2018

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Ann Oper Res
DOI 10.1007/s10479-016-2280-7

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Abstract Humanitarian operations in developing world settings present a particularly rich opportunity for examining the use of big data analytics. Focal non-governmental organizations (NGOs) often synchronize the delivery of services in a supply chain fashion by aligning recipient community needs with resources from various stakeholders (nodes). In this research, we develop a resource dependence model connecting big data analytics to superior humanitarian outcomes by means of a case study (qualitative) of twelve humanitarian value streams. Specifically, we identify the nodes in the network that can exert power on the focal NGOs based upon the respective resources being provided to ensure that sufficient big data is being created. In addition, we are able to identify how the type of data attribute, i.e., volume, velocity, veracity, value, and variety, relates to different forms of humanitarian interventions (e.g., education, healthcare, land reform, disaster relief, etc.). Finally, we identify how the various types of data attributes affect humanitarian outcomes in terms of deliverables, lead-times, cost, and propagation. This research presents evidence of important linkages between the developmental body of knowledge and that of resource dependence theory (RDT) and big data analytics. In addition, we are able to generalize RDT assumptions from the multi-tiered supply chains to distributed networks. The prescriptive nature of the findings can be used by donor agencies and focal NGOs to design interventions and collect the necessary data to facilitate superior humanitarian outcomes.

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Published online: 04 August 2016

Keywords Resource dependence · Developmental sector · Humanitarian outcomes · Non-profit organizations · Big data

1 Introduction

Delivering humanitarian services in developing countries is an activity that affects the well-being of literally hundreds of millions of vulnerable citizens and the society. This segment of the economy is often referred to as the developmental sector. Delivering such services requires performing a stream of activities: material flow, information exchange, and synchronized resource transfer. This synchronization effort in developing countries is often managed at the field level by a focal non-governmental organization (NGO). A focal NGO is an entity that marshals the necessary resources, identifies needs, and has the receptive infrastructure and human resources in place to deliver the necessary humanitarian services. Consequently, in the developmental sector this focal NGO becomes accountable to stakeholders including donors, international developmental agencies, governmental entities, and the communities they serve. This accountability, therefore, creates expectations in data flow.

Many focal NGOs simultaneously engage in a variety of value stream activities in the areas of education, healthcare, and income generation. Each value stream may service thousands of citizens, making this sector a potentially data-centric and data-intensive operation. The opportunity to apply big data analytics in this context, therefore, is particularly rich. The focal NGO responsible for the implementation deliverables is dependent on a number of nodes along the supply chain including donor base; international developmental agencies; federal (central), state, and local governments; and the local communities. As such, these nodes expect the focal NGO to deliver on promised outcomes. Based upon this dependency, the nodal actors can pressure the focal NGO to use big data as a mechanism to provide deliverables quickly at low cost and set the stage up for continued or/expanded operations.

Big data in the developmental sector context has the potential to transform the capacities of NGOs to simultaneously deliver on time and at low cost, and be more resilient in the long run in ways that perhaps would not have been imaginable in the past. Currently, most NGOs simply reporting data have yet to use data as a strategic initiative. This shift has recently become true in the for-profit context and is likely to have the same transformation potential in the developmental sector. Today it is possible, by adopting big data as a basic strategic initiative, to transform NGO supply chain processes and facilitate innovation; perhaps such initiatives could even change the very nature of the (developmental sector) ecosystem (Brown et al. 2011). A key factor for successful humanitarian operations is situational awareness, which entails observing the elements of the context, combining and interpreting it, and projecting on it to make predictions about impending events (Mehrotra et al. 2013). Big data has the potential to create new organizational capabilities, to add value, and to surmount key challenges (Wamba et al. 2015) facing the developmental sector.

