment. Table 1.1 provides an overview of the research methods employed for this dissertation.

Table 1.1. Overview of this dissertation's research methods.

Chapter	Method	n
Chapter Error! Reference source not found. – RQ 1	Literature	Crisis information management
	Interviews	25 interviews
	Document analysis	147 reports, datasets
Chapter 3 – RQ 2	Literature	Cognitive dissonance theory, Prospect theory, Dual process theory
	Online experiments	471 participants in total - 400 mTurk general public crisis-affected - 50 mTurk government and non-profit workers

		- 21 crisis experts
Chapter 4 – RQ 3	Literature	Sensemaking, Adaptive management, Crisis management
	Workshop experiment	22 participants, mostly crisis experts
Chapter Error! Reference source not found. – RQ 4	Literature	Nudging theory
	Online experiments	606 participants in total (mTurk workers)

In the following, this dissertation's research approach is outlined per research question.

1.3.1 Interview and document analysis to assess data bias in crisis response

RQ 1: *What systematic factors lead to data bias in crisis response?*

For **RQ 1**, this dissertation systematically assesses the causes that lead to biased datasets in complex crises and the effects of these biases on data-driven decision-making. The main background literature used are studies on crisis information management challenges. The ongoing humanitarian crisis in Yemen is selected as a case study as the United Nations describe it as the most severe humanitarian crisis (OCHA, 2021). Through interviews with local Yemeni response organizations, international non-governmental organizations (iNGOs), UN, and donor agencies active in the humanitarian response to the Yemen crisis, it will be possible to understand what constitutes data bias and how it influences decision-making. Findings from the interviews are combined with document analysis, in which reports and datasets created through information management and used in decision-making by humanitarian organizations in Yemen are analyzed. The scientific contribution of Chapter 2 is twofold. First, this research extends previously reported information management challenges and links them to concrete data biases. Second, this research shows how the multi-level response system handles data biases and investigates whether actors can reduce data biases.

1.3.2 Online survey experiments to understand cognitive biases in crisis response

***RQ 2**: How are crisis decision-maker groups affected by cognitive bias*

For **RQ2**, this dissertation studies the susceptibility of different crisis decision-maker groups: crisis-affected people from the general public, government and non-profit workers, and crisis experts. These three groups are selected because of the societal relevance of studying the general public's response to crises, as well as comparing the general public's response to crises to the main two groups of professional crisis responders, i.e., governmental and non-governmental institutions and crisis experts. Through online experiments, the strengths of four cognitive biases are measured for the three groups. For the experiment design, this dissertation relies on previous studies that found and described various information processing biases in urgent and uncertain situational contexts. The experiments in this dissertation confront participants with fictional crisis response scenarios. Cognitive biases studied are anchoring bias in resource estimation, confirmation bias in information selection, framing bias in differently worded response options, and susceptibility toward bias blind spot. The scientific contribution of Chapter 3 is a better understanding and comparison of the susceptibility toward the bias of crisis experts, responders, and laypeople.

1.3.3 Workshop experiment to investigate the interplay between data and cognitive bias in crisis response

***RQ 3:** Does confirmation bias lead crisis decision-makers to rely on biased data?*

RQ3 is addressed through a realistic, scenario-based workshop experiment. The theoretical focus here lies on merging two streams of the literature, i.e., studies on confirmation bias and research on data bias in complex systems. Participants are experienced crisis information managers and decision-makers. Their task is to assess (biased) information and prioritize resource allocation in response to an infectious disease outbreak. Participants are divided into groups. Each group must analyze the provided data for a respective country and decide where to allocate treatment centers. Data collection takes place during the experiment via observation. This observation allows the study of experts' handling of biased information in the analysis and decision-making process. To measure whether confirmation bias further reinforces data bias, participants must finish a final task where they select the most relevant datasets from a list of supporting and opposing datasets. The scientific contribution of Chapter 4 is threefold. First, it merges two unconnected research streams, i.e., studies on confirmation bias and data bias. Second, it provides a novel understanding of how data and cognitive bias interact and to what extent they reinforce each other. Third, Chapter 4 discusses how sensemaking and adaptive approaches support bias identification and mitigation.

1.3.4 Online experiment to test the effectiveness of bias mitigation nudges in crisis response

RQ 4: *What are effective nudging intervention to reduce bias in crisis response?*

Addressing **RQ4**, this dissertation reports on an online experiment that tested the effectiveness of a warning and a default nudging intervention to mitigate confirmation bias when supporting information is biased. The experiment design is facilitated by literature on nudging theory and studies that suggest various effective nudging interventions in domains similar to crisis response. Participants make an initial decision at the beginning of the experiment and then receive a set of biased supporting and unbiased opposing information, which they have to rate by its importance. Finally, participants are asked if they would stick to their initial decision or, based on the reviewed information, would change their initial decision. Participants are randomly divided into a control, default nudge, and warning nudge condition. Confirmation bias is measured per group, and the group mean comparisons give insight into which intervention reduced confirmation bias the most. The scientific contribution of Chapter 5 is the direct comparison between nudging interventions and establishing which intervention is the most effective in mitigating confirmation bias in crisis response.

Figure 1.3 summarizes the overall research approach of this dissertation, including the main theories and literature, research questions and applied methods.

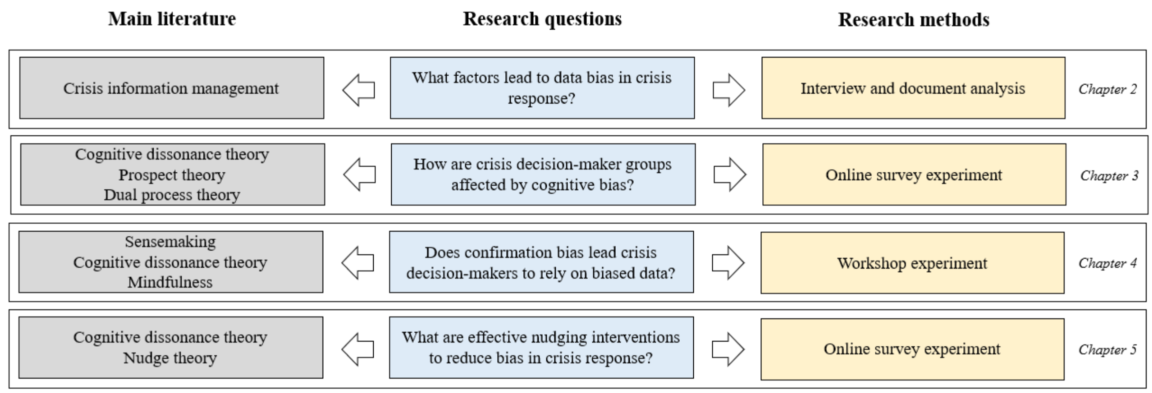


Figure 1.3. The research design framework of this thesis.

2 Reinforcing data bias in crisis information management: The case of the Yemen humanitarian response

This chapter is based on: Paulus, D., de Vries, G., Janssen, M., Van de Walle, B. (accepted for publication). Reinforcing data bias in crisis information management: The case of the Yemen humanitarian response. *International Journal of Information Management*. The first author conducted the literature review, designed and conducted the data collection and analysis process and wrote the manuscript. The co-authors provided feedback on the data collection and analysis process and earlier versions of the manuscript.

2.1 Introduction

When violent conflicts erupt in countries and create humanitarian crises, the toll on societies is immense. Information management is the central component that enables the coordinated response to crises (Yang & Hsieh, 2013). The objective of crisis information management (CIM) is to inform decision-making (Dwivedi et al., 2020), and the importance of accurate, reliable, and trustworthy information for crisis response is evident (Bharosa, Lee, & Janssen, 2010; Leong, Pan, Ractham, & Kaewkitipong, 2015; Treurniet & Wolbers, 2021).

Establishing effective information management in humanitarian crisis response is inherently complex (Auvinen & Nafziger, 1999). The response system consists of multiple levels (Hobbs, Gordon, & Bogart, 2012). On the field level, response organizations implement the actual operational response activities (e.g., provision of relief material). The field level is also where the primary data on crisis severity and affected people's needs are created (Jacobsen & Fast, 2019). Organizations in the field are local, national and international non-governmental organizations (NGOs) as well as United Nations agencies (Marshall, 2018). Each organization has its own mandate, structure and capacities. During the response, organizations join the humanitarian cluster system, which is supposed to increase interoperability between organizations and facilitate information sharing (Noureddine Tag-Eldeen, 2017). The gathered data is shared with the intermediate level, i.e., organizations' headquarters, which review the primary data and decide on resource allocation (e.g., deployment of staff and funds) to the field. Finally, on the strategic level, governmental donors review response organizations reported information and decide on funding to different crisis hotspots globally (Stewart & Ivanov, 2019).

All actors involved in the crisis information exchange and decision-making system are pressured to operate under urgency (Palttala, Boano, Lund, & Vos, 2012). In addition to time-pressure, humanitarian organizations face funding gaps that lead to resource and capacity constraints (Goetz & Patz, 2017).

The factors of complexity, urgency, and resource constraints can give rise to biases because robust collection of high-quality data becomes challenging. So far, CIM literature has discussed challenges to data collection, sharing and use, including time and political pressure, physical access constraints, lack of incentives and interoperability (Altay & Labonte, 2014; Comes, Van de Walle, & Van Wassenhove, 2020; Day, Junglas, & Silva, 2009; Fast, 2017; Maxwell, Hailey, Kim, Mccloskey, & Wrabel, 2018; Villa, Urrea, Andrés Castañeda, & Larsen, 2019).

However, previous literature has fallen short of detailing what concrete biases emerge in crisis datasets and how biases affect the multi-level response system. The complex political, organizational and technical crisis environment can provide different causes for biased information. Yet, studies so far have not categorized different forms of data bias in crises. Understanding biased information in crisis response is important, because biases can lead to systematic misrepresentations of issues, geographic areas, or demographic groups (Jo & Gebru, 2020). If biases are repeated and remain uncorrected, the humanitarian principle to provide aid to the most-affected people might not be obtained due to biased data (Paulus, Fathi, Fiedrich, Van de Walle, & Comes, 2022). As crisis response becomes more data-driven (Lentz, Michelson, Baylis, & Zhou, 2019), biases in the data that underlies models and algorithms need to be identified and mitigated to address crisis-affected people's needs adequately.

This research provides an in-depth study of how datasets become biased in crises and how decision-making in crisis response gets affected by biased information. We apply a mixed-method approach combining interviews with document analysis. As our case study, we select the contemporary most severe humanitarian crisis, i.e., the conflict in Yemen (United Nations, 2020).

Our research has implications for crisis information management overall. Measuring progress toward the implementation of the UN Sustainable Development Goals (SDGs) is highly dependent on data collected in the field (UNECE, 2021). Biases in these datasets will complicate, or even make impossible, drawing conclusions on whether or how far SDG target goals were reached.

The objective of this study is to understand what and how biases emerge in CIM and how biased crisis information affects decision-making in the multi-level response structure. We conducted interviews with humanitarian managers and analysts active in the Yemen crisis response and complemented these findings with a document analysis consisting of reviewing reports and datasets published by humanitarian organizations operating in Yemen.

In the next section, we discuss the literature on crisis information management in humanitarian response and the issue of data bias in CIM. In Section 2.3, we describe our interview and document analysis approach. Our findings are presented in Section 2.4. We discuss our findings in light of previous CIM literature and present our contributions to theory and practice in Section 2.5. Section **Error! Reference source not found.** concludes the paper.

2.2 Crisis information management and data bias

2.2.1 Data-driven crisis management

Information management frequently happens under time pressure, with a lack of data, high stakes at risk, and limited resources (Citroen, 2011). In humanitarian crises, these factors tend to be extreme (Carroll & Conboy, 2020; Gralla, Goentzel, & Fine, 2016). For example, the United Nations World Food Programme provides emergency food aid to millions of people in Yemen (United Nations World Food Programme, 2020). The conflict has continuously led to new situations of displacements of population groups. Responding to displacements requires that the lives and well-being of thousands of people need to be urgently protected, raising the stakes extremely high. At the same time, there is deep uncertainty for responders over the concrete needs of displaced people and options to respond (Hasani & Mokhtari, 2019). Further, funding gaps for humanitarian assistance are wide, drastically limiting available resources (United Nations, 2019a).

To support crisis response, information management integrates data collection and analysis to establish the evidence base for crisis severity, population needs and response capacities. The information products created (e.g., reports, fact sheets, infographics) inform the planning and decision-making (Vittorio Nespeca, Comes, Meesters, & Brazier, 2020), especially with regard to the effective allocation of funding, staff and material resources (Zhou, Wu, Xu, & Fujita, 2018).

Two main levels of crisis management are described in the literature: the operational and the strategic level. The main decision types at both levels are allocation problems (Fink & Redaelli, 2011; Juric & Shamoug, 2017). Donor agencies are mainly active on the strategic level of crisis management. They need to take a bird's eye view of different crisis contexts around the world to assess and compare situations (De Geoffroy, Léon, & Beuret, 2015). Governmental donors provide the majority of funding for humanitarian response (Development Initiatives, 2018). The strategic level needs to decide what funding to allocate to different crisis hotspots around the world. The management or headquarters of the organizations receiving the funds need to decide how to best allocate staff and resources to their operational focal points (Knox Clarke & Campbell, 2020). They are therefore located between the operational and strategic levels, and responsible for enabling the operational response and informing donors about crisis situations. On the operational level, the actual crisis response activities are implemented by response organizations. The operational level is largely the realm of local and international humanitarian organizations. Response organizations need to make decisions in the form of what specific population groups and geographic areas to prioritize with what type of relief material (Campbell & Clarke, 2018; Knox Clarke & Campbell, 2020; Obrecht, 2017).

Actors on each level require reliable, up-to-date data to inform decisions. To collect primary data on the crisis situation, organizations in the field conduct household surveys, interviews, focus-group discussions, and field observations (Patel, King, Phelps, & Sanderson, 2017). The collected data is cleaned, structured, analyzed, and reported to organizations' headquarters, where it is used to inform organizational internal decisions on staffing and resources (Comes, Vybornova, & Van de Walle, 2015) but also sent further upstream to the strategic donor level to request funds.

According to crisis management theory, the operational and strategic levels are supposed to collaborate closely and conduct joint information management (Comes, Bergtora Sandvik, & Van de Walle, 2018; Jensen & Hertz, 2016). Because resources and capacities are limited, the joint CIM process allows organizations to receive and exchange information that could not be gathered alone. The objective of sharing humanitarian data is to close information gaps, between what information is available and what needs to be known, and build a common understanding of humanitarian needs and required response capacities (Hendriks & Boersma, 2019).

The dynamic crisis response context gives rise to informal networks and fragmented information management processes besides the formal cluster approach (Comes et al., 2020; Wolbers, Boersma, & Groenewegen, 2018). These networks are loosely defined groups of organizations that engage in data sharing and non-sharing dynamically throughout the response. The fragmented situation requires that *"[humanitarian] decision-makers need to break out of their information and coordination bubble and monitor their environment to understand emerging trends and adapt their decisions"* (Comes et al., 2020). This implies that, while organizations should be able to close information gaps through the join CIM approach (Crowley & Chan, 2011), data gaps often remain because fragmentation limits data sharing.

2.2.2 Data bias in crisis information management

Crisis circumstances challenge information management processes. Humanitarian response is plagued with data gaps, missing information, and incomplete datasets (Dodgson, Hirani, Trigwell, & Bueermann, 2019). Assessing and improving data quality is a primary information management challenge in humanitarian response, with practitioners being greatly concerned about the quality of the data they work with (United Nations, 2019b).

In scientific measurements, we differentiate between random non-systematic error and non-random systematic error, i.e., bias (Vogt & Johnson, 2015). *Random errors* might result from noise in the measurement or data collection environment, or other unpredictable and uncontrollable phenomena. *Systematic errors*, i.e., bias, might result from continuous, structural problems that skew a measurement in a specific direction. Random errors vary with each measurement and might be corrected through repetitive application of the same measurement approach (Taylor, 1997). Systematic errors, i.e., biases, do not vary between measurements but remain persistently skewed and thus cannot be corrected through applying repetitive measurement techniques (ibid.).

In CIM, the differentiation between non-systematic and systematic error, i.e., bias, is important because random errors remain largely unpredictable and a consequence of operational time pressures, dynamic changes, technological shortcomings, as well as individual skills and capacities of data collection personnel. On the other hand, systematic bias can result from underlying structural issues and phenomena, e.g., historical, social, and political inequalities, but also from environmental and organizational reasons (Jo & Gebru, 2020). Our definition of systematic data error, i.e., bias, includes both intentional as well as unintentional distortion of data.

Crisis response cannot adequately address the needs of affected people if data biases misrepresent the humanitarian situation (Dodgson et al., 2019). Biases can affect decision-making by repeatedly misrepresenting specific geographic areas, social groups, or issues (Bender, Gebru, McMillan-Major, & Shmitchell, 2020). When data biases remain unidentified and uncorrected in crises, operational and strategic decisions will be affected negatively, and the humanitarian principle of providing aid to the most-affected people can be missed (Paulus et al., 2022). Figure 2.1 depicts the data-decision-interdependencies between the different levels of humanitarian crisis response and how the system can become affected by systematic and non-systematic data errors.

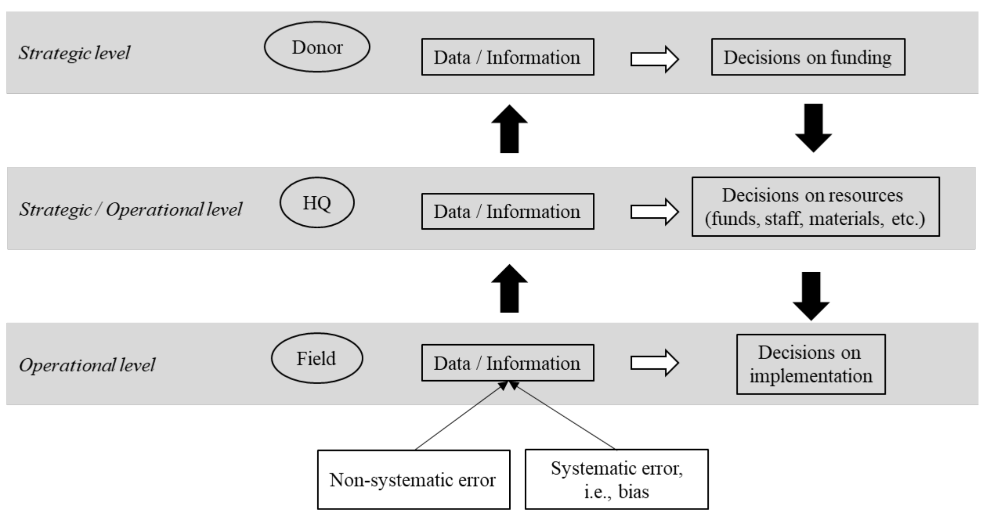


Figure 2.1. Data-decision-interdependencies within the multi-actor system of humanitarian crisis response.

We distinguished between non-systematic and systematic data errors, i.e., bias. When biases cascade between the different CIM levels, they can systematically skew the understanding of the crisis within the whole response system. Hence, this study addresses the need for a deep understanding of how biases emerge in complex crises. To our knowledge, a systematic assessment of data bias in humanitarian CIM has been absent.

Traditionally, the study of data bias was mainly a concern of the statistics domain, where researchers were interested in how far a model estimator diverged from the true value of the estimated parameter in the real world. With the advent of artificial intelligence and machine learning, the scientific debate around bias has significantly increased (Dwivedi et al., 2021). The causes and consequences of algorithmic bias, often as a result of systematically skewed training data, are today not only studied in computer science but also increasingly in sociology and the humanities (Holstein, Vaughan, Daumé, Dudík, & Wallach, 2019).

In this paper, we use the term *data bias* to refer to datasets that, intentionally or not, deviate from the real-world phenomena the data is supposed to represent. In other words, biased datasets show a *"divergence between the true distribution and digitized input space"* (Jo & Gebru, 2020). Using Wang and Strong's (1996) data quality framework to our definition of biased data suggests that data bias especially violates intrinsic data quality (i.e., objectivity), contextual data quality (i.e., completeness), and representational data quality (i.e., representational consistency).

2.2.3 Known challenges in crisis information management

To facilitate our investigation of data bias in CIM, we turn to previous studies that have described challenges to CIM. We go one step further than previous studies and distinguish systematic from non-systematic challenges to see what challenges might act as sources of bias. This guides our assessment of different types of bias in our own analysis later on.

Previously, CIM literature identified several factors that impede CIM but has not directly linked those factors to potential biases that might emerge and systematically influence crisis information.

Examples of previously identified factors are: Inaccessibility, Incompatible formats, Information shortage/overload, Low information priority, Source identification difficulty, Storage media-activity misalignment, Unreliability, and Unwillingness (Altay & Labonte, 2014; Day et al., 2009). Bharosa et al. (2010) found challenges to information sharing in crises on the individual, organizational and affected population levels. Relief workers, they found, neglected to share information with actors who needed it, while being eager to accumulate information for themselves. Schwendimann (2011) reported that data collection in crises is hindered by access constraints due to political and bureaucratic interference, safety and security concerns, as well as capacity gaps. According to Fast (2017), crisis circumstances affect data collection to lead to systematic deviations in datasets, i.e., imbalanced data availability for different geographic areas, response priorities, and groups of affected people. Maxwell et al. (2018) highlighted political interference from authorities on data collection, analysis, and reporting of results in conflict crises (Maxwell, Hailey, Kim, et al., 2018; Maxwell, Hailey, Spainhour Baker, & Janet Kim, 2018). Hendriks and Boersma (2019) also identified political influence, and the reliance on politically motivated data reporting, as a challenge in flood disaster response. Wolbers et al. (2018) described information delays and breakdowns and the utility of fragmentation as a crisis coordination strategy to deal with information uncertainty, ambiguity, and time pressures. Comes et al. (2020) emphasized the fragmented nature of dynamic organizational networks in crises in which data is shared within sub-networks of organizations but not with organizations outside these networks, even though they would benefit from them.

Based on the previous findings regarding diverse CIM challenges, in Table 2.1 we synthesize them into a framework that distinguishes between systematic and non-systematic factors that impede CIM. The purpose of the framework is to act as a baseline for our own analytical approach. We use the framework, i.e., the categorized challenges previously identified, to code those challenges reported by our own interviewees and the datasets and reports we assess.

Table 2.1. Framework of systematic and non-systematic factors challenging CIM.

Non-systematic CIM challenge	Systematic CIM challenge	Source	Context
Lack of incentives, Lack of understanding of inter-organizational dependencies	Institutional mandates, objectives and values	Bharosa et al. (2010)	Disaster
Incompatible formats, Information shortage/overload, Low information priority, Source identification difficulty, Storage media-activity misalignment, Unreliability, and Unwillingness	Inaccessibility	Day et al. (2009); Altay & Labonte (2014)	Disasters

Inadequate reporting mechanisms, Lack of incentives	Socio-cultural issues, Inaccessibility, Concerns over misrepresentation, Political influence	Fast (2017)	Conflicts and disasters
Unmet information needs (data gaps), Inadequate reporting mechanisms / Data definitions, Delayed data collection or problematic reporting	Concerns over methodological weakness, Unclear sampling approach, Capacity gap, Delayed or refused permits and bureaucratic hurdles, Political influence	Maxwell, Hailey, Kim, et al. (2018); Maxwell, Hailey, Spainhour Baker, & Janet Kim (2018)	Conflicts
Delayed reporting, Difficult validation and verification	Political influence, Inaccessibility	Hendriks and Boersma (2019)	Disasters
Information discontinuities, Delayed data	Institutional mandates, objectives and values	Wolbers et al. (2018)	Disasters
Inadequate reporting mechanisms / Data definitions, Unmet information needs (data gaps), Unable to verify, Competition and exclusive networks, Delayed data collection, or problematic reporting	Inaccessibility, Safety and security concerns	Comes et al. (2020)	Conflicts and disasters

2.3 Research method

The objective of this study is to provide an in-depth understanding of the types of data bias in crisis information management and how they affect the multi-level structure of the response system. This requires an investigative approach to data collection and analysis.

We employed a mixed-methods research design (i.e., interviews and document analysis) for our selected case study – Yemen. Combining interviews with document analysis helped add context, probe statements, and acquire sufficient depth (Owen, 2014). The interview study enabled us to collect first-hand experience of humanitarian analysts and managers, i.e., their perspectives on what constitutes the most pressing challenges to information management. The document analysis allowed us to examine raw data, analysis results, and reports created as information products for decision support by the humanitarian response community in Yemen.

We used previous studies presented in Section 2.2, specifically the synthesized framework of CIM challenges, to develop an effective interview script and document analysis guide. The combined data repository of interviews and documents provided a rich source of information management challenges in data collection, sharing, and analysis. This allowed us to understand the causes and consequences for data biases. Following an open coding approach (Corbin & Strauss, 1990) we analyzed the interview transcripts and documents. The open and iterative coding and analysis approach enabled us to identify common themes and issues that emerged in the collected data (Evans & Price, 2020) and constituted data biases in response organizations' crisis information management.

2.3.1 Yemen's complex humanitarian crisis

The international humanitarian system responds to dozens of ongoing crises around the world. For our study, we aimed to select a case that provided a large pool of response organizations that could be contacted for interviews. The humanitarian responses to the conflicts in Syria and Yemen were the largest in terms of the required funding for the years 2019-2021[1], the time period of this study. In contrast to the Syrian crisis, where displacement happens across borders into neighboring countries on a large scale with the humanitarian response following, the situation and response in the Yemen crisis are mostly happening within Yemen's country borders. This localized character makes focused research more feasible. The United Nations describes the situation in Yemen as the world's worst humanitarian crisis, followed by the Syrian crisis (United Nations, 2020). The humanitarian situation in Yemen has worsened dramatically since the onset of conflict in 2014. Two-thirds, e.g., 20 million out of the population of 30 million of Yemenis, are estimated to need humanitarian assistance (ibid.). Based on these issues, we chose the crisis in Yemen as our case study.

Since the onset of the crisis in Yemen, the humanitarian response community has described information management as critical (United Nations, 2015). Significant problems in the response

[1] Humanitarian funding data via https://fts.unocha.org/appeals/overview/2021. Last accessed June 3, 2021.

were the inaccessibility of active-conflict areas, political and bureaucratic hurdles but also social issues, including the greater difficulty for women to access assistance (ibid.).

In June 2019, the United Nations World Food Programme (WFP) halted its emergency food delivery in parts of Yemen for hundreds of thousands of food-insecure people. The reason behind this exceptional move was that WFP accused one party in the conflict of data manipulation, which led to wide-scale aid diversion (Reuters, 2019; WFP, 2018). The conflicting party was accused of adding people affiliated with the party to lists of beneficiaries to divert aid supplies.

The WFP episode illustrates how political bias in data, and the concerns over it, can influence crisis decision-making and have adverse effects on affected populations. It also demonstrates that data in crises is more than an objective resource for information management. It is created and used within the crisis' political, social, cultural, and organizational environment (Jacobsen & Fast, 2019).

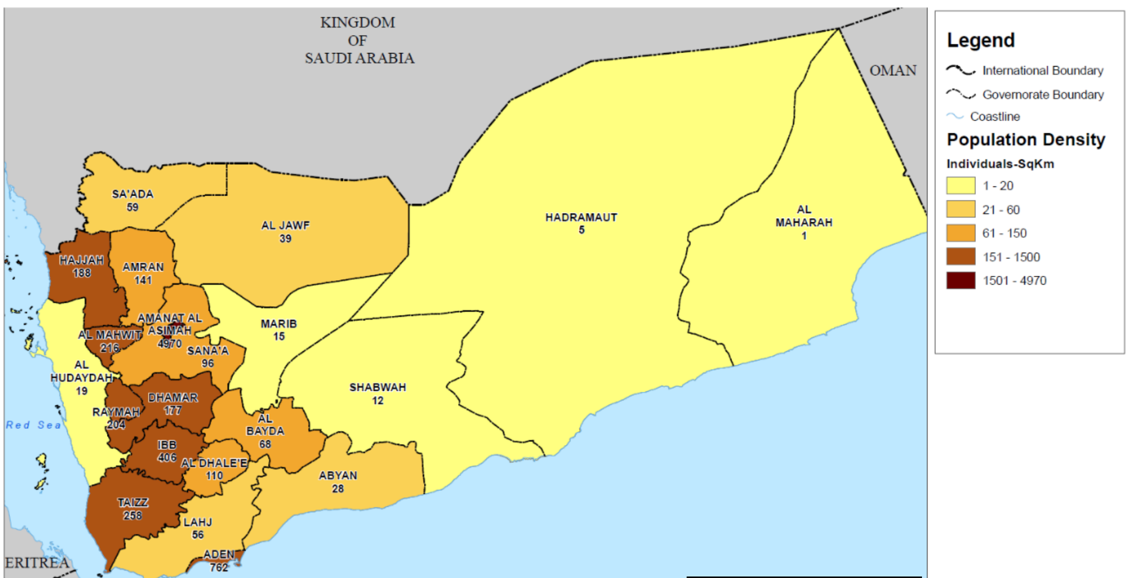
In 2019, nine UN agencies and 32 international non-governmental organizations were present in the country, representing the international community responding to the crisis (United Nations, 2019c). Together with 77 local Yemeni organizations, the Yemen crisis response was coordinated (ibid.).

While the scholarly attention to data bias in crisis response has been limited, the practical implications are clearly visible. Figure 2.2 shows three maps depicting different key indicators of the humanitarian situation in Yemen. It shows the population density (top), areas controlled by different conflict parties (middle), and the outcomes of the IPC[2] food security analysis across the country (bottom). The IPC analysis is the key information product for food security decision-making in humanitarian response (Baldauf, 2021). It is the standardized, systematic assessment that establishes the evidence base on food security in a country. The result of the IPC analysis is a ranked overview of what geographic areas should be prioritized for emergency food aid. Donors, as well as response organizations, use the result of the IPC analysis to base decisions on fund and resource allocation on (Maxwell, 2019). However, as Figure 2.2 shows, no IPC analysis was done

[2] IPC = Integrated Food Security Phase Classification

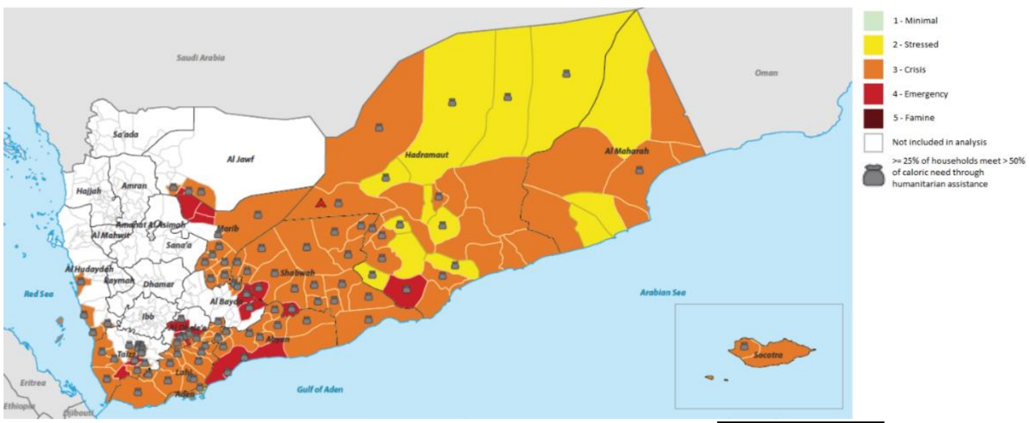
for the most densely populated areas within Yemen. Most of these areas are in the north and either under the control of the Houthi militia or contested by the conflict parties, i.e., active conflict zones. The result are data white spots, and thus analysts and managers lack IPC data for the most populated areas.

The Yemen IPC example makes the problem of bias within humanitarian datasets evident. The strategic and operational importance of IPC data pronounces the potential negative impact of biases on response decisions.



Source: UN OCHA

Source: Reuters



Source: IPC

Figure 2.2. Maps of Yemen. Top: Population density map. Middle: Areas under control by different conflict parties. Bottom: Food security assessment (IPC). Note the white spots (missing analysis and data) in the bottom map correspond to the most densely populated areas at the top, which are also under militia control or contested by conflict parties, as shown in the middle map. As a result, no IPC data is available for the most densely populated areas that are strongly affected by the conflict.

2.3.2 Data collection

In the data collection stage, we interviewed analysts and managers of response organizations active in Yemen, and collected documents and datasets created, used, and shared by response organizations in Yemen.

2.3.2.1 Interviews

2.3.2.1.1 Sampling strategy

The selection of interviewees followed a purposeful sampling approach to have a diverse and representative sample. The population of this research consists of all organizations active in the coordinated response to the Yemen crisis: response organizations as well as donor organizations.

To identify the response organizations, we downloaded a list[3] published by the United Nations that contains all organizations actively involved in the joint response in Yemen during the year 2019. These organizations are part of all thematic clusters active in Yemen and are either local Yemeni organizations, international NGOs, or UN agencies. The document lists 120 organizations: 77 local Yemeni organizations, 32 international non-governmental organizations, and nine United Nations agencies.

To identify the donor organizations, we were looking to recruit representatives from the top donor agencies that provided the majority of funding to the Yemen crisis response and who were signatories of the *Grand Bargain*. The Grand Bargain is a commitment by major humanitarian organizations and donors (World Humanitarian Summit, 2016). One of its goals is to improve information management. Therefore, participants from Grand Bargain signatory organizations are more likely to provide deep insights into the humanitarian sector's information management practices. This resulted in a list of 20 donor agencies.

To build up our interview sample, we employed a three-step approach to identify the contact email addresses of analysts and managers in response and donor organizations. In step 1,

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[3] https://reliefweb.int/report/yemen/yemen-organisations-monthly-presence-3w-april-2019. Last accessed June 14, 2022.

we searched for reports published by all organizations in the sample. We searched the reports for email contact information to analysts and managers responsible for the organization's information management and response activities in Yemen. To ensure interviewees could talk about IM challenges, they needed to have official positions as analysts or managers with several years of experience. If step 1 did not result in a contact email address, we followed step 2. In step 2, we contacted the organizations through their general contact email addresses and asked for a referral to analysts or managers responsible for Yemen within the organization. If an email address was not received for an organization in step 2, we followed step 3. In step 3, we used the contact forms on organizations' websites to ask for referrals to their analysts or managers active in Yemen.

We applied the above three-step approach to our list of 120 response organizations and 20 donor organizations between January and March 2021. In our invitation emails, we introduced the researchers, invited analysts and managers to a 30-45 minutes research interview, and explained that the focus of the interview was on information management challenges in the Yemen response. As soon as an interview was confirmed, we proceeded with the actual interview while additional invitations were followed up.

Previous reviews in the information management and systems domain have proposed conducting between 15-30 interviews for case study research (Marshall, Cardon, Poddar, & Fontenot, 2013). To reach saturation, enough information to replicate the study needs to be collected, there is no new information received from the most recent interviews, and no new codes emerge in the analysis (Fusch & Ness, 2015). After completing 20 interviews with response organizations and 5 interviews with donor organizations, we reached theoretical saturation as no new information was found during the interviews, our sample included representatives of each organization type from each thematic response cluster, and no new categories of information management challenges that could be linked to data biases emerged.

