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S.I.: DESIGN AND MANAGEMENT OF HUMANITARIAN SUPPLY CHAINS

A methodology for developing evidence-based optimization models in humanitarian logistics

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Abstract

The growing need for humanitarian assistance has inspired an increasing amount of academic publications in the field of humanitarian logistics. Over the past two decades, the humanitarian logistics literature has developed a powerful toolbox of standardized problem formulations to address problems ranging from distribution to scheduling or locations planning. At the same time, the humanitarian field is quickly evolving, and problem formulations heavily rely on the context, leading to calls for more evidence-based research. While mixed methods research designs provide a promising avenue to embed research in the reality of the field, there is a lack of rigorous mixed methods research designs tailored to translating field findings into relevant HL optimization models. In this paper, we set out to address this gap by providing a systematic mixed methods research design for HL problem in disasters response. The methodology includes eight steps taking into account specifics of humanitarian disasters. We illustrate our methodology by applying it to the 2015 Nepal earthquake response, resulting in two evidence-based HL optimization models.

Keywords Humanitarian logistics · Mixed methods · Research design · Field research · Optimization · Case study

1 Introduction

As the number of people affected by disasters continues to grow each year, there is an increase in academic publications that propose conceptual frameworks and optimization models for humanitarian logistics (HL) problems (Banomyong et al. 2019; Dubey et al. 2019). HL optimization models can support effective and efficient decision-making, especially if

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problems are complex. However, a recent review shows that the current HL publications tend to focus on traditional optimization problems without much consideration for the specific disaster context (Besiou and Van Wassenhove 2020). Field-driven evidence in studies with optimization models and optimization-driven decision support systems in the HL literature is scant (Boonmee et al. 2017; Kovacs and Moshtari 2019; Banomyong et al. 2019; Besiou and Van Wassenhove 2020): the majority of optimization models and decision support systems are based on unverified assumptions and examined through hypothetical data. Moreover, optimization, models have been criticized for not capturing the full complexity and rich context of HL (Pedraza-Martinez and Van Wassenhove 2016; Kovacs and Moshtari 2019; Kovacs et al. 2019; Besiou and Van Wassenhove 2020).

Several strategies have been suggested to address this gap, such as conducting multidisciplinary research (Baharmand et al. 2016), contacting practitioners to formulate research questions (Kunz et al. 2017), and following mixed methods research designs (Galindo and Batta 2013; Gutjahr and Nolz 2016; Habib et al. 2016; Kovacs and Moshtari 2019) that use field research to develop optimization models for HL problems (Starr and Van Wassenhove 2014; Kunz et al. 2017; Kovacs and Moshtari 2019; Besiou and Van Wassenhove 2020). A major challenge in this endeavor is combining qualitative and quantitative research traditions. While also quantitative data can and has been collected in field research, we focus on combining qualitative methods that are frequently used in HL field research with optimization models.

There are two notable challenges for following mixed methods research design: (a) methodological issues, whereby publications often do not present their approach of translating qualitative findings into quantitative models and (b) a lack of consistency of the underlying paradigms (Guba and Lincoln 1994). As a result, a lack of consistency between research paradigm, data collection and model formulation can often be observed in research papers that build optimization models from field research (Holguín-Veras et al. 2013; Besiou et al. 2018). Our paper aims to address this gap by investigating the following research question:

- RQ: *how can relevant and evidence-based optimization models for HL in disasters response be developed?*

Our objective is to propose a mixed methods research design that is adapted to the context of HL. To this end, we designed a novel research methodology consisting of eight steps (seven main steps plus one optional) to develop evidence-based models for HL problems (cf. Sect. 3). For each step, we provide a detailed description about the methodological decisions involved and recommend strategies for researchers to ensure rigor and relevance of their study. We validate the proposed design by using the case of the 2015 Nepal earthquake and demonstrate how two optimization models for location-allocation problems in HL can be developed from field research. Our rationale for the case selection is twofold: (i) the earthquake was one of few recent natural disasters requiring system-wide emergency activation that we wanted to study; (ii) we had the opportunity to conduct the field study a few weeks after the earthquake and observe humanitarian operations providing us with access to crucial data.

The rest of our paper is organized as follows. In the next section, we provide an overview of the relevant background. Our proposed research steps are presented in Sect. 3. In Sect. 4, we show the application of our methodology to the Nepal case and present our location-allocation models as a result of the analysis. In Sect. 5, we discuss the features of our evidence-based models and the relevance of our proposed research methodology. Then, we conclude in Sect. 6 with implications and limitations of our study.

2 Background and research contribution

Research design refers to a framework for planning research and answering research questions. Qualitative and quantitative research designs have different characteristics in terms of the paradigm, the focus, objectives, data collection/analysis methods, and research outcomes (Johnson et al. 2007; Guba and Lincoln 1994). Based on these characteristics, we provide an overview of HL literature in this section with respect to three streams: quantitative research, qualitative research, and mixed methods research. For this, we draw from 18 systematic literature reviews that have been published in the HL literature over the last 10 years (2011-2021) (the list of considered review papers is provided in Appendix A). As Kovacs and Moshtari (2019) argue, a detailed and rather extensive review of qualitative or quantitative methods can often be found in HL review papers. We complement our overview with insights from the wider operations management literature whenever relevant studies in the HL literature are sparse.

2.1 Quantitative research in humanitarian logistics

The quantitative research design is often used to quantify a phenomenon. The main goal of quantitative research design is to (dis-)prove existing theories by measuring variables and their relations. Under this perspective, associated to positivism or post-positivism, the reality exists (realism) or is assumed to exist (critical realism), the investigator is capable of studying a phenomenon without influencing it or being influenced by it (objectivist), and both entities are considered to be independent. In that sense, the research design is deductive where questions and/or hypotheses are subject to empirical testing and replicable findings are considered 'true' (Guba and Lincoln 1994).

According to recent reviews on HL literature, the majority of research papers that follow a quantitative research design propose optimization models to address different HL problems including location, allocation, routing, evacuation, scheduling, or combinations of them (Galindo and Batta 2013; Anaya-Arenas et al. 2014; Behl and Dutta 2019; Banomyong et al. 2019). However, as highlighted by Özdamar and Ertem (2015) and Besiou and Van Wassenhove (2020), optimization models in HL face two challenges: first, a lack of models which analyze relevant problems in disasters with realistic features. Second, most HL models are computationally expensive and hardly correspond to the constraints of time pressure, high workload, and presence of multiple stakeholders for decision making in the context of disasters response (Baharmand et al. 2020). In fact, some review papers (e.g. Anaya-Arenas et al. 2014; Kunz et al. 2017; Trivedi and Singh 2018) assert that a large part of optimization models in HL research fail to address a specific disaster context although ignoring the context will suggest solutions that may be useless or impossible to implement (Pedraza-Martinez and Van Wassenhove 2016).

To address uncertainties and complex interactions, some papers combine simulation and optimization. One common way of implementing such an approach is that simulation models use inputs generated by optimization procedures to evaluate a solution (e.g., Fikar et al. (2016) or Dufour et al. (2018)). The simulated output acts in the following step as an input for the optimization procedure and this loop is repeated until a stopping criterion is met. HL papers that use this combined approach mainly implement numerical experiments which are developed randomly and lack evidence from the field, as noted by Gutjahr and Nolz (2016).

Overall, the suit of optimization models used in HL research displays two other major weaknesses despite their dominance in the literature. The first is the validity of assumptions upon which the design and findings are based, given the complex nature of issues investigated (Galindo and Batta 2013; Pedraza-Martinez and Van Wassenhove 2016; Kunz et al. 2017). The second is the tendency in the literature to improve and combine optimization models to address standard HL problems, while few scholars have tried to explore how models can be used for new and emergent problems (Besiou and Van Wassenhove 2020). The narrow focus of the optimization models has therefore limited their use to support practitioners in different disasters contexts (Kunz et al. 2017; Kovacs and Moshtari 2019). As such, optimization models have often been recommended for theory-testing or validation in logistics research (Kovács and Spens 2007).

2.2 Qualitative research in humanitarian logistics

Qualitative research design is often used to understand concepts, thoughts or experiences. It aims to create meaning, explore and investigate new, often social phenomena and develop theory. Under this perspective, associated with constructivism, the reality is understood as multiple mental constructions product of human intellects (relativism), the investigator creates knowledge through its interaction with the phenomenon (subjectivist) and thus, both entities are interactively linked (Guba and Lincoln 1994). In that sense, this design is inductive and often used for building theory and exploration. It adds the details and can also give a narrative voice to the results.

The majority of qualitative research in HL are case and field studies (Vega 2018). A field study provides access to rich data and offers opportunities to explore the interaction between multiple actors (Spens and Kovács 2006). The common methods in qualitative studies are: in-depth face-to-face and telephone interviews (Holguín-Veras et al. 2022), interviews with field observations (Van de Walle and Comes 2014), field surveys (Zissman et al. 2014), discussion groups (Powell 2011), or simulation games (Lukosch and Comes 2019; Gralla et al. 2016). A method that has received increased attention from the HL community is qualitative content analysis (QCA), a method that is suitable "for making inferences by objectively and systematically identifying specified characteristics of messages" (Holsti 1969). The method has been used in HL to conduct literature reviews (Kunz and Reiner 2012; Seifert et al. 2018), analyze content from websites (Vega and Roussat 2015), and NGO reports (Vega and Roussat 2019). Three different approaches for QCA exist, namely conventional, directed and summative (Hsieh and Shannon 2005). While the first two follow an inductive or deductive category development respectively, the latter aims at "identifying and quantifying certain words or content in text with the purpose of understanding the contextual use of the words or content". A similar approach to qualitative analysis is thematic analysis (Braun and Clarke 2006), a method for "identifying, analysing and reporting patterns (themes) within data". Although both are used interchangeably (Sandelowski and Leeman 2012), the main difference relies on the identification of the latent content of written text, as in content analysis themes are reached based on word frequency, while in thematic analysis the themes emerge when these capture something important in relation to the overall research question (Vaismoradi et al. 2006).

