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Research article

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

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ABSTRACT

The complex and uncertain environment of the humanitarian response to crises can lead to data bias, which can affect decision-making. Evidence of data bias in crisis information management (CIM) remains scattered despite its potentially significant impact on crisis response. To understand what biases emerge in complex crises and how they affect CIM, we conducted a combined interview and document analysis study. Focusing on the largest humanitarian crisis in the world, i.e., the conflict in Yemen, we conducted 25 interviews with managers and analysts of response organizations, and assessed 47 reports and datasets created by response organizations in Yemen. We find evidence of a cycle of bias reinforcement through which bias cascades between field, headquarters and donor levels of crisis response. Researchers, as well as practitioners, need to consider these underlying biases and reinforcement loops because they influence what data can be collected when, by whom, from whom, and how the data is shared and used. To the CIM literature, we contribute an in-depth understanding of how four types of data bias emerge in crises: political, accessibility, topical, and sampling bias.

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).

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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 3, we describe our interview and document analysis approach. Our findings are presented in Section 4. We discuss our findings in light of previous CIM literature and present our contributions to theory and practice in Section 5. Section 6 concludes the paper.

2. Crisis information management and data bias

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 (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. 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

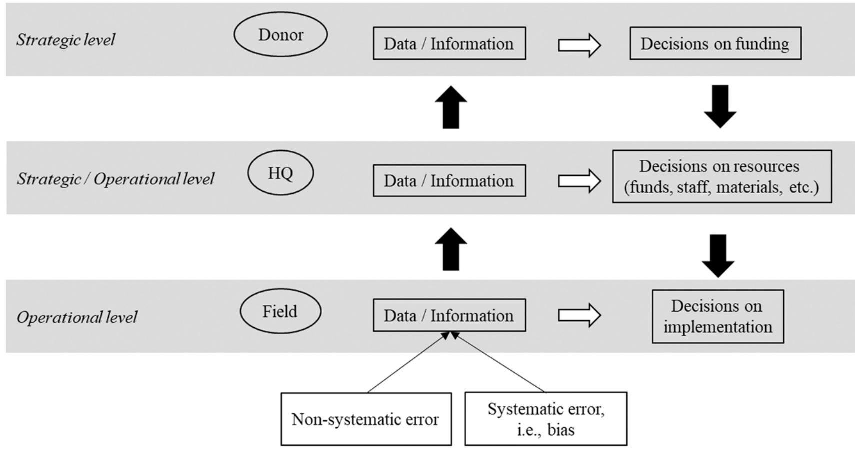

Fig. 1. Data-decision-interdependencies within the multi-actor system of humanitarian crisis response.

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). Fig. 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.

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).

2.3. 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

Table 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

these networks, even though they would benefit from them.

Based on the previous findings regarding diverse CIM challenges, in Table 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.

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, 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.

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 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