2.3.2.1.2 Interview process

All interviews were conducted between January to April 2021 via Skype or Zoom. At the start of each interview, participants were asked if the interview could be recorded, and briefed that the data would be anonymized, and treated confidentially according to the ethical standards of

Delft University of Technology[4]. Then, the interviewer (the first author) introduced himself, the interview's research background, and the topic: information management challenges in the Yemen crisis response.

The interview started after the interviewee consented to their data being used for research purposes. Only one interviewee did not consent to record the interview but consented to notes being taken during the interview.

We used a semi-structured interview technique. Previous information management studies in humanitarian response had used semi-structured interview techniques successfully (Crowley & Chan, 2011; Van de Walle & Dugdale, 2012; Van Den Homberg, Meesters, & Van de Walle, 2014). The semi-structured approach allowed us to define a set of key questions that needed to be addressed in each interview while at the same time having enough flexibility to ask pertinent follow-up questions depending on the interviewees' backgrounds and responses (see interview script in Appendix A). Our interview script was designed to gain a comprehensive understanding of the complete information management process of each of our interviewees' organizations and what factors influence data quality, availability, and completeness (see Figure 2.3).

Our interview script was developed based on the CIM literature discussed in Section 2.2. At the beginning of each interview, we started with the organizational context and the decisions that required data and analysis in the interviewee's organization (Nespeca, Comes, Meesters, & Brazier, 2020; Zhou et al., 2018). From there, we asked for definitions of data needs and data collection methods to acquire needed data (Gralla, Goentzel, & Van de Walle, 2015; Patel et al., 2017). This was followed by questions on the concrete data processing and analysis steps of our interviewees and their organizations. During each data-related step the interviewees described, we asked them to reflect on "challenges", "problems" and "issues" their organizations faced while working with data. The semi-structured interview technique allowed us to raise the same main questions to all interviewees and then raise follow-up questions to individual answers to generate

[4] https://www.tudelft.nl/en/about-tu-delft/strategy/integrity-policy/human-research-ethics. Last accessed June 14, 2022.

a deep understanding of each interviewee's main data-related challenges. Finally, we asked about the consequences of the challenges on information management and decision-making.

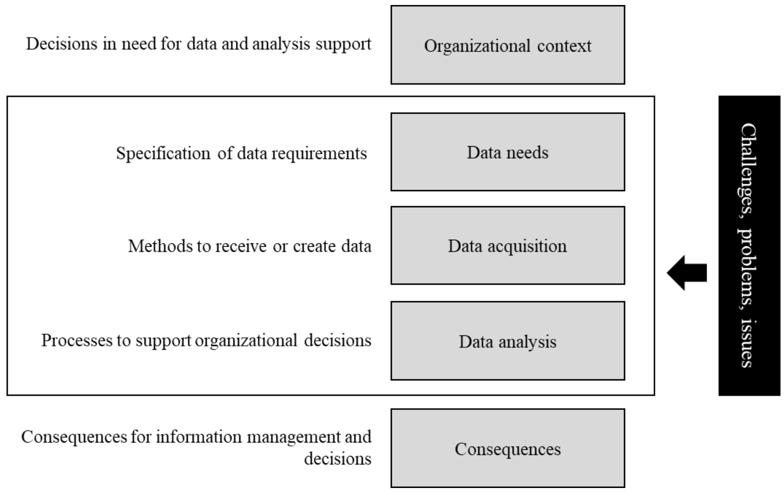

Figure 2.3. Structure and main concepts of each interview.

2.3.2.2 Document identification and inclusion criteria

Our objective was to identify a set of documents that is a representative sample of information management products created during the Yemen crisis response. We considered documents from a diverse set of organizations (local Yemeni organizations, international NGOs, UN agencies, donor agencies), including reports, datasets, funding proposals, survey results, situation briefings, and meeting notes, and representing a broad set of different thematic clusters within the Yemen crisis response.

The Assessment Capacities Project (ACAPS) repository provides an inventory of 157 documents, including reports, datasets, websites, situation reports, analysis, and infographics on the Yemen crisis. These are published by humanitarian organizations, donor agencies, academic and research institutions active in all thematic clusters in Yemen.

We downloaded the ACAPS list[5] that contained metadata of all 157 documents in the repository. To access the full documents, we followed a three-step approach. In step 1, we used the direct URL links in the metadata file to access and download each document. If the URL link was not functioning, we followed step 2. In step 2, we used Google search to search for the document titles and organization names. When the Google search did not lead to the documents, we followed step 3. In step 3, we accessed the organizations' websites to search for the missing documents. If the document was still inaccessible after step 3, we excluded the document from our analysis, which resulted in the exclusion of 36 documents. Having assessed the excluded documents' titles, publishing organizations, and thematic foci, we concluded that the excluded documents would not have provided new insights as they were closely aligned with documents that remained in the sample.

The ACAPS repository further holds a set of documents that represent short briefs only providing broad information on the Yemen crisis in general, high-level briefings to the UN Security Council, interactive dashboards in which data cannot be dated, and economic market overviews. Excluding these documents led to the removal of 50 documents. Finally, we reviewed the remaining documents regarding whether they provide insight into the data collection and analysis methodology or related information management processes. 24 documents did not provide any information on these matters and were excluded. 47 documents remained in the sample. Our final sample, therefore, included 47 documents (Figure 2.4). The coding and analysis process for these documents is described in the Data Analysis section.

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[5]https://docs.google.com/spreadsheets/d/1Q0mq1mCoxoDSYcL8EmeAXTKmbh9m1EPF/edit#gid=635595446. Last accessed June 14, 2021.

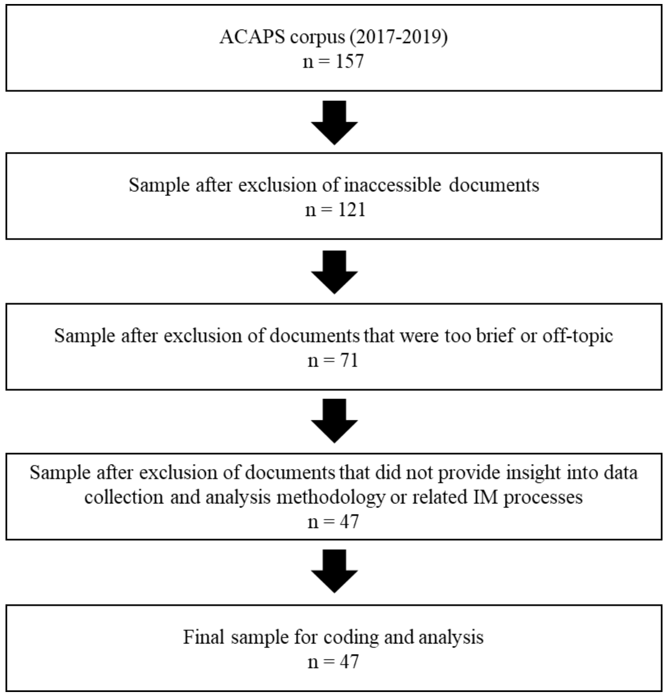

Figure 2.4. Overview of the identification and exclusion process of information products created by the humanitarian crisis response community in Yemen.

2.3.3 Data analysis

The advantage of combining interview and document analysis was that we could analyze input from practitioners, gained through our interviews, side-by-side with reports and datasets created, used, and shared by response organizations. In the document analysis, we studied the inputs and outcomes of information management processes directly. This allowed us to identify information management challenges, e.g., data gaps, under-representations, sampling and analysis shortcomings within the underlying data and developed information products. The interviews gave us insights into the processes and contexts that led to how these documents and datasets were created and what factors influenced data collection and the creation of information products.

We conducted the interview and document analysis in parallel. This allowed us to create coherent codes between both data sources, which facilitated the axial coding process, where open codes generated from the interview transcripts and documents were categorized into broader categories.

After signing a GDPR compliance agreement, an interview transcription service provider transcribed the interviews. After completing the transcriptions, the first author carefully reviewed all transcriptions and corrected mostly organization and location names as well as humanitarian abbreviations. After this process, the transcribed interviews were imported into the ATLAS.ti software for qualitative data analysis.

For the document analysis, we created a matrix in MS Excel to store each document's metadata and capture quotes and notes from the documents that pertained to information management challenges in general or data bias concretely. Of most value for our research were Method, Data Collection, and Analysis sections as well as footnotes in the documents. These provided the most insights into what data was collected and how, as well as how it was processed and analyzed by response organizations. When documents reported challenges during the data collection, processing and analysis processes, these challenges were also mentioned in the respective sections we focused on. For example, when data collection teams could not travel to certain areas due to safety concerns or because authorities did not grant permits, which was stated in the documents, we copied these sections into our matrix. This allowed us to discover issues that led to misrepresentation within data, data collection and analysis challenges, or information management impediments in general.

We used a context analysis approach consisting of open coding, axial coding, and selective coding (Corbin & Strauss, 1990; Zuiderwijk & Spiers, 2019). Each interview transcript and document was coded individually in the first round of open coding. In this phase, emerging codes were closely coupled with the raw data. Open coding allowed us to stay flexible regarding what issues were perceived as challenges to information management. The authors discussed the emerging codes and made adaptations to code names. Axial coding was used in the second phase to create categories of open codes that share specific characteristics. In the axial coding phase, it became evident what information management challenges were related to actual biases in collected, shared and used data. We further distilled the axial codes into selective codes. In the process of generating the selective codes, four main types of bias emerged: political, accessibility, issue, and sampling bias. These results are presented in more detail in Section 2.4.

2.4 Results

2.4.1 Reinforcing data bias in the multi-level crisis response system

Challenges in data collection, use, and sharing were abundantly reported in both our data sources, i.e., interviews and documents. Data quality issues were reported by representatives of all levels within the crisis response system in Yemen. Because our sample included representatives from the field, headquarters, and donor level, we find support for the assumption that issues with data, non-systematic errors as well as biases, cascade through the joint CIM process, affecting operational and strategic decision-making.

"[We] are based here in [donor country capital] so we're mostly more serving the decision making at the strategic and at the programme level since we're not there in the field. But we do of course rely on field information […]" [I15]

"We always try to push first to get more data [to get] more resources from donors, […] getting more access to people […], getting more information from the government and local authorities, and also reaching out to the people themselves, [to be] able to know what is needed." [I09]

Of particular concern are mechanisms within the multi-level response structure that facilitate the reinforcement of data biases. One example is that interviewees reported donors fund data collection efforts for issues that are priorities of donors and which are not necessarily the key issues of concern the response organizations see in the field (I03, I04, I22). This is similar to what interviewees mentioned about donors' push for evidence-based programming (I08, I17). Donors provide funds specifically to strengthen the evidence on their priority topics. Response organizations are required to collect data based on these *earmarked* funds. This extends the influence of issues important to the donors, who strengthen the argument to continue to support their priority concerns while other concerns remain neglected. However, to collect data and establish evidence on underfunded, critical issues (e.g., SGBV[6], domestic abuse, recruitment of

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[6] SGBV = sexual and gender-based violence

children into armed groups), organizations require funding in advance to build capacities for data collection (e.g., shelters and safe places, psychological support). Because evidence is not available, donors are reluctant to provide funds for certain issues. Consequently, because funding is lacking, data gaps and biases remain, evidence gaps cannot be filled and donors remain unconvinced that understudied issues should be funded. The circle continues, and biases are reinforced (Figure 2.5).

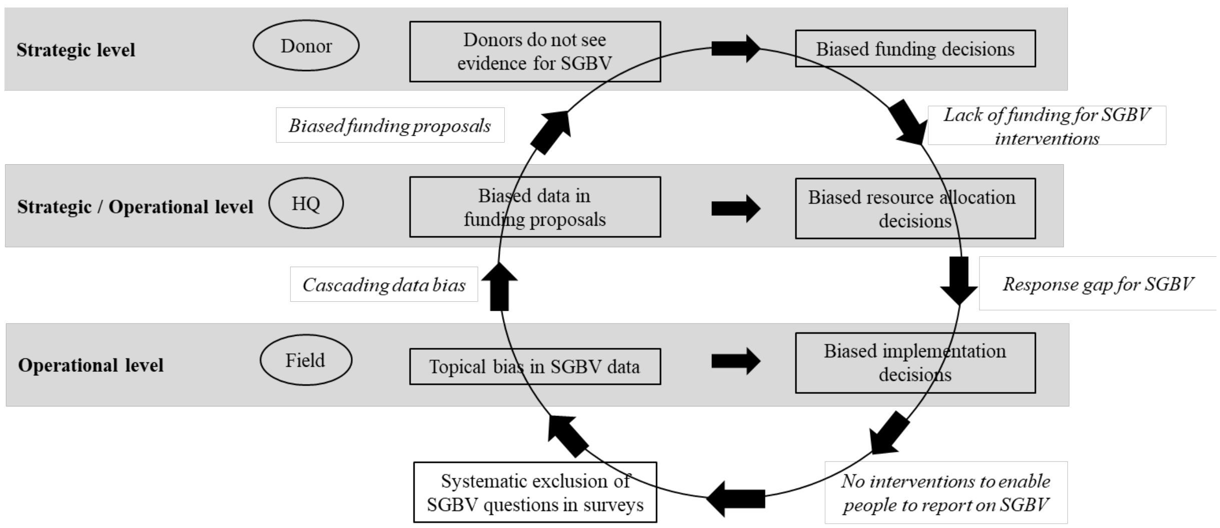

Figure 2.5. Cycle of reinforcing data bias. Data biases cascade and are reinforced within the multi-level crisis response system.

2.4.2 Systematic bias in CIM

While our interviewees, as well as assessed documents, only reluctantly named certain challenges concretely as biases, what constituted actual bias emerged during our coding process. We used the framework developed in Section 2.2 to guide the coding process. For example, previous studies have found that political and inaccessibility challenges exist in CIM. However, previous research has stopped there, while we went one step further and assessed whether these challenges led to actual systematic error, i.e., bias, in datasets and reports.

The factors listed in Table 2.2 stand for challenges organizations faced during their information management work. These challenges were grouped into broader categories. Revisiting the categories in the final, selective coding iteration, led to the identification of four main categories of bias, each of them influencing data collection, use, and sharing in a systematic way.

Our interviews and document analysis support the assumption that data biases affect crisis information management. Four types of bias emerged from our analysis. *Political bias* skews the available data in ways that favor political actors within the conflict in Yemen. *Accessibility bias* misrepresents specific geographic areas affected by the crisis, especially underrepresented is data from active conflict zones. *Topical bias* makes important phenomena invisible in available data because parts of surveys are rejected by authorities or not accepted by affected people. *Sampling bias* affects data collection and analysis methodologies, often because of time and capacity constraints, resulting in samples lacking representativeness. **Error! Reference source not found.** depicts the process of distilling these four main types of bias from our data.

Table 2.2. The four systematic biases and how they relate to factors from the framework of CIM challenges.

Type of bias	Factors leading to bias	Examples of factors demonstrating systematic distortion of data
Political bias	Political influence (I01, I02, I03, I04, I08, I09, I10, I11, I12, I14, I15, I17, I21, I22, I23, I24, D02, D28, D30)	• *lists of beneficiaries are being manipulated (I24)* • *politics keeps numbers of covid-19 cases low (I10, I22)* • *biggest donors drive the funds where they have a political interest (I21)* • *political powers drive/influence IPC assessments (I21)* • *over- and underreporting of fatalities during active fighting (D02)*
	Delayed or refused permits; bureaucratic hurdles (I01, I05, I10, I13, I14, I17, I19, I22, I23, D09, D10, D11, D15, D18, D42)	• *assessments were blocked by authorities in the North of Yemen* (I17) • *interrupted data collection by authorities (D09)* • *authorities delay and impede data collection (I23)*
Accessibility bias	In-access (I01, I02, I03, I08, I09, I10, I11, I14, I15, I16, I17, I20, I21, I22, I23,	• *not able to collect data in the North (I03, I09, I11, I17, I21, I23)* • *very difficult to get information, from areas where nobody can access (I20)*

	D04, D05, D11, D19, D20, D22, D23, D25, D28, D30, D32, D33, D35, D37, D39, D41, D43)	• *IPC assessment was only done in Southern governorates (I21)* • *only 16% of numbers were verified because of access constraints (D23)* • *Access constraints lead to inaccurate, incomprehensive, out-of-date data (I22)*
	Safety and security concerns (I02, I03, I04, I10, I11, I12, I14, I17, I18, I20, I23, D03, D04, D19, D21, D29, D33, D35, D36)	• *Capacity and safety concerns led to no assessment in some districts (D35, I23)*
Topical bias	Socio-cultural issues (I03, I04, I05, I08, I11, I16, I23, D05, D14, D19, D39)	• *families and authorities won't speak about children in the armed forces (I8)* • *issues of SGBV, child labor, domestic violence, marital rape not allowed by authorities in questionnaires (I23)* • *SGBV and child recruitment is happening, but no numbers are available (D39)*
	Interviewee bias (I08, D34)	• *after 6 years of conflict people know what to respond to get supplies (I8)*
Sampling bias	Unclear sampling approach (I01, I03, I04, I08, I11, D05, D09, D10, D11, D12, D21, D31)	• *choosing the proper sample will prove your point (I8)* • *20% of people were not on the food list (I11)*
	Capacity gap (I03, I07, I11, I12, I16, I22, D36, D42)	• *organizations lack resources to create master lists of IDP sites and schools (I08, I16)*
	Concerns over methodological weakness (D18, D43)	• *analyses use contradicting household sizes (D18)* • *cell phone-based data collection biased towards better-off groups (D43)*

	Concerns over gender bias (D06, D13, D14, D26, D27)	• *assessments, KIIs[7] included mostly males (D06)*

2.4.2.1 Political bias

Several sources of political bias emerged from the interviews and document analysis. These ranged from direct political influence on reported key variables, survey design, and project priorities regarding location and topic, to bureaucratic hurdles and delays, reputational concerns, donor pressures, and organizational policies and mandates.

Most often mentioned were political influences on collected data that stem from the authorities in Yemen as well as governmental donors and agencies' strategic levels. Authorities, especially the Houthis controlling the North, influence where data collection should occur, when, by whom, with whom, and on what issues. Organizations that want to conduct questionnaires on humanitarian needs have to get approval from authorities before permits are granted. Questions on sexual and gender-based violence, domestic abuse, and the recruitment of children into the armed forces are deemed inappropriate and must be redacted or removed.

The lack of survey questions on specific topics and access denials to specific areas lead to blind spots in the collected data. Authorities try to influence the training of enumerators and infiltrate survey teams with their own staff to control interview and survey processes. The presence of representatives from authorities has been reported to influence the responses of the interviewees.

"I spent six months collecting data, data, data from Yemen […] the numbers have been crunched 17 times, each time that the numbers don't satisfy the donors or the leadership of the agencies, [the feedback is] "Let's change the angle, let's change the population because we want this number rather than this number […]" It makes the whole exercise completely pointless[…]. There's no honesty[…] because we need to respond to those political pressures, we are not

[7] KIIs = Key Informant Interviews

immune from where the donors want us to go, where the authorities want us to go, where our own agencies want us to focus […] So why are we spending so much time on crunching this and doing this analysis if at the end of the day it's going to be edited for political correctness?" [I08]

"Scarce or biased reporting, as well as limited media access to the sites of violence, may indeed result in substantially different fatality estimates arising from the same event, uncertain figures, or one-sided coverage of conflict events in certain areas. This partially explains why official estimates, which rely on selected data from health facilities, tend to be significantly lower compared to what is perceived to be the real impact of the conflict in Yemen." [D02]

There are competing data interpretations of situations that stem from different organizational roles, mandates, and policies. For example, there are different interpretations between authorities and organizations regarding the actual number of internally displaced people (IDPs). While the UN coordination office (OCHA) reports its own estimates about IDP needs, authorities complain the UN does not use the official numbers created by institutions controlled by the authorities. The response organizations are left with uncertainty amid this struggle for interpretation.

"[…] we are looking to support children in IDP camps, to gather information about their needs, our main actors […] is [the] executive unit, [an] government institution […]. And they are responsible [for] IDP camps. So we are just trying to [communicate with OCHA but] it's not allowed to communicate with them. Why? The reason I think, the IDP information raised by OCHA in the HRP is not the same information that's been raised from the executive unit, and there is a conflict between them. [The] executive unit is asking [organization], 'Why are you not accepting the data that I'm raising? I am the formal institution, the government. Why are you disgracing that information?' [I16]

Organizations strive for good relations with donors, including artificially satisfying project goals, which were described as *"pleasing the donors"*. This pleasing leads to reports of numbers of beneficiaries that are not in sync with reality but instead with donor priorities.

"I conducted a lot of interviews with different organizations, whether they are national or international organizations. So they kept explaining to me that pleasing the donor is their aim or main target. […] they are trying just to target the estimated number in the project proposal." [I04]

2.4.2.2 Accessibility bias

Accessibility bias emerged mainly through unequal restrictions by authorities, safety and security concerns, as well as conflict dynamics.

To access areas for data collection, responding organizations need official permits from the authorities. Organizations described the bureaucratic procedures to apply for permits as cumbersome. Organizations are often required to provide additional information, to change project proposals, face significant delays, or do not receive access permits at all.

"The challenge is the access constraints, that you cannot go to any place unless you have an authorized permit from the local authorities." [I22]

"Administrative constraints remain among the most prevalent access difficulties facing humanitarian actors in Yemen, particularly in the signing of sub-agreements and associated approvals for programmatic activities and movements." [D30]

A cause for the bias in the Yemen response has been the unequal access constraints between the North and South of the country. Authorities controlling the northern governorates heavily restricted organizations' access to data collection on food security. Because the northern part of the country hosts the majority of the country's population, collected data significantly underrepresented large amounts of the population.

"So, if we are talking about these data gaps […] this year all the IPC assessment are done only in the southern governorates because [in] the north, the Houthis have an excuse to do the assessment […] there is some political powers that are driving these assessments and […] the assessment ends […] with a lower number of population because the southern governorates [have only] 30% of the population in Yemen." [I21]

Further, accessibility bias results from concerns over safety and security for data collection teams in active conflict areas and the spread of infectious diseases. Both causes have led to more available data from safe and secure areas and less data from the most-affected areas.

"This [safety and security] was really the biggest challenge for us, because […] we had more than one virus spreading in Yemen. There was mainly the COVID-19, but we also had […]

Cholera and Dengue Fever, and so it was very dangerous. […] So for me to take out the team to get information was a big challenge and a big risk.” [I02]

“Due to the current war […], three districts have been excluded […] as being considered highly risky areas. In addition some sub-districts and villages were excluded from the sampling frame due to; 1) villages considered as unreachable and 2) villages considered as risky […]” [D04]

2.4.2.3 Topical bias

Interview and document analysis further revealed several instances where data was biased toward specific topics covered in assessments, surveys, questionnaires, and other data collection forms. Topical bias emerged mainly through traditional cultural values, unequal resource pools between organizations, and an often neglected interviewee bias.

An example cause for topical bias is the perception of sexual and gender-based violence (SGBV), domestic violence, and recruitment of children into the armed forces as taboo topics within large parts of Yemeni society. Organizations are often required to exclude questions on these topics from surveys and are expected not to bring these topics up during interviews. The resulting datasets do not adequately represent these topics, and evidence is lacking in datasets even though organizations can observe these topics in the field.

“[…] most of the organizations face a lot of difficulties implementing the protection intervention, […], most of the governmental sides, they believe that these interventions or activities are not appropriate for the Yemeni culture. Especially if there’s SGBV, they would find it’s like a taboo topic, that we should not talk about it.” [I04]

“As family resources diminish and the war intensifies, recruitment and use of children by armed groups has escalated. Although verified cases are relatively low at 1,675, real numbers are undoubtedly much higher.” [D39]

Our results reveal that data in crises can be skewed towards topics that correspond to mandates of organizations that control the most resources**.** Organizations with the most resources roll out the largest surveys, collect the most data and establish the most substantial evidence.

However, their organizational mandate determines what surveys they conduct, which does not need to be the objectively most significant concern in the humanitarian response.

“Where I see it in Yemen is this obsession with food insecurity, and you know, I think a lot of that is that the [organization] is big enough and they’ve got a lot of resources and they can […] go out and do these surveys. You see this everywhere, so there’s this huge focus on food insecurity in Yemen, but I’m not sure it’s really the biggest issue I guess. It’s just not what we see.” [I03]

Another source for topical bias is interviewee subjectivity**.** The crisis in Yemen has lasted for seven years, and affected people have been questioned about their needs several times per year. They understand that organizations and donors make decisions based on their interviews and focus-group discussions. This awareness can lead respondents to answer questions in ways they believe might be the most beneficial. Response organizations seldom take this potential interviewee bias into account.

“I mean the accuracy of the data is also sometimes questionable […], because we know that especially when it’s a protracted humanitarian crisis, families or individuals tend to respond what they believe we want to hear from them. I think that there’s often a bias that is not really taken into consideration […] I mean […] after six years in conflict people tend to know how they need to respond to make sure that they will receive [aid].” [I08]

2.4.2.4 Sampling bias

Interviewees and document analysis revealed several causes that have led to biases in sampling strategies. Especially document analysis revealed that reports on assessments often lack a detailed and transparent description of methods and sampling approaches. Sampling bias emerged mainly from misrepresenting social groups during data collection, wishful thinking as a cognitive bias, and unsuited tools and methodologies.

Organizations raised concerns over the rigor of sampling strategies. Rather than through randomization, groups of respondents are selected based on characteristics that likely lead to a certain conclusion or based on recommendations from community representatives. Both reasons frequently lead to gender imbalance in collected data, with males being overrepresented and females underrepresented.

"I mean you can demonstrate any kind of malnutrition or any kind of risk of early marriage, you choose your sample differently, you target a certain population group, or geographical location, and eventually you can end up saying that you have a huge problem of child marriage and malnutrition […]" [I08]

"The assessment team used a combination of household level questionnaires, and observation, sampling 53 out of total population including IDP households, using random sampling: 87% men […] and 13% women […]. The community […] is conservative and highly patriarchal presenting a challenge in having women respondents." [D13]

Organizations can be overconfident in the robustness of their assessments and analyses, a sign of wishful thinking. Conducting large household surveys and the resulting data volume leads to a belief that analyzing the large quantity of data will lead to robust results. However, data collection methods, including survey design and sampling, often have flaws, making the data, and analysis results questionable.

"I kind of call it the magic of numbers right? If people go out and do a big survey, you get a final number, then they seem to think that it's a very like robust and great thing. But when you go through and look at how that data is collected, it has biases and blind spots to just the same extent as you would talking to a politician or a local leader." [I03]

Network outages and user interface flaws can affect data collection tools and sharing methods. When districts have no mobile network coverage, collected data becomes difficult to transmit and more data will be available from less affected areas. Data input must often be done manually because authorities do not allow electronic data collection, which leads to data entry errors.

"[Some districts are a] little bit far and there is no mobile network there, sometimes you need immediate intervention. You know about the problem or the crisis itself, but sometimes there is no data [before] you have to go to work in the field" [I06]

"So the hardship also is that they don't have phones that can be used to take photos of the records they fill, so this creates a great challenge for the data entries who are overwhelmed with a lot of data and they have to concentrate and focus on each name, on each field that they have to

enter so it creates a lot of mistakes and sometimes you can't get hold of it or see where is the mistake unless you are an expert in the field." [I22]

2.4.3 Non-systematic CIM challenges

The analysis further found support for factors impeding CIM as mentioned in previous research and outlined in Section 2.2, but also revealed previously not reported factors that hinder CIM in non-systematic ways. The criteria to distinguish random from systematic challenges, i.e., bias, was whether challenges were caused by dynamic, unpredictable root causes in the crisis context leading to random errors or by structural, repetitive root causes leading to bias.

Table 2.3 gives an overview of the identified non-systematic factors in the interview transcripts and documents. Factors often reported were difficulties in data verification, comparability of data definitions, and delayed reporting. Interestingly, the data provides evidence for issues of cognitive bias such as *wishful thinking*, i.e., organizations putting trust into problematic data as it is the only data available or when it fits into a model of understanding. Another interesting finding is that a lack of resources to pay health workers' incentives leads to hospital staff being unwilling to cooperate in data sharing with response organizations in the health sector.

Table 2.3. Non-systematic factors that hinder CIM.

Non-systematic Factors impeding CIM	**Examples of factors demonstrating random distortion of data**
Unable to verify data (D01, D02, D17, D20, D22, D23, D24, D25, D39, D40)	• *verified only 15-16% of displacement numbers (D22, D25)* • *difficulty in verifying exact location of incidents (D02)*
Inadequate reporting mechanisms (D40)	• *reported numbers are tip of the iceberg because inadequate reporting mechanisms (D40)*
Different data definitions (I03, I07, I18, I19, I16, I22, D02, D03, D05, D08, D11, D13, D14, D23)	• *different organizations use different names for the same schools (I16)*

Delayed data collection or problematic reporting (I03, I04, I07, I08, I10, I18, D02, D03, D04, D16, D20, D29, D47)	• *reporting is too slow, data gets stuck in the pipeline (I03)* • *postponed data collection due to active conflict (D04)*
Anecdotal data (D16, D17)	• *anecdotal evidence of recruitment of children into armed groups (D17)*
Date entry errors (I03, I04, I09, I22, I23)	• *manual data inputs create mistakes (I03, I22)*
Lack of leadership (I07, I13, I18)	• *no political support for improved data transparency on ministry level (I13, I18)*
Lack of incentives (I07, I11, I13)	• *health workers cannot be compensated and thus will not share data (I22)* • *no concrete incentive for better data traceability (I13)*
Wishful thinking (I03, I08, I11, I12)	• *no critical evaluation of raw data and relying on partner organizations' analysis (I12)* • *assuming data is correct because it fits into a model of understanding (I08)*
Fears about public image and reputation (I03, I11)	• *no corrections of erroneous data for fear of showing or admitting organizational shortcomings (I11)*
Competition and exclusive networks (I02, I03)	• *local organizations cannot get into the closed circle of international organizations (I02)*

2.5 Discussion

2.5.1 Reflection on literature and theoretical contribution

In this study, we investigated the research gap around systematic information challenges, i.e., biases in complex crisis response. We differentiated two components of the CIM literature that have been treated inseparably before (Altay & Labonte, 2014; Comes et al., 2020; Day et al., 2009; Fast, 2017; Maxwell, Hailey, Spainhour Baker, et al., 2018), i.e., systematic and non-systematic data challenges. Below we discuss several implications of our findings for crisis information management literature. We specify propositions that can be considered in future empirical and experimental research.

Our theoretical contribution concerns the emergence of bias reinforcement loops within the multi-level crisis management structure. Previous studies investigated the structure of crisis management processes, differentiating strategic, intermediary, and operational levels (De Geoffroy, Léon, & Beuret, 2015; Campbell & Clarke, 2018; Knox Clarke & Campbell, 2020; Obrecht, 2017). Research has repeatedly emphasized the importance of information sharing between these levels to establish a coherent situational understanding and align decisions (Comes, Bergtora Sandvik, & Van de Walle, 2018; Jensen & Hertz, 2016). Our findings show that biases cascade, and are reinforced, within the multi-level crisis response system. The mechanism behind the emergence of bias reinforcement cycles can be summarized as follows.

Due to crisis complexities, time pressures, resource gaps, and political ambitions, response organizations collect data in biased ways. The biased data is used in reports and other information products to brief organizations' leaderships who in turn brief donors using the biased information. Decision-makers are unable to identify or correct biased information, but strive to act data-driven using whatever information is available. This, however, means that decisions are made based on biased data. Because biases distort the availability and quality of information, they create an imbalance in the coverage and completeness of reported issues within the crisis. Underreported issues might be the result of bias rather than their actual absence within the crisis context. In data-driven crisis decision-making, funding is not, or only reluctantly, provided for underreported issues. Thus, funds continue to lack for understudied issues, data collection efforts remain under-resourced and not prioritized, and the cycle of bias continues.

Proposition 1: *Data sharing within the multi-level crisis response structure perpetuates biases as data-decision interdependencies between organizations, headquarters and donors are set up for timely response rather than information accuracy.*

Proposition 2: *Organizations' leaderships and donor decision-makers are unable to correct for biases in crisis data as they lack access, resources, and political ambition to implement debiasing measures.*

Proposition 3: *The data-driven approach of funding allocation decisions in complex crisis response makes decisions prone to biases, as decisions follow the strongest available evidence from the field which does not necessary represent the actual priority issues in the crisis context.*

Previous studies discussed the data collection methods of response organizations (Patel, King, Phelps, & Sanderson, 2017). The collected data informs decision-making through reports and other briefing material (Nespeca, Comes, Meesters, & Brazier, 2020). Our findings show that political, accessibility, topical and sampling biases influence the collected data.

Because political ambitions drive conflict crises, the influence of politics on the available data for humanitarian response needs to be considered (Colombo & Checchi, 2018). Political actors have an incentive to control how a humanitarian situation is reported and portrayed in the media (Zeitzoff, 2017) and to report data in ways that fit their political agenda (Sandvik, 2016). It is a significant concern that conflict parties assert political influence on data collection and analysis (Maxwell, Hailey, Spainhour Baker, et al., 2018). The political landscape of crises can therefore shape datasets. However, the resulting politically biased data might be the only data available for response organizations. Correcting for political bias is challenging for humanitarian actors because they have to abide by policies implemented by authorities to not lose operational permits (Comes et al., 2020). Our findings support this observation by showing that political actors influence what data is collected by whom, from whom, when, and where.

Proposition 4: *The strength and direction of political bias in information in complex crises that are driven by political conflict, are dependent on the degree of political control in the areas of the humanitarian response.*

Organizations carefully control their information and use it as a strategic and competitive advantage (Cao, Duan, & Cadden, 2019), and humanitarian organizations are no exception: as they must convince donors to provide funds for their cause, the information they hold has not only operational but also strategic value (Toyasaki & Wakolbinger, 2019). The shift toward evidence-driven allocation decisions in donor agencies (De Geoffroy et al., 2015) further leads to more funds being allocated to topics that are best backed up by data evidence. Larger organizations, which control more resources, have more capacity to collect data and establish evidence on their causes and mandates. Topics prioritized by smaller organizations might become neglected because of less data availability. This imbalance leads to a topical bias.

Proposition 5: *Larger availability of resources available for mandated data collection increases issue-specific data availability but distorts overall data completeness, widening data gaps and blind spots.*

The time- and resource-constrained response environment (Villa et al., 2019) further leads to methodological weaknesses in data collection, yet decision-makers must act urgently under uncertainty (Janssen & van der Voort, 2020). Robust sampling approaches are often not feasible to implement, potentially leading to sampling strategies that result in biased datasets, i.e., sampling bias. We find that crisis data collection is likely conducted primarily with male interviewees in traditionally conservative and patriarchic societies. Our findings add to the evidence of sampling biases, such as gender bias, in data collection methodologies during crisis response (Affleck, Selvadurai, & Sikora, 2018; Sharma, Scott, Kelly, & Vanrooyen, 2020). Another example are phone-based surveys that lead to more data being collected from 'better-off' households (USAID, 2018).