An important point to notice is that the use of these methods is not mutually exclusive. In Holguín-Veras et al. (2012b) (2010 Haiti earthquake), Laguna Salvadó et al. (2015) (Ebola crisis), Comes (2016) (2013 typhoon Haiyan), Comes et al. (2020) (Syria Crisis) and Baharmand et al. (2016) (2015 Nepal earthquake), researchers incorporate the following in their field study: a timeline of events, decisions, and information flows; collecting and archiving relevant document for further review; interviews and focus groups with respondents at different positions within distinct organizations; and observations. Using a combination of above-mentioned methods, scholars aim to ensure they build or validate knowledge on post-disaster HL with evidence from the field (Chan and Comes 2014). Qualitative research in HL based on field studies aim to embrace the contextual richness of the field, which is often missing in studies that solely rely on quantitative models. Research that use data from field studies in disaster contexts usually address problems in the organizational and social settings (e.g., Comes (2016), L'Hermitte et al. (2016), or Wolbers et al. (2018)).

Qualitative research designs show some drawbacks, particularly with respect to concretely supporting decision-making in HL. First, due to the focus of qualitative studies on theory building and understanding processes or phenomena (Sushil, 2019), their value for solving concrete HL decision problems is limited. Second, the qualitative research process in disaster contexts is often challenging (Vega 2018). For instance, researchers are subject to a high degree of stress, severe time pressure, access problems, information overload, irregular working conditions, or safety and security risks (Lukosch and Comes 2019; Chan and Comes 2014). Third, generalizing case study and field study findings is a challenge given the specificity of different contexts of disasters and humanitarian operations. One way to integrate rich field findings into modeling in HL research is using a mixed methods research design (Kovacs and Moshtari 2019).

2.3 Mixed methods research in humanitarian logistics

Mixed methods research combines quantitative and qualitative research and thereby offers more informed, complete, balanced and useful research results (Johnson et al. 2007). The combination of qualitative and quantitative research can occur at any stage of a study cycle (e.g., approaches, methods, data collection and analysis) (Akhtar 2018). With regards to paradigm, mixed methods research offers four perspectives –i.e. pragmatism, transformative-emancipation, dialectics, and critical realism– that influence research design, theory use, relationships, inferences, and data reporting (Shannon-Baker 2016). While pragmatism can be objective and/or subjective, transformative – emancipation tends to be more objective, dialectics remains reflective and critical realism leans toward subjectivism. The methods and inferences from data used by all four vary with the purpose, but the four share the advantage of providing a better understanding, breadth, depth, validity, internal consistency and generalization, as well as the ability to derive "bottom up" research questions.

There are two main categories of mixed methods designs (a) qualitative study informs a quantitative analysis and (b) a quantitative analysis informs a qualitative study. Our study belongs to the first category: we aim to derive a method that allows to translate the results of a first qualitative part into a quantitative optimization model. Therefore, we review some similar studies in this category.

In the HL literature, research papers often use data collected from field studies to address HL problems using optimization models in two directions: (a) using data to develop new problem formulations, or (b) using data as input to parametrize, reformulate or extend existing problems. Holguín-Veras et al. (2012a) highlight the importance of co-creation to develop optimization models. As such, Charles et al. (2016) propose a model developed in close collaboration with an HO for analyzing the impact of alternative sourcing strategies and service level requirements on operational efficiency in humanitarian supply chains. Similarly, Laguna-Salvadó et al. (2019) developed a multi-objective model in collaboration with the Red Cross for managing sustainable humanitarian supply chains using information mainly gathered from field research. Also, Baharmand et al. (2019) and Baharmand et al. (2020)

develop multi objective models in collaboration with the World Food Programme to locate temporary distribution centers in the aftermath of sudden onset disasters where the models' parameters, assumptions, and objectives have been derived from a field study.

According to Kovacs and Moshtari (2019), a key challenge is the lack of clarity regarding how mixed methods design is used in HL contexts; without clear research design, the studies cannot be replicated. Mixed methods studies have been reported in several forms and types with multiple levels and methods of data collection and analysis. This results in a lack of specificity and detail, for instance, around methods of data analysis and procedures used in the interpretation of findings (Kunz 2019). To address the gap, Kunz (2019) present an automated quantitative content analysis approach that allows researchers to analyze secondary data (e.g., online reports and white papers) quickly and reliably to extract the contents' quantifiable aspects. However, Kunz (2019)'s approach does not support an exhaustive qualitative analysis of primary and secondary data, neither does it offer any approach for interpretation to develop new or inform previous optimization models. Moreover, some articles do not use theory when presenting techniques used for data collection and analysis (Vega 2018; Oloruntoba et al. 2019). This leads to two misconceptions: these studies are not methodologically rigorous and the method maintains a bias toward verification due to the lack of rigor (Pedraza-Martinez and Van Wassenhove 2016).

We think if the aforementioned issues are properly addressed, the mixed methods design could effectively examine HL problems, and facilitate the development of relevant and rigor optimization models, as has also been noted in recent studies (e.g., Besiou and Van Wassenhove 2020; Kovacs and Moshtari 2019; De Vries and Van Wassenhove 2020).

2.4 Research contribution

The mixed methods research design can be used to gain a fuller picture and deeper understanding of the HL problems. Its main advantage is to relate complementary findings to each other that are derived by using methods from the different methodological traditions of qualitative and quantitative research (Kelle 2006). However, our review revealed that the mixed methods research design has not been documented in the HL literature in a reproducible way. HL papers often give little space to the discussion of analysis, and do not make transparent how they combine or analyse field findings to inform quantitative models. Hence, a gap often separates field data from model formulation.

In this paper, we make a headway in addressing this gap. We aim to provide a methodology that can help investigating HL problems that cannot be addressed by pure qualitative or quantitative research, such as the many complex decision problems that humanitarian logisticians are facing. We design a step-by-step mixed methods research methodology for conducting an evidence-based study in HL in the context of natural disasters response. We specifically address the question how to translate the insights from a field study into an optimization model formulation. To show the application of our proposal, we demonstrate how we used this methodology through a case study of the 2015 Nepal earthquake.

3 Proposed research methodology

To develop our proposed research methodology for using field work to develop an optimization model, we adapt existing mixed methods research design from the Johnson et al. (2007)'s study. We focus on the quantitative dominant mixed methods research. As John-

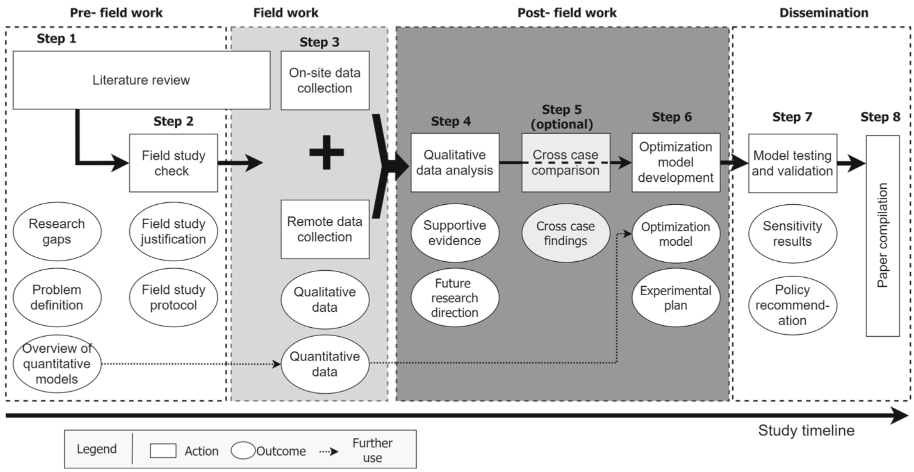

Fig. 1 Proposed research methodology

son et al. (2007) note "*Quantitative dominant mixed methods research is the type of mixed research in which one relies on a quantitative, postpositivist view of the research process, while concurrently recognizing that the addition of qualitative data and approaches are likely to benefit most research projects.*" This design is particularly useful when a researcher needs to identify important variables to study quantitatively, when the variables are unknown or less-known (Tashakkori and Creswell 2007). To design the methodology, we combine practices of papers that study disaster settings qualitatively with those that develop optimization models to address decision-making problems in HL.

Figure 1 shows our proposed research methodology, which is composed of four stages. Every stage includes one or more steps. Two layers can be distinguished in each step: process(es) (rectangle) and outcome(s) (ellipse). The initial pre-field work stage focuses on the literature and relevant theories to identify/analyze research gaps. The field work, the second stage, includes collecting and analyzing data from primary and secondary sources. The third stage is the focal point of this design: the translation of the qualitative data into a new or adapted optimization model. Finally the last stage, i.e., dissemination, is concerned with validating the model and publishing the outcome.