Historically, NGOs' data flows have been reactive in nature and have included simple reports on past activities with profit/loss statements as part of their annual reports. Data generated for annual reports generally has lacked a predictive element. An example of a reaction would be if, after a disaster strikes, an NGO starts to assess needs and marshal resources. By the time this coordination is finalized, the response is often quite costly (Altay et al. 2013) and delayed. Rather, an NGO could take a predictive approach, identify villages/communities that are particularly vulnerable, and focus on interventions in making them resilient *prior to* the onset of a disaster. Big data analytics could potentially be a key driver in this type of thinking.

For example, big data analytics could be used by NGOs to identify the links between literacy, malnutrition, and agricultural yields; NGOs could also evaluate the capacity of a community to be resilient to disasters. Thus, carefully tailored investments in education, nutrition, and seed variety could be customized at the village level to create more resilient communities. In the long run, this would reduce total development cost and protect a large percentage of the vulnerable population (Altay et al. 2013).

The pull for such a transformative approach would necessarily emanate from the resource providers. The resource providers have the necessary power to pressure a focal NGO to adopt big data analytics and to specify the necessary outcomes. To explain this possible relationship we rely on resource dependence theory (RDT). Waller and Fawcett (2013), in their first editorial on big data and predictive analytics, list RDT as one of the management theories that could potentially help explain how the ability to use bid data for supply chain decisions could affect an organization's power in comparison to its suppliers or customers. Following along these lines, this study answers the following research questions: (1) What is the applicability of RDT in the developmental sector supply chains? (2) How are big data attributes associated with the different types of humanitarian value streams? and (3) What are the links between data attributes and humanitarian outcomes? By answering these questions, we will be able to provide a prescription to resource providers within the supply network (donors, international agencies, governmental entities, and the local communities) on the proper pressure to be applied on focal NGOs in order to create big data, ensuring superior outcomes.

In order to answer these research questions, we will employ qualitative (case) methodology coupled with a literature review. Given that all of the data (cases) in our study are from interventions in India, the findings may be bounded within the Indian context.

The rest of this paper extends our understanding of RDT, especially as it relates to humanitarian supply chain management. Furthermore, we identify an important link between big data and the developmental literatures.

2 Literature review: big data

Data is not scarce in humanitarian operations. Often, there is an overload of data in the form of reporting requirements (King 2005). Altay (2008) notes that it is the lack of "comprehensive, cross-functional information, accurate and current" data rather than any "lack" of data per se that most affects humanitarian supply chains. Data management and exchange are not only a prerequisite for all other flows in a humanitarian intervention, but they are also the principal source of all network decision making and coordination (Altay and Labonte 2014).

2.1 Humanitarian data

Humanitarian data can take on various forms, but much of it falls into four broad categories: (1) situational awareness, which provides information about the latest conditions, needs, and locations of the targeted communities; (2) operational/programmatic data which is necessary in order to plan and implement humanitarian assistance programs; (3) background information on the history, geography, population, socio-economic structure, infrastructure, and culture of the country; and (4) analysis which allows us to interpret the collected information in context (King 2005).

Data flow in humanitarian interventions is most closely associated with data collection (e.g., recording physical needs, locations, vulnerabilities, and capacities), information processing (e.g., compiling data into a repository for knowledge management and resource allocation decisions), and information sharing with network partners (via a range of platforms, technologies, and formal and informal structures, whether one-to-one, one-to-many, or many-to-one) (Altay and Labonte 2014).

Given the importance of information flows in humanitarian operations and the various forms/dimensions of data, the distributed nature of the networks, and the necessity to combine/interpret data to form predictions, this field is an excellent candidate for big data analytics.

2.2 Big data analytics

The volume of available data emanating from humanitarian projects is potentially immense. However, big data constitutes more than just the amount or size of the data. Russom (2011) argues that it is not just the *volume* (i.e. large number of records data) but also the *velocity* (i.e. frequency of data generation and/or delivery) and *variety* (i.e. multidimensional data generated from a variety of sources and formats) that makes big data rich and transformative. In other words, a relatively small data set generated by various sources in multiple formats and updated frequently is also considered big due to its variety and velocity and would enhance the current capabilities of organizations to capture, store, compute, communicate, and predict it. In addition, Forrester Research (Gogia et al. 2012) added *value* to the list of big data attributes to highlight the importance of extracting economic benefits from the available data. Later, a fifth attribute, namely *veracity* (i.e. the inherent unpredictability of some data requiring filtering) was added to the list of Vs to define big data (White 2012).