Proposition 6: *As complex crisis response is embedded in the social, cultural, and political context of the crisis environment, historically disadvantaged demographics and social, political or cultural groups, are further marginalized through data collection efforts.*

2.5.2 Implications for practice

The findings of this research have several implications for crisis response practice. Crisis response practitioners and policymakers need to become aware of issues of bias in the data they use for decision-making. Response organizations need to invest in identifying and mitigating biases as they threaten the objective and neutral delivery of aid. However, this will be challenging. The political and organizational system used to respond to humanitarian crises can have some inherent biases. The institutional structure and preferences of actors, especially political actors, are to blame for such bias. Stakeholders in complex conflict crises are not neutral and act upon their own mandates, objectives, and values. Response organizations such as NGOs cannot solve problems of bias when causes for bias are deeply rooted in the fabric of the response system and its stakeholders.

Crisis responders face a stark challenge as they have to choose between timely and accurate crisis response. Acting swift has been the dominant approach so far but as data collection and analytics methods advanced, the need for higher accuracy increased. Humanitarian organizations are pressured to invest in and extend their capacities to accurately and timely collect data, implement automated verification mechanisms, accelerate analysis and the development of reports and briefing material for decision-making. Researchers and practitioners increasingly use novel analytical approaches to reduce uncertainty, come to quick decisions and plan resources efficiently in crises (He, Zhang, & Li, 2021; Sipior, 2020). Our findings are relevant for the growing debate about advanced data analytics tools, such as machine learning, in the crisis response sector and the algorithmic biases that may be inherently present and impact decisions for vulnerable communities (Weidinger et al., 2021). Our findings show that data biases influence crisis decision-making, even for relatively small datasets. It is likely that these biases will persist in larger datasets, and are reinforced by machine learning or other computational algorithms.

2.5.3 Limitations and future research directions

In our interviewee sampling process, we focused on English-speaking managers and analysts. Similarly, the ACAPS document corpus relied solely on English documents. The influence this language preference had on our data collection is hard to estimate. Including Arabic-speaking interviewees and documents in Arabic would have certainly enriched the understanding of the consequences of biased response decisions as experienced by local populations.

To improve our study's internal validity, we only report findings that we could corroborate in multiple interview transcripts and documents. During interviews, we did not inform participants that our study is on data bias, nor did we use the term in our questions. Rather, we used terms such as “CIM challenge”, “data quality”, “data issues”. This minimized the possibility that interviewees were influenced to overly report on issues of bias even if those were not perceived as the main challenges.

As in any other case-based research study, the question of external validity and generalizability of our findings to other crisis contexts has to be answered. Indeed, crises vary across political, historical, sociocultural, severity, and capacity dimensions. However, as the joint information management process is widely applied in humanitarian response, and as the international humanitarian organizations in our research are actively present in most humanitarian crises (Marshall, 2018), our findings may be more broadly applicable than just for the specific crisis of Yemen.

The main drivers of bias we identified in the case of the complex crisis in Yemen, such as political pressures, inaccessibility, resource, and organizational constraints, have also been reported in assessments of other complex crises, such in Afghanistan and Syria. Therefore, further bias studies in other crises contexts will likely support our findings from the Yemen case.

We want to note that sources of bias might be different between complex crises and disasters or emergencies. For example, inaccessibility of information is a challenge for various crisis and disaster contexts. During disasters such as earthquakes, floods, and landslides, inaccessibility mainly results from damage to physical infrastructure, i.e., roads and rails. During complex crises like conflicts, in-access results mainly due to political and bureaucratic impediments as well as safety and security concerns.

We propose two main avenues for future research. First, future research should deepen the understanding of the causes and consequences of biased information in crisis response. Our data collection and analysis approach incorporated a diversity of sources throughout the Yemeni response system. However, the biases we identified might be differently strong and have different impacts in different crises, and future studies should make these differences explicit. Second, mitigating systematic biases in complex crises is a difficult endeavor, but strategies are needed to cope with them. Future research needs to investigate how the biases identified in this work can be, at least partly, reduced through organizational and technical means available to humanitarian organizations. Institutional changes might be needed to avoid that biases being an inherent part of the system. For example, the context of crisis response is inherently political. Some international donors and response organizations aim to influence local politics through international aid. Furthermore, powerful local forces might influence lists of beneficiaries and decisions. Such political bias stems from the crisis response playing field and the exercise of power over the playing field. Hence, the political situation and forces need to be understood before bias can be reduced. Mitigating such bias is complicated and should be the study of future research.

2.6 Conclusion

This research investigated data bias in crisis information management in the case of the complex crisis in Yemen. We conducted 25 interviews and analyzed 157 documents from local and international response organizations as well as from donor agencies involved in response to the world's largest humanitarian crisis.

Our findings show evidence for four types of data bias within crisis information management: political, accessibility, topical, and sampling bias. Biases cascade within the complex, multi-level crisis response system, affecting response organizations in the field, their headquarters, and donor agencies. Biases remain uncorrected due to cycles of bias reinforcement that emerge due to the data-decision-interdependencies between operational and strategic actors in the response system. Striving for evidence-based decision-making is set to fail in circumstances where generating hard evidence from high quality and sufficient volume of data is impossible.

3 The influence of cognitive bias on crisis decision-making

This chapter is based on: Paulus, D., de Vries, G., Janssen, M., & van de Walle, B. (2022). The influence of cognitive bias on crisis decision-making: Experimental evidence on the comparison of bias effects between crisis decision-maker groups. *International Journal of Disaster Risk Reduction*, *82*, 103379. https://doi.org/10.1016/j.ijdrr.2022.103379. The first author conducted the literature review, designed and conducted the data collection and analysis process and wrote the manuscript. The co-authors provided feedback on the data collection and analysis process and earlier versions of the manuscript.

3.1 Introduction

Decisions in crises are made by crisis experts, response organizations (i.e., often government and non-profit organizations), and the crises-affected people from the general public (Adame, 2018; Comes, Van de Walle, & Van Wassenhove, 2020).

While crisis responders strive to make optimal choices, they have to do so in the urgent and uncertain crisis environment. Human reasoning is often guided by mental simplifications and shortcuts that can ease and accelerate judgment in the form of heuristics but can also lead to flawed understandings, estimations, and decisions in the form of cognitive biases (Brooks, Curnin, Owen, & Bearman, 2020; Comes, 2016). Biases can have grave consequences in high-stakes scenarios where decision outcomes can substantially affect people's lives (Becker, Paton, Johnston, Ronan, & McClure, 2017; Makinoshima, Oishi, & Imamura, 2022; Reis et al., 2021). The understanding of bias effects in crisis decision-making is still underdeveloped, which is why scholars have called for more research on biases in crises (Campbell & Clarke, 2018; Castañeda, 2019; Comes, 2016). Understanding if and how strongly biases are present in crisis decision-making is an important step toward addressing the issue and the goal of this paper.

This research investigates the effect of four cognitive biases in crisis responders' estimation, judgment, and decision-making tasks. Three of these belong to the most influential cognitive biases on human information processing (i.e., framing effect, anchoring bias, confirmation bias). The fourth bias (i.e., bias blind spot) addresses how aware decision-makers are about their own biases, which is an important prerequisite for effectively mitigating negative bias effects, i.e., debiasing.

When making numerical estimates, people can be prone to *anchoring bias*, i.e., their estimates can be skewed due to potentially arbitrary perceived informational cues (Mussweiler & Strack, 1999). Because access to complete and non-contradictory information is unlikely in crises (Fast, 2017), decision-makers might get exposed to new information that is contradictory and inconclusive, requiring them to decide what information to trust (Van de Walle, Brugghemans, & Comes, 2016). In such situations, people have shown confirmation bias. *Confirmation bias* means that people strongly prefer information that confirms their previous decisions, even when contradicting information is of equal quality (Vedejová & Čavojová, 2020). Choosing between crisis response options can further be influenced by how the options are presented. This phenomenon is called the *framing effect* (Beratšová, Krchová, Gažová, & Jirásek, 2018). How information is provided and by whom might affect crisis decision-makers' preference for certain response options, for example, during supply shortages (Castañeda, 2019).

We report on three online survey experiments with scenario tasks to measure the effects of these three biases on crisis decisions. We focus on three groups: 1) *crisis-affected people of the general public*, because they make up the largest population during crises, 2) *governmental and non-profit workers*, because they are responsible for the main crisis response efforts and often collaborate in the response, and 3) *crisis experts*, because their advice to policymakers and practitioners is vital during crisis response efforts.

We contribute to the theoretical understanding of crisis decision-making by investigating the strengths of these biases, as well as, whether different decision-maker groups are affected differently by these biases. Based on our results, we outline design suggestions for crisis information systems that can support debiasing efforts during crisis response by considering user biases.

The paper is structured as follows. In the next section, we describe the characteristics of crisis decision-making, the way decision-makers process information, and describe the cognitive biases investigated in this study. This leads to the formulation of 16 hypotheses. We then describe our research design and survey experiments, followed by the presentation of our results. Finally, we discuss the implications of our findings on crisis information system design principles.

3.2 Background

We review the theoretical underpinnings of crisis decision-making, information processing, and cognitive bias in the following subsections. We then focus on four biases to develop our hypotheses.

3.2.1 Stakeholder groups within crisis response

We follow a definition of the term crisis as given by Boin, ’t Hart, Stern, and Sundelus (2005). According to them, the key components of a crisis are the threats (to the population, the environment, etc.), the uncertainties around what is happening and going to happen, and the urgency to act (ibid.). When a crisis, such as COVID-19, disrupts a society’s social fabric, the general population is primarily affected. Globally, there have been over 6.2 million deaths related to COVID-19 (World Health Organization, 2022). Unemployment and poverty have increased during the pandemic (United Nations, 2021a). Countries in the global north faced severe, unanticipated challenges and were often unprepared, resulting in ineffective policies to protect communities (Haug et al., 2020). This could be predicted as previous research found that established crisis management practices are insufficient to handle transboundary crises (Boin, 2019). COVID-19 further worsened ongoing humanitarian crises in the global south, where protracted conflicts had already put stress on existing social and health infrastructure (United Nations, 2021b). *Affected people* have faced life-threatening circumstances by visiting public spaces or going to work, and many had to make life-altering choices to protect themselves and their families (Angeli & Montefusco, 2020). COVID-19 further showed the stress crises put on essential services that are provided by *governmental and non-profit organizations*, such as public health care, and the distribution of ventilators for clinics or the allocation of materials such as masks. Response efforts are influenced by advice from *crisis experts* who make decision recommendations with regard to potential future trends (Bavel et al., 2020). In summary, crisis-affected people, governmental and non-profit workers, and crisis experts must make frequent decisions during urgent, uncertain, high-stakes, and resource-constraint circumstances.

3.2.2 Biases in crisis estimation, judgment, decision-making

The urgency and uncertainty of crises require that decisions are satisficing rather than optimal (Comes et al., 2020). Quick decisions are paramount. Decision-makers rationalize using fast heuristics and utilize fast estimations and judgments (Kahneman, 2011; Klein et al., 2010). People in crises likely rely more on heuristics because of the difficulty of formulating problems in ill-defined contexts (Gralla, Goentzel, & Fine, 2016) and bounded rationality, i.e., the limitations of their cognitive resources to receive, process, and store information (Simon, 1956). Because people are *'cognitive misers'* and avoid cognitive load as much as possible in uncomfortable situations, they will rely on quick and congenial heuristics that confirm previous assumptions and reduce cognitive dissonance to arrive at decisions (de Vries, 2017; Fiske & Taylor, 1991). What information is processed, how the information is processed, and the results of the processing affect the decision made.

During the onset of the COVID-19 pandemic, governments around the world were trying to make sense of the highly uncertain situation while having the pressure to decide fast to protect their populations from more serious infection waves. How influential a piece of information on a decision-maker is, is determined by the information source, message, topic, and recipient (Hollnagel & Woods, 2005). Dual-process models, such as the heuristic-systematic model and elaboration-likelihood model, divide information processing into two categories: a systematic/central and a heuristic/peripheral approach (Chaiken, 1980; Petty & Cacioppo, 1986). Because affected people and government and non-profit workers find themselves confronted with issues they are not experienced with, they are more likely to use the heuristic approach. Klein and colleagues studied how experts make decisions under urgency, uncertainty, high-stakes, and resource constraints (Klein, Calderwood, & Clinton-Cirocco, 1986; Klein, Calderwood, & Clinton-Cirocco, 2010). They found that experienced firefighters successfully use quick and simple heuristics to build mental plans for plausible solutions to practical problems rather than a time-consuming approach that weighs decision options against each other. Finally, people usually combine the two approaches during information processing (Petty, Cacioppo, Strathman, & Priester, 2005). Through our study, we add to the understanding of the role of experience and domain knowledge in crisis information processing and decision-making.

To assess the influence of cognitive biases on crisis decision-making, we focus on four concrete biases: framing effect, bias blind spot, confirmation bias, and anchoring bias (**Error! Reference source not found.**). Evidence from domains with similar decision contexts shows these biases are present in emergency healthcare, infrastructure safety, forensics, and tense political situations (Burggraaf, Groeneweg, Sillem, & Van Gelder, 2019; National Research Council, 2015; Satya-Murti & Lockhart, 2015). These domains have aspects in common with crises. What makes crises distinct is the magnitude of disruption, i.e., crises affect societal systems as a whole.

For example, decisions in emergency management operations, e.g., ambulance calls, need to be made in extremely urgent contexts with high stakes (Al-Dahash, Thayaparan, & Kulatunga, 2016). An analogy is the outbreak of COVID-19 in the Wuhan district in China. The outbreak was first handled as an emergency, affecting a limited area (Wu, Chen, & Chan, 2020). Over time, the outbreak significantly worsened, ultimately developing into a crisis that is still affecting entire societies all over the world. Our selected biases are likely to happen during circumstances having characteristics similar to crises as they fall into our definition given above (Knox Clarke & Campbell, 2020). For example, in emergency healthcare, confirmation bias can guide doctors to only test their preliminary assumptions, ignoring alternative assumptions, consequentially leading to wrong patient treatment (Garcia-Alamino, 2020; Pines, 2006). In sentencing decisions, arbitrary informational cues that have nothing to do with the trial, nor the defendant, can lead to anchoring bias in judges that affect the lengths of prison sentences (Englich, Mussweiler, & Strack, 2006). In deciding on the treatment of a novel infectious disease, people can be susceptible to the framing effect. The latter refers to decisions being determined by how the decision options are presented rather than by the actual predicted decision outcomes (Tversky & Kahneman, 1981). An important requirement to reduce such bias effects on decision-making is the awareness of the own biased behavior. Yet, research on the bias blind spot phenomenon shows that people often see themselves as less biased than others (Pronin, Lin, & Ross, 2002). The anchoring bias, confirmation bias, framing effect, and bias blind spot have been shown to negatively affect decision-making in various domains. When biases remain undetected and uncorrected in crises, biased decision-making can have significant societal consequences. Biased response decisions might be inadequate and fail to address affected-people's humanitarian needs (Comes, 2016). Table 3.1 synthesizes the literature review.

Table 3.1. Overview of cognitive biases selected for this study.

Bias	Explanation	Example	Example sources
Framing effect	Being influenced as to how information is being presented.	Choice between risky options; Climate change adaptation behavior	de Vries, 2017; Tversky & Kahneman, 1981
Bias blind spot	Ranking one's behavior as less biased than the behavior of others.	Students, and citizens rank themselves as less biased than their peers.	Pines & Strong, 2019; Pronin et al., 2002
Confirmation bias	Overly select information that is in line with one's preconceptions.	Public policy preferences; consumer purchase choices	Fischer et al., 2011; Jonas, Schulz-Hardt, Frey, & Thelen, 2001
Anchoring bias	Overly rely on initial, skewed information.	Estimating stock prices, travel durations, lengths of rivers etc.	Tversky & Kahneman, 1974; Yasseri & Reher, 2018

3.2.3 Hypothesis development

The research gap we address is the lack of empirical data on the influence of the four biases on concrete crisis response tasks such as estimation, judgment, and decision-making. Understanding biased crisis decision-making is critically important, and identifying and mitigating biases has potentially significant societal benefits through improved decision quality. We discuss the four selected biases and develop our corresponding hypotheses in more detail below.

Framing Effect. People are affected by how information is presented, especially when choices are phrased as more or less risky. This is called the framing effect (Tversky & Kahneman, 1981). For example, when confronted with a task that frames the consequences of options in response to a new infectious disease as either sure or probable lives saved, people favor response options that lead to a certain amount of people being surely saved. When the consequences are framed as sure and probable lives lost, however, people favor options that will lead to a probable loss of lives. In general, people tend to choose sure gains over probable gains and probable losses over sure losses when confronted with risky choices (Kühberger, 1998). *Prospect theory* explains that people perceive losses as more significant than gains (Tversky & Kahneman, 1981, 1992), while they prefer a probable loss over a sure loss and a sure gain over a probable gain. In other words, people are more risk-averse when confronted with framed gains and more risk-seeking when confronted with framed losses (Penţa & Băban, 2018).

Crisis management literature provided evidence that experienced crisis managers show susceptibility to framing effects, similar to laypeople, but there exists no direct, empirical comparison (Roberts & Wernstedt, 2019; Wernstedt, Roberts, Arvai, & Redmond, 2019). Studies have shown that previous experience and knowledge can reduce the susceptibility to the framing effect (Beratšová et al., 2018; Olsen, 2015). Therefore, we hypothesize crisis-affected people and government and non-profit workers to be significantly susceptible to differently framed decision options for crisis response, while crisis experts are not susceptible. When comparing the three groups, we expect that the group of crisis experts will be less influenced by the framing effect than the other two groups.

Crisis framing hypotheses

H1a, H1b, H1c, H1d: Crisis-affected people (H1a), as well as government and non-profit workers (H1b), show a significant difference in selection behavior when having to choose between either sure versus probable lives saved and between sure versus probable lives lost when having to choose between two options for the response to COVID-19. Crisis experts do not show this susceptibility (H1c) and will further show weaker framing bias than the other two groups (H1d).

Bias blind spot. People tend to think they are less biased than others. A phenomenon called the bias blind spot (Pronin et al., 2002). The bias blind spot is explained by the combination of two concepts, namely introspection illusion and naïve realism (Scopelliti et al., 2015). *Introspection illusion* refers to people's *'charitable self-assessments'* when they reflect on the reasons for their thought processes (Scopelliti et al., 2015). *Naïve realism* then leads people to see these self-assessments as unmediated and truthful (Pronin et al., 2002). Bessarabova et al. (2016) mentioned sports team favoritism as an example of people's bias blind spot. A fan sees their own prediction of a team's performance as more accurate than the prediction of others. This is because their own thought process is easier available to them, and each logical step they made leading to their final assessment seems logical for them. Because people do not have this direct access to the thought processes of others, they do not acknowledge that they could have equal or even more merit (ibid.). Scopelitti and colleagues summarize the pitfalls of the bias blind spot: *"When people are unaware of their bias, they are unlikely to adopt corrective strategies to avoid the sources of bias that influence their judgment. Consequently, people who are more susceptible to bias blind spot are* *less prone to improve their decision making by engaging in bias reduction strategies, responding to training, and taking advice"* (Scopelliti et al., 2015, p. 2482-2483).

For the mitigation of negative bias effects, one's susceptibility to bias needs to be known to decision-makers. Being self-aware about one's own biases is an important first step in debiasing (Satya-Murti & Lockhart, 2015). Concerning bias blind spot, existing evidence suggests that experienced experts are less susceptible to bias blind spot than non-experts (Pines & Strong, 2019). Therefore, we hypothesize crisis-affected people and government and non-profit workers show a significant bias blind spot, while crisis experts do not. Comparing the three groups, we expect crisis experts to show less biased blind spot compared to the other two groups.

Crisis bias blind spot hypotheses

H2a, H2b, H2c, H42: When asked to reflect on their decision-making behavior as well the decision-making behavior of others during crisis response, crisis-affected people (H2a), as well as government and non-profit workers (H2b), rank themselves as significantly less biased than others. Crisis experts do not show this behavior (H2c) and will further show a weaker bias blind spot than the other two groups (H2d).

Confirmation bias. Research has found that people tend to focus their information retrieval efforts on information that is more likely to confirm their already made assumptions (Jonas et al., 2001; Klayman, 1995; Kosmidis, 2021; Nickerson, 1998). Cognitive dissonance theory (Festinger, 1957, p. 556) explains this self-confirming behavior, suggesting that *"after people commit to a [...] decision, they gather supportive information and neglect unsupportive information to avoid or eliminate the unpleasant state of post-decisional conflict known as cognitive dissonance"*.

Crisis urgency likely leads people to stick to preliminary decisions rather than invest time and cognitive effort into re-evaluating past decisions and switching preferences. Because of the urgency to act in crisis environments, decisions have to be made quickly without proper consideration and weighing the benefits and drawbacks of decision options against each other. Confirmation bias would allow crisis decision-makers to follow their preliminary assumptions and reduce the time required for testing other assumptions (Berthet, 2021; Charness, Oprea, & Yuksel, 2021; Nickerson, 1998). Crisis decision-makers frequently find themselves confronted with decision dilemmas, for example, on whether to implement a novel technology that eases certain crisis response tasks but which raises privacy concerns (Paulus, De Vries, Meesters, & Van de Walle, 2019; Sandvik, Jacobsen, & McDonald, 2017). Decisions have to be made about whether or not to implement, adopt, and use novel technologies that might ease crisis response but which put risks to people's privacy and information rights (Greenwood, Howarth, Poole, Raymond, & Scarnecchia, 2016). After such a decision is made, throughout the unfolding crisis, new information can become available that either support or oppose one's decision on whether or not to rely on such technologies. The question then becomes to what extent crisis decision-makers will try to confirm their previous decision or try to question and disconfirm it critically.

Previous experimental research found that information selection can be accuracy-motivated or defense-motivated, while both can lead to confirmation bias (Schwind & Buder, 2012). People with less knowledge in a domain, who consequently have not yet developed a stance on the topic, are likely to be accuracy-motivated and select information that is perceived as providing the most utility. Because they might develop a preference directly after becoming aware of the issue, preference-consistent information might seem to provide the highest utility (Schwind & Buder, 2012). Having more domain knowledge leads people to develop a stance on the topic and give more relevance to it. Ascribing higher relevance to an issue can lead to defense-motivated behavior in decision-makers, which further leads to upholding already made assumptions, thereby leading to confirmation bias (Taber & Lodge, 2006).

Therefore, we hypothesize that the three crisis decision-maker groups will be susceptible to confirmation bias when choosing between a technology vs. privacy dilemma and subsequently selecting supporting or opposing information. We expect no significant differences between the groups regarding the strength of the confirmation bias.

Crisis confirmation hypotheses

H3a, H3b, H3c, H3d: When confronted with a decision dilemma, crisis-affected people (H3a), government and non-profit workers (H3b), and crisis experts (H3c) will search for significantly more information that supports rather than opposes their previous decisions. There will be no significant difference in the strength of the confirmation bias between the three groups (H3d).

Anchoring bias is one of the most established cognitive biases (Furnham & Boo, 2011). Experimental research showed that people tend to anchor their judgment around initial information, which influences their assessment of the range of plausible solutions to a decision problem (Tversky & Kahneman, 1974; Yasseri & Reher, 2018). People anchor their numerical estimations on initial cues that can be arbitrary and extreme. An explanation for the anchoring phenomenon is that perceived cues lead decision-makers to engage in effortful deliberation regarding the validity of these cues. This deliberation effort reduces decision makers' ability to assess the full range of possible answers and limits it to a solution space that is closely related to the perceived cues (Englich et al., 2006).

Decision-makers in crises need to decide quickly but often receive important information only in small subsets sequentially over time rather than the complete dataset at once (Altay & Labonte, 2014). Therefore, the perceived cues are often the only information available to decision-makers, and consequently, they might rely heavily on them even when the information is skewed. Estimating available resources is a common task in crisis response (Colombo & Checchi, 2018). Affected people need to estimate their resources to plan individual response efforts, e.g., the application to crisis response funds. Government and non-profit workers need to estimate their organizational resources to plan crisis response efforts and to understand if certain affected areas or population groups need to be prioritized. Crisis experts need to estimate the resources of the overall crisis response network to advise policymakers on where gaps in the response could be. Anchoring estimations on an initial piece of information might seem beneficial to crisis decision-makers because it can accelerate decisions and potentially lead to anchoring bias.

There are contradictory findings on whether anchoring bias is reduced when decision-makers have more experience and domain knowledge in the task at hand. While some research found domain knowledge to reduce the anchoring effect (Wilson, Houston, Etling, & Brekke, 1996), a majority of studies have shown that anchoring is significantly present in people with knowledge and experience in the domain in question (Englich & Mussweiler, 2001; Englich, Mussweiler, & Strack, 2005; Englich et al., 2006; Englich & Soder, 2009; Mussweiler, Strack, &

Pfeif, 2000; Northcraft & Neale, 1987). Therefore, we hypothesize that the three crisis decision-maker groups are susceptible to anchoring bias when making numerical estimations on available crisis response resources. We further do not expect significant differences between the groups concerning the strength of the anchoring bias.

Crisis anchoring hypotheses

H4a, H4b, H4c, H4d: When given a high numerical anchor information, crisis-affected people (H4a), governmental, and non-profit workers (H4b) as well as crisis experts (H4c), will estimate available resources for crisis response significantly higher than when given a low numerical anchor information. There will be no significant difference in the strength of the anchoring bias between the three groups (H4d).

3.3 Research method

Based on the above-discussed state of the literature, we formulated a set of hypotheses for each of the four types of bias (H1-H4 above). We designed three online survey experiments (one for each of our three decision-makers samples) to test our hypotheses. Each experiment consisted of the same tasks and measures to test for the four cognitive biases. The details of the research framework are described in the subsections below and summarized in Figure 3.1.

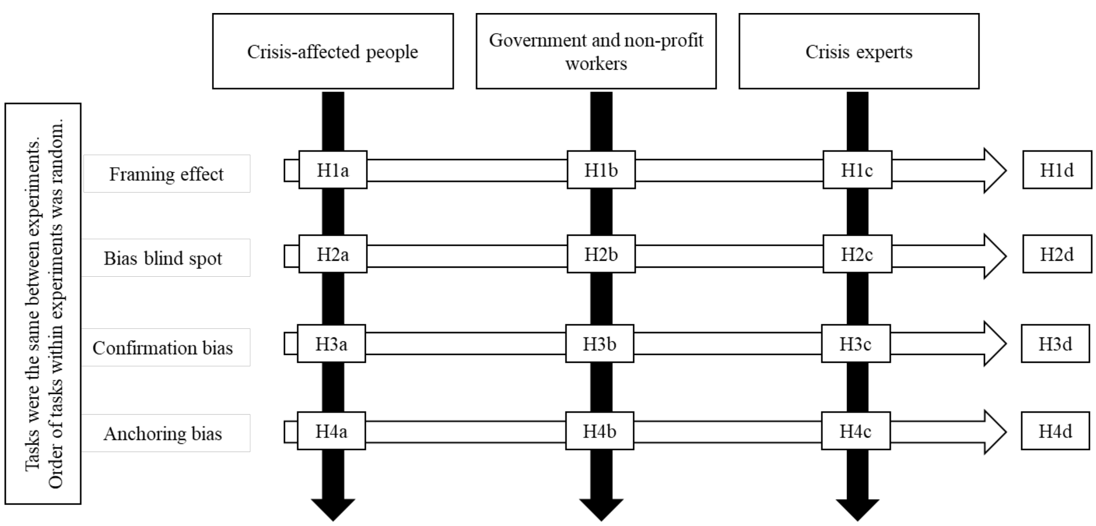

Figure 3.1 Overview of the research framework for this study.

3.3.1 Participants

We conducted three online survey experiments, one for each of our three crisis decision-makers groups: crisis-affected people, governmental and non-profit workers, and crisis experts. For the crisis-affected people experiment, we recruited participants through Amazon mTurk with the option to only include workers with the ‘mTurk master’ attribute to reduce the likelihood of arbitrary responses by the participants. For the government and non-profit workers experiment, we recruited Amazon mTurk workers with the option to only include governmental and non-profit employees in the mTurk selection process.

Completing a survey experiment took approximately 10 minutes. MTurk respondents were paid between USD 1.10 and USD 1.50 for a completed experiment, in line with usual mTurk compensation guidelines for researchers (Robertson & Yoon, 2019). Amazon mTurk was found to provide a reliable, balanced participant recruitment pool representing the broader population and comparable to other samples typically used for similar studies (Pennycook et al., 2019; Q. Wang, Li, & Singh, 2018).

In the crisis experts experiment, we targeted a sample of experienced humanitarian crisis responders. The survey was distributed via social media (Twitter and LinkedIn) and addressed humanitarian workers in local organizations, international non-governmental organizations, United Nations agencies and offices of donor country governments. The final sample of experts included representatives from all main organization types in humanitarian crisis response. Crisis experts received no remuneration for taking part in the survey experiment.

3.3.2 Data collection procedure

We collected data through the three survey experiments between March and June 2021 while the COVID-19 pandemic still heavily affected countries and populations globally. All groups received a link to the survey experiments, which were implemented in the survey software Qualtrics. All respondents started on an introduction page, explaining the objective and scope of the study and the target group the study is aimed at (Appendix B). Participants were told there was no right or wrong answer to any of the questions, that they could stop the survey at any point, that their data would be treated anonymously, and that they could contact the researchers if they wanted to have their data to be removed. After the participants agreed to the terms, the experiments started. Participants were first asked to answer some general questions to capture descriptive statistics about each of the three groups (Appendix B). After filling out the general questions, the actual survey experiment tasks were presented in random order to the participants. These tasks are described in the following subsections.

3.3.3 Experimental tasks and measures

Anchoring bias, confirmation bias, and framing effect were assessed through scenario tasks. Bias blind spot was assessed through the participant's self-reflection about past decision-making behavior during Covid-19. The order of display of the elements was random among participants for each group. As discussed below, all experimental tasks and measures were based on well-established methodological approaches reported and verified in previous literature.

Framing effect. We used a measure that is based on the original, classic framing *'Asian disease experiment'* from Tversky and Kahneman (1981) to measure how susceptible participants were to differently framed choice options. We asked participants to imagine being a crisis program manager and having to decide between two program options in response to COVID-19. Participants were randomly assigned to either a gain or a loss frame. Participants in the gain frame had to choose between two options, one promising that a certain amount of lives will be surely saved, the other option promising a probable amount of lives being saved. Participants in the loss frame also had to choose between two options, one promising that a certain amount of lives will be surely lost, the other option promising a probable amount of lives being lost.

The measure captures results in two variables, one dichotomous independent variable (two conditions: gain frame, loss frame), and one dichotomous dependent variable (two options: sure option, probable option). Using a Fisher's exact test or chi-square test respectively, we could test for a significant framing effect in the participants' selections. The exact item can be found in Appendix B.

Bias blind spot measure. We measured the bias blind spot in participants by asking them to reflect on their decision-making behavior as well as on the decision-making behavior of other people during crises[8]. We integrated this measure by giving respondents short descriptions of eight biases and asking them to rate how strongly they agree that each bias influenced the decision-making of others and themselves. Participants selected how strongly they disagree/agree with each description on a 7-point Likert scale. This creates a within-subjects design with 16 variables, two for each of the eight biases (self-ranking, ranking of others). In addition, for each participant two means could be computed, one based on all ratings of a participant regarding their biased decision-making, the other mean based on all ratings of a participant regarding their perception of others' biased decision-making. Dependent samples tests could then be used on the two means for each participant as well as the individual differences of the *own versus others* pairs. The exact item can be found in Appendix B.

Confirmation bias. In our confirmation bias item, respondents were first given a short text about the plans of a company to field test a novel technology that is supposed to use artificial intelligence (AI) and satellite technology to make crisis assessments easier. Respondents were asked if they would partner with the company to facilitate the field test (yes/no). After answering the question, respondents were told that there was new information available on the topic of AI-supported crisis assistance. They were given ten short summaries of statements, five supporting the use of AI-supported humanitarian assistance, and five opposing it. Participants were told to select those summaries (as many as they wanted) for which they would like to receive the corresponding articles in full. This created a within-subjects design with two variables per participant storing the count of selected supporting and selected opposing information respectively. By conducting a dependent samples test, we tested if participants selected more summaries that confirmed their preliminary choice and therefore exhibited confirmation bias. The exact items can be found in Appendix B.

*Anchoring bias***.** To measure anchoring bias, we used a 1x2 between-subjects design. Participants were randomly divided into a low-anchor or a high-anchor condition. The scenario of

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[8] In the two survey experiments with crisis-affected people and government and non-profit workers, the measure for the bias blind spot was phrased with regard to 'COVID-19'. In the survey experiment with crisis experts, the measure for the bias blind spot was phrased with regard to a recent humanitarian crisis context of the participants.

the measure was COVID-19 resource allocations provided by the United Nations to individual countries. The United Nations allocated different amounts of funds to countries in the global south, ranging from USD 60,000 to USD 58 million per country. These minimum and maximum values were used as low and high anchors respectively. Participants were then asked to enter their estimates of the average resources provided to all countries. The measure captures results in two variables. One dichotomous independent variable (two conditions: high anchor, low anchor) and a continuous dependent variable (participants' estimates). Conducting an independent samples test can then reveal if there is a significant anchoring bias in the participants' responses depending on whether they were in the low or high anchor condition. The exact item can be found in Appendix B.

3.4 Results

3.4.1 Sample descriptions

In the three survey experiments combined, a total of 531 respondents participated, 460 crisis-affected people, 50 government and non-profit workers, as well as 21 crisis experts. In the sample of crisis-affected people the mean age was 35.85 (SD = 11.02), and 138 females and 271 males participated. In the sample of government and non-profit workers, the mean years of work experience was 16.06 (SD = 12.44), and 16 non-profit and 34 government workers participated. The mean years of work experience in the sample of crisis experts was 10.69 (SD = 7.3) and participants represented all types of organizations in crisis response, including local and international organizations, UN agencies, research and academia, as well as the private sector.

3.4.2 Results for crisis framing hypotheses (H1a, H1b, H1c, H1d)

Participants showed a more risk-seeking behavior in the loss-condition and risk-averse behavior in the gain-condition. We tested for significance in the difference between the two conditions per group using Pearson Chi-Square and Fisher's exact tests[9]. In all three groups,

[9] Pearson Chi-Square test is most suitable for larger samples, therefore it was used for the groups of crisis-affected people and government and non-profit workers. Fisher's exact test is most suitable for smaller samples, therefore it was used for the group of crisis experts.

significant differences were found in participants' response option selection behavior, depending on whether participants were in the loss- or gain-condition (**Error! Reference source not found.**). The framing effect significantly influenced participants in all three groups. Therefore, we found support for H1a, H1b but not for H1c because crisis experts were significantly affected as well.