The proposed research methodology is specifically intended for the HL context. HL operates in an exceedingly uncertain and dynamic environment that is far beyond the unidirectional, linear logistics in other contexts (Day 2014). Applying the proposed research methodology to HL research has therefore the following merits. (a) The methodology benefits from field study with qualitative methods. This has been noted as particularly appropriate for understanding HL contexts "*allowing researchers to deal with complexity, context and persona and their multitude of factors, relationships and fuzzy phenomena*" (Cassell and Symon 2006). (b) The methodology uses mathematical modeling (optimization) which helps to ensure generalizability of results while accounting for the context of study. The importance of considering context in HL studies has been noted in many studies (e.g., Pedraza-Martinez and Van Wassenhove (2016)).

In this section, we explain every step in detail except for Step 8, Paper compilation, which has been widely covered in the literature.

3.1 Step 1: Literature review

Whether the problem emerges from a sudden or slow onset disaster, or focuses on long-term (protracted) crises, the literature review constitutes the starting point of the proposed research methodology. This first step helps to identify gaps in the literature and formulate the research question and problem upon those gaps, or to inform or clarify a formulated research question or problem coming from the field. In both cases, the literature review may start before or right after the event and can continue throughout the data collection (and sometimes data analysis). The review consists of four main parts, some of which can be completed in parallel.

i For known problems, review the literature regarding the main problem that is going to be studied in the field. Distinguish the category of the decision problem (e.g., location, allocation, transportation, routing, scheduling, etc. or a combination of them) that the model will be developed for and recognize the contextual requirements. Several survey papers that review multi-criteria models (e.g. Gutjahr and Nolz (2016)) can be used for positioning the problem category. Prepare an overview of available and relevant models for the problem to understand how it is formulated. For new or emerging phenomena, review relevant blog posts, whitepapers, and practitioners discussion papers in gray literature.

ii Collect secondary data related to the situation to get an overview of the context and get a better understanding of what to expect in the field. Situation reports, country profiles, infographics and maps are some of the types of documents that can be reviewed at this stage.

iii Define or refine the research question, objectives and purpose.

iv Develop an early stage conceptual model of the problem based on literature review and insights from the secondary data.

The purpose of the research as well as the type of question will determine the appropriate qualitative method and data collection techniques, following Ellram (1996) and Handfield and Melnyk (1998) classifications. In HL literature, the case study is the most common qualitative method (Jabbour et al. 2019), and has been used for exploratory, descriptive, explanatory and even predictive purposes (Vega 2018). Other qualitative methods such as delphi studies or focus groups have also been used in HL research but to a lesser extent. Therefore, for the purpose of this article, the proposed design will focus on the case study method. As pointed out by Gammelgaard (2017), the research design depends on the aim of the case and thus, it is important to explicitly specify this issue to ensure rigor and argument that support the following methodological choices.

3.2 Step 2: Field study design

The next step is to determine the case study design by asking two questions for crafting case study research in HL: what and how practically (Vega 2018). The *what* question relates to the unit of analysis (cf. Patton (2002)), which in HL can vary from people, to organization(s), regions, crises, phases or a combination of those. Determining the focus of the study has important implications on the generalizability of results and thus, the consecutive optimization model. Therefore, the unit of analysis should be thoroughly described and argued.

Once the unit is defined, the *how practically* question addresses case selection and the related data collection techniques and analysis. Although a number of case sampling techniques coming from social sciences can and have been implemented in HL research, in many occasions case selection is a matter of access and opportunity. Flyvbjerg (2006) differentiates case selection between random (i.e., to avoid systematic biases in the sample) and information-oriented (i.e., to maximize the utility of information from small samples and single cases). Given the previously acknowledged restrictions regarding access to data, the latter is often the best suited technique to undertake case studies in HL. This includes extreme/deviant cases, maximum variation cases, critical cases and paradigmatic cases. Whatever the adopted technique, it is important to explicitly account for as data collection and analysis techniques rely on it.

The remaining parts of this step relate to quality criteria and research protocol. According to Halldorsson and Aastrup (2003), internal validity, external validity, construct validity and reliability are commonly accepted criteria in logistics research (cf. Ellram (1996); Yin (2009)). However, Guba and Lincoln (1989) put forth the concept of *trustworthiness* as an alternative suitable quality criterion for logistics research. Trustworthiness is composed of four dimensions (credibility, transferability, dependability and confirmability) that echo the conventional paradigm presented above. Guba and Lincoln (1989) conclude that these dimensions can be expressed by three issues:

1. Truth-value: correspondence with ‘reality’ as interpreted by respondents (credibility) or survival of falsification attempts.
2. Transferability and contextualism.
3. Trackability and explicity: explicating and documenting the process and its decisions (dependability), the sources of data and interpretations (confirmability) as well as the theories and questions underlying interpretations.

Following Pedrosa et al. (2012) and in accordance with Halldorsson and Aastrup (2003), we suggest to follow the previous three criteria to ensure quality of case studies in HL. Truth-value can be ensured through long-term field work, pilot interviews or peer debriefing. Transferability can be reached by using purposive sampling techniques and data saturation. Trackability can be ensured by a thorough description of the study methods and the establishment of a track record trial for both data collection and analysis.

Finally, the last step concerns the creation of the field study protocol, a document that outlines the procedures involved in the data collection. It normally entails an overview of the case (background information, theoretical framework and research question), key concepts and theories, data collection procedures (access to the site, data collection plan, privacy issues, questionnaire / survey), a detailed line of questions or set-up and timing of focus groups or experiments, and an outline for the final report (Mills et al. 2010; Yin 2009).

3.3 Step 3: Data collection

The third step relates to data collection in the field and remotely. There are different techniques that have been used in qualitative inquiries such as direct observation, indirect observation and the many types of interviews (Ellram 1996). The latter is the most common technique in HL research (Vega 2018). In addition, data triangulation is used in most of the case studies to complement interview data and observations, and to embed events or interviews into a timeline. Official documentation and reports, guidelines, academic literature, press articles, direct observations and presentations have been used as means to study a phenomenon from different perspectives. For quantitative data collection in the field (if required) to support the qualitative inquiries, surveys or questionnaires have been suggested in the literature (Kovacs and Moshtari 2019).

On-site and remote data collection must follow the prepared protocols. Regarding informants, a myriad of sampling techniques are found in the literature (e.g., Miles and Huberman (1994)) but not all fit the characteristics of the humanitarian context. As pointed out by Vega

(2018b), when conducting case studies in HL, non-probabilistic techniques are more suitable due to the limited knowledge of the population and the impossibility to determine the sample in advance. A technique that is widely used in logistics and operations management research is theoretical sampling (Manuj and Mentzer 2008), which favors a theory-driven choice of informants over a representative one. Other sampling techniques (e.g. quota, snowball or sequential) can be also used in addition to the theoretical (Vega 2018) as a means to cross-validate preliminary results and to reach theoretical saturation, i.e., the point when additional interviews do not reveal new insight (Manuj and Mentzer 2008; Gralla et al. 2016; Comes et al. 2020).

An additional important source of evidence that is found in the aftermath of any disaster is written documentation such as overviews, situation reports, information bulletins, updates, daily flashes and action plans, or graphic documentation such as infographics, dashboards and maps available through official websites, such as Reliefweb.int or Humanitarianresponse.info. Increasingly, also quantitative data is made available through platforms such as the HumanitarianDataXchange website. Compared to the secondary data collection performed in the first step, here the search is delimited by the object of study, and the documents are used as an additional source to ensure data triangulation.

This sort of data collection has been already used in logistics and supply chain management research (Seuring and Gold 2012) as well as HL research (Seifert et al. 2018; Vega and Roussat 2019). It follows a precise and rigorous process that ensures trackability and starts with delimiting the material to be collected by identifying the source, defining the search criteria (e.g., scope, time, format) and filters that match the research objectives. Later on, the material collected from all documentary sources, the decisions made during the process and the final sample to be analyzed is described. While observations and field interviews need to be done on-site, complementary online data collection, or Skype or phone interviews can also be carried out remotely, or via back office support (Chan and Comes 2014).

3.4 Step 4: Qualitative data analysis

The fourth step relates to finding similarities, differences or patterns that emerge from the collected data, both from interviews and written documentation. This process known as *coding* is a technique for organizing substantial amounts of qualitative data into conceptual categories to make sense of the information collected. A code is thus a label to which units of meaning, i.e. words, phrases or paragraphs, are assigned (Miles and Huberman 1994). The importance in the process is put on the concept and its meaning, not the word or specific phrasing. The process normally involves at least two levels of coding, and depending on the source (i.e. interviews or documents) the approach can differ.

When analyzing interview data, several authors (Ellram 1996; Miles and Huberman 1994; Strauss and Corbin 1990) refer to two levels of coding. The first level (open) refers to organizing the data by categories that relate to research questions, hypotheses or research objectives. A good advice is to prepare a list of provisional codes based on the first results from the literature review. At this stage, it is also possible to develop a sub-set of codes that belong to the provisional list in order to structure the information found in each code. The second level (pattern or axial) seeks to identify relations between the categories found during the open coding, providing greater insights into the data. It also helps to identify which codes or subsets need deeper consideration or are irrelevant and should be dropped. It is important to understand that the coding process is iterative rather than sequential.