Mining and analyzing such vast amounts of data that is rich in content can potentially transform decision-making processes and improve outcomes by allowing enhanced visibility of operations and identifying opportunities for process change (McAfee and Brynjolfsson 2012). Therefore, big data has the potential to essentially transform humanitarian aid supply chains.

2.3 Big data in supply chains

In the corporate sector, more data is available today in supply chains simply because greater detail is/can be captured.. With the help of technologies (e.g. RFID, cloud, IoT) and methodologies, companies that did not record daily sales by location and by stock-keeping unit now do capture more data in multiple points along the supply chain. Sanders (2014) explains how companies like Walmart, UPS, and Amazon have been utilizing big data analytics to enhance their supply chain operations. Dubey et al. (2015) highlight the importance of big data in sustainable manufacturing practices. Additionally, Schoenherr and Speier-Pero (2015) explain the benefits of using big data analytics in supply chain management (as well as the barriers companies experience) based on a survey of supply chain executives. The top three benefits they found are more-informed decision making, improvement in efficiencies, and enhanced demand-planning capabilities. And finally, Hazen et al. (2016) provide examples of applications for descriptive, predictive, and prescriptive analytic methods along with research directions. Despite the sheer amount of data available, the degree to which these data can be used is determined by their quality (O'Reilly 1982). Hazen et al. (2014) delve into the topic of data quality in supply chains using accuracy, timeliness, consistency, and completeness as four dimensions of data quality in the supply chains.

2.4 Big data in humanitarian operations

Big data analytics in humanitarian operations has been developed for rapid response. For example, Google developed analytics to predict the timing of H1N1 flu outbreaks on a spatial basis (Walker 2014), while Walmart analyzed point-of-sale data to lower logistical costs and to improve the flow of supplies to stores in locations that are affected by a hurricane (Waller and Fawcett 2013). The potential use of big data in healthcare operations and medicine has been reviewed by Raghupathi and Raghupathi (2014) and Austin and Kusumoto (2016), respectively. Rather than studying epidemics or disasters, Delen et al. (2011) focus their attention on a constant humanitarian problem–namely, the blood reserve supply chain–and demonstrate the use of operations research, data mining, and GIS-based data analytics to improve blood inventory management.

For humanitarian organizations operating in complex and dynamic environments, visibility of mission-critical assets and their allocation and coordination across affected populations represent a challenge. Therefore, real-time access to information regarding the position and availability of these resources could be a part of the decision-making process (Manocha 2009). In a study, Wamba et al. (2015) explain how the New South Wales State Emergency Service (NSW SES) in Australia used big data analytics to synchronize command and control centers of seventeen regional headquarters. This allowed the NSW SES to move critical assets across the state to deliver emergency services and, in the long run, to inform strategic decision making about where to invest in the future (Wamba et al. 2015). The strategic decision making and allocating of resources in humanitarian networks could potentially be applied to projects in the developing world in order to improve outcomes.

2.5 Humanitarian outcomes and big data

The supply chain literature in the context of NGO project management identifies four critical outcomes: duration; cost; reputation and propagation; and deliverables (Prasad et al. 2013). Research shows that durations, costs, reputation/propagation, and deliverables are associated with the level of generated information and shared understanding (Prasad et al. 2013). In this research, given our supply chain network, we adapt thereputation/propagation construct to fit a greater context. This modified construct is entitled “resilience”. Supply chain networks need to be efficient and responsive so that they can not only survive, but also thrive in the long run. Resilience includes the ability to grow, propagate, and adapt to a changing environment. Big data can be employed to understand resilience in supply chains (Papadopoulos et al. 2016).