In the sample of crisis-affected people, 174 out of 207 participants in the gain-frame chose the sure gains option and 33 selected the probable gains option. 129 participants selected the sure losses option in the loss-frame, while 74 participants selected the probable loss option. In the sample of government and non-profit workers, 18 out of 23 participants in the gain-frame chose the sure gains option and five selected the probable gains option. 13 Participants selected the sure losses option in the loss-frame, while 14 participants selected the probable loss option. In the group of crisis experts, nine out of twelve participants in the gain frame chose the sure gains option and three selected the probable gains option. Only two participants selected the sure losses option in the loss condition while seven selected the probable loss option.

Table 3.2. Results table for H1a, H1b, H1c. Chi-Square and Fisher's exact tests for 2x2 factorial designs.

	H1a: Crisis-affected people	*H1b: Governmental and non-profit workers*	*H1c: Crisis experts*
Pearson Chi-Square	**.000**	**.029**	
Fisher's Exact Test			**.03**
N	459	50	21

A binomial logistic regression was performed to investigate the likelihood that participants of each of the three groups chose the sure or the probable option in the framing task (**Error! Reference source not found.**). The logistic regression model was statistically significant ($\chi 2(4) = 58.537$, $p < .000$). The model explained 14.7% (Nagelkerke R2) of the variance in selection behavior. Both predictor variables, framing condition (Wald = 50.094, $p < .000$) and experiment group (Wald = 4.26, $p = .039$) were statistically significant. Groups were coded (1=crisis-affected people. 2=government and non-profit workers, 3=crisis experts) and as the odds ratios of the analysis shows, the effect reduces with increasing group codes, meaning crisis experts show the least bias effect. We, therefore, find support for H1d.

Table 3.3. Result table for H1c. Binomial logistic regression for two categorical independent variables (framing condition, sample groups) and one dichotomous dependent variable (chosen response option).

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. lower	95% C.I. higher
Condition	1.444	0.204	50.093	1	0.000	4.238	2.841	6.323
Group	-0.412	0.2	4.26	1	0.039	0.662	0.448	0.979
Constant	-0.417	0.576	0.524	1	0.469	0.659		

Condition: gain frame; loss frame
Group: crisis-affected people; government and non-profit workers; crisis experts

3.4.3 Results for crisis bias blind spot hypotheses (H2a, H2b, H2c, H2d)

In all three survey experiments, participants' ranked themselves as less biased than others when making decisions. We tested for significance in the difference of participants' *self vs. others* ranking using Wilcoxon signed-rank tests[10]. The tests found significant differences between participants' self-assessment and their assessment of others' decision-making in all three groups (Table 3.4). We, therefore, found support for H2a, H2b but not for H2c, because crisis experts were significantly affected as well.

In the group of crisis-affected people, participants rated each bias stronger in others than in themselves. In the government and non-profit workers group, participants rated almost all biases stronger in others than in themselves. In the group of crisis experts, participants rated most biases stronger in others than in themselves.

To test for group differences, two means were calculated for each respondent for both their ranked decision-making behavior and their ranked decision-making behavior of others (i.e., the

[10] Wilcoxon signed-rank tests were chosen because of several outliers and the non-normality of the data.

mean of the 8 biases ranked for their own and others' ranked behavior). Then the difference of the *'own versus others'* means' was calculated for each respondent, building our continuous dependent variable.

Table 3.4. Result table for H2a, H2b, H2c. Wilcoxon signed-rank tests for within-subjects designs.

	Mean	Anchoring	Automation	Confirmation	Law-of-the-instrument	Innovation	Information	Framing	Authority
H2a: Crisis-affected people									
Z	-7.149	-5.564	-5.775	-3.861	-3.12	-1.957	-2.688	-3.556	-8.74
Asymp. Sig (2-tailed)	**0.000**	**0.000**	**0.000**	**0.000**	**0.002**	**0.05**	**0.007**	**0.000**	**0.000**
N	458	441	439	436	429	435	437	434	436
H2b: Government and non-profit workers									
Z	-4.873	-4.003	-4.065	-3.119	-3.595	-2.719	-5.113	-1.132	-3.434
Asymp. Sig (2-tailed)	**0.000**	**0.000**	**0.000**	**0.002**	**0.000**	**0.007**	**0.000**	0.258	**0.001**
N	50	49	47	47	47	49	48	49	46
H2c: Crisis experts									
Z	-3.664	-1.551	-2.816	-2.12	-3.092	-1.85	-1.755	-2.366	-3.725
Asymp. Sig (2-tailed)	**0.000**	0.121	**0.005**	**0.034**	**0.002**	0.064	0.079	**0.018**	**0.000**
N	20	18	18	20	20	20	20	20	20

Our independent variable had three categories, one for each sample group. A Kruskal-Wallis H test[11] was conducted to determine if there were differences in ranked behaviors between sample groups (Table 3.5). Distributions of our dependent variable were not similar for all groups, as assessed by visual inspection of a boxplot. Ranked scores were significantly different between the different groups ($\chi2(2) = 29.795$, $p < .000$). Subsequently, pairwise comparisons were performed using Dunn's procedure with a Bonferroni correction for multiple comparisons. This posthoc analysis revealed statistically significant differences in ranked scores between the crisis experts (mean rank = 135.55) and crisis-affected people (mean rank = 278.20) ($p < .000$). Further

[11] Kruskal-Wallis H test was chosen because of several outliers, non-normality and unequal variances between the three groups.

significant differences were found in ranked scores between governmental and non-profit workers (mean rank = 190.65) and crisis-affected people ($p < .000$). No significant differences were found between crisis experts and government and non-profit workers. Yet, crisis experts showed a lower bias susceptibility than government and non-profit workers. We, therefore, find partial support for H2d.

Table 3.5. Result table for H2d. Kruskal-Wallis H test for one categorical independent variable (groups) and one continuous dependent variable (ranked behavior).

	Test statistic	Std. Error	Std. Test statistic	Sig.	Adj. Sig.
Ranked scores (μ own biased behavior – μ others' biased behavior)					
Crisis experts - Government and non-profit workers	-55.01	40.319	-1.364	0.172	0.517
Government and non-profit workers - Crisis-affected people	-87.643	22.697	-3.861	0.000	**0.000**
Crisis experts - Crisis-affected people	-142.653	34.812	-4.098	0.000	**0.000**

Each row tests the null hypothesis that the sample distributions are the same.
Asymptomatic significant (2-sided tests) are displayed. The significant level is .05.
Significant values have been adjusted by the Bonferroni correction for multiple tests.

3.4.4 Results for crisis confirmation hypotheses (H3a, H3b, H3c, H3d)

To test for confirmation bias, we first counted the numbers of selected supporting and opposing information per participant. We then calculated the means of the selected supporting and opposing information for each of our three groups. Finally, we used Wilcoxon singed-rank tests to check for significant differences between the means of the groups[12]. The result reveals that crisis-affected people selected supporting information significantly more often than opposing information (Table 3.6). Interestingly, the group of government and non-profit workers shows a borderline significance and also similar means of numbers of selected supporting and opposing information as the group of crisis-affected people.

We assume the absence of a significant effect can be explained by the small sample size of government and non-profit workers. A larger sample might have uncovered a significant

[12] Wilcoxon signed-rank tests were chosen because of several outliers and the non-normality of the data.

confirmation bias in the group of government and non-profit workers. Of further interest is the result within the group of crisis experts who tended toward disconfirmation. While not significant, crisis experts selected more opposing than supporting information. We, therefore, find support for H3a but not for H3b and H3c.

Table 3.6. Results table for H3a, H3b, H3c. Wilcoxon signed-rank tests for within-subjects designs.

	H3a: Crisis-affected people	*H3b: Governmental and non-profit workers*	*H3c: Crisis experts*
Z	-4.497	-1.703	-0.521
Asymp. Sig. (2-tailed)	**0.000**	0.089	0.602
N	459	50	21
Mean count of selected supporting information	M = 1.75, SD = 1.17	M = 1.78, SD = 1.13	M = 1.38, SD = 1.24
Mean count of selected opposing information	M = 1.38, SD = 1.13	M = 1.30, SD = 1.34	M = 1.67, SD = 1.53

To test for difference between the three groups, the selected confirming and selected disconfirming information was counted per participant and the difference was calculated, building one continuous dependent variable. The independent variable had three categories, one for each sample group. A Kruskal-Wallis H test[13] was conducted to determine differences in counts of selected confirming and selected disconfirming information between the three groups. Distributions of our dependent variable were similar for all groups, as assessed by visual inspection of a boxplot. Counts of selected supporting/opposing information were not statistically significantly different between the three groups ($\chi2(2) = 2.328$, $p = .312$). We, therefore, find support for H3d.

3.4.5 Results for crisis anchoring hypotheses (H4a, H4b, H4c, H4d)

In all three survey experiments, participants' estimates for available crisis resources were influenced by anchoring bias. Mann-Whitney U tests[14] were conducted to test for significant

[13] Kruskal-Wallis H test was chosen because of several outliers, non-normality and unequal variances between the three groups.

[14] Mann-Whitney U tests were chosen because of several outliers and the non-normality of the data.

differences between the high vs. low anchor conditions in each of the three groups (Table 3.7). Participants in the low anchor condition gave significantly lower estimates than participants in the high anchor condition. In the sample of crisis-affected people, the mean of respondents' estimates in the high anchor condition was USD 87.66 million and USD 30.32 million in the low anchor condition. In the sample of government and non-profit workers, the mean respondents' estimates in the high anchor condition were USD 86.1 million and USD 11.42 million in the low anchor condition. In the sample of crisis experts, the mean of respondents' estimates in the high anchor condition was USD 17.96 million and USD 11.42 million in the low anchor condition.

Table 3.7. Results table for H4a, H4b, H4c. Mann-Whitney U tests for between-subjects designs.

	H4a: Crisis-affected people	*H4b: Government and non-profit workers*	*H4c: Crisis experts*
Mann-Whitney U	4328	35.5	14.5
Z	-9.654	-4.176	-2.33
Asymp. Sig. (2-tailed)	**0.000**	**0.000**	**0.02**
N	309	39	19
Mean estimate with high anchor	USD 87.66 million	USD 86.1 million	USD 17.96 million
Mean estimate with low anchor	USD 30.32 million	USD 11.42 million	USD 11.42 million

We tested for significant differences between the groups using two-way ANOVA with robust estimators[15]. The analysis revealed that the groups were not significantly different in the strength of the anchoring effect (p = .74). We, therefore, found support for H4a, H4b, H4c and H4d.

3.4.6 Summary of results

To summarize, most hypotheses were supported, some however not, and one could only be partially supported. Table 3.8 summarizes all hypotheses of this study together with our main results.

[15] Two-way Anova with robust Huber M-estimators was used because of outliers, non-normality and unequal variances of the data.

Table 3.8. Summary of this study's hypotheses and main results.

Hypothesis	**Result**
Framing effect	
Hypothesis 1a – Crisis-affected people show framing bias	Supported
Hypothesis 1b – Government and non-profit workers show framing bias	Supported
Hypothesis 1c – Crisis experts do not show framing bias	Not supported
Hypothesis 1d – Crisis experts show weaker framing bias than the other two groups	Supported
Bias blind spot	
Hypothesis 2a – Crisis-affected people show bias blind spot	Supported
Hypothesis 2b – Government and non-profit workers show bias blind spot	Supported
Hypothesis 2c – Crisis experts do not show bias blind spot	Not supported
Hypothesis 2d – Crisis experts show weaker bias blind that the other two groups	Partially supported
Confirmation bias	
Hypothesis 3a – Crisis-affected people show confirmation bias	Supported
Hypothesis 3b – Government and non-profit workers show confirmation bias	Not supported
Hypothesis 3c – Crisis experts show confirmation bias	Not supported
Hypothesis 3d – No differences in strength of confirmation bias between groups	Supported
Anchoring bias	
Hypothesis 4a – Crisis-affected people show anchoring bias	Supported
Hypothesis 4b – Government and non-profit workers show anchoring bias	Supported
Hypothesis 4c – Crisis experts show anchoring bias	Supported
Hypothesis 4d – No differences in strength of anchoring bias between groups	Supported

3.5 Discussion

3.5.1 Contribution to theory

Crisis management literature has stressed the potential negative influences of cognitive biases in crisis decision-making (Becker et al., 2017; Comes, 2016; Makinoshima et al., 2022; Reis et al., 2021). However, empirical evidence has been lacking, especially concerning different bias effects between different crisis stakeholder groups. We started from the assumption that crisis contexts lead decision-makers to be prone to biases but that there would be differences between decision-maker groups concerning the strength of certain biases. As our results show, we find support for this assumption. Overall, crisis experts were the least biased in our experiments. They showed no confirmation bias and even selected more disconfirming information rather than information that supported their preliminary decisions. This suggests that experts chose to challenge their initial decision and deliberately looked for information that disproves their preliminary assumption. This might be explained by the strong professional background of our expert participants (mean number of years of crisis work experience over ten years.). The technology vs. privacy dilemma that was used as the scenario in our confirmation bias task is a well-known crisis problem (Sandvik, Gabrielsen Jumbert, Karlsrud, & Kaufmann, 2014). Our results suggest crisis experts are more critical on the subject and try to assess their information options carefully. While this might prompt defense-motivated behavior that could lead to stronger confirmation bias (Taber & Lodge, 2006), our results suggest otherwise.

People in crises might have valid reasons, or even no alternative at all, to rely on quick heuristics when information is uncertain, and decisions need to be made quickly (Gralla et al., 2016). Experience seems to be an important moderator in mitigating the negative effects of biases and strengthening the positive effects of heuristics. In their observations of firefighters' decision-making, Klein and colleagues found that experience can lead to positive decision outcomes in situations of crises when quick, heuristics-based approaches are used (Klein et al., 2010). Similarly, previous research found experience and domain knowledge to be mitigating the framing effect and bias blind spot (Beratšová et al., 2018; Olsen, 2015; Pines & Strong, 2019). This is further supported by our group comparisons. We found that susceptibility to the framing effect and bias blind spot is weaker in crisis experts than in our other participant groups. Nevertheless, even though the framing effect and bias blind spot were lower in the group of crisis experts than in the other two groups, both biases still significantly affected experts' decisions. This is an important result for crisis management literature, as it implies that debiasing measures in crises need to be designed for laypeople as well as experts. Similar observations have been made in the sensemaking literature that found experienced emergency responders can fail to make sense of urgent and uncertain situations, for example, when informational cues are misinterpreted (Maitlis & Christianson, 2014; Weick, 1993).

3.5.2 Implications for crisis information systems design

Previous studies have described information systems that support people in crises with information and decision support (Ai, Comfort, Dong, & Znati, 2016; Fertier, Barthe-Delanoë, Montarnal, Truptil, & Bénaben, 2020; Turoff, Van de Walle, & Chumer, 2004). The general public, for example, has access to mobile apps that inform about measures people can take to reduce the impacts of a crisis on their livelihoods (Abbas & Michael, 2020; Eisenstadt, Ramachandran, Chowdhury, Third, & Domingue, 2020; Tan et al., 2017; Wymant et al., 2021). Experts and response organizations have access to more specialized systems, for example, to monitor social media streams, integrate various data sources, and provide modelling for resource allocation (Beydoun, Dascalu, Dominey-Howes, & Sheehan, 2018; Yang, Su, & Yuan, 2012). Literature on crisis IS design principles focused on information gathering, data management, and decision support services (Ai et al., 2016; Fertier et al., 2020; Turoff et al., 2004; Yang et al., 2012).

We argue that crisis IS would benefit from incorporating cognitive bias mitigation measures as they have been proposed in other domains, for example high-stakes financial decisions (Bhandari, Deaves, & Hassanein, 2006) and web search (Rieger, Draws, Theune, & Tintarev, 2021).

Participants in all three groups were significantly influenced by how crisis response options were being framed. Participants showed a more risk-avoiding behavior in the positive-frame condition, and a risk-seeking behavior in the negative-frame condition. Our findings have implications for the reporting, proposal and resource allocation process in crisis response that is often facilitated through IS. Crisis-affected people and response organizations request resources from donor agencies through an often competitive proposal process and donor agencies decide which proposals to fund (Stoddard, Poole, Taylor, & Willitts-king, 2017).

- **Crisis IS design principle: debiasing framing effect.** Information systems that support organizations in developing proposals should provide different framing options and present potential outcomes of these options, e.g., how differently framed plans on what to do with allocated resources likely affect decisions by donors. Previous research highlighted the effectiveness of implementing warning messages with negatively framed advice in information systems (Xiao & Benbasat, 2015). Information systems used by donor agencies also need to be able to detect potential framing effects and include warning messages that warn about the potential influences of framing on their decision-making. Future studies in the field of machine learning and artificial intelligence for crisis response could look into natural language processing approaches that can distinguish between different frames of information.

In our bias blind spot task, participants in all three groups ranked others' decision-making as more biased than their own. This was particularly strong in crisis-affected people, while crisis experts seem to be least prone to the bias blind spot. Being aware of one's susceptibility to bias is an important first step to debias (Bessarabova et al., 2016; Pronin, 2007). Low self-awareness of one's own biases leads people to ignore advice from experts and to deprioritize efforts to improve their own decision-making process (Scopelliti et al., 2015). Crisis-affected people, as well as government and non-profit workers, might therefore disregard expert advice during crisis response.

- **Crisis IS design principle: debiasing bias blind spot.** IS should account for potential over-confidence in their users, encouraging them to acknowledge and mitigate their own biases. When systems support the awareness of one's own susceptibility to bias, reducing negative bias effects becomes more likely. Another debias option is the establishment of a so-called *red teams* or *devil's advocates* (Satya-Murti & Lockhart, 2015). The role of these teams is to critically observe and provide critical feedback during the information management and decision-making process, especially on assumptions that are taken for granted, so that blind spots are less likely to be overlooked.

In our confirmation bias task, the sample of crisis-affected people showed a significant confirmation bias in line with previous studies (Charness et al., 2021; Jonas et al., 2001). This indicates that crisis-affected people chose to confirm rather than disconfirm their initial decision and deliberately looked for information that approved their preliminary assumption. While participants working at governmental and non-profit organizations also chose more confirming than disconfirming information, their result was borderline significant. Previous research has highlighted the effectiveness of flagging potentially biased information to reduce confirmation bias in information systems (Moravec, Kim, & Dennis, 2020).

- **Crisis IS design principle: debiasing confirmation bias.** Rather than only providing information that is wished for by decision-makers, systems should balance information supply with information that also opposes users' assumptions to mitigate confirmation bias (Bhandari et al., 2006). Nudging theory suggests that subtle hints to valid but opposing information can be effective means to reduce confirmatory information selection toward more balanced user behavior (Rieger et al., 2021).

In our anchoring bias task, participants focused on a realistic estimate of available resources around the artificial anchor we provided. All three participant groups estimated available crisis resources subsequently lower when given low-anchor information, and higher when given high-anchor information. This was expected as the tendency of people to anchor numerical estimates on arbitrary informational cues is strong in both lay people (Yasseri & Reher, 2018) as well as experts (Englich et al., 2006). Our results add to the literature that demonstrates the ubiquitous strength of the anchoring effect, by providing evidence that anchoring also influences critical estimation tasks by crisis decision-makers.

- **Crisis IS design principle: debiasing anchoring bias.** Crisis IS should take the anchoring tendency of users into account, by keeping track of what cues were presented and what estimation tasks are to be done by users. IS can then guide users to enlarge their scope of potentially reasonable estimates, instead of keeping it to biased limits. Crisis IS could implement modelling functions that support sequential decision-making under uncertainty. When information is limited at first and only becomes available over time, deep uncertainty models can provide insights into ranges of plausible scenarios even when information is limited (Auping, Pruyt, & Kwakkel, 2017).

3.6 Limitations and Future research

We acknowledge that potentially many types of bias can influence crisis response. To keep the focus of this research clear, feasible, and concise, we selected anchoring, framing, and confirmation bias because they are powerful, well-established information processing biases. Furthermore we selected bias blind spot as it is useful to understand people's ability to self-identify biases in their own decision-making. We are calling for future research with larger sample sizes on other forms of bias in crisis response as well as a focus on observing biases in actual crisis response or training exercises. This can limit the potential for self-reporting bias in experimental participants.

In our study, we focus on individual confirmation bias. Nevertheless, a form of organizational confirmation bias might arise because of organizational mandates, experience, and standard procedures, resulting in reduced organizational learning and fewer decision corrections when conflicting information suggests course corrections. While out of scope for our study, it is certainly interesting to focus on in future research.

Identifying what biases influence crisis decision-making needs to be followed up with research on effective interventions that reduce bias effects, i.e., debiasing techniques. Experimental research on different debiasing techniques can inform such interventions. Previous debiasing research has suggested several types of debias techniques that can be differentiated by the effort required to achieve the desired level of debiasing (Arnott & Gao, 2019). Extensive training sessions can be conducted with decision-makers to understand their own biases and learn ways to mitigate them (Sellier, Scopelliti, & Morewedge, 2019). Medium-effort interventions can be achieved through information systems, short courses and video lectures (Cheng & Wu, 2010; Morewedge et al., 2015). Recent studies on information systems designed to support crisis response emphasize integrating various data sources (Chaudhuri & Bose, 2020; Fertier et al., 2020), and we suggest extending such systems with functionalities that can identify and mitigate potentially biased behaviors of its users.

We argue that frugal, low-cost, low-effort debiasing interventions might best suit the time- and resource-constraint crisis context (Daniel, Khandelwal, Santen, Malone, & Croskerry, 2017; Nagtegaal, Tummers, Noordegraaf, & Bekkers, 2020). For example, consider-the-opposite interventions can reduce anchoring bias and confirmation bias (Huang, Hsu, & Ku, 2012; Nagtegaal et al., 2020). Similarly, prompting warnings in information systems about potentially framed information can reduce the susceptibility to the framing effect (Cheng & Wu, 2010). Such measures implemented in information systems for crisis response could prompt decision-makers that information contrary to their initial assumptions might be equally important or correct. Weick described the response to crises when expectations are violated and established frames of understanding seem to be no longer valid, as a sensemaking process of individuals and groups (Weick, 1993). Through sensemaking, decision-makers try to re-evaluate their understanding of a crisis and give meaning to their observations and actions (Comes et al., 2020; Weick, 1993). As such, we argue that sensemaking support systems can play an important role in debiasing crisis decisions (Muhren, Van den Eede, & Van de Walle, 2008).

Our experimental findings should be compared to future observations during crisis response exercises or real-world crisis response operations. A limitation with these approaches is that intervening in real-life events would be subject to many influences, which would limit generalizability.

Four our experiments, we recruited Amazon mTurk workers. mTurk workers are online users who voluntarily sign up for paid assignments, fulfilling tasks such as classifying images, translating texts or answering surveys. mTurk provides a large pool of potential survey respondents and previous studies found that results drawn from mTurk samples are comparable to samples from more traditional approaches (Pennycook et al., 2019; Wang et al., 2018).

3.7 Conclusion

We found experimental evidence that cognitive biases, such as anchoring bias, confirmation bias, framing effect, and bias blind spot, can influence crisis decision-making. These biases affect estimations of available crisis resources, information selection in technology versus privacy dilemma, choices between differently framed crisis response options, and the ability to identify biases in one's decision-making. Not all stakeholder groups are equally susceptible to biases, however. While crisis-affected people of the general public showed to be susceptible to all four biases studied in our experiments, government and non-profit workers as well as crisis experts were only susceptible to anchoring bias, framing effect, and bias blind spot, but not to confirmation bias. Crisis experts showed a tendency to disconfirm their preliminary assumptions. Overall, crisis experts were less susceptible to bias than the other two groups but still showed significant exposure to anchoring, framing, and bias blind spot.

We add to crisis management literature by showing that experience and domain knowledge can reduce the susceptibility bias in crises. Given the extraordinarily high stakes of crisis response, where, as can be seen in the COVID-19 crisis, millions of people can be affected, the research gap regarding the effects of biases on crisis decision-making and potential debiasing strategies require further attention.

We stress one point for future research. Debiasing interventions need to be investigated, especially for crisis information systems. We discussed the implications of our findings on crisis IS design principles that future research can further experimentally evaluate as a starting point. What interventions work to reduce biases for different decision-makers in various contexts could potentially lead to great benefits for all societal stakeholders affected by crises.

4 The Interplay of Data and Cognitive Bias in Crisis Information Management

This chapter is based on: Paulus, D., Fathi, R., Fiedrich, F., Van de Walle, B., Comes, T. (2022). On the Interplay of Data and Cognitive Bias in Crisis Information Management. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-022-10241-0. The first author conducted the literature review, designed and conducted the data collection and analysis process and wrote the manuscript. The co-authors provided feedback on the data collection and analysis process and earlier versions of the manuscript.

4.1 Introduction

Infectious disease outbreaks have been on the rise (Smith et al., 2014), with the COVID-19 pandemic being the prime example that epidemics, if not controlled, lead to severe humanitarian crises and exacerbate poverty and hunger in the Global South (United Nations, 2021b). To respond to epidemic crises, information is central. Previous research has advocated for digital resilience via information systems, models, and algorithms that address the deluge of information and foster the stability of the digital ecosystem itself (Schemmer, Heinz, & Baier, 2021). Constantinides et al. (2020) define digital resilience as "*[...] the phenomena of designing, deploying, and using information systems to quickly recover from or adjust to major disruptions from [...] shocks*." Crises, however, put digital resilience to the test, especially the ability to rapidly adapt to a dynamic and highly volatile information environment.

The exceptional circumstances of crises put enormous pressure on crisis information management (CIM) as it needs to happen rapidly, despite tremendous uncertainty, and is often heavily resource-constrained (Comes et al., 2020; Schippers & Rus, 2020). These characteristics pose a double challenge: (a) data may not be available or is biased given limited access or data collection regimes, or it may be noisy, uncertain, and conflicting; and (b) the cognitive processes of crisis information managers and decision-makers may be under strain, given the urgency and high stakes of the situation.

Regarding (a), in crises, relevant data is often unavailable because of access constraints or destruction of infrastructure or because decisions have to be made quicker than it takes to collect and analyze data (Fast, 2017). This can lead to representational bias in data that potentially over- or underrepresent issues, social groups, or geographic areas (Fast, 2017; Galaitsi et al., 2021). If such biases remain undetected and untreated in CIM, information products used to support decision-making will also become biased.

Regarding (b), crises pose significant challenges to the cognitive processes of information managers and decision-makers. Humans tend to be influenced by cognitive biases, especially in situations of urgency, uncertainty, risks, and high-stakes (Phillips-Wren, Power, & Mora, 2019). The concept of cognitive biases originates from the idea of bounded rationality that postulates, human thinking (within the complex world surrounding it) is limited, which prevents people from being purely rational (Simon, 1955). Confirmation bias is among the most prominent cognitive biases in crises (Brooks et al., 2020; Comes, 2016; Modgil, Singh, Gupta, & Dennehy, 2021). It leads people to search and select information that confirms their previous assumptions and decisions and neglect disconfirming information (Nickerson, 1998). Consequently, crisis responders might disregard valid and important information only because it conflicts with or does not confirm their initial assumptions.

We argue that the interplay of data bias and confirmation bias threatens the digital resilience of crisis response organizations. The consequences for crisis response can be particularly severe when data bias and cognitive bias reinforce each other in sequential decisions over time. When initial assumptions are made based on biased data, confirmation bias may lead people to further rely on information that confirms their initial biased assumptions. This might lead to a vicious cycle that hampers adaptation and prolongs initially wrong decisions rather than correcting them. Conventionally, the literature suggests that decisions in crises need to be adaptive to new information (Turoff, Chumer, Van de Walle, & Yao, 2004). The principle of strengthening the adaptive capacity to manage uncertainty is underlying a broad range of literature on adaptive management in crises and (digital) resilience (Schiffling, Hannibal, Tickle, & Fan, 2020; Tim, Cui,

& Sheng, 2021). However, we know little about the effectiveness of such adaptive approaches against the backdrop of combined data and confirmation bias.

A potential counter-strategy to mitigate the negative consequences of biases on CIM is mindful debiasing. Mindfulness means being more aware of the context and content of the information one is engaging with (Langer, 1992), thereby becoming less prone to confirmation bias (Croskerry, Singhal, & Mamede, 2013). In a mindful state, information managers are more open to new and different information (Thatcher, Wright, Sun, Zagenczyk, & Klein, 2018). In contrast, when being less mindful, people rely on previously constructed categories and neglect the potential novelty and difference within newly received information (Butler & Gray, 2006).

This exploratory study investigates the interplay of data and confirmation bias in a sequential setup. Through a three-stage experiment with experienced practitioners, we studied how our participants dealt with biased data, and in how far they were able to correct initial decisions, or whether path-dependencies to biased decisions emerged. Based on our findings, we outline how mindful debiasing can support the detection and mitigation of data and confirmation biases in crisis response.

The remainder of this paper is structured as follows: the next Section reviews the relevant literature related to CIM, digital resilience and biases, and provides the research gap and research questions this paper is addressing. Section 4.3 describes the research design and methods, and Section 4.4 provides the results from our experiment. In Section 4.5, we discuss our contributions to literature and practice. In Section 4.6, we reflect on the limitations of this exploratory study, and Section 4.7 concludes the paper.

4.2 Background

4.2.1 Crisis Information Management

4.2.1.1 Approaches and Tools to Crisis Information Management

Crisis information management (CIM) entails the formulation of data needs, identification of data sources, data collection, cleaning and structuring, data analysis, and the design and development of information products (Currion, Silva, & Van de Walle, 2007). The objective of CIM is to support decision-making by providing trustworthy, accurate, and actionable information.

With the rise of Big Data and Artificial Intelligence, larger humanitarian organizations have invested in analytics capacity (Akter & Wamba, 2019). While the potential for working with unstructured data for predictive analytics has been recognized, many humanitarian organizations active in the Global South do not possess the resources for large investments into information technology and statistical sophistication (Baharmand, Saeed, Comes, & Lauras, 2021; Prasad, Zakaria, & Altay, 2018). In these contexts, large parts of CIM are still supported through common office information systems such as Microsoft Excel and Google Spreadsheets (United Nations, 2020c). These are used, amongst others, to store survey responses, conduct data integration, and develop information products, e.g., maps, tables, and infographics (Thom et al., 2015).

Especially in sudden-onset disasters, organizations frequently surge additional data analyst capacity to rapidly strengthen their CIM and digital resilience. Often, these are remotely working digital volunteers, that have been regarded as cost-effective, additional analyst capacities to support CIM (Castillo, 2016; Poblet, García-Cuesta, & Casanovas, 2018). These external analysts contribute to CIM by supporting tasks such as data collection, analysis as well as the development of information products for decision support (Chaudhuri & Bose, 2020b; Hughes & Tapia, 2015; Karlsrud & Mühlen-Schulte, 2017). External analysts have also contributed to epidemics CIM, e.g., in the 2014 West Africa Ebola outbreak (Hellmann, Maitland, & Tapia, 2016), or the Covid-19 response (Fathi & Hugenbusch, 2021).

Figure 4.1 shows on the left side an information product developed by external analysts during the 2014 Ebola outbreak. The product highlights the major challenges of access to data and shows that the mobile phone network corresponds to the areas of the officially reported cases (WHO map at the right-hand side of Figure 4.1), clearly an indication of the widespread data biases, whereby access and phone coverage hampered reporting. Other information products created through such joint CIM processes include Excel and Google spreadsheets, graphs, and 1-pager summarizing results of social media data analyses (Hughes & Tapia, 2015).

(a) MapAction map showing mobile phone coverage

(b) WHO map of hot-spots of Ebola cases.

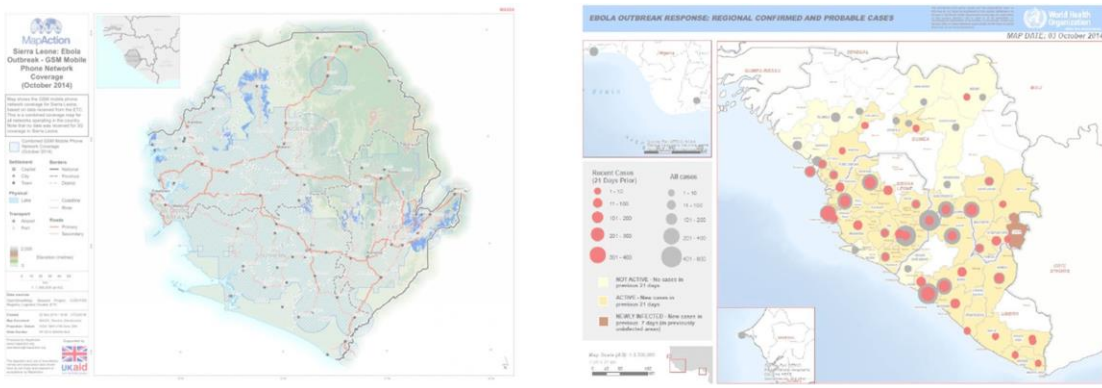

Figure 4.1. Map comparison for Sierra Leone during the 2014-2016 Ebola outbreak

Tasks and responsibilities frequently shift in crises (Nespeca, Comes, Meesters, & Brazier, 2020), requiring information managers and decision-makers to interact with data in different ways. While external analysts are primarily turning raw data into information, decision-makers are concerned with interpreting the situation and putting received information into context by using experience, communicating with partners, acting, and reacting.

4.2.1.2 Sensemaking and Situational Awareness

While much work on decision-making in crises focuses on optimizing for isolated decisions, crises are typically characterized by nested and interdependent decisions, driven by cognition and experience. This process is recognized by the literature on sensemaking, whereby decisions are part of a broader collective process of meaning-making (Tina Comes et al., 2020; G. Klein & Moon, 2006; Weick, 1995). Important components of sensemaking are information seeking, processing, creating, and using (Muhren et al., 2008). Data-driven approaches, e.g., predictive analytics, can support sensemaking by revealing internal and external cues. Sensemaking is also influenced by an organization’s mandate, strategy and modes of operation (Zamani, Griva, Spanaki, O’Raghallaigh, & Sammon, 2021), and especially describes how people deal with ‘gappy’ information environments (Muhren et al., 2008).

Early studies on the work of external analysts emphasized the added value they bring to CIM by their remote and flexible structures (Bott & Young, 2012; Meier, 2012; Ziemke, 2012). It has been argued that their work contributes to the situational awareness of response organizations

(Hughes & Tapia, 2015; Starbird & Palen, 2011). To achieve situational awareness successfully, however, it is important to switch between goal-driven and data-driven approaches (Endsley, 1995; Endsley, Bolté, & Jones, 2003; Fromm, Eyilmez, Baßfeld, Majchrzak, & Stieglitz, 2021). While for goal-driven approaches, informational cues are intentionally considered in the pursuit of a set goal, data-driven approaches refer to open exploration of perceived cues that can lead to changes in priorities and readjustments. Situational awareness requires to alternate between these two forms because stringent goal-focus will lead to neglect of cues in the data, while stringent data-focus will be perceived as overly taxing (Fromm et al., 2021).

4.2.2 Digital Resilience and Crisis Information Management

4.2.2.1 Defining Digital Resilience

There are diverging perspectives on what constitutes digital resilience and whether it plays at the level of the physical infrastructure, the people or groups using the infrastructure, or the interplay among both. Some authors focus on the impact of digital technology on the user, stressing the importance of (access to) information in crises. For instance, according to Wright (2016), “digital resilience means that to the greatest extent possible, data and tools should be freely accessible, interchangeable, operational, of high quality, and up-to-date so that they can help give rise to the resilience of communities or other entities using them.” Others focus on the resilience capabilities of individuals to process digital data and engage with virtual environments (UK Council for Internet Safety (UKCIS), 2019).