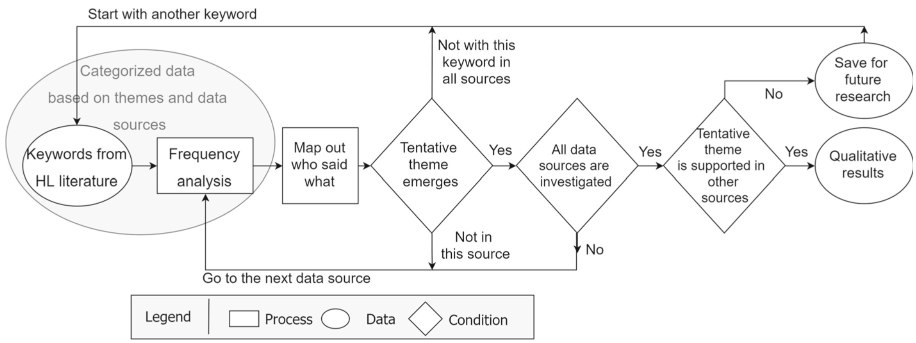

Fig. 2 Suggested approach for qualitative data analysis

Analyzing written documents can also entail various levels. As previously explained, two approaches can be adopted to analyze written documents, namely thematic and content analysis. Thematic analysis focuses on identifying 'themes' that refer to something important from the data with regards to the research question that represents meaning within the data set (Braun and Clarke 2006). It starts with preparing and getting familiar with the data (i.e. reading and re-reading the data), generating initial codes (i.e. interesting features) and searching for themes (i.e. collating codes). Then, a first level of analysis will focus on reviewing the themes in relation to the coded extract, while a second level will do the same but in relation to the entire data set to generate a thematic map. It finalizes with generating clear definitions and names for the themes (Braun and Clarke 2006).

A summative content analysis, on the other hand, focuses on the objective, systematic, quantitative and qualitative study of published information (Hsieh and Shannon 2005). The first level (manifest) refers to the search of occurrences of identified words or codes that emerge from the literature review (Elo and Kyngäs 2008). Qualitative Data Analysis Software like Atlas.ti or NVivo offer tools that can perform this analysis and return a list of the most frequently used words from which the researcher should pick those in relation to the codes established in the open coding. Another possibility is to use the software's query tools and perform a stemmed search of the keywords, looking to identify synonyms and related words. In both cases, the resulting words become the starting point for the following level of analysis. Latent content analysis, the second level, refers to the qualitative analysis of the content found in the manifest content analysis. The goal of this level is to examine the context in which the keywords were used to understand their meaning and further code them into the previously established set of codes during the open coding. Recently, some tools have been developed based on supervised machine learning for automated content analysis dealing with complex interpretations of text (Pilny et al. 2019). However, we explain the manual approach here.

Either thematic or content analysis is adopted, an iterative process is required to compare carefully the emergent unit of meaning with the evidence from previous steps in order to assess how well or poorly it fits the overall code. When a pattern from one data source is corroborated by evidence from another, the finding is stronger and better grounded. When evidence conflicts, we propose to reconcile the evidence through deeper probing of the meaning of the difference. At other times, this conflict exposes random patterns or biased thinking in the analysis. The analysis is complete when all keywords or codes are used and further investigations are carried out. Resulting themes that are supported by other sources are further used in the cross-case comparison step.

3.5 Step 5 (optional): Cross case comparison

The aim of this optional step is to search for cross-case patterns. To ensure the generalizability of findings from a case study and avoid reaching premature or false conclusions, mostly due to limited data or different biases, literature suggests to search for cross-case patterns (Meredith et al. 1989; Eisenhardt 1989) to improve the external validity of the findings and build stronger evidence (Besiou and Van Wassenhove 2020). As De Vries and Van Wassenhove (2020) argue, the diversity of humanitarian contexts makes the scope and characteristics of HL problems highly case-dependent. As such, analysis of one case study, as often seen in HL literature (Trivedi and Singh 2018; Banomyong et al. 2019), is generally insufficient to produce generalizable findings.

To ensure that the researcher captures novel findings that may exist in the data, Eisenhardt (1989) proposes three tactics for cross-case pattern searching. The first tactic focuses on selecting dimensions and use these to look for within-group similarities and intergroup differences. The second tactic uses pairs of cases to list similarities and differences between each pair. Finally, the third tactic relies on the division of data by data source and corroboration of findings using evidence from different sources. Based on these three tactics, we propose a cross-case pattern search approach which is illustrated in Fig. 3. The central idea is that we constantly compare theory (academic literature) and best practices to support or decline qualitative results. Beside academic literature, information for comparing cases can be collected from field reports and evaluations (e.g., via Reliefweb.intl, Humanitarianresponse.info, HumanitarianDataeXchange) or white papers (e.g., from ALNAP, elrha) and guidelines (from the HOs).

Using this approach, two directions are considered. The first direction refers to those insights from other cases that (a) support findings from field study such as identified characteristics, concepts or assumptions, or (b) provide basis for further examination of them.

The second direction refers to those findings that shape future research agenda. If after carrying out data analysis, a researcher could not find convincing material to interpret the finding, we suggest to include the corresponding finding as a direction for future research.

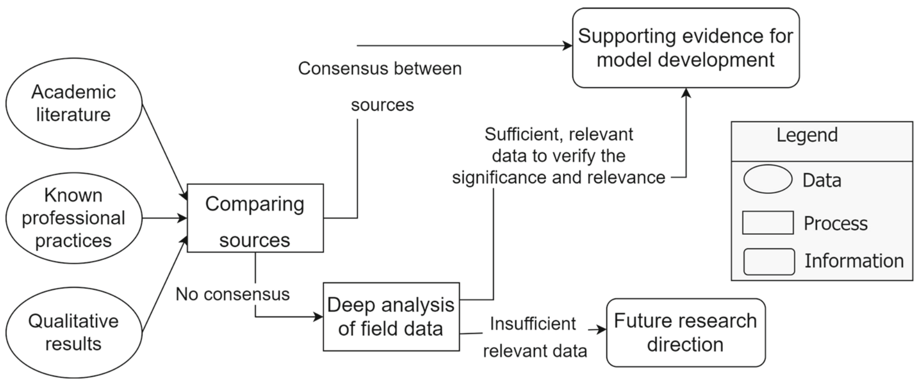

Fig. 3 Suggested approach for cross-case comparison (adapted from Eisenhardt (1989))

3.6 Step 6: Developing the mathematical model(s)

This is the final step in the Post- field work phase. In this step, a researcher may choose to develop a mathematical optimization or simulation model or to shape hypotheses for statistical analyses. In any case, further quantitative data may need to be collected (for instance through surveys or questionnaires) (cf. Sect. 3.1). In this paper, we exclude quantitative data collection from the step for the sake of brevity. We also assume that the researcher pursues developing mathematical optimization models.

Due to the multiple criteria nature of most decision-making problems in HL (Gutjahr and Nolz 2016; Gralla et al. 2014), we assume the multi-criteria decision analysis as the preferred methodology in the mathematical modeling phase. We acknowledge that the traditional multi-criteria decision analysis cycle of problem formulation and preference elicitation can be followed. However, we suggest the following approach adapted from Charles and Lauras (2011) due to its simplicity (Gupta et al. 2016) (for a more generic paper, we refer to Tsoukiàs (2008)). Charles and Lauras (2011) suggest three steps based on business process modeling notion (BPMN) to convert conceptual information included in a BPMN model into quantitative information. We adapt Charles and Lauras (2011)'s three steps into a four-step systematic approach for developing multi-criteria models using outcome from previous steps.

i Apply adjustments to the problem definition and scope, and its contextual requirements, e.g. data requirements or modeling approach, with respect to field findings and supporting evidence.
ii Extract the problem features (objectives, parameters, variables, and constraints) from the literature summary and field findings given the scope and the context of the problem.
iii Compare how the problem is modeled in the literature with how practitioners deal with it in practice versus how it should be dealt with (as there might be a practical gap). If there are divergences, look for evidence in qualitative findings regarding why practitioners are acting differently. If they are doing so due to constraints in disaster contexts (lack of access to sufficient reliable data, time, and computational resources), then revise the features and objectives of the model according to contextual requirements.
iv Develop the model for further quantitative analysis (this analysis will be carried out through an experimental design).

The experimental design should be developed in connection to the research question(s). The experimental design should reflect the motivation for the objective function, as well as the procedure for testing which variations in variables and parameters are the most relevant. It must answer questions related to why (motivation), what (purpose), and how (process). Our review of several online templates revealed some common questions that are often used to prepare an experimental design, as listed in Table 1.

3.7 Step 7: Model testing and validation

To investigates the relations between uncertain parameters of an optimization model, and the stability of the observable outcome (Saltelli et al. 2008) sensitivity analysis is required. The sensitivity analysis is recommended to be conducted on all the significant parameters of the optimization model that are subject to variation. Particularly the ones that intervene in the objective function(s) of the model. An effective analysis should include univariate (simple) analysis and multivariate analysis (Weathers et al. 2009). Moreover, a thorough sensitivity analysis with regards to instance size is necessary to show the performance of the solution method and the quality of results. Leiras et al. (2014) note that benchmarking HL models

Table 1 Some example questions for developing the experimental design derived from online templates

Target	Example questions
Why? Clarifying the motivation.	Why would it be important for you to run this experiment with such objective functions?
	Why would it be important for others to run this experiment?
	What are your expected outcomes?
What? Clarifying the purpose.	What are your variables (independent and dependent)?
	What are key parameters and their data requirements?
	What are your ideas on trying to solve the model?
How? Clarifying the roadmap.	What steps are included in the procedure?
	How will you measure your independent variable?
	How will you measure the resulting change in the dependent variables?
	How long do you expect to complete your experiment?

would be ideal to ensure that the proposed formulation is scalable and is robust to the input in terms of computational performance. While sensitivity analysis can facilitate extracting managerial insights, Pedraza-Martinez and Van Wassenhove (2016) contend that it should be combined with validation by practitioners.