In the developmental sector, examples of deliverables include such metrics as the number of children provided with nutritional supplements as part of their midday meal program, grades/marks earned in school, level of malnutrition, income of Self-Help Group (SHG) members, agricultural yields, delivery times of relief supplies, and so on. The lead-time refers to the length of time between when an intervention is envisioned to the execution of deliverables to the targeted communities. The lead-time could also refer to the length of time needed to move waste between the supplier and buyers within the informal solid waste sector. The lead-times units can vary in terms of days for humanitarian relief operations to years for SHG income growth. All interventions generally have a monetary value associated with them; thus, a unit cost for the service provided for each value stream can be quantified. Finally, many NGOs would like their interventions not only to continue over the long run, but also to propagate their model to other surrounding communities or augment their services to include other forms of value stream activities. Thus, an NGO providing primary education might want to couple its existing program with preventative healthcare services.

We believe big data analytics would mediate better outcomes (deliverables, lead-times, costs, and resilience) if pressure is applied by resource providers on the focal NGO to ensure big data is adopted.

3 Theoretical background on resource dependence

In this research, we examine how resource dependence theory (RDT) at a strategic level may help explain the big data phenomenon in the developmental sector supply chains and their corresponding outcomes. The proceeding sections present a review of prior developmental sector research in light of the assumptions of RDT.

3.1 Resource dependence theory (RDT)

Organizations engage in collaborations with external stakeholders (i.e., nodes) in order to manage their dependency on critical resources. Resource dependence theory explains how dependence on resources external to the organizations relates to focal organizational actions, network exchanges, and outcomes (Aldrich and Pfeffer 1976; Emerson 1962; Pfeffer and Salancik 1978). In other words, it is a theory of power and influence that originates due to resource dependence and external constraints.

Resource dependence theory (RDT) can aptly explain how NGO activities, operational processes, decisions, and humanitarian outcomes can be explained by their dependence on governments, donor agencies, and community supports. Some of the basic principles of RDT pertinent to our research setting include: (1) Focal NGOs in a supply network depend on resources that are controlled by actors external to the organizations. This open systems approach to RDT suggests that organizations are embedded in social networks of diverse actors, such as donors, government agencies, and international partner NGOs; (2) The need for resources and their constraints create interdependencies (Pfeffer 1987). As a result, social context (e.g., inter-organizational information flows, partnerships, control, power dynamics) becomes important to the focal NGO's financial and operational resilience; (3) Inter-organizational power dynamics are important to understanding NGO activities, data expectations, operational processes, tactics, and strategies. The possession of critical resources enables certain partners and nodal actors (e.g., donor, regulatory agency) to exert power in order to influence NGO operations (including information expectations) and hence, indirectly impact outcomes.

3.2 Resource dependence, power, and organizational activities

Organizations engage in transactions with external actors. Because organizations are not self-contained or self-sufficient, they are dependent on the cooperation of other actors; this is particularly evident in the developmental sector. In return, the cooperating actors may exert power and demand certain sets of actions from the focal NGOs. According to Frooman (1999), the more critical a given resource, the more power an actor can exert over other involved actors to influence their behavior. This type of pressure may necessitate the exchange of information (Pfeffer and Salancik 1978).

The emphasis on power, as explained by dependency on resources (funding, relationship, etc.) can be considered pivotal to understanding the big data phenomenon in the non-profit sector. Non-profit financial vulnerability is believed to influence NGO collaborations, organizational processes, and actions. Actors in the non-profit sector engage in intra-sector collaborations with other non-profit organizations and cross-sector collaborations with for-profit firms and government agencies in order to achieve efficiencies to obtain funds, to provide service, and to increase long-term fiscal sustainability (MacIndoe and Sullivan 2014). Due to building inter-organizational ties to ensure access to valuable resources, organizations engage in data-centric strategies, including collecting and sharing big and complex data to facilitate the necessary network outcomes.