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

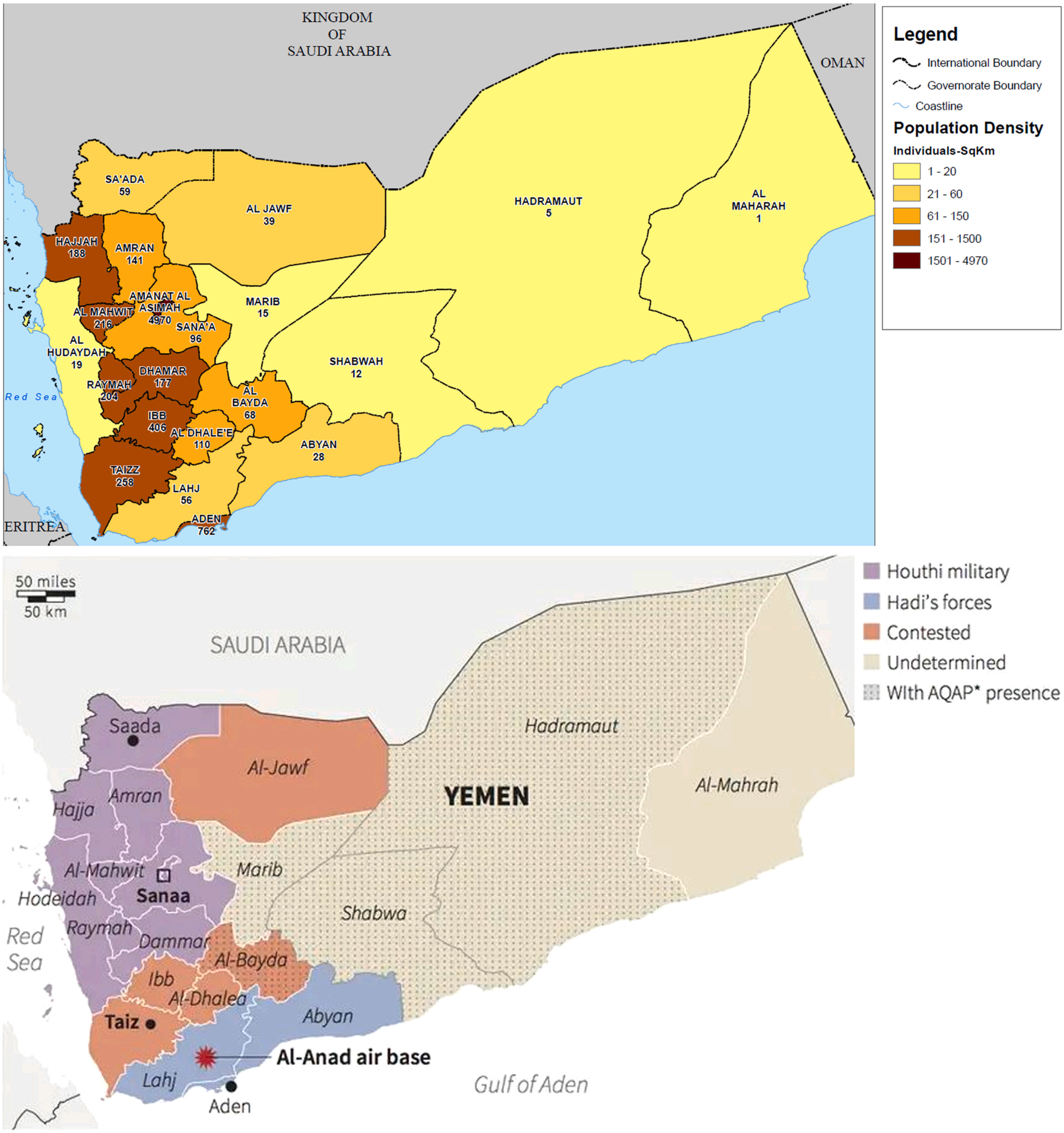

Fig. 2. Maps of Yemen. Top: Population density map. Middle: Areas under control by different conflict parties. Bottom: Food security assessment (IPC). Note the white spots (missing analysis and data) in the bottom map correspond to the most densely populated areas at the top, which are also under militia 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.

limited, the practical implications are clearly visible. Fig. 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

[2] IPC = Integrated Food Security Phase Classification

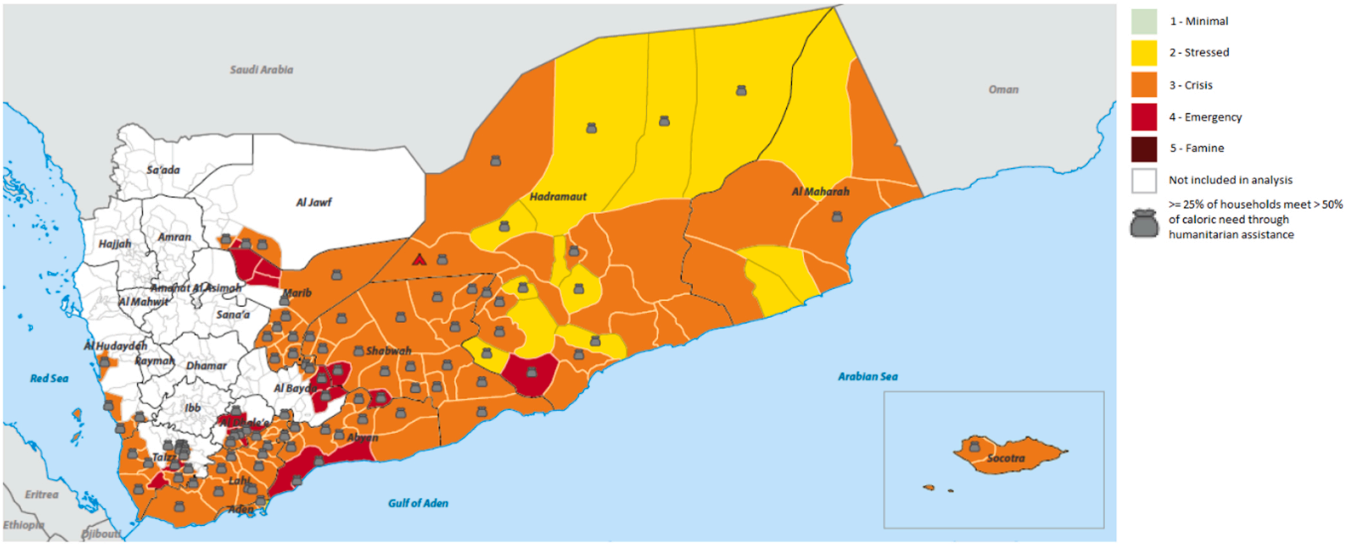

Fig. 2. (*continued*).

and resource allocation on (Maxwell, 2019). However, as Fig. 2 shows, no IPC analysis was done 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.