Validation aims to bridge rigor and relevance of optimization models in the HL research and can be carried out through face validation, cross validation or historic validation (Balci and Gass 2013). In our research methodology, the Step 7 addresses the following two actions: evaluating and refining. The main task in this step is to return to the practitioners to validate the model results and potentially implement the study's recommendations in practice. Pedraza-Martinez and Van Wassenhove (2016) refer to this step as “closing the loop" and there are some examples in the HL literature (e.g., Acimovic and Goentzel (2016) and Laguna-Salvadó et al. (2019)). Pedraza-Martinez and Van Wassenhove (2016) assert that validating results with practitioners facilitates building a trust which can allow researchers to convince practitioners to spend more effort in collecting better data and in working more closely with academia.

4 Application to the 2015 Nepal earthquake

On April 25, 2015, and a mere 17 days later, Nepal was hit by two major class earthquakes, measuring 7.8 and 7.3 on the Richter scale, respectively. These earthquakes affected roughly 5.5 million people, leaving nearly 9,000 casualties, and caused approximately 7.1 billion US dollars in economic damages (Government of Nepal 2015). On April 26, 2015, due to the severe damages of the first earthquake, the Government of Nepal declared the need for humanitarian assistance.

During June 21-29, 2015, nearly eight weeks after the disasters and just before the beginning of the recovery phase, a multidisciplinary research group conducted a field study in Nepal. The primary objective of the field research was to study challenges and bottlenecks in HL, specifically in relation to decision-making, information management, and coordination.

In this section, we explain how we followed the proposed research methodology to study the relief distribution centers location-allocation problem in sudden-onset disaster response and to develop a relevant optimization model based on field-driven insights. In the location-allocation problem, to facilitate the distribution of the received relied items in the affected country, the decision-makers (DMs) must determine the location for setting up the temporary distribution centers, and decide the allocation of the scarce resources to them (Baharmand et al. 2019).

4.1 Step 1: Literature review

We were finalizing a literature review on different literature streams in humanitarian supply chains (Baharmand and Comes 2015) when the 2015 Nepal earthquake happened. Hence, we did not have to conduct an ad-hoc review in the aftermath of the disaster. Here, we elaborate on the relevant findings of the literature review (research gaps and the problem definition) that informed the second step of our research methodology (cf. Fig. 1).

Research gaps: With respect to optimization models, our review revealed three main gaps in the literature, partly supported by previously conducted literature reviews (Anaya-Arenas et al. 2014; Galindo and Batta 2013). First, we found that scholars used unrealistic constraints when proposing mathematical models for HL problems including unlimited capacities for transportation and warehousing. Moreover, we noted that very few studies used multiple objectives in their proposed models, despite the presence of several actors working in HL with different mandates and objectives. Second, we found that scholars rarely considered multi-period models for HL problems in the sudden-onset disasters response. Rather, researchers mainly focused on static problems that discard the fact that characteristics of HL problems (such as access to working road infrastructure) change over time, even during the relatively short phase of disaster response. Third, we identified a lack of studies that accounted for uncertain parameters of HL problems in disaster response in the mathematical models.

Problem definition and scoping: In the immediate aftermath of a sudden-onset disaster, one of the first tasks for the logisticians is to establish a network of facilities to distribute relief items to beneficiaries in urgent need. Designing such networks involves taking critical decisions under time pressure, whose time- and cost-efficiency affects the overall performance of the response (Jabbour et al. 2019). Location-allocation decisions are central to the humanitarian disasters response. These decisions determine the ideal location (and sometimes the number) of the logistics hubs or distribution centers, and the quantity of resources allocated to them for distribution. The requirements for the location-allocation decisions can differ based on the characteristics of the disaster and the disaster phase.

4.2 Step 2: Field study

Following our research methodology, our preparation for the field research continued by carrying out the field study check step. Figure 4 illustrates our rationale for the check questions following Gammelgaard (2017) and Vega (2018).

Our field research protocol aimed at investigating three main research questions. First, how relief distribution networks are designed in practice. Second, what specific challenges and bottlenecks exist in designing and implementing relief distribution networks. Third, what best practices practitioners use (if any) to overcome such challenges and bottlenecks. Our HL interview protocol included qualitative and quantitative questions covering aforementioned three research questions [1]. An early stage theoretical model of HL, illustrated in Fig. 5, was

[1] The field research and interview protocols can be shared upon request.

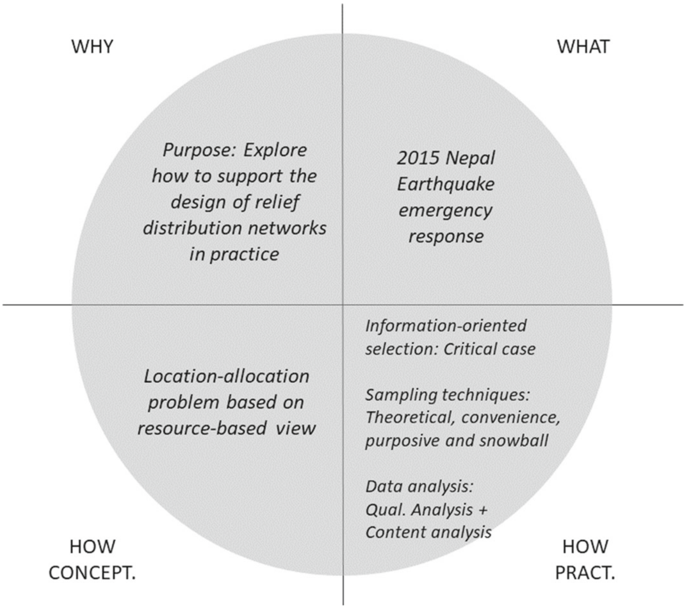

Fig. 4 Illustration of field study check questions

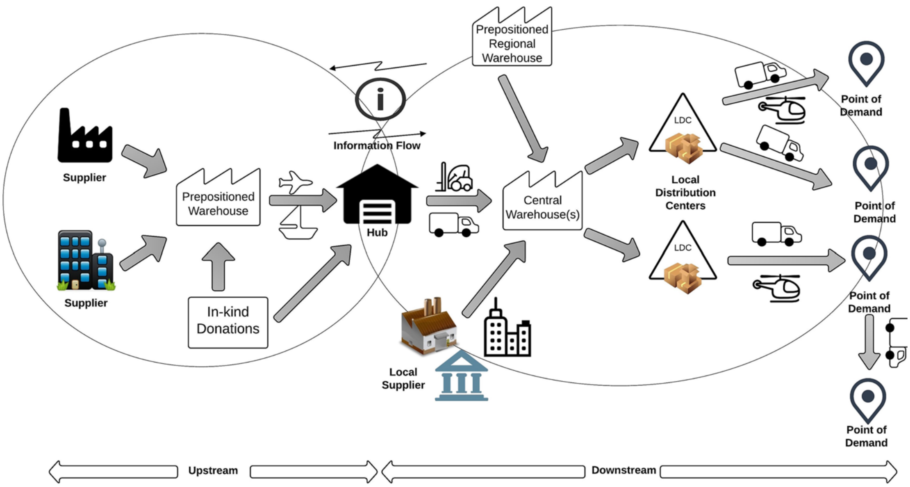

Fig. 5 The early stage theoretical model for relief distribution networks in Nepal

also developed before the trip. The model shaped the basis for investigating our first and second research objectives.

The Nepal case responds to both an opportunistic and an information-oriented selection. While the former describes a case selection based on the emergence of a new case, the latter helped us to confirm the richness of the case with relation to the defined problem. In that sense, the 2015 Nepal earthquake case can be seen as a critical case from which logical deductions can be drawn and potentially be applied to other similar cases Flyvbjerg (2006). Following a combination of sampling techniques (i.e. theoretical, convenience, purposive and snowball), we developed our first contact list based on the pre-established connections in local and international non-governmental organizations (NGOs) as well as UN-related organizations in Nepal. The interviewee selection was done according to (1) expertise, experience, and background of the contact (logistics, information management, coordination) (2) responsibility in targeted organization and being involved directly in Nepal response (3) presence in Nepal during the field study. Our initial list was filled in with names of logisticians or country managers collected from these online resources: ReliefWeb, HDX, and LogCluster. Establishing the first connection with contacts was done by sending emails containing a brief explanation of research plan, team objectives, the time frame of presence at Kathmandu, and the way that interviewee can contribute. After providing requested information for respondents and under their confirmation, first schedule of interviews was set and the interviewee list was uploaded through a shared folder. Eventually the first interviewing plan was made.

We also established a remote expert team composed of senior scholars to support the field researchers. The expert team provided inputs regarding how to improve data collection process, how to find relevant contacts in the field, and how to organize field trips. We also started to collect the situation-related information in early May 2015 from a variety of online sources.

4.3 Step 3: Data collection

We carried out our on-site data collection in Kathmandu, Nuwakot, and Rasuwa districts in close collaboration with local agencies. We conducted 31 interviews with key informants based at multilateral agencies and international NGOs (iNGOs) between June 24th 2015 and July 10th, 2015 (some interviews were conducted remotely). Among them, 16 interviewees were logisticians with at least ten years of experience in humanitarian response (cf. Appendix B). At the time of our research, they were working at: multilateral agencies (UNOCHA; WFP); Nepali branches of iNGOs (Oxfam; Cordaid; IFRC; World Vision International (WVI); Handicap International; Islamic Relief Worldwide (IRW); Humedica); and Nepal based NGOs (Kathmandu Living Labs (KLL); United Mission to Nepal (UMN); Nepal Red Cross Society). All interviews took less than one and a half hours and they were recorded after the consent of interviewee(s).