3.3 Resource dependence and organizational outcomes

Pfeffer and Salancik (1978) discussed "outcome-interdependence" in the context of RDT. Outcome interdependence may explain the relationship of competitors (where one's gain may result in another's loss) and collaborators (e.g. employees of the same organization may enjoy shared benefits of a particular policy or organizational practice). This outcome interdependence also relates to organizational actions. This notion of outcome-dependence is particularly applicable as the performance benefits are of shared interest between and among their stakeholders in the development sector.

Network outcomes are dependent on nodal actors, communities, and organizational stakeholders. Resource dependence theory becomes relevant to the development sector here because power-based interdependence characterizes the relationships and processes between and among actors. This interdependence has the ability to shape the focal organizational activities to achieve its desired outcomes, e.g., deliveries of supplies post-disaster, better grades/marks in school, improved attendance, higher inoculation rates, and so on. These processes include the management of data attributes that can influence organizational outcomes.

3.4 Resource dependence theory in the developmental sector

Resource dependence theory literature associated with the developmental sector is quite limited. Under the RDT assumptions, organizational structure, behavior (i.e., actions), and outcomes (e.g., performance, effectiveness) are partially explained by their environments or contexts, which provide critical resources to organizations. To date, some of the most commonly explained management contexts examined through the lens of RDT include strategic alliances, networks, business groups, and supply chain management (Hillman et al. 2009).

Heimovics et al. (1993) applied RDT in the non-profit sector to examine the role of leadership. They found that in order to manage their organization's resource dependence on the environment, effective non-profit chief executives engage in political actions. Fraczkiewicz-Wronka and Szymaniec (2012) compared the importance of internal and external resources for making strategic decisions and discovered that public hospitals use a resource dependence approach to manage their relationships with external stakeholders and to set organizational long-term goals. More recently, RDT has gained attention from researchers in the non-profit sector, especially in explaining organizational actions and performance. For instance, MacIndoe and Sullivan (2014) recognized that resource dependence among actors explains the nature and frequency of collaborative activities non-profit organizations (NPOs) undertake. Overall, the resource dependence of NPOs increases the likelihood of collaborations both within and across value streams.

Macedo and Pinho (2006) found that resource dependence theory has the power to explain the market orientation strategies of non-profit organizations (NPOs). The link between resources (e.g., source and degree of resource dependence) and the focal organization's orientation to serve its donors (vis-à-vis its commitments to delivery services to beneficiaries) stands out as an important finding. The findings of the study by Silverman and Patterson (2011) indicate that dependence on public funding and perception of donors are associated with how NPOs balance their program-related vis-à-vis political/advocacy-related activities. The empirical results demonstrate that sustaining NPO activities relate to maintaining a strong individual donor base. Maintaining a strong base of individual donors is important for the long-term resilience of the organization and its activities. A strong individual donor base also implies power asymmetry among the focal and nodal actors. This asymmetry could potentially affect accountability requirements and information expectations.

Donor power could shape non-profit reporting quality and the use of various performance measures such as outcome measurement (Anheier 2005; MacIndoe and Barman 2013). Prior studies found that public funding decreases decision-making autonomy in NPOs (e.g., Jung and Moon 2007; Nikolic and Koontz 2008; Verschuere and De Corte 2014). Philanthropic support from private and/or for-profit organizations also shapes non-profit activities. Hodge and Piccolo (2005) found that private philanthropic support was positively associated with the effectiveness of non-profit boards, which led to increased fiscal oversight.

Seo (2011) explored how different organizational behaviors relate to the resource dependence patterns (RDP) in non-profit organizations. The study also sought to understand the relationship between resource dependence patterns and NPO performance. The empirical findings suggest that resource diversity and resource competitiveness have direct impact on NPO outcomes. More specifically, the origin of resources has substantive and wide impact on NPOs' organizational behaviors, actions, and structures. For example, high resource dependency on government funding was found to be positively associated with a higher degree of hierarchy and data formalization.