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.

3.2.1. Interviews

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, 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 min 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 and 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.

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

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

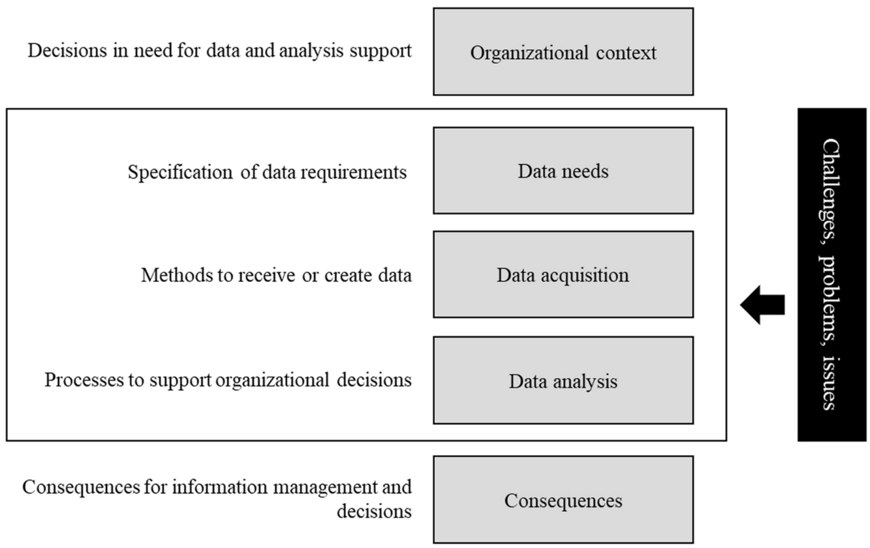

Fig. 3. Structure and main concepts of each interview.

according to the ethical standards of the authors' research institution 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 the Appendix). 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 Fig. 3).

Our interview script was developed based on the CIM literature discussed in Section 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 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.

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,

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

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

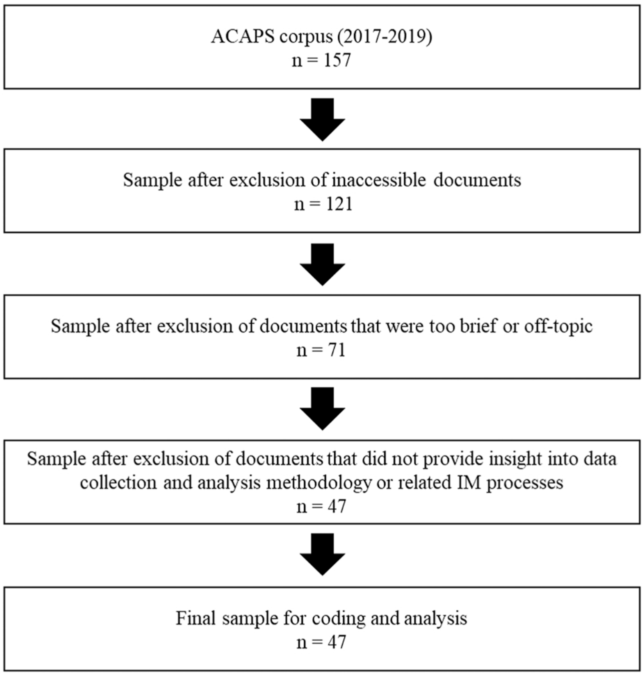

Fig. 4. Overview of the identification and exclusion process of information products created by the humanitarian crisis response community in Yemen.

therefore, included 47 documents (Fig. 4). The coding and analysis process for these documents is described in the Data Analysis section.

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 4.

4. Results

4.1. Reinforced 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 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