Here, we take an information systems perspective, understanding digital resilience as a phenomenon that emerges from the interaction of people with data through digital tools and infrastructure. We follow a crisis-related definition that describes digital resilience as a means to cope with disruptions: *“[...] digital resilience [...] refer[s] to the phenomena of designing, deploying, and using information systems to quickly recover from or adjust to major disruptions from [...] shocks.”* (Constantinides et al., 2020). Crisis information management needs to foster digital resilience by supporting flexibility, agility, and adaptability (Turoff, Chumer, et al., 2004). Our definition also covers specific aspects of digital resilience during epidemics (Ma’rifat & Sesar, 2020), namely the collection and analysis of outbreak data, as well as the use of analysis results to inform crisis response. Since CIM incorporates data collection, analysis, and sharing to support crisis decisions, it is directly linked to digital resilience.

4.2.2.2 Challenges to Digital Resilience in Crisis Information Management

Previous literature identified several challenges to CIM that affect different functions (Lauras, Benaben, Truptil, & Charles, 2015; Bartel Van de Walle & Comes, 2015) at different hierarchical levels (Bharosa et al., 2010). We argue that data and cognitive biases can emerge as consequences to these challenges and affect CIM by posing threats to digital resilience in terms of hampering the rapid recovery from crises. We use the challenges described below to design our experiments, described in Section 4.3.

Information has to feed into the fast crisis decision-making process (Lauras et al., 2015; Turoff, Chumer, et al., 2004; Warnier, Alkema, Comes, & Van de Walle, 2020). The time pressure reinforces the tendency to focus only on information that is immediately available (Higgins & Freedman, 2013), which may induce a range of biases (Maule, Hockey, & Bdzola, 2000). Information needs also rapidly change during different crisis stages (Gralla, Goentzel, & Van de Walle, 2015; Hagar, 2011; Nespeca et al., 2020), posing challenges to the agility and flexibility of information management (Lauras et al., 2015).

As the destruction of infrastructure or lack of access may affect different regions to different degrees (Altay & Labonte, 2014), datasets are often geographically imbalanced or biased. Demographic biases can influence the data further. Especially in the Global South, the most vulnerable groups might not have access to mobile phones and therefore are not included in mobile phone data to track and trace population movements (IOM, 2021). Underrepresentation of geographic areas or social groups can lead to violations of the humanitarian imperative to ‘leave no one behind’ (Van de Walle & Comes, 2015).

Relevant information about the crisis situation is often uncertain. Uncertainty is an umbrella term for information that is unavailable, incomplete, ambiguous, or conflicting (Comes, Hiete, Wijngaards, & Schultmann, 2011; Tran, Valecha, Rad, & Rao, 2021). To reduce uncertainty, people likely use the tools and methods they are most familiar with. This behavior could lead to what is known as the law-of-the-instrument, which states that people tend to overly rely on a particular familiar tool (Johnson & Gutzwiller, 2020).

The high volume, velocity, and variety of irrelevant data can quickly lead to information overload, particularly when the veracity of data has to be evaluated as well (Schulz, Paulheim, & Probst, 2012). This issue has become particularly prominent with the ubiquity of social media (Gupta, Altay, & Luo, 2019), which makes it virtually impossible to filter and process all available data on time (Starbird & Palen, 2011; Van de Walle et al., 2016). Information overload has been shown to induce confirmation bias (Goette, Han, & Leung, 2019). Confronted with an overload of information, it is hard to identify any gaps in the available data, leading to exploiting what is known rather than exploring what could be known (Comes et al., 2020).

In the high stakes decision contexts of humanitarian crises, tremendous potential losses are combined with the irreversibility of decisions (Kunreuther et al., 2002). High stake situations have been shown to induce a large number of biases, ranging from a tendency to focus on short-term perspectives as well as an over-reliance on social norms and emotional cues (ibid.). For example, high-stakes decisions can lead decision-makers to exert groupthink, which is manifested by overconfidence and a strive for in-group harmony, rather than critical self-reflection (Kouzmin, 2008).

4.2.3 Biases in Crisis Information Management

As we have shown, the characteristics of crises provide a breeding ground for data biases and cognitive biases (Comes, 2016). Here, we zoom into two of the most prominent biases that are relevant in the interplay of information and decision-making: data and confirmation bias.

4.2.3.1 Data Bias in Crisis Information Management

Data can become biased due to historical, social, political, technical, individual, and organizational reasons (Jo & Gebru, 2020). Representational data bias is among the most common forms and a broad category of data bias. It comes from the "divergence between the true distribution and digitized input space" (ibid.). In practice, that often means that a dataset systematically deviates from the real-world phenomenon the data is supposed to represent, for example, leading to the under-representation of geographic areas or social groups.

Data bias can be understood as a flaw of a dataset, negatively affecting the quality of the data and potentially causing damages and losses in organizational processes (Storey, Dewan, &

Freimer, 2012). Especially in sensitive contexts, data bias has been shown to replicate and reinforce existing inequalities (Bender et al., 2020; Jacobsen & Fast, 2019). Urgency and overload combined with uncertainty are common causes for data bias in crises (Fast, 2017).

In epidemic response, the misrepresentation of infection rates has been documented during the 2014-2016 Ebola outbreak in West Africa (Fast, 2017). Similarly, during the COVID-19 pandemic, different testing, tracing, or counting strategies have resulted in incomplete datasets and incomparable statistics (Fenton, Neil, Osman, & McLachlan, 2020).

We look at representational bias in two key variables for epidemic response: numbers of infections and treatment capacity. Representational bias in those two variables can lead to a flawed understanding of the outbreak's severity and the available capacity, leading to misallocations and delayed or ineffective response.

One of the hopes in using additional analytic capacity is that this additional capacity identifies additional information and thereby helps overcome data bias. To test if additional external capacity actually helps in overcoming data bias, we draw inspiration from traditional hidden profile experiments (Lightle, Kagel, & Arkes, 2009; Stasser & Titus, 1985). These experiments evaluated groups' decision-making performance. Group members received two sets of information, one set that contains the same information for all group members and another set that is different between group members. Only by joining the different, individual information sets together groups can identify the hidden profile, which is crucial to make the optimal decision. Hidden profile experiments have shown that generally groups overly discuss common information and neglect individual information so that the hidden profile remains hidden and the groups make an inferior decision (Lightle et al., 2009; Stasser & Titus, 1985).. This behavior was also found in experiments on crisis decision-making (Muhren, Durbić, & Van de Walle, 2010). However, previous experiments did not specifically look at representational bias in crises and whether adaptive approaches to surge additional analyst capacities help to improve the identification and mitigation of biases.

4.2.3.2 Confirmation Bias in Crisis Information Management

A cognitive bias that hampers adequate adaptation to new information is confirmation bias. Research on confirmation bias has shown that people tend to limit their information retrieval efforts to information that is more likely to confirm their assumptions (Nickerson, 1998). Because information that opposes preliminary assumptions increases discomfort (Hart et al., 2009), it may be discarded, and wrong assumptions remain undetected, leading to flawed decision-making (National Research Council, 2015). Confirmation bias, like cognitive biases in general, are often characterized as a byproduct of information processing limitations: because of urgency and overload, people use biases as mental shortcuts to judge and decide quickly.

The urgency of crises likely fosters confirmation bias because relying on already formed assumptions accelerates decision-making. Domain experts, however, can show the opposite behavior and deliberately seek disconfirming information (Klein & Moon, 2006). Counterfactual mindsets have been shown to be an effective debiasing strategy (Kray & Galinsky, 2003). However, we know little about the potential influence of confirmation bias on the information search and selection behavior of experienced crisis responders.

In this study, we investigate if crisis decision-makers and analysts are susceptible to confirmation bias and if they search for non-confirmatory data as a debiasing strategy. It could be possible that the deliberations between experts induce counterfactual mindsets, which, in turn, lead to a more critical assessment of prior decisions. However, path-dependencies may arise, whereby confirmation bias leads decision-makers and analysts to confirm assumptions in subsequent decisions, even though they were made based on biased data.

Previous research measured confirmation bias through tasks with two parts (Fischer, Lea, et al., 2011; Jonas et al., 2001). First, participants made a preliminary decision between two options on a certain matter. Then, they were presented a set of information, which often are summaries of articles on the matter participants just made their preliminary decision on. For example, ten summaries of articles are presented, five supporting participants' preliminary choice, and five opposing it. Participants are then asked to select the articles they would like to receive in full. The experiment finishes, and participants are told there will be no full articles because it is unnecessary for the experiment. The researcher later counts the numbers of selected supporting and opposing article summaries and conducts a significant test for the difference. If significantly more supporting summaries were selected, we speak of confirmation bias.

4.2.4 Research Gap and Research Questions

In dynamic situations such as crises, information on the best course of action continuously changes. Therefore, the literature advocates for agile and adaptive management in epidemics (Janssen & van der Voort, 2020; Merl, Johnson, Gramacy, & Mangel, 2009) or, more generally, in crises (Anson, Watson, Wadhwa, & Metz, 2017; Charles et al., 2010; Schiffling et al., 2020; Turoff, Chumer, et al., 2004).

Response organizations often lack sufficient capacities to respond. Therefore, remotely working external analysts are added as surge capacity. There is some hope that via this additional capacity, exploratory search strategies may be favored that help overcome the responsive and exploitative strategies of decision-makers. At the same time, the remote nature of the work of analysts may add to the biases they are subject to (Comes, 2016) and may make especially data interpretation harder (Comes & Van de Walle, 2016). Therefore, it is not yet known how and in how far the interplay of analysts and decision-makers in sequential decisions reduces or amplifies biases. In this paper, we investigate whether the surge of additional analyst capacity is effective to mitigate bias effects.

In sequential decisions, initial biases might limit the ability to effectively adapt, even though adaptation is widely described in the crisis management literature as key to managing the uncertainties and data biases that often prevail at the onset of a crisis (Mendonça, Beroggi, & Wallace, 2001; Quarantelli, 1988). Potentially, representational data bias and confirmation bias reinforce each other, leading to amplified biases. This is especially harmful if path-dependencies arise whereby the initial data bias does not only influence initial decisions but leads to flawed decision trajectories through confirmation bias.

Figure 4.2 depicts the interaction of the identified main challenges within the external analyst-supported CIM process. The response organizations activate external analysts in the first step (1). In steps (2) and (3) external analysts and decision-makers conduct information management and decision-making under the influence of the crisis, which can lead to biases. Information management and decision-making need to identify and mitigate biases to lead to unbiased results (4). Finally, the resulting information and decision are either influenced by biases, or bias mitigation was successful (5).

We are interested in (RQ 1) whether the surge of external analysts leads to unbiased information products for decision support, (RQ 2) if the joint CIM process between analysts and decision-makers facilitates debiasing, and (RQ 3) if data bias and confirmation bias reinforce each other leading to path dependencies in sequential decisions. We address the following research questions:

- RQ 1: Is surging external analysis capacity effective in identifying and mitigating data bias?
- RQ 2: How do external analysts and decision-makers jointly handle data bias in the decision process?
- RQ 3: Does confirmation bias create path dependencies whereby biased assumptions persist in sequential decisions?

We used an exploratory, three-stage experiment to examine these research questions, which is described in detail in the next Section.

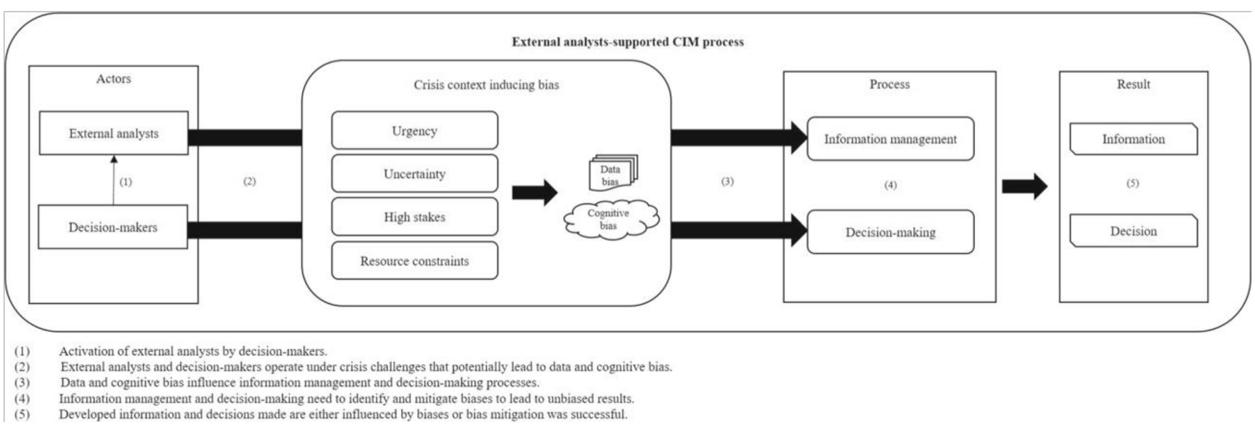

Figure 4.2. External analyst-supported crisis information management process

4.3 Research Design & Methods

We conducted an exploratory study with three stages to address the three research questions (Figure 4.3). RQ 1 and RQ 2 were addressed through a scenario-based workshop with experienced practitioners in the fields of crisis decision-making and external analysis for CIM support. RQ 3 was addressed through an online survey with the same participants. Figure 4.3 depicts the research questions together with the corresponding experiment stages, data collection, and analysis methods.

The experiment was designed to observe the crisis information management and decision-making process in a controlled environment. The controlled environment enables observation without interfering with the real response and allows us to conduct the experiment with three different groups. Yet, by designing realistic information flows, creating time pressure and providing the typical tools, the scenario is sufficiently realistic enough to inspire the same ways of thinking that external analysts or decision-makers also show in real epidemics. Through this setting, it was possible to observe the practices, communication and interactions within and between the participant groups. The experiment took place at the TU Delft Campus in The Hague in January 2020.

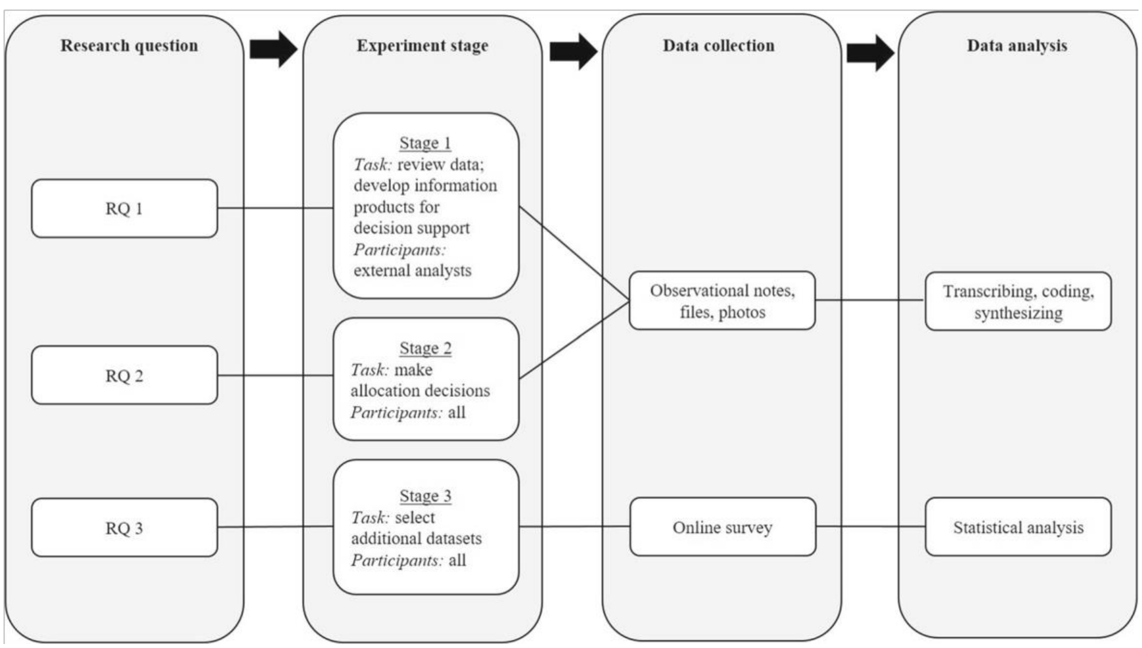

Figure 4.3. Research design

4.3.1 Participants

4.3.1.1 Recruitment

Participants had to have work experience as external analysts or decision-makers in crises to be eligible for participation. The recruitment was done based on the competencies required to fulfill the tasks of our experiment. These competencies included technical skills such as merging tabular data in MS Excel or a similar tool and developing and interpreting crisis information products such as maps and graphs. In addition, participants needed to be affiliated to an established crisis response organization, data analytics organization, or research institute on crisis or epidemic management. The authors had contacts to a network of potential candidates through previous research. This enabled us to recruit participants who had the required skills and experience. The participants were recruited internationally from various countries. **Error! Reference source not found.** lists the descriptive information of our participants.

Table 4.1. Descriptive information of all participants during the experiment. EA = External analyst, DM = Decision-maker

Group	Role	Organization	Competencies
Reloupe	EA	Humanitarian Openstreetmap Team	Mapping and open data for humanitarian action
	EA	MapAction	Mapping and open data for humanitarian action
	EA	Mark Labs	Data analytics for environmental and social transformation
	EA	510 (Red Cross)	Emergency data support, predictive impact analysis and digital risk assessment
	DM	TU Delft	Student with no prior experience
	DM	Red Cross	Emergency response, volunteer assistance, emergency training
	DM	Dorcas	Poverty reduction and crisis response
	DM	US Department of State	Senior humanitarian analyst
	DM	Municipal Health Service	Doctor of infectious disease control
Republic	EA	Standby Taskforce	Mapping and open data for humanitarian action
	EA	Virtual Operations Support Team	Social media data analysis in crisis response
	EA	Standby Taskforce	Mapping and open data for humanitarian action
	EA	TU Delft	Student with no prior experience
	DM	ZOA	Emergency relief and reconstruction of regions struck by disasters or conflicts
	DM	Red Cross	Emergency Relief Coordinator

	DM	World Vision	Disaster management, economic development, education, faith and development, health and nutrition and water.
Noruwi	EA	510 (Red Cross)	Emergency data support, predictive impact analysis and digital risk assessment
	EA	MapAction	Mapping and open data for humanitarian action
	EA	Leiden University	Development of data-driven decision support tools for humanitarian organizations
	EA	TU Delft	Student with no prior experience
	EA	Humanity Road	Social media data analysis in crisis response
	DM	TU Delft / European Commission Humanitarian Aid Office	Emergency and crisis management
	DM	Maastricht University Faculty of Health, Medicine and Life Sciences	Public health expert
	DM	Ministry of Foreign Affairs (NL)	Senior humanitarian advisor

4.3.1.2 Sample

Twenty-four participants participated in the experiment, of which twenty-one were experienced in crisis management (eleven external analysts and ten decision-makers), and three were students. We added three students to create an element of reality to the group compositions as staff turnover is high in crisis response teams, with new and inexperienced staff needing to be integrated (Denis, Hughes, & Palen, 2012; Fathi, Thom, Koch, Ertl, & Fiedrich, 2020). Based on the background and experience of the participants, they were given either the role as an external analyst or as a decision-maker. Participants within the group of external analysts were part of professional disaster relief organizations as well as organizations representing different fields of expertise such as digital mapping, social media analysis, and data analytics. The group of decision-makers consisted of representatives from different governmental and non-governmental crisis response organizations from numerous countries, including The Netherlands, Germany, the United Kingdom, and the United States. **Error! Reference source not found.** gives an overview of all participants, their corresponding organizations, and competencies.

Recruiting experienced professionals for a scientific experiment leads to a smaller pool and thereby also lower participant numbers as compared to experiments with students or the general public. As the objective of this exploratory experiment was to gain insights into information management and decision-making approaches by actual practitioners, relying on samples drawn from student populations or the general public would have been inadequate.

Our sample size is in a similar range as comparable exploratory studies on information systems and information management (Antunes, Pino, Tate, & Barros, 2020). Such exploratory studies provide a valid approach to build theory and identify metrics, mechanisms, processes, and concepts that can be investigated further in subsequent empirical research (ibid.).

4.3.1.3 Group Compositions

We divided the participants into three groups of seven to nine members. The group sizes match real-world work team sizes of external analyst-supported CIM processes (Denis et al., 2012). Further, members of geographically distributed teams of up to nine members have been shown to participate more actively and are more committed to and more aware of the team's goals than in larger teams (Bradner, Mark, & Hertel, 2003). Our groups were purposefully mixed with participants having complementary skills and expertise so that each group included experts on mapping and data analytics on a similar level. Therefore, the number of participants and the group compositions are a good representation of real-world teams.

4.3.2 Scenario Design

The fictional scenario of our experiment was an epidemic outbreak happening simultaneously in three countries. The experiment was inspired by the 2014-2016 Ebola outbreak in Guinea, Liberia, and Sierra Leone. The three country groups had to assess the situation in their respective country by analyzing the data provided during the experiment with the goal to support decisions on where (in which districts) to place treatment centers. The experiment resembled the main challenges of crisis information management, as mentioned in Sections 4.2.2 and 4.2.3, by putting participants under time-pressure (urgency), providing incomplete and low-quality data (uncertainty), requiring participants to make high stakes sequential decisions on treatment center placements and having to do so with a shortage of resources.

Before each stage of the experiment, we gave a brief introduction about the scenario and the participants' tasks. Each stage was concluded with a reflection moderated by the researchers.

4.3.3 Materials and Introduction of Representational Data Bias

As our participants were experienced practitioners, the data used in the experiment had to resemble reality closely. We used original data from the 2014-2016 Ebola epidemic. The datasets selected for inclusion were on infection rates, infrastructure capacities, demographics, and geography. We adjusted the original data for three reasons. First, some of the participants had been involved in the 2014-2016 Ebola response and should not have a head-start by already being familiar with the data. Second, our experiment required us to introduce a controlled representational bias into the data. Third, the original datasets were too large for the time frame of the experiment. The original data was downloaded from the Humanitarian Data Exchange platform and we adjusted it as described in the following.

*The infection rate is the key variable in epidemic response. We adjusted the original data so that infection rates were higher and more cases occurred in a shorter time. We retained columns from the original datasets and removed auxiliary columns to avoid information overload in the participants (**Error! Reference source not found.**). We included infection data for the first four months of the fictional outbreak (Table 4.3). Inspired by hidden profile experiments, in our experiment, one district per country was created with substantially more total cases than the other districts in the country. The data of this district was split among group members' datasets (*

Table 4.4). This implies that only by joining their datasets participants were able to identify the district with the most cases. If the bias remained undetected and untreated, the resulting information products would also become biased.

Table 4.2. Step 1: Retrieving original data from the West-Africa Ebola outbreak. Here truncated to show reported cases of infections. One row is one reported case

Country	Location	Epi week	Case definition	Ebola data source	...
Liberia	GRAND BASSA	25 to 31 August 2014 (2014-W35)	Confirmed	Patient database	...
Liberia	GRAND BASSA	08 to 14 September 2014 (2014-W37)	Probable	Patient database	...
Liberia	GRAND BASSA	15 to 21 September 2014 (2014-W38)	Probable	Patient database	...
Liberia	GRAND BASSA	22 to 28 September 2014 (2014-W39)	Probable	Patient database	...
Liberia	GRAND BASSA	13 to 19 October 2014 (2014-W42)	Confirmed	Patient database	...

Liberia	GRAND BASSA	20 to 26 October 2014 (2014-W43)	Confirmed	Patient database	...
Liberia	GRAND BASSA	20 to 26 January 2014 (2014-W04)	Probable	Situation report	...
Liberia	GRAND BASSA	27 January to 02 February 2014 (2014-W05)	Confirmed	Situation report	...
Liberia	GRAND BASSA	27 January to 02 February 2014 (2014-W05)	Probable	Situation report	...
Liberia	GRAND BASSA	03 to 09 February 2014 (2014-W06)	Confirmed	Situation report	...
Liberia	GRAND BASSA	17 to 23 March 2014 (2014-W12)	Probable	Situation report	...
...	...	...	...	...	...

Table 4.3. Step 2: Adjusted dataset based on the original data to resemble the infection rate and adapt the data to our fictional country and outbreak

Country	District	Month	Case definition	Ebola data source
Noruwi	Aameri	1	Confirmed	Situation report
Noruwi	Aameri	1	Probable	Situation report
Noruwi	Aameri	1	Probable	Patient database
Noruwi	Aameri	2	Probable	Situation report
...	...	...	...	...
Noruwi	Aameri	3	Confirmed	Patient database
Noruwi	Aameri	4	Probable	Patient database
Noruwi	Aameri	4	Probable	Situation report
Noruwi	Aameri	4	Probable	Situation report

Table 4.4. Step 3: Introduction of representational bias. We created biased versions of the adjusted datasets from step 2. The biased versions were distributed among participants. The bias is here introduced in the district of Niprusxem. The district has the most cases in the unbiased dataset, but the least cases in the biased datasets. One group member only receives data for month

1 (displayed). Each other group member also only receives data for one month (not displayed). Only by joining the datasets, the unbiased case numbers could be received.

	Unbiased					Biased				
Districts	M1	M2	M3	M4	Total	M1	M2	M3	M4	Total
Aameri	4	12	44	140	200	4	12	44	140	200
Baldives Saintman	3	21	27	147	198	3	21	27	147	198
Bana Cadi	1	2	24	54	81	1	2	24	54	81
Grethernquetokong	1	8	12	52	73	1	8	12	52	73
Janmantho	1	6	19	39	65	1	6	19	39	65
Lemau	4	4	92	140	240	4	4	92	140	240
Mau Cari	1	4	20	49	74	1	4	20	49	74
Menia	1	1	20	32	54	1	1	20	32	54
Niprusxem	*5*	*20*	*125*	*160*	*310*	*5*	*0*	*0*	*0*	*5*
Samac Iali	1	3	17	62	83	1	3	17	62	83
Southdos Dinia	3	12	66	129	210	3	12	66	129	210
Thesey	1	3	24	37	65	1	3	24	37	65
Usda Nilia	1	4	14	29	48	1	4	14	29	48
Walof	1	2	12	42	57	1	2	12	42	57
Total	28	102	516	1112	1758	28	82	391	952	1453

Infrastructure and capacity data During the 2014-2016 Ebola outbreak, mapping healthcare facilities and their capacities became a crucial task for crisis information management. However, up to 60 % of values in the original data on health infrastructure and capacities were missing, highlighting once more the high uncertainty analysts are confronted with. In addition, values had unclear and ambiguous meanings, making interpretation difficult. We adjusted the original datasets to include a reduced number of key variables. In the original datasets, detailed capacity data, i.e., numbers of beds per treatment center, was incomplete for 58 % of entries. We mimicked this representational bias in our adjusted datasets. Only one participant per group received capacity data on the number of beds per facility. The other group members received the same dataset but with an empty column for capacities.

Demographic and geographic data Demographic data are part of the common operational datasets in crisis response (Bartel Van de Walle, 2010). They are used to understand the overall population distribution in terms of age, gender, and geographic location. By providing a sense of population density and bordering regions, they become very important in predicting trends in epidemic outbreaks. We collected the original data, replaced country and district names with randomly generated names, and slightly adjusted the demographic numbers. We further included randomly generated maps corresponding to the three randomly generated countries and districts. The maps were distributed to the participants in digital and printout versions.

Data volume Data volume differed slightly between the groups, with no large differences that could have significantly eased or complicated one group's data review and analysis process (Table 4.5).

Table 4.5. Dimensions of datasets handed to groups. Dimensions given in rows x columns

Group	Dataset	Dimensions
Noruwi	Infection cases	1759×4
Noruwi	Demographics	15×22
Noruwi	Capacity	58×19
Reloupe	Infection cases	1724×4
Reloupe	Demographics	14×5
Reloupe	Capacity	64×19
Republic	Infection cases	3142×4
Republic	Demographics	36×22
Republic	Capacity	87×19

Participants' access to the data We created Google accounts for each participant, and the created datasets were uploaded into the Google Drive folders of each participant. This allowed us to distribute the created datasets to the members of each group while making sure the introduced bias was identifiable. A print-out sheet with login information for the Google folder was created for each participant. Each participant received a laptop to access the files. The laptops had MS Office pre-installed for the information management work on the data. Further tools also used by our participants in their professional work, including RStudio Online and Google Spreadsheets, were also available.

4.3.4 Experimental Setup and Procedure

To address the first two research questions (Is surging external analysis capacity effective in identifying and mitigating data bias? and How do external analysts and decision-makers jointly handle data bias in the decision process?), we set up the first two stages of the experiment. To address research question three (Does confirmation bias create path dependencies whereby biased assumptions persist in sequential decisions?), we conducted an online survey with the same participants.

4.3.4.1 Experiment Stage 1

Stage 1 was conducted only with the group of external analysts. They were divided into the three groups we had defined in the planning of the experiment (Table 1). Each group was responsible for the information management for one country affected by the fictional outbreak.

Participants were told their group's objective was to review the available data and develop information products that could be used in stage 2 of the experiment for the prioritization of districts that needed most urgent assistance. As all participants were used to preparing information products for crises, they were free to decide which information products to create (e.g. maps, tables, graphs, etc.). Participants were briefed they could use the MS Office Suite installed on the laptops provided to them, or any other online tools they would use in their professional work. Because of participants' experience, the importance of developing accurate information was clear to them. This includes the checking of data issues, gaps and comparing information quality among group members. We gave them no indication that they could expect the data they received was perfect, accurate and unbiased. Rather, we briefed them that the experiment should be seen as a simulation of a real case, with challenges that can be expected from real epidemic crises. Participants were briefed they had 2.5 hours for their task.

After the introduction, the three groups formed in three rooms, equipped with laptops and information sheets that contained user-login information for each participant to access the available data. The groups were asked to present the developed information products and suggestions for response decisions at the end of experiment stage 1.

4.3.4.2 Experiment Stage 2

In stage 2, decision-makers joined each of the three groups. Participants were briefed they had to make resource allocation decisions by placing treatment centers in priority districts of their respective countries. External analysts had to brief the decision-makers on the outbreak situation, priority issues, and districts using the information products developed by them in stage 1. Each group received a limited amount of treatment centers (in the form of small building blocks) that could be placed in districts of the fictional countries on printout maps. Participants were told that each treatment center, i.e., building block, had a fixed capacity of ten beds. We implemented resource constraints by limiting the number of available treatment centers and beds. Thus, not all districts could be fully equipped to respond to the rising infections and prioritization decisions had to be made. Participants were briefed that all decisions had to be made within 60 minutes.

After the introduction, the three groups formed in three rooms, equipped with laptops and the information products developed in stage 1. The groups were asked to present their final decisions at the end of the experiment.

4.3.4.3 Experiment Stage 3

To address the third research question after stage 2 was completed, all participants were asked to fill out an online survey on site. The research objective was to assess whether confirmation bias would lead to path-dependencies toward decisions that were made based on biased information. A significant confirmation bias result would mean that participants preferred to seek information that confirmed their previously formed assumptions, even when they were influenced by biased datasets.

The survey referred to participants' previous decision from stage 2, where they selected a priority district to which most treatment centers were allocated. In stage 3, participants were briefed that new information was available after they had made prioritization and allocation decisions. Their task was to select from a list of datasets those ones that they found most important to support further information management and decision-making. The survey item and confirmation bias measure is described in Section 4.3.5.2.

4.3.5 Data Collection and Analysis

4.3.5.1 Experiment Stage 1 and 2

In stages 1 and 2, one observer per group took notes of the information management processes, communication, and interaction within the groups. Photos were taken to document intermediate results and processes, for example of post-its on the printout maps. After the session, the group members' files of the information products created on the laptops were saved and analyzed by the researchers.

We conducted structured observations of the first two stages of the experiment that included the use of protocol sheets with guiding questions. Data collection through researcher observation is highly suitable in interactive experimental settings with dynamic group discussions. The goal was to capture verbal data, i.e., what is discussed, how by whom and when, as well as interactions among group members (Steffen & Doppler, 2019). Since an observer must select which person and interaction is the object of observation (selection problem), a result bias can occur (ibid.). We addressed this potential issue by briefing observers beforehand on the observation protocol and guiding questions. Thus, before beginning an observation, researchers numbered participants in a common format to protocol activities in a standardized way, quickly and effectively. The protocol guideline included example observation items and was divided into three different sections: (1) description of workshop site, (2) communication and interaction description, (3) general impressions. The complete observation protocol is provided in the Appendix C. The collected data was evaluated through qualitative content analysis (Döring & Bortz, 2016). The main activity was to summarize the collected observational data and reveal content related to our research questions. We further evaluated the information products developed by the participants in addition to conducting the qualitative document analysis. We proceeded in three steps:

1. Paraphrasing: To reduce the volume and complexity of the observational data and of the created information products, the first step was to identify passages that carry content relating to our research questions and delete passages that did not. In this process, the different data forms (text passages of the sheets and information products, e.g. maps) were analyzed separately.

2. Coding: In the second step, all paraphrases representing the main content were summarized in a single document. The separate paraphrases were coded and structured to answer our research questions and find explanations for these answers. We conducted two coding iterations to develop a set of coded categories of the observed discussions and activities.

3. Analyzing: In the final step, we analyzed the structured content with regard to our research questions. Through this content analysis, we were able to systematically evaluate and analyze all observation sheets and information products and present key results.

The first author coded the data in the first iteration. The resulting codes and corresponding observational notes were discussed with the second author. Adjustments were made to some of the coded categories, followed by the second iteration of coding by the first author. After review by the whole author team, the final categories of codes were agreed on. Table 4.6 presents example observation notes and coded categories.

Table 4.6. Example observation notes taken during the experiments and respective coded categories

Example observation notes	Coded category
Express need for information: transportation network	Requirements for additional data
Discussing data gaps: more background data on the country, transmission data, spread on daily basis needed	Requirements for additional data
Should we merge our data?	Debias behavior
Questioning why they have different datasets. Trying to understand the cause of the data bias	Debias behavior
One person uploaded their files into a shared folder, all others used the data from there	Data sharing
Receiving data from other groups	Data sharing
Deliberation of format of final information product for decision support	Discussion on decision recommendations
Information product proposal: curve by day, what is happening, did people die or not	Discussion on decision recommendations
Using familiar tool to create digital, layered map	Data work
Creation of (biased) aggregates for numbers of cases	Data work
Not sure what the most important dataset is	Interpretation of data
Need to know: where is the death rate the highest?	Interpretation of data
the data is not very clean; possibly underreporting	Communicating data limitations
we had different datasets between group members	Communicating data limitations
Decision-makers studying the developed map	Interpretation of situation

Discussion of possible causes for the outbreak	Interpretation of situation
Need to make a decision; what do we have and what is missing	Allocation strategy
where NOT to put centres?	Allocation strategy
Communication of available recources/capacities	Discussing capacities
Clarification of center capacities	Discussing capacities

4.3.5.2 Experiment Stage 3

In stage 3, participants were asked to complete the online survey on site. The survey was implemented in a Google Form and distributed to each participant. The survey prompted the participants with the following text: "Below are the summaries of 10 new datasets that are available. You can request the full version of those datasets but you only have limited time and resources to evaluate them all in detail. Select as many datasets as you want. District X is the district you have identified in the last session as the most critical district."