Although research focusing on big data in the non-profit sector has been gaining momentum, the question of how donors influence NGOs' big data-related efforts in the developmental sector remains largely unaddressed. Furthermore, our understanding needs to be generalizable to the supply chain network structure.

3.5 Resource dependence theory within the supply chain network context

In understanding the relevant body of knowledge, we now review power, resource dependence, information/data attributes, and structure literatures in the context of supply chain networks.

Paulraj and Chen (2007) find that under the conditions of supply chain uncertainty, firms can strengthen inter-firm coordination between supply partners by recognizing and embracing the notions of resource dependence. This study used RDT to highlight how coordination and relationship-specific assets between suppliers can mitigate supply chain uncertainties.

Extensive studies examining resource dependence and power have been conducted in the area of downstream operations within supply chains (Brown et al. 1983, 1995; Skinner et al. 1992; Wilkinson 1979). Power has been found to be a key construct in understanding relationships among supply chain network partners (Cox 2006). Power in supply chains can influence data flows, attributes, and expectations, and there can be significant power asymmetries among the various supply chain players (Brown et al. 1995). Pressure properly applied by one powerful nodal actor may be able to increase coordination among supply chain partners, resulting in improved operational outcomes (Brown et al. 1983) as it helps integrate different elements of the supply chain (Maloni and Benton 2000). In the developmental sector, it would be interesting to see how potentially powerful supply chain nodal actors: (1) apply pressure on a focal NGO, and (2) could affect humanitarian outcomes.

In the context of supply chains, the relative power of supply chain actors can be attributed to dependency-related factors. Differing attributes of suppliers and buyers in terms of market share, ratio of the number of buyers to suppliers, dependency on a single source of revenue, relative cost of switching from one actor to another, terms, standardization of commodity, and information asymmetry (Cox 2006) have been found to influence relative power. Power may also be exerted when one party owns proprietary materials and networks (Webster 1995) and is able to mitigate uncertainty (Maloni and Benton 2000) and dependency on suppliers (Awaysheh and Klassen 2010). However, in the developmental sector, these factors might vary. In the recent literature, a connection has been drawn between the role of information integration, information power, and the various forms of power (William and Moore 2007). Likewise, similar patterns might exist in the humanitarian supply chains in the developmental sector.

Links between resource dependence, information flows, and outcomes have also been noted. In the context of information systems, Hart and Saunders (1997) examined the inter-organizational linkages for electronic data interchange (EDI) focusing on buyer-seller dyads. They proposed that relative resource dependence and power relations between buyers and sellers may influence the adoption, level of use, and further expansion of EDI-related practices. In a similar vein, other empirical studies demonstrated that the exertion of power and degree of inter-organizational dependence help explain the adoption and implementation of e-business, information, and data exchange systems (Chong et al. 2009; Premkumar and Ramamurthy 1995). Also, Pennings et al. (1984) note that inter-organizational resource dependence is positively associated with forward integration decisions of the focal organizations into their distribution channels. In addition, they found that the interest in obtaining superior information about recipient customers (communities) plays an important role in forward integration decisions. We believe that a similar form of integration would possibly lead to improved deliverables, shorter lead-times, and lower costs in the developmental sector.

The structure of the supply chain network potentially influences dependencies, power, information/data expectations, and outcomes. Much of the current literature assumes a dyadic perspective of power between buyers and suppliers in the supply chains (Ambrose et al. 2010). However, to understand power in supply chains, multiple echelons (Cox et al. 2001) and more complex sets of behaviors need to be examined, including the interplay which exists at vertically dyadic levels, horizontally dyadic levels (Stevenson and Spring 2009), and in evenly distributed networks. Such patterns are quite common in the developmental sector context.

In attempting to answer some of the pressing questions remaining in this line of research, we plan to use a qualitative case study. The case study will explore the nature of the relationships between various types of humanitarian interventions, resource dependence among network actors, power asymmetries, data attributes, and outcomes in the developmental sector.