Furthermore, we complemented our field interviews with notes taken during field visits to Kathmandu, Nuwakot and Rasuwa districts (June 23rd-29th, 2015). As shown in Fig. 6, our field trip focused on severely hit districts. Moreover, documents collected from online sources and articles of local newspapers were considered. We used online sources (Reliefweb, Logcluster, HDX, and MapAction) to collect meeting minutes, maps, reports, and white papers. For newspaper articles, we collected those newspapers that were published in English during the timeline of our stay: The Kathmandu Post, and The Himalayan Times. We note that data from social media were not collected as the focus of our work was on HL. We argue that social media data can be used to analyze the assessment gaps and sentiment (different focus compared to HL) (Palen and Anderson 2016; Wamba et al. 2019; Giannakis et al. 2020), and requires a specific protocol for data collection, noise cleaning, data analysis and data interpretation (Crumbly and Carter 2015; Tacheva and Simpson 2019).

4.4 Step 4: Qualitative data analysis

We combined our data sources for indexation, as shown in Fig. 7. This figure shows approximately the share of each main theme from the categorized data. Some data that could be

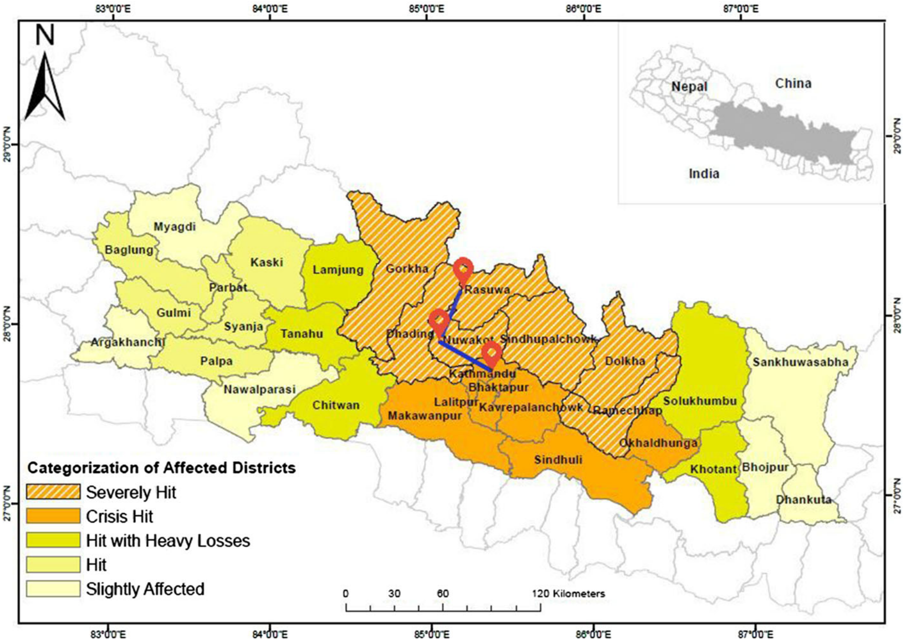

Fig. 6 Affected areas by 2015 Nepal earthquake and our visits during field study (map from Government of Nepal (2015))

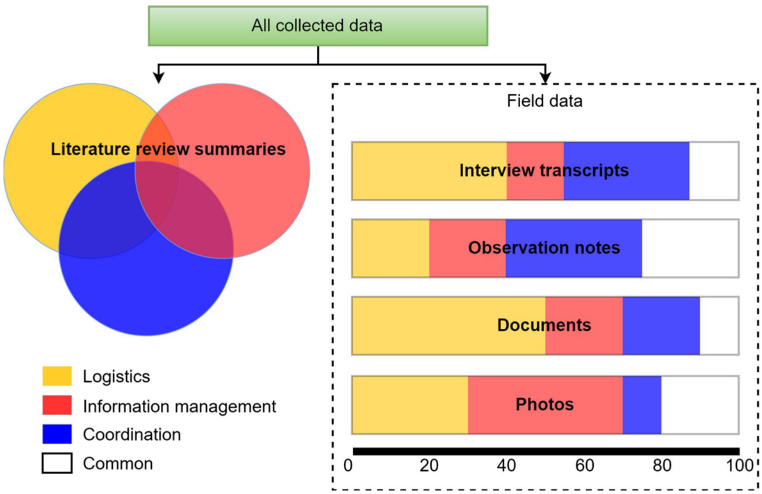

Fig. 7 Categorized data for Nepal case

categorized under two or three themes, shown as ‘common’ in Fig. 7. To avoid biases, four researchers did the categorization individually and conflicts were solved under the supervision of a senior researcher.

In the category of logistics, we had transcripts for 16 interviews; observation of relief operations of five HOS namely UN WFP, IFRC, Humedica, Cordaid, and WVI noted through three field trips to severely affected areas in Kathmandu, Rasuwa, and Nowakut as well as other data sources such as 18 maps, 74 documents, 388 photos, and summaries of 68 reviewed articles.

For qualitative data analysis, we followed a hybrid approach, combining interpretive thematic analysis based on a coding schema and inductive coding based on emerging codes (Fereday and Muir-Cochrane 2006). Coding schema was informed by our preparatory literature review where the following keywords were extracted: 'location', 'locating', 'allocation', 'transportation', 'warehouse', 'hub', 'staging area', 'distribution center', 'relief distribution', 'relief network', 'humanitarian supply chain', 'humanitarian logistics', 'decision', 'decision-making', 'decision support system', 'model', and 'scenario'.

Given the aforementioned keywords, we conducted the iteration process as explained in Sect. 3.4. In the following, we present some qualitative results that emerged with respect to our first two research questions:

- Relief distribution networks in humanitarian response are established ad-hoc. They are highly depend on the characteristics of the affected area.
- Locating temporary distribution centers and allocating resources to them (i.e., distribution centers location-allocation) is one of the very first critical decision that field-based DMs often make right after arrival.
- Locating staging areas and temporary distribution centers is often done by operational decision-makers mainly based on experience from previous operations and in-place plan from the preparedness. Key criteria include accessibility to the road network and availability of space.
- Despite the complexity of situation in the aftermath of disaster, practitioners show reluctance to use mathematical models for location-allocation decisions. The reason could be that the majority of models fail to account for field constraints with respect to information, capacities, etc.
- Several redundancies, delays, and backlogs were observed in the operations. The main reason for redundancy was uncertainty. Another reason could be the lack of using decision support models.

4.5 Step 5: Cross-case comparison

Given the results from the Nepal case, we carried out the cross-case comparison following the steps explained in Sect. 3.5. We selected and used available reports for the following cases to conduct the cross case comparison step: Haiti earthquake (2010), Typhoon Bopha (2012), and Typhoon Haiyan (2013). Our rationale for selecting these cases was threefold. First, all events were large-scale sudden-onset disasters, and shared this characteristic with the Nepal earthquake. Second, they evolved into humanitarian emergencies, whereby international assistance was provided. Third, reports of the related humanitarian operations can be downloaded from online sources such as Reliefweb.int.

Given the process outlined above, we identified some key evidence to be considered in the next steps:

- Considering the context is of great importance when developing location-allocation optimization models. Neglecting to mention which context the model is developed for and under what circumstances, leads to models that are not practical in the field.
- The information that field-based DMs need for their location-allocation decision-making processes gradually becomes available after the disaster. This entails differences between how decisions are made in the first weeks of immediate response, and thereafter. Thus, an

exhaustive optimization model for the whole time-frame of the response cannot respond to the contextual requirements.

- Considering multiple decision criteria is of great importance in location-allocation optimization models. Some criteria that practitioners often referred to are: effectiveness, the unsatisfied demand in all targeted affected areas; efficiency, logistics costs including facility, human resource, and transportation costs; and responsiveness, supply-side travel time, which contains the time required for shipping items from main entry points (MEPs) to staging areas (SAs) and from SAs to points of demands (PODs).
- While in the later phase of the disaster, aid is prioritized based on needs assessments, field-based DMs initially rely on pre-disaster data, such as the latest census report for estimating the demand. While using stochastic data modeling can assist decision-making under uncertainty, such data modeling approaches are hardly applicable initially due to the contextual constraints. Accordingly, we observed use of deterministic analyses (mainly paper-based) with some scenarios for varied demand (location and size) or supply (type and amount).
- The set of candidate sites for location decision is known. Practitioners considered only locations that remained accessible through main roads and have access to a helipad.

4.6 Step 6: Developing location-allocation optimization models

The qualitative part informed our problem definition, data modeling, decision criteria, timeline, assumptions, and other modeling requirements. According to our field findings, the location-allocation problem in the immediate response can be schematically illustrated as in Fig. 8. In the immediate response, DMs must determine where to locate and set up distribution centers (staging areas in our study) to store shipped items for last mile distribution and how to allocate scarce resources to them. For logistics decisions in this phase, the supportive evidence indicate that DMs often focus on response time and logistics costs. In the relief phase, the problem changes to optimizing the location (keep or relocate staging areas) and the resource allocation decisions given that after the immediate response: (i) more concrete information regarding the demand catalog becomes available (need assessment results); (ii) some new entry points may be opened or come back to operation; (iii) transportation status may change (infrastructure or fleets); and (iv) relief operation targets may change (priorities). Our case findings support that DMs usually focus on response time, demand coverage and logistics costs in the relief phase.