In stage 2, participants had to allocate treatment centers to the districts with the highest priority (referred to as "District X" in the survey). In the survey, ten summaries of ten fictional datasets were given in one-sentence statements.

Five dataset summaries supported that District X was indeed a priority district, whereas the other five dataset summaries opposed this. An example of a summary of a supporting dataset is *"Dataset 9: District X has a high amount of health care workers infected." An example of a summary of an opposing dataset is "Dataset 10: District X has a low amount of heath care workers infected."*

Participants did not receive any data to review besides those summaries, and after the survey was completed, they did not receive the datasets they selected, as it was not necessary to measure confirmation bias (Fischer, Lea, et al., 2011; Jonas et al., 2001). The complete confirmation bias measure can be found in Appendix C.

The response data from the survey was imported into SPSS for statistical analysis. Following the measures of confirmation bias in previous studies, we first counted the selected supporting and opposing datasets per participant. Then, we used a paired samples test to identify whether the mean counts of selected confirming and opposing datasets were significantly different.

4.4 Results

In the following, we present the results for our three research questions.

4.4.1 Impact of External Analysis Capacity on Data Biases

In the first stage of the experiment, all three groups of external analysts identified differences between group members' datasets and discovered that the data providing the numbers of infections were biased.

Example observation: *EA8 is looking up the data for Niprusxem. He says he only has month 2 for this and that this is strange. Asks to see EA12's data. EA9 says she only has month 3. EA12 has month 4. EA9: We have different datasets!*

However, the bias within the capacity data remained undetected in all three groups (see Table 4.7). This led to the development of information products that were overly focused on the outbreak situation and overlooked existing capacities.

Table 4.7. Overview of identified data biases per group

Group	Bias in infection data	Bias in capacity data
Noruwi	Identified	Not identified
Reloupe	Identified	Not identified
Republic	Identified	Not identified

Figure 4.4 shows the results of the coding and categorization process of our qualitative content analysis. The figure provides a summary of the sensemaking process within the groups. It shows the share of each coded category (in percent) within the overall activities of the groups during five time intervals of 30 minutes each.

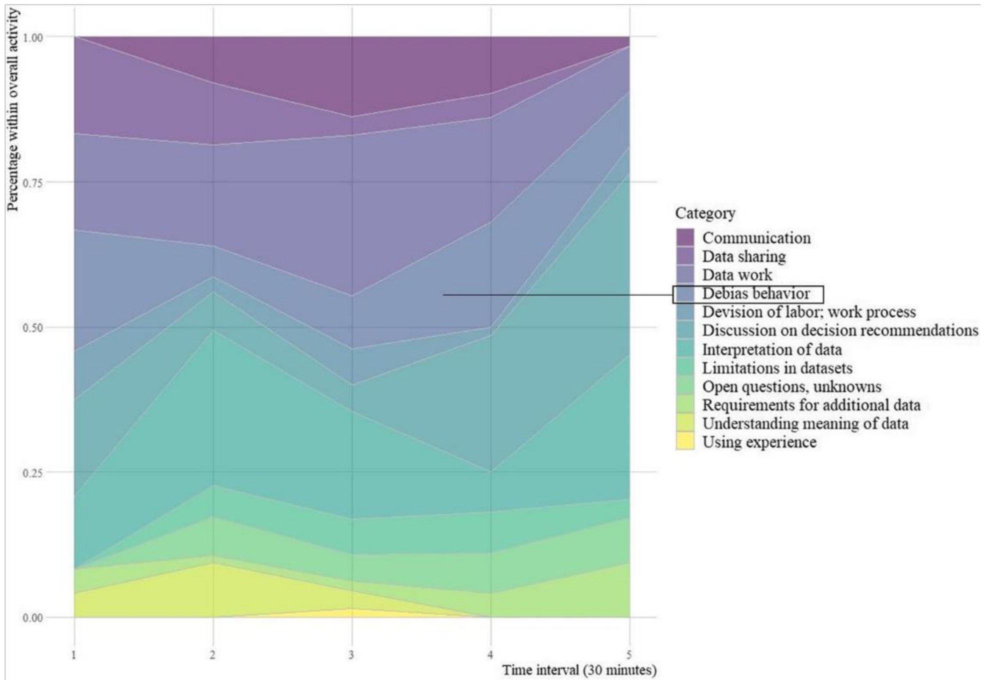

Figure 4.4. Experiment stage 1 results of the coding and analysis process. The figure shows the share (in percentage over time) of the coded categories within the overall activities of the groups. Debiasing efforts were not sufficiently followed up upon and, towards the end of the experiment, largely replaced by discussions on decision-making recommendations

In the initial phase, participants rushed into downloading the datasets stored in their individual Google accounts and started the data analysis by importing the data into their preferred information systems (e.g., Excel, RStudio). Participants familiarized themselves with their own data and identified differences in the data of their group members. Figure 4 shows the share of data work remained constant during the first two time intervals (i.e. first 60 minutes). It became the dominant category during the third interval and then lost importance by making room for an increased focus on decision-making recommendations. Figure 4 also shows the groups started with attempts to integrate datasets as debiasing behavior in the first interval.

Example observation: *EA10 suggests to the group to upload the data into Google Drive so he can easily merge them.*

These attempts were, however, not efficiently followed-up upon, and the share of debiasing behavior was reduced in the second time interval.

After an initial familiarization with the data, a collective sensemaking process started to emerge, characterized by intensive socializing, working, and experimenting with the data. The groups discussed how to define priority districts and what should be the key variables. This led to debiasing behavior gaining significance slightly and reaching its peak at the second last interval when groups recognized that datasets remained biased. The sensemaking process did not lead to due attention to biases. When differences between the group members' datasets were recognized, measures taken by the groups were insufficient to debias the data. One reaction was that one group member would upload their biased dataset into a shared folder, and the other group members would from then on use this data folder as the single-point-of-truth. From that time on, all group members accessed the same biased data. This behavior might be explained by groupthink, as the individual members of the groups strived to establish harmonic relationships, characterized by conformity and the minimization of conflict rather than openly articulating the disconfirming information they held.

Participants struggled with the non-availability of data they wished to have and perceived the data quality of some datasets to be too low to build accurate situational awareness and determine priorities. With the end of the experiment stage approaching and time pressure increasing, groups tasked individual members with creating information products, i.e., maps, graphs, and tables.

Example observation: *EA11: Data quality is questionable, it is not meaningful to go into data analysis in the last 20 minutes, must be quick... I need to think of the report, we should still name projects or tasks that our organizations would work on.*

At this point, it became increasingly difficult for the groups to mitigate any data biases because individuals would turn their own data into information for decision support, and no critical data assessments were done. Figure 4.4 shows Interpretation of data and decision-making recommendations dominated the last time interval and debiasing behavior was again neglected.

Even though all groups identified the bias within the infection data, the groups failed to successfully debias the data. Successful debiasing would have required that members of each group merge their datasets for infection rates and infrastructure capacity. However, even though the bias was recognized, each group relied on the data of only one of its members in the design of information products. Remarkably, one group identified early during the experiment that its members had received biased data and shared their finding with the other groups, but still all groups presented results based on biased data at the end of the experiment.

The resulting information products of each group showed numbers of infections in the most affected districts that were lower than the complete and unbiased information they could have acquired by merging their datasets. Figure 4.5 shows one example of a developed information product. It depicts that the district with the most cases in the unbiased dataset was presented with biased numbers based on only one of the participants' datasets.

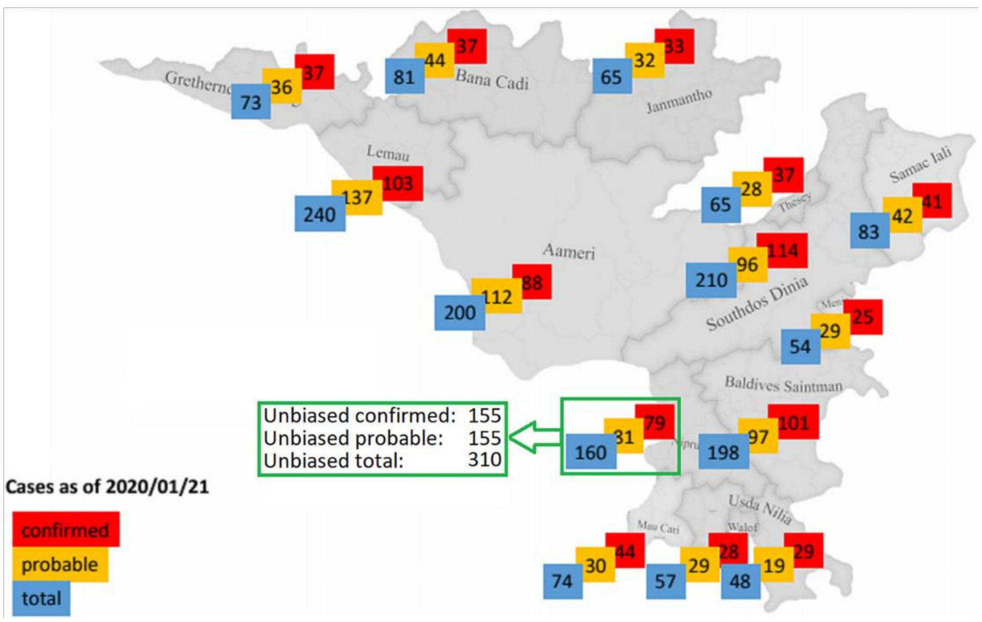

Figure 4.5. Example information product resulting from stage 1. Country map shows the numbers of cases per district (colored by the participants in red, yellow, and blue). The green box (added by us) shows that the unbiased numbers of cases for the most affected district were much higher than those reported in the information product developed by the participants

Overall, an explanation for the unsuccessful debiasing is the strong perception of time pressure and the experienced urgency by participants to deliver an information product in time that is presentable and actionable for decision-makers. Even though the additional analyst capacity is meant to alleviate the time pressure, they are subject to the same biases of exploiting, rather than exploring data (Comes et al., 2020). Analysts were not able to develop unbiased information products for decision support, since the data was accepted with its flaws, and information products needed to be developed anyway based on the low-quality data.

4.4.2 Data Bias in the Decision Process

In experiment stage 2, all three groups relied on the biased datasets and resulting biased information products from stage 1 in their discussions on treatment center placement decisions. External analysts briefed decision-makers using the biased numbers of infections.

Example observation: *They decide to place treatment centers based on the case numbers, and also want to place them along the border. EA12 shows the map of the confirmed cases to the DMs.*

As described Section 4.4.2, no group was able to identify the data bias on existing bed capacities during information product development. Consequently, no detailed capacity data was communicated to decision-makers, and allocation decisions were made in the absence of detailed data on existing capacities. If the capacity data bias had been discovered, it potentially could have facilitated the groups' allocation decisions.

Decision-makers took the role of advocatus diaboli by critically questioning the underlying data of the developed information products. In their role as decision-makers, they pressured external analysts on the data gaps and data quality issues very early in the experiment.

Example observation: *DM3: why are some areas empty? EA5: the data is not very clean; possibly underreporting. DM1: is the data trustworthy? EA5: we had different datasets between group members.*

Analysts briefed decision-makers on data limitations. This led to the joint understanding that the available data was unreliable to some degree. However, when data limitations were mentioned, decision-makers did not pressure enough. When analysts explained data gaps, other group members, who had access to that missing data, would not step in to clarify. Decision-makers would not press the group sufficiently to mitigate the data bias. Instead, they would pressure to make prioritization decisions for treatment center allocation.

Example observation: *DM5: Based on my experience, you have to make decisions on very little data. Indecision kills.*

Figure 4.6. Experiment stage 2 results of the coding and categorization process. The graph shows the share (in percentage over time) of the coded categories within the overall activities of the groups. Initial discussions on data limitations were not sufficiently followed-up upon and discussions on allocation strategy dominated the group discussions from the second interval onwardshows the results of the coding and categorization process of our qualitative content analysis of experiment stage 2. It shows the share of the coded categories (in percent) within the overall activities of the groups during four time intervals which are 15 minutes each. Deliberations on allocation strategies dominated discussions from the second interval onward till the end of the experiment. It reached its peak during the second last interval, where 35 % of discussions were on allocation strategies.

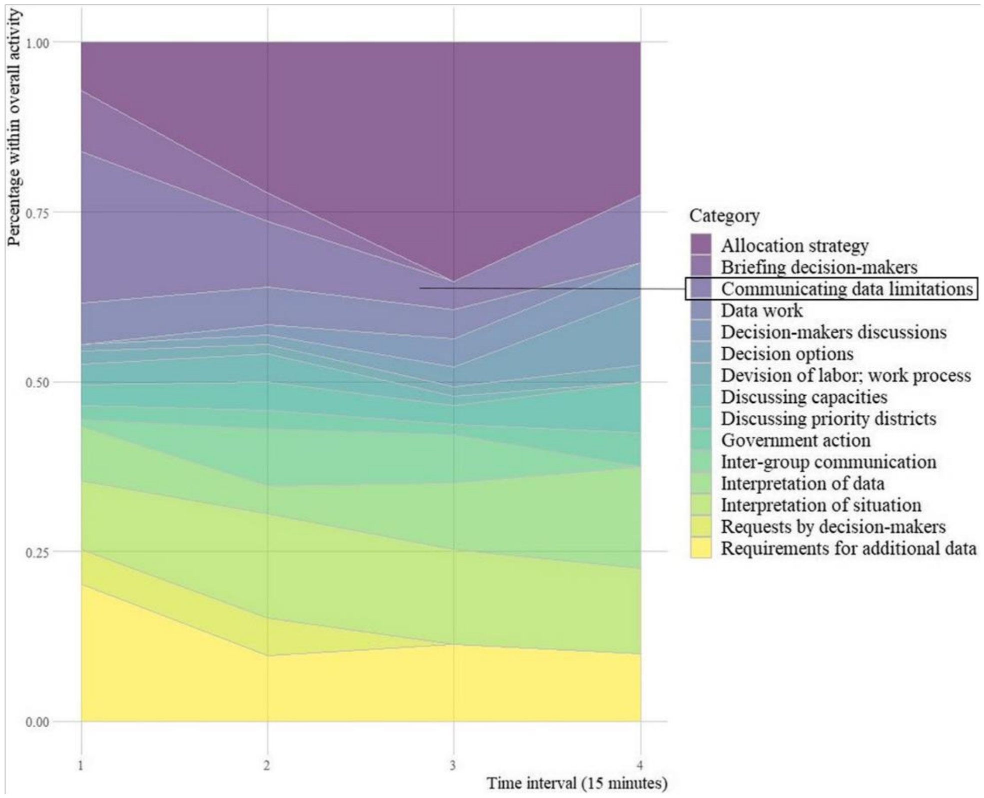

Figure 4.6. Experiment stage 2 results of the coding and categorization process. The graph shows the share (in percentage over time) of the coded categories within the overall activities of the groups. Initial discussions on data limitations were not sufficiently followed-up upon and discussions on allocation strategy dominated the group discussions from the second interval onward

Groups showed stronger debiasing behavior at the beginning of the session, where data limitations were communicated and discussed. However, this focus was reduced over time, only increasing slightly in the last time interval. This pattern of debias neglect was already observed in stage 1.

Requirements for additional data mainly were articulated in the beginning and were then constant throughout the later intervals even though it was communicated to the participants that there would be no additional data provided during the experiment. This behavior shows a heavy dependency on more data and the conviction that more data will help the decision process, even if the quality of the future data is unknown and can be questioned if the currently available data is already of low quality.

Interpretation of the situation out-weighted the interpretation of the data throughout all intervals, showing the influence of the decision-makers who relied more on their previous experience to assess the situation than basing their assumptions on the available data that was known to have limitations.

Overall, the joint information management and decision-making process between analysts and decision-makers did not result in sufficient debiasing, and allocation decisions were made based on biased information.

4.4.3 Persistence of Bias in Sequential Decisions

In the final phase, participants were asked to select additional information that supported or conflicted with their allocation decisions. Our analysis of the survey responses shows that the mean count of selected supporting datasets was higher ($M = 2.94$, $SD = 1.56$) than the mean count of selected opposing datasets ($M = 1.82$, $SD = 1.88$), indicating that participants selected more supporting than opposing datasets. Wilcoxon signed-rank test was used to test if the discrepancy between means was statistically significant. The result reveals significant confirmation bias in the participants' selection of additional datasets ($n = 17$, $z = -2.537$, $p = .011$). We, therefore, find that our participants showed significant confirmation bias and that the bias drives their information selection decisions.

This is particularly concerning as the participants' preliminary decisions were flawed and based on biased information. In stage 3, participants tried to substantiate further their previously biased decisions instead of using the opportunity to counter-check their assumptions. Confirmation bias reinforced their biased assumptions and strengthened their reliance on potentially further biased data.

A significant confirmation bias at this stage is in line with our observations in the earlier stages of the experiment, where participants followed an exploitative and satisficing strategy given the time pressure, rather than an exploratory strategy. Although much of the literature on crisis and disaster management suggests an adaptive approach to manage the uncertainties that typically exist at the onset of a crisis (Comes et al., 2020; Quarantelli, 1988), we found that over time the initial mental models and decisions became deeply ingrained and persistent. As such, it became increasingly difficult for participants to implement a debiasing strategy that allowed them to correct their decision because the initial data biases were never effectively discussed and mitigated, even though new information became available that could have facilitated corrections. Even though they knew that their information had been incomplete and possibly flawed, the participants' debiasing behavior was diminished, and they were overconfident in their decisions. If participants would have laid more focus on discussions on data limitations, they might have been more mindful and showed a more balanced or even disconfirming information selection behavior to correct previously flawed decisions.

4.5 Discussion

4.5.1 Contribution to Literature

Our experimental evidence adds to the theoretical understanding of the role of biases and debiasing strategies in crisis information management (Comes, 2016; Mirbabaie, Ehnis, Stieglitz, Bunker, & Rose, 2020; Ogie, Forehead, Clarke, & Perez, 2018). Our experiments show that a reason for the lack of debiasing efforts is the urgent context of crisis information management and the strong group cohesion that lead to a neglect of critical data assessments within the initial exploratory step of the analysts. Debiasing behavior is particularly strong during the onset of workgroup collaborations. However, these debiasing efforts are increasingly neglected as time pressure builds and mental models are formed. This implies that rather than using additional capacity to broadly scan the available information, the process follows a satisficing strategy, whereby one dataset is 'good enough' to develop information products quickly that are directly actionable and support decision-making. While this might result in a quick approach to address humanitarian needs as allocation decisions are made fast, there is a danger that the decisions made are ill-informed. Because biases remain untreated, information products and decisions become affected by them.

Even though conventionally there is hope that additional data analysts will mitigate the impact of data bias, our findings show that even though biases are detected, they are not mitigated. Hughes and Tapia (2015) emphasized the expertise of external analysts with specialized software. We find that the preference to start data analysis quickly in participants' preferred tools moves the focus away from debiasing efforts. The law-of-the-instrument was clearly present in our groups, especially in the initial phase of the experiment. This indicates that our participants had strong preferences for their preferred information systems. In an effort to understand their own data, participants approached data analysis with tools they were familiar with and knew best. Datasets from other group members, and their potential differences, were not receiving due attention.

Our findings show the interplay of data and cognitive bias in crisis response. We find that confirmation bias can exacerbate the reliance on biased assumptions and that data biases and cognitive biases can reinforce each other, leading to amplified bias effects. As proposed by Comes (2016), and experimentally confirmed in our study, crisis information managers and decision-makers are prone to significant confirmation bias. Our participants significantly more often selected new information that confirmed their previous assumption about priority districts, which was influenced by biased data. This holds true even considering the broad level of experience of our participants, and although they did know the initial data was biased. We therefore show that awareness of bias does not automatically lead to bias mitigation. The urgent, uncertain, and resource-constraint contexts of crisis response have led to calls for adaptive management (Anson et al., 2017; Charles et al., 2010; Janssen & van der Voort, 2020; Merl et al., 2009; Schiffling et al., 2020; Turoff, Chumer, et al., 2004). Our findings indicate that such adaptive approaches can fail due to the interplay of data and cognitive bias.

4.5.2 Mindful Debiasing and Future Research

Future CIM theory needs to further explain the interplay of data bias and cognitive bias, looking into reinforcing and mitigating mechanisms. Crisis situations are known to cause stress in responders, and this stress is known to increase the susceptibility to cognitive biases such as confirmation bias. Especially in data-critical environments like CIM, where responders have to handle various information systems, techno-stress can further increase stress and susceptibility to biases. Mindfulness has been found to alleviate some of this stress (Ioannou & Papazafeiropoulou, 2017) and therefore is a promising strategy to reduce the susceptibility to cognitive bias in CIM. Mindfulness means being more aware of the context and content of the information one is engaging with (Langer, 1992). When crisis information managers are mindful about the context and content of the information they are engaging with, falling into the trap of ever-confirming information-seeking behavior becomes less likely. In a mindful state, information managers would be more open to new and different information, and able to develop new categories for information that is received. In contrast, in a less mindful state, people rely on previously constructed categories and neglect and ignore the potential novelty and difference within newly received information. Being mindful means to increase one's metacognition, i.e., being aware and having a focus on one's own thought processes (Croskerry et al., 2013). Boosted metacognition might be effective in mitigating confirmation bias (Rollwage & Fleming, 2021). Future research should investigate the effectiveness of such debiasing efforts empirically.

Like Ogie et al. (2018), we argue that data created in crises, especially from the affected population, can be subject to a multitude of biases, which have to be taken into account if systems and algorithms are designed that are supposed to turn those data into objective, neutral decision recommendations. In a similar vein as Weidinger, Schlauderer and Overhage (2018), who called for more research on users' perception of novel information systems and technologies for crisis response, we argue, crisis information management literature needs to account for data biases that systematically over- or under-represent issues, social groups, or geographic areas in the form of representational biases. If information management does not account for biases, resulting information products can become flawed and negatively influence decision-making, with detrimental effects for crisis-affected people.

Previous research proposed new forms of information systems, models, and algorithms to support resource allocation decisions in crises (Avvenuti, Cresci, Del Vigna, Fagni, & Tesconi, 2018; Kamyabniya, Lotfi, Naderpour, & Yih, 2018; Schemmer et al., 2021). We argue that such systems need to consider the abilities and limitations of information managers and decision-makers to identify and mitigate biases in the usage of such systems. This includes data biases as well as cognitive biases. We emphasize previously proposed debiasing efforts, e.g., nudging (Mirbabaie et al., 2020), that can be implemented into information systems for crisis response with the objective to mitigate cognitive biases.

Previous research provided examples on effective debias interventions. Interventions can range from fast and frugal options to intensive training sessions (Sellier et al., 2019). Information managers and decision-makers can be trained to counter-check their assumptions by actively seeking disconfirming information and considering the opposite of their preliminary hypothesis (Lidén et al., 2019; Satya-Murti & Lockhart, 2015). Future research needs to test the effectiveness of such interventions in crisis settings.

We reiterate calls for sensemaking support in crisis response (Comes et al., 2020; Muhren et al., 2010). We add to that with our finding that decision-makers can act as advocatus diaboli to their external analyst partners. By trying to make sense of the unfolding situation and posing confrontational questions to external analysts regarding the quality and shortcomings of the data that underpinned developed information products, decision-makers uncovered important data gaps quickly. However, these also have to be effectively followed-up upon to lead to successful debiasing.

4.5.3 Implications for Practice

It can be observed that the response organizations are building up stronger internal crisis information management structures. Where once there were large skill gaps in data analysis and mapping, digital response concepts are now being observed within established organizations (Frank Fiedrich & Fathi, 2021). External analysts are being integrated into permanent structures.

However, our findings suggest that crisis information management needs to invest in detecting, and most importantly, mitigating biases. Even if complete debiasing is not feasible, we give some concrete implications of our findings on crisis information management practice.

First, bias-awareness trainings can highlight the potential influence of biases in information management and decision-making, and provide guidelines for debiasing. We found that work groups initiated debiasing efforts and became aware of biases. Debiasing then however lost its significance in favor of quick analysis results and decision-making. More awareness of the pitfalls of biases might shift the focus to debiasing first, before final information products are developed and decisions are made. Postmortem analysis of information management and decision-making processes after crisis response can be implemented in lesson learnt and debriefing sessions. Further, large-scale crisis response trainings, which are organized annually by major response organizations to train together for real crisis event (e.g., SIMEX, TRIPLEX), should incorporate debias interventions in training agendas.

Second, the development of models, algorithms and information systems to support information management and decision-making in crisis response, should implement functions that help identify and mitigate biases in (a) the datasets used by these systems, and (b) the cognitive processes of system users.

4.6 Limitations

In our paper, we present an initial exploratory study on the interplay of data and confirmation bias in time-critical sequential decisions. Because of the exploratory nature of our study, there are several limitations that can be addressed in future research.

First, and to the best of our knowledge, while our study is the first of its kind that brings external analysts together with decision-makers to study their joint CIM process in a realistic scenario-based experiment, and our participants were all experienced in their roles, the number of participants is a limiting factor in our study. Similar studies have reported larger participant groups, mostly of inexperienced students and other laypersons who are easy to recruit. We suggest to expand on our findings in additional larger-scale experiments and surveys across diverse groups and different professional experiences.

Our experimental design was inspired by hidden profile experiments. In traditional hidden profile experiments (Lightle et al., 2009; Stasser & Titus, 1985), participants are asked to study their received information before joining the group conversation. In contrast, we allowed for discussions from the start because crisis information management is characterized by fast, agile communication. Our approach decreased the chances that participants constructed a rigid mental model of what data they received initially. Two characteristics of our research design counter this shortcoming. First, we allowed for perfect recall, i.e., participants kept all materials during the workshop experiment. Second, participants needed to continuously engage with the data by aggregating, analyzing, and visualizing it, so they had to build a deep understanding of the data during the experiment.

It is a major challenge to simulate a realistic crisis environment in an experimental setting. This includes a realistic but still unknown scenario, decision-making under urgency, uncertainty, high stakes, and constraint resources, allowing for interactive collaboration with multiple actors, and providing equipment that resembles experts' real work environment. Simplifications have to be made to make the experiments controllable. In addition, we had to consider that some organizations might implement and pursue different approaches to information management and decision support than required by the tasks we set. In real-world scenarios, external analysts work with a larger group of colleagues. Because of the framework required by our experiment, for example, the discussions on the creation of the information products had to be objectively observed on site, it was not possible to include further external analysts from those remotely working communities. Here, we suggest to complement our findings with more ethnographic and field studies in real disasters to observe real-world debiasing and decision-making behavior.

4.7 Conclusion

Crisis response organizations integrate external analysts into the CIM process to strengthen their digital resilience. In this capacity, external analysts collect and analyze data and develop information products (e.g., maps, tables, infographics) for decision support. While this extended capacity is meant to improve the evidence base for decisions, the CIM process remains challenged by circumstances of urgency, uncertainty, high stakes, and constraint resources. Consequently, crises are prone to induce biases into the data as well as the cognitive processes of external analysts and decision-makers. We investigated how biases influence the CIM process between experienced external analysts and decision-makers through a three-stage experiment.

Our findings show that data biases, even if detected, influence the development of information products for crisis decision support. We show that effective debiasing does not happen because crisis information managers have a strong commitment and urgency to deliver a presentable information product that is actionable enough for decision-makers to make decisions directly. Efforts for creating information products are prioritized, and debiasing is neglected. In subsequent deliberations and decision-making discussions, decision-makers are influenced by biased information products in their allocation decisions of scarce resources. Confirmation bias amplifies the reliance on problematic assumptions that were formed based on biased data. This implies that the biased, misleading information that shapes initial decisions is perpetuated by a vicious cycle of biased information search that influences future decisions. Our findings indicate that decisions in crisis response can only be effective if initial data and confirmation bias are identified and mitigated. Mindful debiasing could be a successful strategy to improve broad information search and tackle both biases.

5 Countering confirmation bias in crisis decision-making: the effect of nudging

This chapter is based on: Paulus, D., de Vries, G., Janssen, M., Van de Walle, B. (under review). Countering confirmation bias in crisis decision-making: the effect of nudging. The first author conducted the literature review, designed and conducted the data collection and analysis process and wrote the manuscript. The co-authors provided feedback on the data collection and analysis process and earlier versions of the manuscript.

5.1 Introduction

The humanitarian response to crises addresses the hardship of millions of people every year worldwide (United Nations, 2019). Humanitarian crises have immense societal consequences, including the displacement of people and food insecurity. Evaluating the importance of information is crucial within the coordinated response to these crises (Van de Walle & Dugdale, 2012; Yang & Hsieh, 2013). However, due to the high urgency to act, crisis responders frequently have to make decisions on response priorities with contradicting and biased data or no relevant information at all (Comes et al., 2020; Knox Clarke & Campbell, 2020).

A typical data bias in crises is accessibility bias. Humanitarian organizations frequently report that access constraints, e.g., damaged infrastructure or a lack of permits from authorities, limit data collection from specific geographic areas (Labonte & Edgerton, 2013). Inaccessibility leads to imbalanced data availability across crisis-affected regions, resulting in a bias in the available data (Fast, 2017; Maxwell, Hailey, Spainhour Baker, & Janet Kim, 2018). Specifically, data from the least accessible regions are underrepresented in datasets (Maxwell, Khalif, Hailey, & Checchi, 2020).

While the crisis and response efforts continue, new information that helps inform decision-making becomes available over time. However, newly available information is often contradictory (Van de Walle, Brugghemans, & Comes, 2016): some information supports initial decisions while others oppose previous decisions suggesting to change response priorities(Comes, 2016). Confirmation bias literature however suggests that crisis responders evaluate supporting information as more important than opposing information (Curnin, Brooks, & Owen, 2020; Jonas, Schulz-Hardt, Frey, & Thelen, 2001). The danger of biased information evaluation is that inferior decisions remain uncorrected even when better information is available (Kuipers, Verolme, & Muller, 2020). Unbiased information might be seen as less important simply because it opposes previous decisions. Conversely, information supporting earlier decisions might be seen as more important even when it is biased. Given the likelihood of confirmation bias in humanitarian information evaluation, possible mitigation strategies need to be found (Groenendaal & Helsloot, 2021; Wolbers, 2021).

Potentially effective strategies to counter confirmation bias in information management can be drawn from nudging theory (Sunstein & Thaler, 2008). Nudges are subtle hints, for example implemented in information systems, that aim at reducing biased human behavior. Nudging as debiasing interventions is particularly suited in crisis response because it does not require significant time and cost investments to implement (Schneider, Weinmann, & Brocke, 2018).

Warning and *default* nudges have been the most widely studied types of nudges (Hummel & Maedche, 2019). A warning nudge explicitly warns users about their potential biased behavior (Rieger, Draws, Theune, & Tintarev, 2021). The goal of the warning is to interrupt people in their potentially biased automatic over-valuation of supporting and de-valuation of opposing information. The warning aims to trigger a more thorough conscious elaboration of the available information, aimed at understanding the true quality of the available information. A default nudge takes the opposite approach. Rather than warning decision-makers of potential bias, a default nudge pre-selects superior choices in a choice scenario, e.g. an information system user interface. Default nudges, for example, have proven successful in nudging people to a more privacy-conservative behavior in information systems (Baek, Bae, Jeong, Kim, & Rhee, 2014).

Both types of nudges can be implemented in crisis information systems to lead users to a more unbiased information evaluation. However, the literature so far provides no direct comparisons of the two nudging types, and evidence is particularly lacking in the crisis response domain. This research experimentally tests the effectiveness of warning and default nudges to prioritize crisis information correctly in a fictional yet realistic humanitarian crisis scenario.

The following Section reviews previous research on humanitarian information management, confirmation bias, and nudging. Section 5.3 describes the method of our experimental study. Section 5.4 reports the results of the online experiment. Section 5.5 discusses our contributions to crisis management literature and practice. Section 5.6 and 5.7 mention the limitations of this research, give recommendations for future research and conclude the paper.

5.2 Literature background

5.2.1 Data bias and confirmation bias in humanitarian information management

Conflicts affect the physical infrastructure of countries but also disrupt their digital and information infrastructure (Gohdes, 2015). Crisis responders need to constantly re-assess information on the humanitarian needs of affected populations. A key issue is the displacement of population groups due to conflict and Climate Change, with 80 million people having been forcibly displaced between 2010 and 2019 (Sarzin, 2017; United Nations, 2021). Responders face the dilemma of having access to large volumes of irrelevant data leading to information overload (Hiltz & Plotnick, 2013), but lacking relevant, timely, complete, and trustworthy information for decision support (Greenwood, Howarth, Poole, Raymond, & Scarnecchia, 2016; Jacobsen & Fast, 2019).

Crisis uncertainty and urgency induce biases in available datasets (Fast, 2017). We define bias in data as the systematic deviation of a variable within a dataset compared to the actual distribution of the variable in the real world (Jo & Gebru, 2020). A major cause for data bias in crises is what previous studies called *inaccessibility* (Altay & Labonte, 2014; Day, Junglas, & Silva, 2009). Inaccessibility of information refers (a) to geographic areas and demographic groups of affected populations being unreachable for or excluded from data collection and (b) to data and information that is *"known or assumed to exist"* but unavailable for crisis responders (ibid.). Reasons for inaccessibility in crises are manifold: political authorities might deny access to specific geographic regions (Maxwell et al., 2018), response organizations might refrain from accessing insecure combat regions due to staff security concerns, or information might not be shared between organizations because it provides a competitive advantage in acquiring donor funding (Van de Walle & Comes, 2015). These challenges will result in data bias because more information is available from easier-to-access areas and sources and less from others. Geographic areas that are repeatedly unavailable for data collection become blind spots for humanitarian information management and decision-making.

Response priorities need to be set in the immediate aftermath of a novel crisis event, such as conflict-induced displacement. However, in this early phase, decision-makers lack information. When no relevant information is available, decisions still need to be made (Janssen, Lee, Bharosa, & Cresswell, 2010; Klein et al., 2010; Knox Clarke & Campbell, 2020). After initial decisions, new information becomes available as organizations implement data collection efforts to inform follow-up decisions better (Van Den Homberg, Meesters, & Van de Walle, 2014). From the available information, recommendations for decisions are drawn.

While the newly available information is meant to improve future decisions, it is often contradictory and suggests different courses of action, some supporting, others opposing previous decisions (Brooks, Curnin, Owen, & Bearman, 2020; Van de Walle et al., 2016). It is essential to assess the available information and decide which information to rely on to inform follow-up decisions (Comes, 2016). Therefore, responders need to rate what information is more and what information is less important. In an operational sense, this means the quality of the available information needs to be gauged quickly. Because of geographic access constraints in crises, a core attribute of a data quality is its completeness, i.e., how much of the crisis-affected area was reached and assessed during data collection and is thus covered by the dataset. When newly obtained information provides more evidence for a course correction, i.e., opposing an initial decision, a responder should give this information higher importance.