4 Toward a theory of big data analytics in humanitarian services

The developmental sector is ripe for the adoption of big data analytics by NGOs as part of managing the multi-value stream humanitarian services along their supply network. Based on the classification framework developed by Wamba et al. (2015), big data has five attributes:

volume, variety, velocity, veracity, and value. The applicability of this classification framework is well established in the for-profit sector (e.g., Gogia et al. 2012). Wamba et al. (2015) also provide a case study on the applicability of big data analytics in the context of humanitarian services.

Building on Wamba et al. (2015), we would like to demonstrate in this research the viability, measures, and impact of big data analytics when applied to other forms of humanitarian services in the developing world context. Based on our case study, we hope to demonstrate how big data analytics could quite possibly revolutionize how NGOs deliver humanitarian services.

4.1 Case study on focal NGOs

In this study, we use case methodology to examine the applicability of big data analytics to humanitarian projects in the developing world. Case study is an ideal methodology in examining existing events when the relevant behaviors may not be manipulated. A degree of external validity is assured when a range of data sources such as interviews, observations, documents, and artifacts are reviewed. In recent times, scholars (e.g., McCutcheon and Meredith 1993; Meredith 1998; Voss et al. 2002) have suggested the use of case methodology to provide insights and help theory-building in supply chain management. Given the exploratory nature of our research questions, the case study methodology is particularly suited to our purpose.

The delivery of humanitarian services can be viewed as a supply chain network. Often a focal NGO is responsible for managing this network to ensure proper outcomes. In the developmental sector, this network tends to be distributed; a focal NGO interacts with a number of nodes (actors) such as overseas donors (γ), local corporate donors (ι), government schools (η), local corporations (κ), local donors (λ), local councils (φ), self-help groups (β), government entities (π) and government banks (μ), government schools, (η) and even local village councils (*panchayats,* φ). Each humanitarian value stream depends upon a unique combination of actors. These actors provide resources (monetary, material, access, knowledge), but in return, they expect certain outcomes.

In this research, we examine the supply networks of three different focal Indian NGOs providing a total of twelve different humanitarian value streams. Each NGO caters to a number of interventions and correspondingly has its own unique combination of big data expectations. These varied expectations help us to gain a deeper understanding of the connections between resource dependence, power, big data, and outcomes in different humanitarian supply chains in the developing world context.

The three focal NGOs are: (1) Indian Pollution Control Association (IPCA, **I**), an NGO operating within the informal solid waste sector in the National Capital Region (NCR) of India to uplift rag-picker communities while improving the overall recycling rates; (2) Hub-n'-Spoke (**H**) intervention primarily dedicated in providing education (grades 1–10) to indigenous (tribal) communities in rural Andhra Pradesh; and (3) Sodhana Charitable Trust (**S**), whose mission is the development of *dalits* (lower caste members of the society), women, and children in a backward district of India. The three NGOs have different forms of managerial processes and operating environments (urban, rural, tribal). This variance in cases adds to the generalizability of the proposed model.

The basis of the qualitative study has been developed based on multiple methods and multiple forms of data collection. Examples include making site visits, having access to emails and documents (spreadsheets/reports), and conducting structured interviews. The data was not only collected from the respective focal NGOs but also from the corresponding supply chain actors such as overseas donors (γ), government schools (η), local donors (λ), self-help groups (β), government banks (μ), government schools (η), and even local village councils (*panchayats,* φ). This data was collected over an eight-year period, ensuring a degree of generalizability over time. The use of multi-methods and multiple sources of data provides a degree of internal and external validity. In Tables 1, 2, and 3, we note the primary method of data collection. In some cases, the primary source was coupled with secondary and tertiary sources of data.