[6] SGBV = sexual and gender-based violence

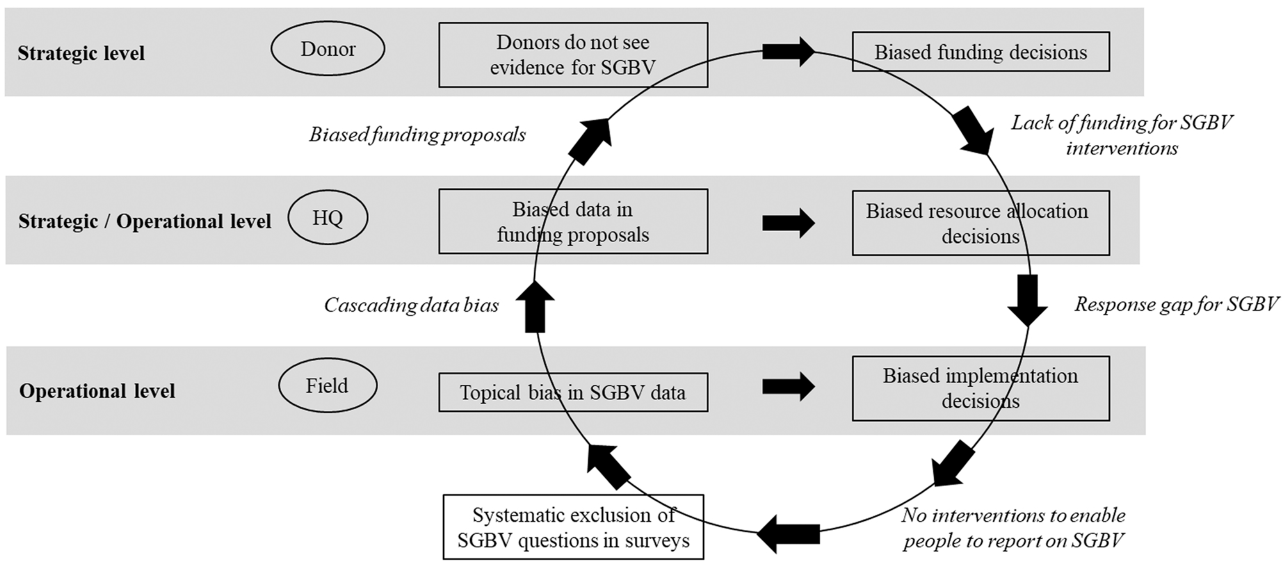

Fig. 5. Cycle of reinforcing data bias. Data biases cascade and are reinforced within the multi-level crisis response system.

understudied issues should be funded. The circle continues, and biases are reinforced (Fig. 5).

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 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 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. Table 2 depicts the process of distilling these four main types of bias from our data.

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 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]

Table 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, D04, D05, D11, D19, D20, D22, D23, D25, D28, D30, D32, D33, D35, D37, D39, D41, D43)	• 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) • 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[1] included mostly males (D06)

[1] KIIs = Key Informant Interviews.

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]

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]

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 1675, 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]

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

Table 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)

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]

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, 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 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.

5. Discussion

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 et al., 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.*

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.

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, socio-cultural, 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.

6. Conclusion

Our 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.

Table 4
List of interviewees.

ID	Interview year	Organization type	Years of experience	Interview duration	Role
I01	2021	Local Yemeni organization	25	32 m	Managing Director
I02	2021	Local Yemeni organization	6	32 m	Executive Director
I03	2021	iNGO / UN	15	39 m	Data Analysis Specialist
I04	2021	iNGO / UN	4	41 m	Project Manager
I05	2021	Local Yemeni organization	4	36 m	Project Manager
I06	2021	Local Yemeni organization	6	29 m	CEO
I07	2021	iNGO / UN	3	40 m	Data Analyst
I08	2021	iNGO / UN	20	35 m	Representative
I09	2021	iNGO / UN	14	32 m	Information Management Officer
I10	2021	iNGO / UN	2	33 m	Information Management Officer
I11	2021	iNGO / UN	4	31 m	Humanitarian Policy Advisor
I12	2021	iNGO / UN	10	32 m	Cluster Coordinator
I13	2021	Donor agency	2	34 m	Technical Architect
I14	2021	iNGO / UN	11	33 m	Cluster Coordinator
I15	2021	Donor agency	6	41 m	Analyst
I16	2021	iNGO / UN	8	31 m	Cluster Coordinator
I17	2021	Donor agency	10	40 m	Humanitarian Advisor
I18	2021	Donor agency	18	27 m	Information Manager
I19	2021	iNGO / UN	27	29 m	Director
I20	2021	Local Yemeni organization	7	38 m	CEO
I21	2021	Local Yemeni organization	15	51 m	Associate Executive Director
I22	2021	Local Yemeni organization	4	31 m	Project Manager
I23	2021	Local Yemeni organization	6	30 m	Project Manager
I24	2021	Local Yemeni organization	8	32 m	Chairman
I25	2021	Donor agency	10	25 m	Humanitarian Advisor

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.

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CRediT authorship contribution statement

David Paulus: Conceptualization, Methodology, Investigation, Data Curation, Formal analysis, Writing – Original Draft. **Gerdien de Vries:** Conceptualization, Methodology, Writing – Review & Editing. **Marijn Janssen:** Writing – Review & Editing. **Bartel Van de Walle:** Writing – Review & Editing.

Table 5
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

(*continued on next page*)

Table 5 (*continued*)

ID	Publication year	Publishing organization	Document title
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

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

See Tables 4 and 5 here.

Interviews.

Interview script.

Duration: ~ 30–45 min.

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

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