According to our findings, the location-allocation optimization model needs to take into account following features:

- Using a deterministic approach in data modeling with ability to include scenarios that are developed systematically;
- Considering two distinct (but related) time-frames: immediate-response and relief;
- Following a multi-criteria methodology given that for the immediate response phase, the focus should be on response time and logistics costs objectives. The extent of demand coverage is an additional key criterion in the relief phase.
- Using flexible structures (decision variables, parameters, constraints) that could be adapted given the problem characteristics in the field.

To develop the models, we combined the outcome of Step 1 (cf. Fig. 1) with the aforementioned evidence from our field work and cross case findings (cf. Sects. 4.4 and 4.5). From there, a set of assumptions was derived for developing the model. For instance, mobile storage units (MSUs) were assumed as storing structures in the SAs. MSUs have been suc-

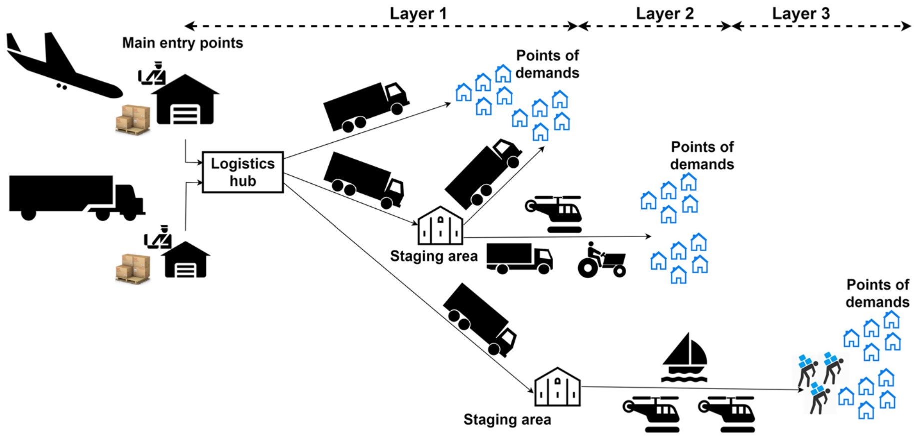

Fig. 8 Schematic presentation of the location-allocation problem in the sudden-onset disasters response (Baharmand et al. 2019)

cessfully and rapidly erected in recent response operations, and thus, they can expedite the relief operations. We also assume that the act of erecting MSUs is conducted by volunteers and does not impose any logistics costs (Baharmand et al. 2019, 2020).

Based on such assumptions and other information about the problem, we defined the following objectives:

$$\begin{aligned} Minimize\,total\,logistics\,costs &= Ground\,transportation\,cost \\ &+ Air\,transportation\,cost \\ &+ Recurring\,cost \\ &+ Human\,resource\,cost \\ Minimize\,total\,response\,time &= MSU\ setup\,time + Operation\,time \\ Minimise\,total\,uncovered\,demand &= Total\,demands - Total\,shipped\,items \end{aligned}$$

While the first two objectives were found critical for the immediate response phase, we considered a model with the three objectives for the relief phase. A complete list of assumptions as well as detailed mathematical formulations of our models can be accessed in Baharmand et al. (2019) and Baharmand et al. (2020).

4.7 Step 7: Model testing and validation

We developed and tested our optimization models in close collaboration with practitioners over a course of approximately two years. The experts were logisticians working on planning the relief operations in UN agencies and HOs. After several iterative discussions, we were able to identify the required capabilities, model them, and ensure that they are implemented correctly. In the model development process, we compared the model calculations with practitioners' data, and investigated those cost or time components that were estimated differently or were left un-modeled. Following the discussions with the practitioners, we finally ensured that the un-modeled costs and times were integrated in the models.

For validation purposes, the data that we used was gathered from online resources. Such data is often available for different type of disasters through information sharing platforms.

Typically, HOs would be provided maps, distances, and logistics prices through the Logistics Cluster in the early stages of response. Such information is also often shared on websites such as ReliefWeb, LogCluster, and HumanitarianDataeXchange as open data. In situations where data is not available or it is incomplete, practitioners use estimates, according to our findings from the field study.

Having collected information about decision-makers' choices in our field research, we also explored the difference between our models' results and the choices of the practitioners. This helped us to investigate the reasons behind (potential) divergences (Baharmand et al. 2019). For instance, we noted that our models did not consider the fairness criterion although this was mentioned a few times in our interviews. Our rationale for excluding fairness from our models was that the practitioners' approach to consider this criterion was not clear and lacked transparency. We could not find sufficient evidence in our cross case comparison step (cf. Sect. 3.5). Some practitioners referred to fairness as the priority of regions and targeted groups whereas others mentioned the timeliness of the deliveries. That said, we found that defining an appropriate objective function for fairness would require a dedicated investigation with practitioners. We acknowledge the few papers that have worked on measuring fairness (e.g,. Holguín-Veras et al. (2013) or Holguín-Veras et al. (2016)), however, the introduced measures in the literature are often data intense. Therefore, we considered working on the fairness objective function as a future research direction for our study (cf. Fig. 3).

5 Discussion

In this section, we discuss two main matters. First, we elaborate on the relevance of the developed models. Second, we discuss the challenges that may arise by following the proposed research methodology.

5.1 Relevance of developed models based on the proposed design

Relevance is defined as "*assess[ing] propositions for which practitioners seek stronger evidence*" (De Vries and Van Wassenhove 2020). Here, we discuss the evidence that support relevance of our models given the following elements: decision criteria, contextual requirements, and experimental plan.

Only few papers can be found within the last decade that explicitly deal with multi-criteria location-allocation problems in humanitarian response after a sudden onset disaster (Anaya-Arenas et al. 2014). Interestingly, the majority of these optimization studies focus on addressing demand coverage and logistics costs (Gutjahr and Nolz 2016; Trivedi and Singh 2018; Jabbour et al. 2019; Zandkarimkhani et al. 2020), while our field research clearly showed that minimizing the response time and logistics costs are of utmost importance for the logisticians in the immediate response phase. Few studies take into account response time and logistics costs for the immediate response, and address both objectives simultaneously (Tzeng et al. 2007; Vitoriano et al. 2011; Lin et al. 2012; Ahmadi et al. 2015; Zokaee et al. 2016). For instance, Zokaee et al. (2016) propose a robust stochastic model to minimize the total costs of the relief chain given a penalty to shortages of relief commodities. However, the parameters of penalty functions are not justified. Overall, the justification for selecting criteria in HL location-allocation models for the disaster response is often missing.

Aforementioned models often fail to reflect critical constraints of the response due to simplifying assumptions: unlimited capacity of locations (e.g., Lin et al. (2012)); single

Table 2 Differences between our field-driven models and state-of-the-art

Research characteristics	Existing location-allocation models in HL literature for sudden-onset disaster response	Our location-allocation models
Considered time-line	Single period (the whole response phase)	Two phases (immediate response + relief phase)
Decision criteria	Mostly single objective considering either demand coverage, logistics costs, response time, or a bi-objective combination of demand coverage and logistics costs.	Logistics costs and response time for the immediate response, and logistics costs, response time and demand coverage for the relief phase
Data modeling type	Both deterministic and stochastic	Deterministic with ability to run quickly in multiple times in different response stages when new information becomes available
Assumptions	Often lacking justification such as incapacitated locations or transportation means	Justified with field data and based on discussions with practitioners
Verification approach	Numerical experiments	Numerical experiments + benchmarking with practitioners' decisions in the real case

commodity (e.g., Maharjan and Hanaoka (2018)); infinite accessible vehicle for distribution (e.g., Cao et al. (2018)); fixed-number of distribution centers (e.g., Noyan et al. (2015)); single period operation (e.g., Orgut et al. (2016)). We adapted our model's assumptions according to field findings. For instance, we considered two periods in our model to explicitly reflect our observations regarding the change of decision-making driven by information, and resulting in different decision criteria and problem characteristics between immediate response and response in the field.

With respect to validation, we found that the majority of reviewed papers use numerical experiments based of fictional cases. Numerical experiments often lack a concrete basis and are developed randomly (e.g., Noyan et al. (2015)). Despite the many calls for relevance, HL literature still frequently uses numerical experiments while this approach brings limited insights to practice (Leiras et al. 2014; De Vries and Van Wassenhove 2020). The limited use of real data can be partly explained by the lack of access. However, owing to our field research, our models use real data for benchmarking and validation. Using data from real operations in the 2015 Nepal earthquake response allowed us to compare our results with decisions of practitioners, investigate the divergences, and revise the model accordingly (if necessary).

Regarding the generalizability of the model, we acknowledge that this would require checking the model results after applying it to several cases. By using the 2015 Nepal earthquake response case (Baharmand et al. 2019, 2020), we have demonstrated that the model can support UN WFP's decision makers with the staging areas location-allocation problem by providing a wide range of balanced alternatives with respect to logistics costs and response time. That said, we expect that our model is capable to support DMs who deal with similar problems in the context of sudden onset disasters response. We refer to checking model results for other cases as a future research direction (also mentioned by Baharmand et al. (2019) and Baharmand et al. (2020)).

Table 2 summarizes the main differences between our field-driven model and existing literature.