Accepting that they might have initially taken a wrong decision is not easy for decision-makers. Confirmation bias literature suggests that when people face contradictory information sets, of which one set confirms a previous decision and another set opposes it, people tend to select confirmatory information significantly more often (Fischer, Lea, et al., 2011; Jonas et al., 2001; Nickerson, 1998). Cognitive dissonance theory can explain this confirmation-seeking behavior (Festinger, 1957). Being exposed to disconfirming information increases a mental (i.e., cognitive) tension that people want to reduce. Therefore, people will favor confirming information (ibid.).

Because of confirmation bias, decisions that should be corrected might remain uncorrected in crises (Paulus, Fathi, Fiedrich, Van De Walle, & Comes, 2022). An overly confirmatory information search behavior is dangerous in urgent, high-stakes decisions (Pines, 2006; Wolbers, 2021). It can lead crisis responders to ignore important information simply because it opposes initial choices (van Stralen & Mercer, 2015). In other words, crisis responders should not exert confirmation bias but rely on qualitatively better opposing information in such situations. This behavior would require crisis responders to overcome their confirmation bias and instead switch to a disconfirming tendency. Otherwise, scarce resources might get misallocated according to wrong priorities, negatively affecting vulnerable communities.

Most studies on confirmation bias used supporting and opposing information sets with equal quality and completeness (Fischer, Lea, et al., 2011; Hart et al., 2009; Jonas et al., 2001). While these studies provided strong evidence for the pervasiveness of confirmation bias, they fail to represent the real-world challenge of crises where information is contradictory and biased. We know less about people's information evaluation behavior when supporting information is biased while opposing information is unbiased (Spezzano, Shrestha, Fails, & Stone, 2021; Westerwick, Johnson, & Knobloch-Westerwick, 2017; Zhou & Shen, 2021). Because people focus more on supporting information, in this research, we investigate how this changes when bias distorts the supporting information.

Depending on the strength of data bias in the newly available information, people might be able to act as their own devil's advocate and reduce their confirmation bias (Lidén, Gräns, & Juslin, 2019). Specifically, when supporting information is only weakly biased while opposing information is unbiased, people might still show confirmation bias because the weak bias is not seen as a major flaw in data quality. However, when supporting information becomes strongly biased while opposing information remains unbiased, people might overcome their confirmation bias because of the strongly increasing cognitive dissonance.

H1 – Strong data bias in supporting information reduces confirmation bias in humanitarian information evaluation.

Nudging can be an effective confirmation bias mitigation approach, as explained in the following Section.

5.2.2 Debiasing through nudging

Literature suggests several forms of debiasing strategies for confirmation bias. Some require significant time and resource capacities, two factors that are severely limited in crisis response (Campbell & Clarke, 2018; Goetz & Patz, 2017). Others, however, are based on nudging theory (Sunstein & Thaler, 2008). Nudges are subtle hints that aim to lead people to make favorable decisions. As relatively low-cost, time-efficient debias interventions, nudges are well suited to crisis response.

Nudging theory posits that subtle hints can significantly influence human behavior (Sunstein & Thaler, 2008). Previous research found that nudging can reduce confirmation bias (Pennycook et al., 2019; Rieger et al., 2021; Thornhill, Meeus, Peperkamp, & Berendt, 2019). The type of nudge plays a vital role in the design of mitigation interventions. In an experimental online study on misinformation, Pennycook et al. (2019) investigated people's accuracy perceptions and sharing intentions of conflicting online information. They found that nudges that shift people's attention to the accuracy of available information increase people's engagement with higher quality information. Other research focused on influencing consumer behavior through nudges framed as social norms (Demarque, Charalambides, Hilton, & Waroquier, 2015). For example, nudging consumers into more ecology-friendly purchase decisions can be effective when consumers are informed about the product's ecological footprint or how many other consumers have bought the product before (ibid.).

However, nudging crisis responders with normative statements is somewhat unrealistic because they are confronted with highly dynamic and uncertain problems to which no clear precedent and thus normative guidance exists (Gralla, Goentzel, & Fine, 2016). However, nudging literature also provides other types of nudges that are better suited for crisis response. Hummel and Maedche (2019) found that *default* and *warning nudges* are the most common nudging interventions studied. Both forms can be implemented in information systems (Schneider et al., 2018), which in turn can support crisis responders to assess information better (Mirbabaie, Ehnis, Stieglitz, Bunker, & Rose, 2020). In their online experiment, Rieger et al. (2021) found that a warning nudge that informed people about their potential confirmation bias in evaluating web search results effectively increased engagement with opposing information. Their warning nudge had two parts: participants received a warning message about their possibly biased behavior and a brief explanation of confirmation bias.

Information processing theories can help explain why warning nudges work. Dual-process theories such as system 1 and system 2 (Kahneman, 2011) and the Elaboration-Likelihood-Model (Petty & Cacioppo, 1986) describe that people process information in roughly two ways. One quick, heuristic or automatic approach that is prone to bias and one more conscious and elaborate approach which can identify and reduce bias. Warnings about potential biased information selection can be successful because they lead people from the heuristic route to a deliberate route (Battaglio, Belardinelli, Bellé, & Cantarelli, 2019). However, while warning nudges have delivered promising results, to our knowledge there has been no investigation into their effectiveness in reducing confirmation bias in humanitarian information evaluation.

H2 – A warning nudge leads to lower confirmation bias in humanitarian information evaluation than no nudge.

Default nudges are often digitally present in information systems, for example to nudge people toward a more privacy-concerned user behavior on websites (Baek et al., 2014). Default nudges work because they reduce the cognitive effort required by decision-makers. Being provided a default option allows people to center their assessment of plausible answers around the default anchor. It takes less cognitive effort to go with the default than it takes to (a) find reasons for why the default value is flawed and (b) find reasons for the right deviation from the default to adjust an answer. People presented with a default choice assume there must be some merit behind the decision for the default (Sunstein, 2017). Similar to research on warning nudges, we want to assess how effective default choices are in reducing confirmation bias in humanitarian information evaluation.

H3 – A default nudge leads to lower confirmation bias in humanitarian information evaluation than no nudge.

For the future design of bias mitigation strategies in crisis information management, it is important to understand what strategy is likely the most effective. A recent review of the nudging literature shows that default nudges yielded the largest effect sizes in experimental studies (Hummel & Maedche, 2019). To verify whether a default nudge is more effective than a warning nudge in reducing confirmation bias in crises, we compare the results between our two interventions. While we expect both types of nudges to reduce confirmation bias, we also expect a default nudge to be more effective in confirmation bias reduction than a warning nudge.

H4 – A default nudge leads to lower confirmation bias in humanitarian information evaluation than a warning nudge.

Lastly, it needs to be established whether a reduction of confirmation bias has an actual impact on decision-making. Less confirmation bias should be associated with better decisions, i.e., a correction of an initial decision.

H5: Lower confirmation bias is associated with more corrected decisions.

Figure 5.1 summarizes the above Hypotheses.

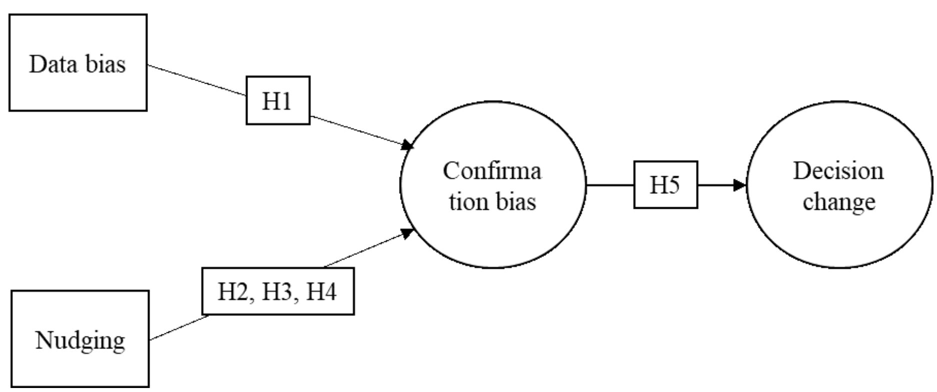

Figure 5.1. Conceptual framework of this study.

5.3 Method

5.3.1 Procedure

We use an online, scenario-based experiment to test our hypotheses. The experiment consists of five parts, outlined in *Figure 5.2*.

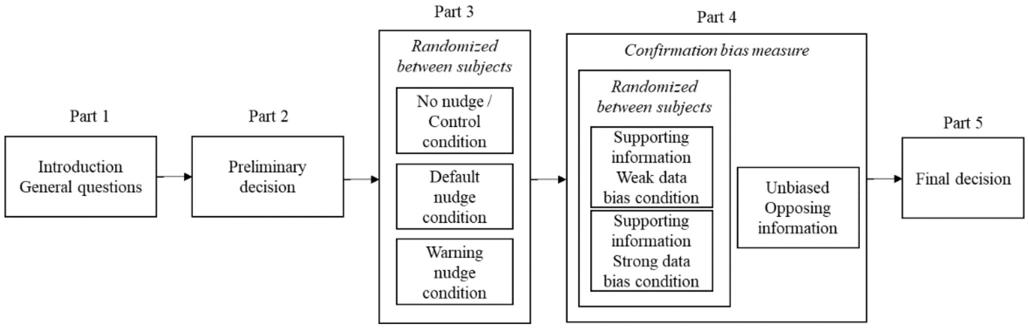

Figure 5.2. Methodological setup and procedure.

In *Part 1*, participants (see 5.3.3 Sampling) are asked to answer general questions about their age, gender, level of education, income, and familiarity with the topic. The objective of the general questions was to ensure homogeneity between our experimental groups because participants' allocation into the experimental conditions was random.

In *Part 2,* participants are introduced to a fictional humanitarian scenario. They are requested to make an initial decision on a response priority (delivery of food or shelter items) without having any relevant information at the time, representing the real-world crisis challenge of uncertainty, urgency and resource constraints.

After making the initial decision, in *Part 3,* participants are randomly allocated into one of three nudging conditions: (1) *no nudge (control) group*, (2) the *default nudge group*, or (3) the *warning nudge group*.

After that, in *Part 4*, participants are further randomly allocated to one of two data bias conditions: (1) the *weakly biased supporting information group* or (2) the *strongly biased supporting information group*. Therefore, the experiment has a 3x2 factorial design with the independent variables *nudging condition* (no nudge/control, default nudge, warning nudge), and *data bias condition* (weak data bias, strong data bias). *Part 4* also gives participants a scenario update that states new but somewhat incomplete and contradictory information is now available. Participants' task is to rate the importance of the new information to inform future decisions. The difference between rated supporting versus rated opposing information establishes our dependent *confirmation bias* variable.

Finally, in *Part 5*, participants are asked to make a final decision, i.e., whether they would stick to their initial decision or change it based on the newly received information. This establishes our dependent *decision change* variable.

5.3.2 Materials and measures

5.3.2.1 Experimental scenario and initial decision (Part 2)

We tailored our experimental scenario to a real-world humanitarian response context. A major problem for crisis response in conflicts is the rapid displacement of population groups (Sarzin, 2017). As conflicts evolve, frontlines change, and as combatants target different areas, the humanitarian needs of affected populations also change (Maxwell, 2019). Managers of humanitarian organizations need to adapt and prioritize response activities according to the changing needs (Hobbs, Gordon, & Bogart, 2012). However, they have to do so in the uncertain information environment crises create (Warnier, Alkema, Comes, & Van de Walle, 2020). A crucial task is to decide whether the distribution of food or shelter items should be prioritized during the immediate response to displacement, while relevant information to support a decision is lacking. Participants were presented the following scenario text and task:

> *Imagine you are the manager of an humanitarian organization. You are working in a country where a conflict affects the population in numerous districts. The situation is worsening quickly. You are under pressure to act fast and deliver aid to people in need. Your organization is specialized in the delivery of shelter and food items. The organization's resources only allow to prioritize one of its two programs (shelter or food). As the manager, you have to decide which program to start right now. You want to make a decision based on the best available data but the data collection has only just started and there is no data available yet. In order to act quickly before data is available, you already have to decide what your organization should prioritize.*
>
> - o *Prioritize food items*
> - o *Prioritize shelter items*

5.3.2.2 Scenario update and confirmation bias measure (Part 4)

The need for additional information to inform future decisions drives data collection efforts (Thieren, 2005). After participants made their initial decisions and were allocated to one of the 3x2 experimental conditions, they received a scenario update. The update informed participants that some time has passed and new but incomplete and contradictory information was available in the form of two datasets. For each dataset, five recommendations summarized their main insights. One dataset and its recommendations supported participants' previous choice of response priority (food or shelter), the other dataset and its recommendations opposed the previous choice. Participants were reminded of their initial decision at the top of the page (*Your chosen priority: [Food / Shelter]*). Participants were told their task was to assess the recommendations by their importance:

> *After some days and while the first aid delivery of your organization is taking place, you receive two datasets that describe the situation. Data collection has been difficult because the conflict makes some districts inaccessible. As a result, the datasets are somewhat incomplete and contradictory. Your headquarter urges you to brief them quickly on the newly available data. They want you to tell them what the most important recommendations are and they don't want to receive contradictory advice. Review the two datasets and the ten recommendations that can be drawn from them below. Rank the importance of each recommendation to brief your headquarter. (1 = Not at all important, 2 = Slightly important, 3 = Moderately important, 4 = Very important, 5 = Extremely important)*

Below the scenario update text, participants were presented with two short descriptions of both datasets and their five corresponding recommendations. See Appendix D for a complete instrument description that shows what was presented to participants in each experimental condition.

<u>Dataset 1 (supporting dataset).</u> As can be seen in the complete instrument description (Appendix D), dataset 1 suggested *shelter* was the priority when participants selected *shelter* as a priority in their preliminary decision. Similarly, dataset 1 suggested *food* was the priority need when participants selected *food* as a priority in their preliminary decision. In other words, dataset 1 was the supporting dataset, confirming participants' preliminary decision. As the supporting dataset, dataset 1 represents either a weak or a strong data bias according to the condition the participant was assigned to. In the weakly biased condition, the supporting dataset covered 80 of 100 districts. In the strongly biased condition, the supporting dataset only covered 20 of 100 districts.

Dataset 2 (opposing dataset). Dataset 2 opposed participants' preliminary decisions (suggesting *food* when *shelter* was selected and vice versa). In contrast to dataset 1, dataset 2 was always an unbiased and complete dataset where 100 of 100 districts were covered.

Nudging. The complete instrument description (Appendix D) further shows how the warning and default nudges were implemented. In the no nudge/control condition, no warning was displayed and no recommendations were rated by default. This means, the importance ratings for each recommendation were blank when participants saw them. In the warning nudge condition, the warning was displayed under the description of the biased supporting dataset, i.e., dataset 1. In the warning nudge condition, also no recommendations were rated by default (i.e., recommendations ratings were blank when participants saw them). In the default nudge condition, no warning was displayed but the recommendations of the biased supporting dataset were rated 1 (=not at all important) by default on the importance scale, and the recommendations of the unbiased opposing dataset were rated 5 (=extremely important) by default on the importance scale.

Confirmation bias measure. As shown above, participants were asked to rate all recommendations' importance for future decisions on a five-point Likert scale. Per participant, the means of the five rated supporting and the five rated opposing recommendations were calculated and the difference between both means was taken which established the dependent confirmation bias variable. This method to assess confirmation bias is comparable to previous studies that measured confirmation bias through testing for significant differences between the mean numbers of selected supporting and the mean numbers of selected opposing information (Fischer, Kastenmüller, et al., 2011; Jonas et al., 2001).

5.3.2.3 Final decision and decision change measure (Part 5)

To test whether lower confirmation bias leads to more corrected decisions, we asked participants if they would change or stick with their initial decision at the end of the experiment (*Part 5*).

In the beginning you made an initial decision on either shelter of food as your priority. You have then received two datasets and different recommendations. Based on that information, if you were to make a final decision now, which response option would you choose?

(Consider if you would stay with your initial decision or switch to another response priority.).

- *Prioritize food items*
- *Prioritize shelter items*

5.3.3 Sampling

Before deploying the experiment, an a priori power analysis for a 3x2 between-subjects ANOVA with $f = 0.25$, $\alpha = 0.05$, and $(1 - \beta) = 0.95$ determined a required sample size of 400 participants. The experiment was conducted online[16] in February 2022. It was implemented in Qualtrics and distributed through Amazon mTurk[17]. Participation was not restricted to countries or regions. Participants above the age of 18 years were eligible to participate. We initially recruited 1,040 participants via the Amazon mTurk platform. Participants were only able to participate once and received USD 1.50 for their participation. 434 participants were excluded because they completed the experiment in less than two minutes, making it unlikely they paid due attention to the experiments' tasks (average completion time of the experiment was four minutes). The remaining 606 participants (gender: 55.3% male, 44.4% female, 0% non-binary/other, 0.3 prefer not to say; age: $M = 36.4$, $SD = 10.3$), were included in testing the four hypotheses. As Table 5.1 shows, random allocation of participants led to homogeneous samples across experimental conditions.

Table 5.1. Sample characteristics of the three nudging conditions.

		No nudge	**Default nudge**	**Warning nudge**
n		226	190	190
Age	*M*	36.5	36.2	36.5
	SD	10.7	10.04	10.2
Gender	*Male*	120 (35.8 %)	114 (24 %)	101 (16.7 %)
	Female	105 (39 %)	76 (28.3 %)	88 (32.7 %)

[16] Initially, the experiment was planned as an in-person experiment. Due to COVID-19, the experiment had to be conducted online.

[17] Studies found that samples recruited through Amazon mTurk are equal in quality compared to other sampling methods (Adame, 2018; Borowski & Stathopoulos, 2020; Loepp & Kelly, 2020; Robertson & Yoon, 2019).

	Prefer not to say	1	0	1
Nationality	*US*	188 (37 %)	165 (32.5 %)	155 (30.5 %)
	India	27 (38.7 %)	19 (27.9 %)	22 (32.4 %)
	Other	11	6	13
Education	*High school*	7 (35 %)	7 (35 %)	6 (30 %)
	College	12 (37.5 %)	9 (28.1%)	11 (34.4 %)
	2 year degree	2 (11.8 %)	6 (35.3 %)	9 (52.9 %)
	4 year degree	135 (35.9 %)	117 (31.1 %)	124 (33 %)
	Professional degree	67 (44.1 %)	50 (32.9 %)	35 (23 %)
	Doctorate	2 (25 %)	1 (12.5 %)	5 (62.5 %)
	Prefer not to say	1	0	0

5.4 Results

To test hypotheses **H1-H4**, we first calculated the confirmation bias measure by building the difference between the importance ratings of supporting and opposing recommendations per participant and then comparing the differences between our experimental conditions. We therefore conducted a two-way ANOVA with the two experimental factors as independent variables (data bias condition, nudging condition) and our confirmation bias measure as the dependent variable. The results are reported in Table 5.2 with post hoc comparisons reported in Table 5.3.

Table 5.2. Results of two-way ANOVA. Independent variables: nudge condition, data bias condition. Dependent variable: confirmation bias

	Type III Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**	**Partial Eta Squared**	**Hypothesis**
Corrected Model	41.210[a]	5	8.242	6.148	0.000	0.049	
Intercept	3.315	1	3.315	2.472	0.116	0.004	
Nudge condition	40.045	2	20.023	14.935	**0.000**	0.047	*See Table 5.3*
Data bias condition	0.659	1	0.659	0.492	0.484	0.001	*H1 not supported*
Nudge * Data bias	0.057	2	0.029	0.021	0.979	0.000	
Error	804.414	600	1.341				
Total	848.160	606					
Corrected Total	845.624	605					

a. R Squared = .049 (Adjusted R Squared = .041)

Table 5.3. Bonferroni post hoc test of two-way ANOVA for multiple comparisons between nudge conditions.

Condition comparison	Mean Difference	Std. Error	Sig.	95% Confidence Interval		Hypothesis
				Lower Bound	Upper Bound	
No nudge - Warning nudge	-0.0424	0.11397	1.000	-0.3160	0.2312	*H2 not supported*
No nudge - Default nudge	**.5366***	0.11397	**0.000**	0.2630	0.8102	*H3 is supported*
Default nudge - Warning nudge	**-.5789***	0.11880	**0.000**	-0.8641	-0.2938	*H4 is supported*

Based on observed means. The error term is Mean Square(Error) = 1.341.
*. The mean difference is significant at the .05 level.

We did not find support for the hypothesis that strong data bias in supporting information reduces confirmation bias in humanitarian information management (**H1 not supported**). **H1** suggested that participants who faced strong data bias in the supporting dataset would rate recommendations from the biased supporting dataset significantly lower than those participants who faced a weak data bias in the supporting dataset. However, both groups of participants, those confronted with a strong and those confronted with a weak data bias in the supporting dataset, did not show significantly different confirmation bias levels. There was no statistically significant difference between data bias conditions, $F(1, 600) = 0.492$, $p < .484$, partial $\eta^2 = .001$.

While there was no statistically significant difference between data bias conditions, there was a statistically significant difference between nudging conditions, $F(2, 600) = 14.935$, $p < .001$, partial $\eta^2 = .047$. Nevertheless, we did not find support for the hypothesis that a warning nudge leads to lower confirmation bias in humanitarian information evaluation compared to no nudge (**H2 not supported**). **H2** suggested that participants who received a warning would rate recommendations from the biased supporting dataset significantly lower than those participants in the no warning condition. However, both groups of participants, those confronted with a warning and those in the no nudge group, did not show significantly different confirmation bias levels. While a warning nudge had a lower confirmation bias score than no nudge ($M_{diff} = -0.042$, 95% CI: -0.316 to 0.231), the difference was statistically non-significant.

We found support for the hypothesis that a default nudge leads to lower confirmation bias in humanitarian information evaluation in comparison to no nudge (**H3 is supported**). **H3** suggested that participants who received default ratings would rate recommendations from the biased supporting dataset significantly lower than those participants in the no nudge condition. Indeed, the participants confronted with default values showed significantly different confirmation bias levels, compared to participants in the no nudge group. A default nudge had a lower confirmation bias score than no nudge (M_{diff} = 0.537, 95% CI: 0.263 to 0.810), a statistically significant difference, $p < .000$.

We further found support for our hypothesis that a default nudge leads to lower confirmation bias in humanitarian information evaluation in comparison to a warning nudge (**H4 is supported**). **H4** suggested that participants who received default ratings would rate recommendations from the biased supporting dataset significantly lower than those participants who received a warning. Indeed, the participant group confronted with default values showed significantly different confirmation bias levels, compared to participants who received a warning. A default nudge had a lower confirmation bias score than a warning nudge (M_{diff} = -0.579, 95% CI: -0.864 to -0.294), a statistically significant difference, $p < .000$.

To test hypothesis **H5**, we used the confirmation bias measure as it was calculated above as our independent variable, and coded the responses by participants to the task in *Part 5* as 0 when a participant did not change their decision, and as 1 when a participants changed their decision. We then conducted binomial logistic regression to test whether the strength of confirmation bias was associated with decision change. The results are reported in Table 5.4.

Table 5.4. Results of binomial logistic regression with dependent variable confirmation bias and independent variable decision change.

	B	S.E.	Wald	df	Sig.	Exp(B)
Confirmation bias	-0.663	0.094	49.323	1	**0.000**	0.516
Constant	-0.851	0.094	82.494	1	0.000	0.427

The logistic regression model was statistically significant, $\chi 2(1) = 65.762$, $p < .000$. The model explained 14.4% (Nagelkerke R2) of the variance in decision change and correctly classified 70.6% of cases. As such, we found that confirmation bias was significantly associated with decision change. More specifically, lower confirmation bias was associated with an increased likelihood of changing decisions ($B = -.0663$, $Wald = 49.323$, $p < .000$). Therefore, **H5** is supported.

5.5 Discussion

5.5.1 Theoretical implications

Previous literature has stressed the potential risks of bias in crisis information management (Curnin et al., 2020; van Stralen & Mercer, 2015) and the importance of mitigation strategies (Wolbers, 2021) but experimental evidence for effective solutions has been lacking. We investigated this knowledge gap by studying how data biases and different nudges affect humanitarian information evaluation and decision-making.

We did not find evidence that confirmation bias is reduced when supporting information is strongly biased. Therefore **H1** was not supported by our experiment. This means, people who are exposed to strongly biased data and people who receive weakly biased data, rate the importance of supporting and opposing information similarly. The finding implies that crisis responders are not responsive to strongly biased supporting information. This might be explained by undervaluing quality issues within humanitarian datasets. Because people experience extreme uncertainty and urgency in crises situations, they neglect critical and effortful data assessments in favor of quick situational judgments, leading to unidentified and uncorrected biases (Paulus et al., 2022).

Our warning nudge that warned participants about the possibility that recommendations drawn from a biased dataset might lead to confirmation bias, did not significantly reduce confirmation bias (**H2**). This is in contrast with literature that found warning nudges effective to reduce confirmation bias (Rieger et al., 2021), A possible explanation is that the warning message created confusion among the participants (Sunstein, 2017). A humanitarian crisis scenario embedded in a fictional conflict is not easily comprehensible for our mostly North American sample that has little to no experience in the humanitarian response to conflicts. The combination of a difficult scenario, involving a high-stake humanitarian decision, contradicting information, and a warning about potentially biased information evaluation might have required too much cognitive effort, leading participants to ignore the warning.

Our findings confirm previous studies on the effectiveness of nudges with default options (Hummel & Maedche, 2019). We find support for the assumption that default nudges influence people's evaluation of humanitarian information. When a default nudge was present, people showed a self-disconfirming tendency, i.e., they saw unbiased and opposing recommendations as more important than biased and supporting recommendations. The finding has implications for the design of crisis information systems that play an increasingly important role for information evaluation (Van de Walle, Van den Eede, & Muhren, 2009). Humanitarian data platforms have been developed to make datasets accessible to the crisis response community and to improve data sharing (Swamy et al., 2019)[18]. Nonetheless, these systems might also exacerbate existing inequalities and mislead humanitarian decision-making when they do not account for potential biases (Mulder, 2020). Our findings suggest to implement nudging interventions based on default values to nudge crisis responders to a more unbiased information evaluation.

Finally, our results show that people with lower confirmation bias have a higher chance to adjust and correct their decisions. This is crucial because previous studies emphasized crisis response needs to be adaptive to new information, i.e., change decisions and courses of action once better information is available (Bharosa, Janssen, Rao, & Lee, 2008; Turoff, Chumer, Van de Walle, & Yao, 2004). This highlights the need for future studies on bias mitigation in crisis response.

5.5.2 Practical implications

Information management and decision-making in the humanitarian response to crises are increasingly supported through information systems, modelling, and machine learning (Yela-Bello, Oglethorpe, & Rekabsaz, 2021). These systems however do not automatically solve the

[18] For example the UN Humanitarian Data Exchange (https://data.humdata.org/).

extreme uncertainty of crises, including the contradiction within available information as well as potential bias in data. Practitioners need to be aware of potential biases and the potentially negative effects biases have on information evaluation and decision-making. Specifically, crisis information systems can incorporate functionality that facilitates bias mitigation. Our findings suggest to implement debias functions based on default nudges rather than warning nudges.

5.6 Limitations and future research

To our knowledge, this research is the first experimental study on confirmation bias mitigation in the humanitarian context. We chose to recruit Amazon mTurk workers and present them a fictional humanitarian scenario. Future research should investigate the effectiveness of bias mitigation strategies with samples of professional crisis responders. As explained above, a possible reason for the non-significant finding of the warning nudge was the cognitive over-burdening of our participants. Experienced crisis responders are more familiar with the type of task we presented in the experiment, have therefore more cognitive resources available and might thus be more susceptible to a warning.

Future experimental studies could be implemented in information systems that are used by humanitarian responders and provide access to real datasets. The most prominent example is the Humanitarian Data Exchange platform[19] managed by the United Nations' Office for the Coordination of Humanitarian Affairs. A user study could test for significant differences in real-world dataset selection when nudging is used or not used.

This study investigated nudging as an intervention strategy to mitigate confirmation bias. As previous research highlighted, other cognitive biases are also likely to affect humanitarian information management and decision-making (Comes, 2016). Future research needs to investigate the effectiveness of nudging and other debias interventions to mitigate the negative effects of cognitive biases other than confirmation bias. Qualitative studies, e.g., interviews and

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[19] http://hdx.org, last accessed July 11, 2022.

field observations, could further add to a deeper understanding of bias effects in crisis response and possible mitigation strategies.

5.7 Conclusion

Because of the urgency, uncertainty and complexity of crisis response, data and confirmation bias likely affect information management and decision-making. Consequently, information might be wrongly evaluated and decisions not corrected when new information becomes available. To find effective bias mitigation strategies that counter the negative effects of biased crisis information management, we conducted an online experiment that compared warning and default nudges.

We find that presenting crisis responders with default options to nudge them toward better prioritization of unbiased information is effective. This finding has implications for crisis information management in general and crisis information system design in particular. Designers of such systems should consider implementing debias functions into user interfaces that nudge users toward higher quality information even if it seems to contradict previous courses of action.

The warning nudge was not effective in our experiment. This might be explained by our sample consisting of lay people rather than experienced crisis responders. The combination of an imaginative humanitarian crisis scenario, a high-stakes decision, the urgency, contradicting information and an additional warning about potential bias, might have overburdened participants, leading them to ignore the warning.

Finally, we show that lower confirmation bias indeed leads to more corrected decisions. This emphasizes the potential of future bias identification and mitigation studies in crisis management literature.

6 Conclusion

Previous literature provided evidence of systematic challenges in crisis information management and identified factors that might trigger biased crisis decision-making. However, the current state of the literature has not linked systematic challenges to actual biases in crisis datasets and reports, and lacks evidence of how cognitive biases affect different crisis decision-makers. This dissertation's scientific objective was to address these knowledge gaps. Through four studies, this dissertation provides four contributions to the literature by (1) studying the causes and consequences of data bias in complex crisis response, (2) measuring the strengths of cognitive biases in humanitarian decision-making, (3) investigating the interplay between data and cognitive bias in crisis response, and (4) finding effective debiasing strategies based on nudging theory.

6.1 Scientific contribution

This dissertation's main scientific contribution is the development of a bias lens on the multi-level–crisis response system that merges the concepts of data bias and cognitive bias. In Chapter 2, this dissertation builds on findings of information management challenges (Altay & Labonte, 2014; Comes et al., 2020; Day et al., 2009; Fast, 2017; Maxwell, Hailey, Kim, et al., 2018; Villa et al., 2019) and extends this knowledge by showing how systematic challenges lead to four types of data bias in crisis response: political bias, accessibility bias, topical bias, and sampling bias. This research further reveals that biased data cascade between operational and strategic levels of the crisis response system, where data biases remain uncorrected because of resource and capacity constraints, decision urgencies, organizational mandates and objectives. On the cognitive information processing side, this dissertation finds in Chapter 3 that experts are less prone to cognitive biases than laypeople with regard to anchoring bias, confirmation bias, framing effect, and bias blind spot. This result confirms previous findings on the role of experience as a moderator of bias reduction (Beratšová et al., 2018; Olsen, 2015; Pines & Strong, 2019). However, even though experts were less bias-affected than laypeople, they still showed significant susceptibility toward anchoring bias, framing effect, and bias blind spot in crisis-related tasks of this dissertation's experiments. Looking at the interplay of data and cognitive bias, this research finds in Chapter 4 that confirmation bias reinforces the reliance on biased data. Crisis responders form early assumptions on biased data because it might be the only available data at the time.

When new information becomes available, confirmation bias leads responders to try to stick with the biased assumptions instead of using unbiased, opposing information to correct assumptions. This finding merges two streams of research, i.e., the confirmation bias and the data bias literature. This research further shows the limits of adaptive management and surging additional capacity during crisis response (Anson et al., 2017; Charles et al., 2010; Janssen & van der Voort, 2020; Merl et al., 2009; Schiffling et al., 2020; Turoff, Chumer, et al., 2004). That is because even when crisis analysts and decision-makers are aware of data biases, efforts to mitigate bias are neglected in favor of quick analysis results. This dissertation shows in Chapter 5 that warnings about potential biases are ineffective. However, presenting users with default options of contradictory but unbiased information reduces confirmation bias and can counter biased information processing in crisis response. This finding contrasts previous knowledge about the effectiveness of warnings (Rieger et al., 2021) and supports the understanding that default nudges are an effective, low-cost bias mitigation strategy (Hummel & Maedche, 2019; Sunstein, 2017).

Figure 6.1 summarizes this dissertation's chapters, their connections between the main concepts, and their scientific contributions.

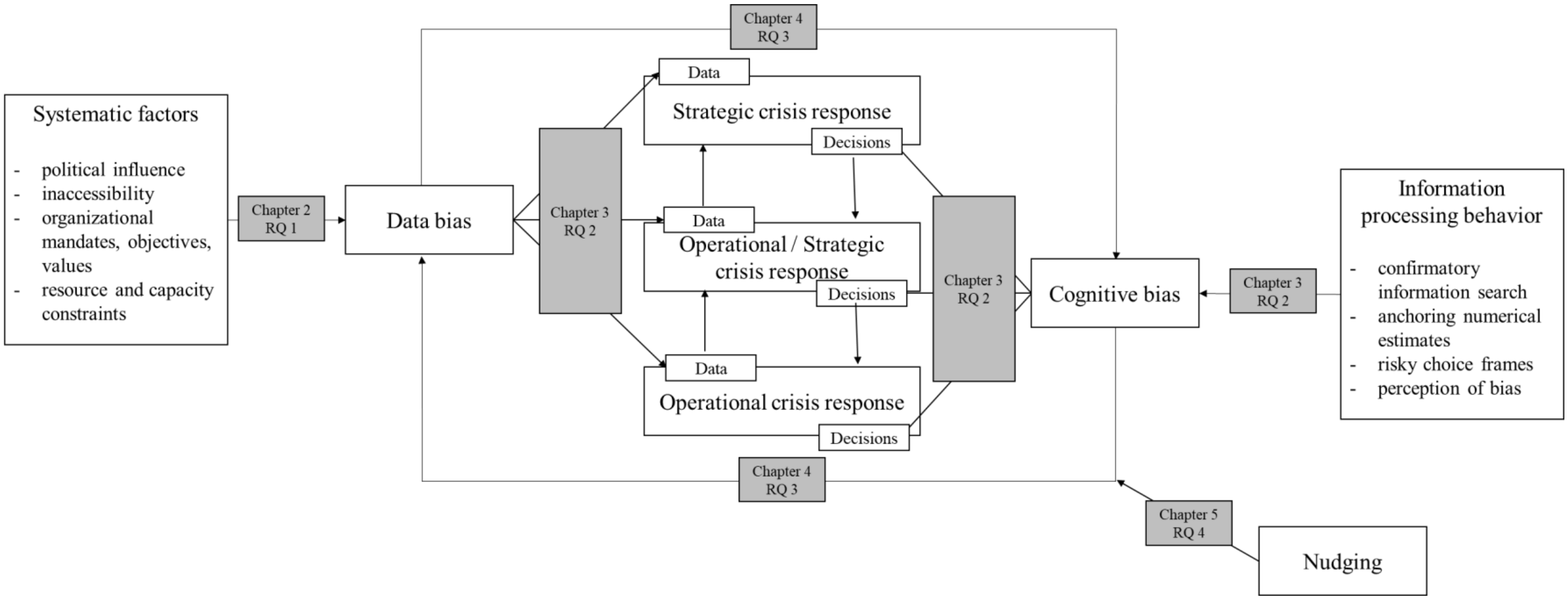

Figure 6.1. Conceptual representation of findings within this dissertation. Chapter 2: Political, accessibility, topical, and sampling data bias affect the three levels of the crisis response system. Data bias is reinforced because of the data-decision-interdependencies between levels. Chapter 3: Crisis-affected people, government and non-profit workers and crisis experts are susceptible toward anchoring bias, framing effect and bias blind spot. Crisis experts are less susceptible than the other two groups. Chapter 4: Confirmation bias reinforces the reliance on biased data. Surging adaptive analyst capacity is insufficient to mitigate bias effects because bias correction is neglected in favor of quick analysis results. Chapter 5: Nudging crisis responders with default options that favor unbiased data is effective to reduce confirmation bias in crisis response.