5.2 Challenges of the proposed research methodology

The context of sudden onset disasters has specific characteristics that imposes limitations on the possible field research designs. By their very nature, time for preparation is short. If the research design should not be ad-hoc, it needs to build on pre-existing insights and expertise to identify clear research questions. Second, the richness of the data collection in the field can be overwhelming. Therefore, a clear scope and framing are indispensable. Third, access to affected areas or to interviewees and DMs may be limited, especially in the early stages of a disaster. Therefore, appropriate sampling strategies need ot be implemented. Lastly, in a disaster, researchers necessarily engage with their interviewees and are immersed in the experience, potentially invoking emotions or biases (Chan and Comes 2014). Here, back-office support can help in maintaining the neutral stance of an observer—and to reflect on the challenges. In addition, qualitative data through interviews in the field may need cross-validation with other resources to avoid biases which can be time and effort consuming. We note that the above-mentioned challenges can be arguably more difficult to address when conducting field studies in conflicts contexts. As conflicts are not in the scope of our study, we refer to working on the related challenges as a future research direction.

Methodologically, not all referred research methods in other disciplines for mixed methods studies can be effectively applied in disaster settings. For instance, filling in surveys and questionnaires requires dedicating enough time, commitment, and focus while practitioners in the very early phase of a disaster response have other priorities. The semi-structured and conversational interview has one main advantage: it provides more flexibility for both sides to share information without formalities and at the same time, it converts the interview meeting into a story telling session that helps interviewees reflect on their experiences.

Also, our field research showed that there are some main considerations that have to be taken into account within the proposed design:

- Targeting interviewees for HL research must be done carefully since some of our respondents, as also noted by Van de Walle and Comes (2014), only had specific knowledge about their responsibility. Because they did not have a holistic perspective of other roles in their corresponding HO, we had to see many people within one HO to obtain sufficient information.
- Combining qualitative data with quantitative approaches demands careful analysis with several iterations for verification and often requires follow-up communications with participants.

The proposed research method follows Wacker (1998)'s general procedure for theory building for case study research. We start by limiting the domain of the proposed methodology to HL research, developed from studied cases, and demonstrating generalizability and abstraction by pointing out wide possible application valid all times and places. We use conceptual definitions from the literature without renaming them and using only short and unique definitions. Further, the relationships between the different concepts were logically explained, demonstrating possible new relations to explore without statistical techniques. Finally, we address falsifiability by proposing ways to avoid unlikely results.

5.3 Implications for theory

Our research has several implications for theory. First, it includes collecting detailed information on problems from the field and enables access to first hand data through close collaboration with practitioners to develop insightful research. Kovacs et al. (2019) note that HL studies should be motivated by a practical problem either (1) by working with humanitarian organizations or (2) by relying on previous explorative studies. Our methodology supports both requirements. We show that a detailed, step-by-step transparent methodology helps to develop evidence-based optimization models with realistic objectives, assumptions, and constraints.

Moreover, our suggested methodology helps to mitigate challenges that may hinder an effective mixed method research in HL. Kovacs and Moshtari (2019), Besiou and Van Wassenhove (2020) and Besiou and Van Wassenhove (2021) highlight the difficulties in collecting field data in the humanitarian context. To address such challenges, recent HL research has mainly focused on survey research (e.g., Behl et al. (2021); Dubey et al. (2020, 2021)). These studies have used surveys for hypotheses testing, for collecting practitioners' viewpoints on the challenges in the humanitarian operations, and for capturing the opinions of stakeholders in disaster-response performance reviews. Using surveys in HL research indicates that empirical methods are of general interest to the HL researchers. However, using surveys (i) for exploratory studies to inform analytical modeling and (ii) in studies for testing the models' findings, as suggested by Kovacs and Moshtari (2019), is still scant in the HL literature. We think that our methodology, can effectively support (i) and (ii) with small changes in Step 3 (substituting the field work with surveys).

Furthermore, our study contributes to better understanding and positioning of explorative mixed method research. (Yin 2009) highlight that explorative field studies are especially needed in research domains that are not adequately well developed, and they require a better understanding of the actors, subjects, problems, and the interactions among them. In the context of humanitarian operations, the problem or topic of the research should not only rely on a gap in the literature review, but it should also be grounded in practice and structured and defined by a group of scholars and practitioners. (Gunasekaran et al. 2018). Our method supports the development of (preliminary) conceptual frameworks and problem definitions that can guide researchers in the subsequent research stages on the factors or dimensions that require data collection.

Besides, our study has implications for research by suggesting how to evaluate qualitative results in a scientific rigorous way and how to incorporate them in a transparent, accessible, and replicable way. To the best of our knowledge, there are still a few HL-related papers that use qualitative methods to inform mathematical modeling and optimization (e.g., Baharmand et al. (2019)). If this is the case, the guidelines presented in this paper should help to increase research rigor in the future. Our methodology can connect different possible qualitative methods with the optimization. It could serve as a decision matrix for authors, editors, and reviewers.

Other implications refer to future research directions, and to opportunities for conducting joint research on these directions. For instance, our methodology can be adapted for other contexts/problems given the clarifications that we presented regarding the methods, constraints, and possible opportunities. With this, we acknowledge that the research-related lessons learned from the 2015 Nepal earthquake case study should be carefully applied in other settings, taking into consideration contextual differences.

5.4 Implications for practice

Kovacs and Moshtari (2019) indicate that studying HL problems using mixed methods helps to have stronger conclusion which would be more acceptable by practitioners. Our methodology not only supports achieving stronger conclusions, but also facilitates research that is relevant for problems in the field. By fostering relevant research, our methodology should help practitioners to apply research outcomes in practice with more confidence. Our study also provides practitioners with more understanding of mixed methods design in HL research, which they can use when calling for or evaluating such studies in their organizations.

Moreover, the design can encourage practitioners to engage more with research activities. From a practical standpoint, the Nepal case showed a challenging concern with respect to finding key informants from different HL stakeholders groups to participate in the field interviews. As HL problems often have a multidisciplinary nature, stakeholders' involvement and collaboration is key in HL research. That said, while the pre-fieldwork step has to be carried out carefully from the researcher side, practitioners participation can help to close the loop more effectively.

6 Conclusions

Mixed methods studies have been described as a promising avenue to bridge the divide between quantitative optimization models qualitative field research in Humantiarian Logistics (HL). Mixed methods research promises a deeper understanding of challenges, and thereby allows researchers to develop more effective solutions. However, HL literature lacks rigorous methodologies regarding how to use mixed methods research designs in the context of humanitarian response. We provide a methodology with eight steps for using qualitative field research to develop optimization models. Most importantly, we describe in detail how findings from a field study can be translated into the problem definition and scope, objectives, parameters, variables and constraints that are at the heart of optimization models. The application of our proposed research methodology on Nepal case showcases the merits of our methodology for developing an evidence-based quantitative decision support while considering the limitations of field research in disasters response, such as the short-time for preparation and access constraints.

Our research has some limitations, which opens avenues for future research. Suggestions in this paper are based on implementing the methodology for one case, and adaptations to other contexts may be needed. Guidelines and protocols for conducting field research for slow onset disasters or conflicts have to be different from the ones that are developed for sudden onset context. Thus, some components of our research methodology, including protocols, have to be adapted for other contexts. Moreover, our research concentrates only on field research; extending the methodology to other set-ups such as experiments or simulations / exercises and games is another future research direction.

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A Considered review papers

A detailed list of review papers that have been considered in our study is provided in Table 3.

Table 3 List of review papers used in this study

No.	Study	Focus
1	Besiou and Van Wassenhove (2020)	Humanitarian operations
2	De Vries and Van Wassenhove (2020)	Humanitarian operations
3	Agarwal et al. (2020)	Humanitarian supply chain management
4	Bruno and Haar (2020)	Humanitarian operations
5	Kovacs and Moshtari (2019)	Humanitarian operations
6	Agarwal et al. (2019)	Humanitarian supply chain management
7	Banomyong et al. (2019)	Humanitarian logistics and humanitarian supply chain performance
8	Behl and Dutta (2019)	Humanitarian supply chain management
9	Jabbour et al. (2019)	Humanitarian logistics and humanitarian supply chain management
10	Seifert et al. (2018)	Humanitarian supply chain management
11	Trivedi and Singh (2018)	Humanitarian relief
12	Boonmee et al. (2017)	Humanitarian logistics
13	Kunz et al. (2017)	Humanitarian logistics
14	Gutjahr and Nolz (2016)	Humanitarian aid
15	Özdamar and Ertem (2015)	Humanitarian logistics
16	Anaya-Arenas et al. (2014)	Relief distribution networks
17	Leiras et al. (2014)	Humanitarian logistics
18	Galindo and Batta (2013)	Disaster management

B Interviews information

Interviews details are provided in Table 4.

Table 4 Details of interviews in the Nepal field research

Interview no.	Interviewee position	Affiliated organization (2015)
1	Senior Logistics Assistant	Relief International
2	Head of mission	Cordaid
3	Head of mission	Humedica
4	Information Management Officer	Islamic Relief
5	Logistics Officer	WFP
6	Head of Emergency Operations	IFRC
7	Technical Director	Actionaid
8	Programme Manager	International Medical Corps
9	Liasion SHO response	Oxfam
10	Logistics Coordinator	World Vision International
11	Program Coordinator	CARE
12	Emergency Team Leader	IOM
13	Executive Director	Transparency International Nepal
14	Deputy Log cluster	Logistics Cluster
15	Information Coordinator	Save the Children International
16	Response Team Leader	British Red Cross

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