6.2 Answers to the research questions

RQ 1: What factors lead to data bias in crisis response?

Chapter 2 extends the literature on crisis information management challenges to understand how systematic challenges lead to data biases. This research finds that systematic challenges in the crisis response environment can lead to four types of data bias: political, accessibility, topical, and sampling bias. Response organizations collect data in biased ways, have to use biased data to inform decisions and share biased data with other response actors because of political influence (Fast, 2017; Hendriks & Boersma, 2019; Maxwell, Hailey, Kim, et al., 2018; Maxwell, Hailey, Spainhour Baker, et al., 2018), inaccessibility (Altay & Labonte, 2014c; Comes et al., 2020; Day et al., 2009), organizational and technical constraints (Bharosa et al., 2010; Wolbers et al., 2018),

Operational and strategic levels of crisis response act under data-decision-interdependencies. Chapter 2 shows that the multi-level response system's interdependencies lead to bias reinforcement loops. Because of systematic challenges, operational actors can only collect data in biased ways. Strategic actors rely on biased data to inform resource allocation decisions to operational actors. Because actors lack time and resources and must align decisions with organizational mandates and objectives, data biases remain uncorrected. Decisions are consequently made based on biased data, leading to causes of biases remaining unaddressed. These bias reinforcement loops create the problem of a response that does not adequately address the crisis-affected population's needs.

Political bias results from the interference of local authorities in data collection, analysis, and exchange, from donor government agencies as well as from within the multi-actor crisis response structure itself. An example of the Yemen crisis is the political prevention of data collection efforts in large parts of the country's north. This prevention leads to a political data availability bias where more data is available from southern governorates. *Topical bias* emerges from imbalanced organizational resources and sociocultural causes. Better-resourced organizations can collect more data and provide more substantial evidence on issues related to their mandates, which do not necessarily need to be the biggest concern within the crisis. Issues that are taboo topics within the crisis-affected society, e.g., recruitment of minors into the armed forces and domestic violence, are underreported. Social norms require a sensitive approach to balance the need to capture relevant data and acknowledge what questions are too sensitive to ask. *Accessibility bias* is caused by the data availability discrepancy between the easier and the more difficult accessible sources of information. Sources can be geographic areas, social groups, or organizations. Geographic areas that are theatres of continued conflict will become data blind spots because data collection is more difficult to implement, and organizations are reluctant to send data collection teams due to security concerns. *Sampling bias* results from the urgency to collect data as fast as possible, the resource constraints that limit the robustness of sampling approaches, and the practical crisis realities in which data collection takes place.

RQ 2: How are crisis decision-maker groups affected by cognitive bias?

For its second contribution, this dissertation in Chapter 3 measured the strengths of anchoring bias, confirmation bias, framing effect and bias blind spot for three different crisis decision-maker groups, i.e., crisis experts, government and non-government workers, as well as crisis-affected people. This research finds that crisis experts were the least biased group. However, experts were still significantly affected by anchoring bias and framing effects. All three groups showed significant susceptibility to bias blind spot, indicating that all types of people who make crisis decisions underestimate the impact cognitive biases have on their estimations, judgments and decisions. Experience seems to be an important moderator in mitigating the negative impact of cognitive bias in crisis response. This finding confirms previous research that showed experience and domain knowledge mitigate biases (Beratšová et al., 2018; Olsen, 2015; Pines & Strong, 2019) and strengthen quick decision-making ability (Klein et al., 2010). Nevertheless, even though the framing effect and bias blind spot were lower in the group of crisis experts than in the other two groups, both biases still significantly affected experts' decisions.

The interaction with information is vital for crisis experts, governmental and non-governmental workers as well as crisis-affected people from the general population. Information on the crisis needs to be evaluated, and correct interpretations and conclusions must be drawn (Van Den Homberg et al., 2014). The study reported in Chapter 2 supports research showing that cognitive biases can interfere with decision-makers' ability to assess information correctly. In turn, incorrect assessment of information can lead to inaccurate estimations, assumptions and decisions (Burggraaf et al., 2019; National Research Council, 2015; Satya-Murti & Lockhart, 2015).

The findings of this research imply that crisis information management tools, such as information systems, should be designed to support users in identifying and mitigating the negative influence of potential cognitive bias. This design implication counts for crisis information systems for the general public, e.g., apps, and systems designed for government and non-government crisis responders and crisis experts, e.g., data repositories, dashboards, and prediction models. The design of crisis information management systems needs to consider the cognitive biases of their users. In Chapter 3, this research suggests four crisis information systems design principles to counter the adverse effects of cognitive bias. These principles need to be experimentally tested for their effectiveness in future research.

RQ 3: Does confirmation bias lead crisis decision-makers to rely on biased data?

The third contribution of this dissertation it that it demonstrates that confirmation bias can reinforce crisis decision-makers' reliance on biased data. Chapters 2 and 3 discuss the problem of data and cognitive bias in crisis response separately. Chapter 4 looks at the interaction between data availability bias and confirmation bias in people's assessment of crisis information. The study in Chapter 4 tested the assumption that additional analysis capacity that is surged adaptively during peak crisis response phases is effective in identifying and reducing biased information evaluation. Chapter 4 finds that crisis analysts prioritize the development of information that is directly usable for decision support. However, they undervalue critical information tasks and overlook the importance of handling biased datasets. The additional capacity of more data analysts is ineffective in reducing the impacts of data bias in crisis decision-making. This finding challenges the claim in crisis management literature that adaptive approaches improve information management outcomes for decision support (Anson et al., 2017; Charles et al., 2010; Janssen & van der Voort, 2020; Merl et al., 2009; Schiffling et al., 2020; Turoff, Van de Walle, et al., 2004). Instead, we find that adaptive capacity is prone to the same biases it should help to avoid. The urgency to develop information based on directly actionable data for decision-making trumps critical data and debiasing efforts. Once assumptions are made based on biased data, confirmation bias leads to a further confirmatory tendency, resulting in a circle of biased self-confirmation, in which opposing information that could correct assumptions is undervalued. Chapter 4 suggests experimentally testing debiasing approaches that suit the resource-scarce and urgent crisis response context and increase people's mindfulness and metacognition regarding overly confirmatory information processing biases.

RQ 4: What are effective nudging interventions to reduce bias in crisis response?

This dissertation's fourth contribution is that nudges that guide crisis decision-makers by using defaults, i.e., pre-ranked decision options, are more effective than warnings about potentially biased selection behavior. Building on Chapter 4 and its finding that confirmation bias and data bias can reinforce each other in crisis response, Chapter 5 tests how confirmation bias can be reduced in such a scenario. Previous studies showed promising results in mitigating confirmation bias through different forms of nudges (Demarque et al., 2015; Pennycook et al., 2019; Rieger et al., 2021). A review study on various forms of nudges found defaults and warnings to be the two most widely applied nudging strategies to mitigate bias (Hummel & Maedche, 2019). However, a direct comparison between the two is lacking. Chapter 5 compared the two forms of nudges, i.e., defaults and warnings, to test their effectiveness in reducing confirmation bias when crisis information is biased. Chapter 5 shows that the nudging intervention that, by default, rates unbiased, contradictory information higher than biased, supporting information successfully reduces confirmation bias. However, the nudging intervention that warns users of their potential biased behavior does not significantly reduce confirmation bias. These findings show that when data bias and confirmation bias come together, the effect of nudging interventions to mitigate confirmation bias is somewhat ambiguous. Chapter 5 finds support for previous research that showed default nudges work when they pre-select better choices (Sunstein, 2017). However, this dissertation does not concur with prior studies that found warning nudges effective in reducing confirmation bias (Rieger et al., 2021).

6.3 Societal relevance and recommended policy strategies

The scientific findings of this dissertation have several important implications for the international humanitarian response system. The digital transformation will influence the humanitarian community further, actors aim to become more data-driven and increase investments in analytics capacities. Problems of bias in the data, as well as cognitive bias in the analytical and decision-making processes of crisis responders and affected-people, should receive wider attention. Given that response efforts will rely more on data, the underlying data that inform decisions need to be checked for and cleaned of biases. Otherwise, the societal consequences can be severe, because crisis response drives into biased directions, i.e., overlooking crisis-affected areas and groups of crisis-affected people that are underrepresented in biased datasets. This dissertation provides recommended strategies for policymakers and information system designers that can guide future decisions on bias mitigation strategies. Implementing these mitigation strategies can contribute to a more effective response to complex crises in the future. Table 6.1 summarizes the recommended strategies.

Table 6.1. Recommended strategies for humanitarian policymakers and designers of crisis information systems to counter negative influences of data and cognitive bias .

Problem	Sub-problem	Strategy
Data bias	Political bias	Humanitarian organizations should invest in transparency, advocacy, and communication to counter political influence on data collection, sharing, and analysis. When political restrictions remain and continue hindering unbiased information management, humanitarian organizations must build and intensify joint, coordinated pressure on political stakeholders.
	Topical bias	Involving local authorities and donor agencies early in data collection efforts eases consensus on what and how data should be collected.

	Accessibility bias	Access constraints can be mitigated through investments in local relationships, trust, and reputation. Organizations with a pro-longed local presence in crisis-affected communities are in a better position to gain access to data.
Cognitive bias	Anchoring bias	Crisis information systems should take the anchoring tendency of users into account by keeping track of what cues were presented and what estimation tasks are to be done by users. Information systems can guide users to enlarge their scope of potentially reasonable estimates instead of keeping it to biased limits. When information is limited at first and only becomes available over time, deep uncertainty models can provide insights into ranges of plausible scenarios even when information is limited.
	Framing effect	Information systems that support organizations in developing proposals should provide different framing options and present potential outcomes of these options, e.g. how differently framed plans on what to do with allocated resources likely affect decisions by donors. Information systems used by donor agencies also need to be able to detect potential framing effects and include warning messages that warn about the possible influences of framing on their decision-making.
	Confirmation bias	Rather than providing information wished for by decision-makers, systems should balance information supply with information that also opposes users' assumptions to mitigate confirmation bias. Nudging theory suggests that subtle hints to valid but opposing information can be effective means to reduce confirmatory information selection toward more balanced user behavior.
	Bias blind spot	Information systems should account for potential overconfidence in their users, encouraging them to acknowledge and mitigate their own biases. When systems support the awareness of one's own susceptibility to bias, reducing negative bias effects becomes more likely. Another debias option is the establishment of so-called *red teams* or *devil's advocates*. The role of these teams is to critically observe and provide critical feedback during the information management and decision-making process, especially on

	assumptions that are taken for granted, so that blind spots are less likely to be overlooked.

6.4 Limitations and future research

To study the emergence of data biases in crisis response, the crisis in Yemen was selected as a case study. As described in Chapter 2, the single case study approach allowed a deep understanding of how datasets and reports produced and used in the Yemen crisis response can become biased. However, the political, organizational, social, and technical environment of other humanitarian crises might lead to the emergence of other forms of data bias, which this dissertation could not identify. Future research should therefore investigate and establish evidence on whether similar biases can be found in other crisis contexts and whether the causes for data bias are similar. Of greater interest would also be the validation of the cycle of bias reinforcement that this dissertation found within the multi-level data-decision-interdependencies between strategic and operational crisis response actors.

Decades of behavioral science research identified hundreds of cognitive biases that affect human thinking, estimations, and judgments. To make this dissertation feasible, in Chapter 3 a small group of cognitive biases that previous research suggested could be influential in crisis information processing, was selected for study. Future research needs to expand on this and provide comparisons of the strengths and directions of other behavioral and information processing biases. As in this dissertation, future studies should differentiate between bias susceptibility of different crisis decision-maker groups, as there might be differences between lay people and experienced crisis responders. These differences will have implications on the design of information products and systems that provide data-driven decision support to these groups.

In Chapter 4, this dissertation developed a method to study the consequences for crisis response when data bias and cognitive bias come together and affect analysts and decision-makers. As the methodological approach was experimental, this dissertation's findings are not yet validated through real-life crisis response operations observations. Future research should consider observing real-life crisis response efforts or simulated crisis response exercises to study how crisis analysts and decision-makers handle biases in datasets and whether they can reduce negative influences of cognitive biases.

Finally, Chapter 5 compared the effectiveness of two different nudging interventions to reduce the influence of confirmation bias and data bias in crisis response. These interventions were chosen for their effectiveness in previous studies and for their simplicity that allows them to be implemented in crisis information systems while taking the resource- and time-constraints of crisis response organizations into account. However, future research should also investigate the effectiveness of more resource-intensive debias interventions such as organizational and individual bias mitigation trainings.

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Appendix A

Interviews

Interview script

Duration: ~ 30-45 minutes

Introduction

- Interview is being recorded, all data will be treated anonymously.
- Why this interview? Topic of the research: influences of data-related factors on humanitarian decision making
- Why you as interviewee? Because you are working with an humanitarian organization on the Yemen crisis and we are interested to capture experiences of humanitarian workers and their information management challenges in Yemen.

Interviewee details

- Name
- Affiliation and Organization
- Currently in Yemen?
- Professional experience

Crisis information management

- Please describe the main humanitarian activities your organization is undertaking in Yemen.
- What data is your organization using to support these activities?
- How do you create or receive this data?
- Can you describe the process of data collection and analysis within your organization in a bit more detail? Maybe using a recent example.
- What obstacles and challenges does your organization face in the use of data for decision-making?
- What are some of the concrete consequences you face because of certain data issues you mentioned?
- How do you counter/support these consequences?

Example follow-up questions:

- You mentioned 'data gaps' in the data. Can you describe how exactly these data gaps look like?
- Regarding the issue of access constraints. How did it affect the dataset you wanted to create?

- Can you provide more information on what you mean by authorities influencing data collection?

Closing

- Are there any additional points you would like to mention that we have not addressed yet?
- Can you name an additional person we could also approach for an interview?
- Thank you for your time

List of interviewees.

ID	Interview year	Organization type	Years of experience	Interview duration	Role
I01	2021	Local Yemeni organization	25	32m	Managing Director
I02	2021	Local Yemeni organization	6	32m	Executive Director
I03	2021	iNGO / UN	15	39m	Data Analysis Specialist
I04	2021	iNGO / UN	4	41m	Project Manager
I05	2021	Local Yemeni organization	4	36m	Project Manager
I06	2021	Local Yemeni organization	6	29m	CEO
I07	2021	iNGO / UN	3	40m	Data Analyst
I08	2021	iNGO / UN	20	35m	Representative
I09	2021	iNGO / UN	14	32m	Information Management Officer
I10	2021	iNGO / UN	2	33m	Information Management Officer
I11	2021	iNGO / UN	4	31m	Humanitarian Policy Advisor
I12	2021	iNGO / UN	10	32m	Cluster Coordinator
I13	2021	Donor agency	2	34m	Technical Architect
I14	2021	iNGO / UN	11	33m	Cluster Coordinator
I15	2021	Donor agency	6	41m	Analyst
I16	2021	iNGO / UN	8	31m	Cluster Coordinator
I17	2021	Donor agency	10	40m	Humanitarian Advisor
I18	2021	Donor agency	18	27m	Information Manager
I19	2021	iNGO / UN	27	29m	Director
I20	2021	Local Yemeni organization	7	38m	CEO
I21	2021	Local Yemeni organization	15	51m	Associate Executive Director

I22	2021	Local Yemeni organization	4	31m	Project Manager
I23	2021	Local Yemeni organization	6	30m	Project Manager
I24	2021	Local Yemeni organization	8	32m	Chairman
I25	2021	Donor agency	10	25m	Humanitarian Advisor

Documents

List of included documents.

ID	Publication year	Publishing organization	Document title
D01	2018	ACLED	Yemen's Urban Battlegrounds: Violence and Politics in Sana'a, Aden, Ta'izz and Hodeidah
D02	n/d	ACLED	ACLED data ACLED Yemen Methodology
D03	2018	Action Contre La Faim; UNICEF	Nutrition and retrospective mortality survey - Highlands and Lowlands - Livelihood zones of Abyan Governorate
D04	2018	Action Contre La Faim; UNICEF	Nutrition and retrospective mortality survey - Highlands and Lowlands - Livelihood zones of Hajjah Governorate
D05	2018	Action Contre La Faim; UNICEF	Nutrition and retrospective mortality survey - Highlands and Lowlands - Livelihood zones of Lahj Governorate
D06	2018	Action Contre La Faim; UNICEF	Rapid response mechanism - Integrated Response Report - IDPs from Al Hudaydah Governorate
D07	2019	Amnesty International	Human Rights in the Middle East and North Africa
D08	2018	CIMP	Civilian Impact Monitoring Report (CIMP)
D09	2018	DRC	Preliminary Field Visit Report: Dubab and Mokha
D10	2018	DRC	Rapid Needs Assessment - Al Khawkhah, Hudeida
D11	2018	DRC	Rapid Needs Assessment - Mokha Dsitrict, Taiz
D12	2018	DRC	Rapid Needs Assessment - Al Maqatera, Lakij
D13	2018	DRC	In-depth Assessment Report Alanad, Khdad, Kadamat-Awad and Kod Al-duais villages Tuban Districts, Lahj Governorate
D14	n/d	DRC	Rapid Needs Assessment Report Shabwa Governorate Districts Alsaeed , Haban , Ataq and Nesab
D15	n/d	FAO	Early Warning Early Action Report on Food Security and Agriculture

D16	2018	FEWS NET; UN	Yemen Food Security Outlook
D17	2019	GCPEA	Safeguard Yemen's Future: Protect Education from Attack
D18	2018	HCT, OCHA	Humanitarian Needs Overview
D19	2018	HRW	Yemen Events of 2018
D20	2018	IDMC	Internal displacement in 2018
D21	2016	ILO	Yemen Damage and Needs Assessment - Crisis Impact on Employment and Labour Market
D22	2018	IOM	Taskforce on Population Movement - Yemen 17th Report. August 2018
D23	2018	IOM	Emergency Tracking Tool: Displacement from Al Hudaydah
D24	2018	IOM	Yemen — Rapid Displacement Tracking
D25	2018	IOM	Emergency tracking tool (ett): displacement from al hudaydah
D26	n/d	IRC	Protection, Participation and Potential; Women and Girls in Yemen's War
D27	2018	Logistics cluster	Yemen Situation Update
D28	2018	OCHA	Yemen - Humanitarian Access Snapshot
D29	2018	OCHA	Yemen Humanitarian Update
D30	2019	OCHA	Yemen: Humanitarian Access Severity Overview
D31	2019	RDF	WASH Needs Assessment Report: Shibam Kawkaban District, Al-Mahwit Governorate
D32	2019	RDP & SULWAN	WASH Needs Assessment Report: In Wusab Al Ali District of Dhamar Governorate
D33	2018	REACH	Al Hudaydah Crisis - Rapid Market Monitoring
D34	2018	REACH	IDP Hosting Site Baseline Assessment Site Profiles: Al Hudaydah, Al Mahwit, Hajjah, Sana'a
D35	2018	REACH	Yemen Joint Market Monitoring Initiative
D36	2018	REACH	Yemen WASH Cluster Assessment
D37	2019	Relief and Development Peer Foundation (RDP)	Situation Report
D38	2018	Sana'a Center for Strategic Studies	The Yemen Review
D39	2017	Save the Children	Yemen's Forgotten Children - The urgent case for funding education and child protection
D40	2017	Save the Children	Yemen Humanitarian Response Situation Report
D41	2018	Shelter cluster	Monthly Situation Report
D42	2018	Shelter cluster	Yemen CCCM Factsheet

D43	2018	World Bank	Yemen Economic Outlook
D44	2018		Country Nutrition Profiles Methodology
D45	2018	Action Contre La Faim; UNICEF	Rapid response mechanism - Multi-sectorial rapid needs assessment - Displacement Crises - Lahj Governorate
D46	2018	Logistics cluster	Yemen Access Constraints as of 31 December 2018
D47	2018	Nutrition cluster	Yemen Nutrition Cluster Bulleting, April - June 2018

Appendix B

Survey experiment introduction texts and general questions

	Crisis-affected people	*Government and non-profit workers*	*Crisis experts*
Scenario and scope	Participants were briefed that the survey experiment was addressed at crisis-affected people and that the objective of the survey experiment was to understand their decision-making behavior in times of crises.	Participants were briefed that the survey experiment was addressed at governmental and non-profit workers and that the objective of the survey experiment was to understand their decision-making behavior in times of crises.	Participants were briefed that the survey experiment was addressed at humanitarian crisis experts and that the objective of the survey experiment was to understand their decision-making behavior in times of crises.
General questions	Participants were asked to indicate their age, gender and to reflect on one recent crisis decision-making context while filling out the survey. They were told the context had to be a recent one in which they had been involved themselves and related to COVID-19.	Participants were asked to indicate whether they were employed at a governmental or non-profit organization. Participants further had to indicate their job title, years of work experience and to reflect on one recent crisis decision-making context while filling out the survey. They were told the context had to be a recent one in which they had been involved themselves and related to COVID-19.	Participants were asked to reflect on one humanitarian crisis response context while filling out the survey. They were told the context had to be a recent one in which they had been involved themselves. Participants were asked to indicate their answer in a COUNTRY, YEAR format. This allowed us to later code responses into sudden-onset (e.g. 'Nepal, 2015') and protracted crises (e.g. 'Yemen, 2019'). Participants further had to indicate if they were stationed inside or outside the country where the response took place, for what type of organization they had worked, their job title, and the number of years of work experience.

Survey experiment measures

Framing effect: gain frame

Imagine you are a humanitarian program manager in a country where 60.000 people are predicted to die from COVID-19. You are responsible for deciding between two programs that both aim to combat the impact of the virus. Funding is only available for one program. Assume that the exact scientific estimates of the consequences of both programs are as follows:

If Program A is implemented, 20.000 people will be saved.
If Program B is implemented, there is 1/3 probability that 60.000 people will be saved, and 2/3 probability that no people will be saved.

Which program would you choose?

Framing effect: loss frame

Imagine you are a humanitarian program manager in a country where 60.000 people are predicted to die from COVID-19. You are responsible for deciding between two programs that both aim to combat the impact of the virus. Funding is only available for one program. Assume that the exact scientific estimates of the consequences of both programs are as follows:

If Program C is implemented, 40.000 people will die.
If Program D is implemented, there is 1/3 probability that no people will die, and 2/3 probability 60.000 people will die.

Which program would you choose?

Bias blind spot

	Perception of own biased behavior	Perception of biased behavior in others	Measure
	Please select how far you agree or disagree with the following statements about your behavior in data-driven prioritization decisions for aid allocation? Only think about your behavior in your previously stated context:	Please select how far you agree or disagree with the following statements about other people's behavior in data-driven prioritization decisions for aid allocation? Only think about other people's behavior in your previously stated context:	
Anchoring bias	When making estimates, I have the tendency to be influenced by the first piece of information encountered in the dataset at hand. The resulting estimate tends to be similar to the first piece of information encountered.	When making estimates, other people have the tendency to be influenced by the first piece of information encountered in the dataset at hand. The resulting estimate tends to be similar to the first piece of information encountered.	7-point-Likert-scale (Strongly disagree, Disagree, Slightly disagree, Neither agree nor disagree, Slightly agree, Agree, Strongly agree, Not applicable)
Automation bias	I have the tendency to favor suggestions from automated decision support systems and to attribute less value to contradictory suggestions made without automation, even when hindsight shows this information is correct.	Other people have a tendency to favor suggestions from automated decision support systems and to attribute less value to contradictory suggestions made without automation, even when hindsight shows this information is correct.	
Confirmation bias	After I have made a decision or formed an assumption, I have the tendency to prefer to search and select information that confirms my assumptions rather than disconfirms them.	After they have made a decision or formed an assumption, other people have the tendency to prefer to search and select information that confirms their assumptions rather than disconfirms them.	
Law-of-the-instrument	I can show a strong reliance on a familiar tool or method, while attributing less value to alternative approaches. The behavior can be summarized in the phrase: 'If all you have is a hammer, everything looks like a nail.'	Other people can show a strong reliance on a familiar tool or method, while attributing less value to alternative approaches. The behavior can be summarized in the phrase: 'If all you have is a hammer, everything looks like a nail.'	
Innovation bias	I have the tendency to show optimism towards an innovation's usefulness, while paying less attention to its drawbacks or limitations.	Other people have the tendency to show optimism towards an innovation's usefulness, while paying less attention to its drawbacks or limitations.	
Information bias	I tend to believe that the more information that can be acquired to make a decision, the better, even if that extra information is irrelevant for the decision.	Other people tend to believe that the more information that can be acquired to make a decision, the better, even if that extra information is irrelevant for the decision.	
Framing effect	I have the tendency to draw different conclusions from the same information, depending on how that information is presented and who presents it.	Other people have the tendency to draw different conclusions from the same information, depending on how that information is presented and who presents it.	

Authority bias	I have the tendency to follow the 'loudest voice in the room' and attribute greater weight to the opinion of authority figures (organizations or persons) when forming my opinion.	Other people have the tendency to follow the 'loudest voice in the room' and attribute greater weight to the opinion of authority figures (organizations or persons) when forming my opinion.	

Confirmation bias: preliminary decision

Imagine a novel artificial intelligence and machine learning system is being developed that aims to accurately predict future COVID-19 infections using big data analytics. The system promises to ease the prediction of trends especially in countries and areas where manual assessments are difficult to implement. First experimental results of the system's utility were reported as promising. The company behind the system now plans real-world field tests and is looking for a partner organizations.

Imagine you are the head of an humanitarian organization and are approached by the company. Do you agree to partner with them to conduct the field tests?

Yes
No

Confirmation bias: information selection

($^+$ marks supportive information; $^-$ marks opposing information. Not visible to respondents. Display order of items was random.)
Imagine there is new information available regarding such artificial intelligence and machine learning systems, their benefits and risks in predicting COVID-19 infections. We summarized some of the most important articles in one-sentence statements below.

If you had the time to read those articles in full, which ones would you choose? You can select as many as you want, but your time to properly study the articles is probably limited.

- Machine learning becomes more and more precise in predicting infections$^+$.
- Novel IT systems allow organizations to save costs in data analysis$^+$.
- Data analytics will be made much quicker due to the availability of novel algorithms$^+$.
- Machine learning modelling has become the most reliable technology for predicting infectious disease spread$^+$.
- Artificial intelligence has made crisis response more efficient$^+$.
- The rights of people in need are being systematically ignored in the adoption of novel IT systems in crisis response$^-$.
- Machine learning cannot accurately predict the needs of the most vulnerable populations because it relies on data that is incomplete and inaccurate$^-$.
- Crisis response should not be used as an experimentation field for novel information systems$^-$.
- The benefits of artificial intelligence and machine learning for crisis response are overestimated$^-$.
- The risks of misuse of artificial intelligence and machine learning outweigh the benefits$^-$.

Anchoring bias: high-anchor

The United Nations allocated COVID-19 relief emergency funding to 49 countries in 2020. What do you think was the average amount of funding allocated per country? Note that the highest amount allocated to a country was USD 58 million.

Enter your estimate in USD as a number between 0 and 999999999 with no periods, commas or blank spaces.

Anchoring bias: low-anchor

The United Nations allocated COVID-19 relief emergency funding to 49 countries in 2020. What do you think was the average amount of funding allocated per country? Note that the lowest amount allocated to a country was USD 60.000.

Enter your estimate in USD as a number between 0 and 999999999 with no periods, commas or blank spaces.

Appendix C

Observation protocol

A. General description on site	B. Communication and interaction description	C. General impressions
How does the workspace you are observing look? (Seating arrangement, communication devices, support materials, additional characteristics, etc.)	Describe the sequence of events over time (e.g., information search, prioritization, processing, request, sharing, group discussion, decision-making, …)	Tone of the discussion (rational, empathic, humorous, etc.)
Participant coding	Which information is shared among the participating V&TCs?	Speedy vs. lengthy discussions?
Was communication rather face-to-face or mediated via technology?	Are additional information sources used?	Attitude of individual participants (engaging, negative, overwhelmed, …)
	How is the need for information expressed and communicated?	To what extent was available information not shared / retained?
	Which decisions are anticipated to be supported by the V&TCs?	Additional comments
	Describe how and why specific types of information products are selected and created for the decision-makers.	
	Which information is included and why?	
	Which technology and other decision aid materials are utilized and how?	

Confirmation bias measure

Below are the summaries of 10 new datasets that are available. You can re-quest the full version of those datasets but you only have limited time and re-sources to evaluate them all in detail. Select as many datasets as you want. District X is the district you have identified in the last session as the most critical district.

- *Dataset 1: District X has less treatment capacity than infection cases.*
- *Dataset 2: In district X the infection rate is likely to increase.*

- *Dataset 3: District X has high infrastructural damage.*
- *Dataset 4: District X has a low percentage of people reached.*
- *Dataset 5: District X has more treatment capacity than infection cases.*
- *Dataset 6: In district X the infection rate is likely to decrease.*
- *Dataset 7: District X has low infrastructural damage.*
- *Dataset 8: District X has a high percentage of people reached.*
- *Dataset 9: District X has a high amount of health care workers infected.*
- *Dataset 10: District X has a low amount of heath care workers infected.*

Appendix D

Complete overview of the instrument.

Displayed to participants (placeholders in brackets dependent on experimental condition)	
	Importance rating (1-5)
Dataset 1: For this dataset, **[Data_Bias_Condition]** districts were assessed. This dataset suggests that [**Priority_Choice]** is the priority need. **[Nudge_Condition]** • **[Priority_Choice]** is the most important aspect of the response right now. • Severe weather conditions are projected, people need to receive **[Priority_Choice]**. • Food items can wait, **[Priority_Choice]** is more important right now. • Additional funding for **[Priority_Choice]** items needs to be provided as soon as possible. • Capacities to provide **[Priority_Choice]** to affected people are overstretched and need to be extended quickly.	***[Nudge_Condition]***
Dataset 2: For this dataset, 100 of 100 districts were assessed. This dataset suggests that **[Priority_Opposite]** is the priority need. • **[Priority_Opposite]** is the most important aspect of the response right now. • Severe malnutrition is projected, people need to receive **[Priority_Opposite]**. • Shelter items can wait, **[Priority_Opposite]** is more important right now. • Additional funding for **[Priority_Opposite]** items needs to be provided as soon as possible. • Capacities to provide **[Priority_Opposite]** to affected people are overstretched and need to be extended quickly.	***[Nudge_Condition]***

Placeholder explanation

Data_Bias_Condition: If participant is in weak data bias condition *'80 of 100'* is displayed. If participant is in strong data bias condition *'20 of 100'* is displayed.
 	
Priority_Choice: If participant selected '*shelter'* as priority, *'shelter'* is displayed. If participant selected '*food'* as priority, *'food'* is displayed.
 	
Priority_Opposite: If participant selected '*shelter'* as priority, *'food'* is displayed. If participant selected '*food'* as priority, '*shelter'* is displayed.
 	
Nudge_Condition:
• If participant is in the no nudge/control condition
    o No additional text is displayed.
    o Importance ratings are empty.
• If participant is in the warning nudge condition
    o The following additional text is displayed: *'<u>Caution:</u> These recommendations can lead you to show confirmation bias (the tendency to overly try to confirm your previously chosen priority). Recommendations drawn from the other dataset might help you to adjust your previous decision.'*
    o Importance ratings are empty
• If participant is in the default nudge condition

- No additional text is displayed.
- The importance ratings for dataset 1 recommendations are set to 5 (*extremely important*) by default, and the importance ratings for dataset 2 recommendations are set to 1 (*not at all important*) by default.

List of Tables

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ACAPS	Assessment Capacities Project
CIM	Crisis information management
GDPR	General Data Protection Regulation
HNO	Humanitarian Needs Overview
HRP	Humanitarian Response Plan
IDP	Internally Displaced People
iNGO	International Non-Governmental Organization
IPC	Integrated Food Security Phase Classification
OCHA	Office for the Coordination of Humanitarian Affairs
SDG	Sustainable Development Goals
SGBV	Sexual- and Gender-based Violence
UN	United Nations
WFP	World Food Programme

Curriculum vitae

David Paulus was born in Bad Wildungen, Germany, on August 24, 1988. He holds a BSc. in information logistics (2012, HFT Stuttgart) and a MSc. in information systems (2014, HS Pforzheim). During his studies, he worked for the Fraunhofer Institute (IAT) and GIZ on online platforms and open source trainings that supported sustainable societal development. Between 2014-2017, he worked for the United Nations University (UNU-EHS), where he developed information systems and learning materials around climate change adaptation and disaster risk reduction with partner institutions in Algeria and Indonesia. From 2017-2018, he implemented a research project at TU Delft on open humanitarian data and decision-making together with local and international partners in The Philippines. From 2018-2022, he was a PhD Researcher at TU Delft and focused on biases in crisis data and decision-making. In 2022, he started to work as a Data Engineer for the United Nations Operations and Crisis Center in New York.

Publications

Publications related to this dissertation

1. Paulus, D., de Vries, G., Janssen, M., Van de Walle, B. (accepted for publication). Reinforcing data bias in crisis information management: The case of the Yemen humanitarian response. *International Journal of Information Management*.

2. Paulus, D., de Vries, G., Janssen, M., & Van de Walle, B. (2022). The influence of cognitive bias on crisis decision-making: Experimental evidence on the comparison of bias effects between crisis decision-maker groups. *International Journal of Disaster Risk Reduction*, *82*, 103379. https://doi.org/10.1016/j.ijdrr.2022.103379

3. Paulus, D., Fathi, R., Fiedrich, F., Van de Walle, B., Comes, T. (2022). On the Interplay of Data and Cognitive Bias in Crisis Information Management. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-022-10241-0

4. Paulus, D., de Vries, G., Janssen, M., Van de Walle, B. (under review). Countering confirmation bias in crisis decision-making: the effect of nudging

Other publications

5. Paulus, D., Meesters, K., & Van de Walle, B. (2018). Turning data into action: Supporting humanitarian field workers with open data. In K. Boersma & B. Tomaszewski (Eds.), *Proceedings of the International ISCRAM Conference (Vol. 2018-May*, pp. 1022–1029). Rochester, NY, USA: ISCRAM.

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