4.2 Humanitarian supply chain networks

The informal solid waste sector has grown up in developing countries due to the inability of the formal municipality or deputized corporate sector to collect solid waste in urban centers. This informal sector, consisting of individuals, families, groups, or small enterprises, carries out unregistered and unregulated waste management activities (Schübeler et al. 1996). IPCA's (**I**) primary activity consists of organizing the informal solid waste (W) value stream emanating from some 300,000 individuals and a host of corporate entities. IPCA accomplishes this by empowering some 40-plus rag-picker groups. These rag-picker groups operate in *godowns* (warehouses): areas where they live, sort waste, and work. IPCA provides long-term contracts with suppliers of waste and buyers (aggregators) of sorted waste (glass, plastics, paper, etc.). To ensure that the network is efficient, IPCA provides transportation/logistical support, technology, and disposal of certain forms of waste (e.g. organics). Other types of humanitarian value streams include providing primary education (E) to rag-picker children in the *godowns* and basic healthcare (H) to rag pickers and their families. Each value stream creates its own data requirements and expectations that are shaped by the respective supply chain nodes. In Fig. 1, we provide a simplified mapping for the various value streams, important actors, and data requirements/expectations. Furthermore, the power relationships (strength and direction) between the nodal actors and focal NGOs are also identified. For the solid waste stream (W), Indian Pollution Control Association (**I**) is dependent on buyers of aggregated waste (relationship ε), 40+ rag-picker communities (relationship β), corporate supporters (relationship κ), residential and commercial clients (relationship χ), government land (relationship π), and universities (relationship ϕ) (Table 1). The education (E) and healthcare (H) value streams are dependent on overseas NGOs (relationship γ), access to government schools for children in the network (relationship η), and local donors (relationship ι) (Table 1).

The Hub-n'-Spoke (**H**) intevention consists of a network of six hamlet schools (the "spokes") and one "hub" hostel. This network provides primary education to 169 children in grades 1–5 and secondary education (grade 6–10), healthcare, and food to 68 children in the hostel. Although the primary objective of this network is education, other services have been provided to the six hamlets including: (1) disaster recovery from Cyclone Hudhud and brush fires; (2) preventative healthcare and hygiene; (3) village lighting; and (4) increase in agricultural yields. In Fig. 2, we provide a simplified mapping of the various value streams, important nodal actors, power relationships, and some data requirements/expectations for the Hub-n'-Spoke intervention. In Table 2, we see that the educational (E) value stream is primarily dependent upon overseas NGOs (relationship γ), government schools (relationship η), and the local *panchayats* (relationship φ). In contrast, the healthcare (H) intervention is dependent on the local government rural healthcare network (relationship δ) and overseas NGOs (relationship γ). In our data collection we found that the Agricultural (A) value stream is dependent on overseas NGOs (relationship γ) and research/training institutions (relationship ϕ). After Cyclone Hudhud, we found that in the case of disaster relief (*DREL)* operations, the focal NGO was dependent on overseas NGOs (relationship γ), local corporate supporters (relationship κ), and local donors (relationship λ). On the other hand, for disaster

Table 1 IPCA(**I**) focal NGO: resource dependence and power, network actors, big data and humanitarian outcomes

Value stream	Environment	Degree of **Dependence** and ***Power*** on (**I**) by nodal actors	Big data (volume, velocity, variety, veracity, value)	Outcomes related to big data
Solid waste management stream (W)- IPCA (**I**)	High degree of resources is internally generated in the solid waste (profitable) sector. However, there is increased competition from the formal sector (e.g. municipalities)	Buyers of aggregated waste (ε). A large number of buyers competing for quality supplies from IPCA[a] (**Low dependence** and ***power*** in relationship ε)	Low degree of data. Informal data on trends, patterns, and the importance of quality of sorting shared with buyers	
		40+ Ragpicker communities (β). Dependent on reliable and quality supplies from communities[a]. Over 80,000 ragpickers compete with each other[b] (**Medium** degree of dependence and ***low power*** in relationship β)	Low degree of data. Informal data on current market prices, trends, and contracts with clients	
		Corporate supporters (κ). Partnership with IPCA is part of Corporate Social Responsibility (CSR) and mitigating potential problems[c] Set floor prices for certain types of recyclables[a]. (**Low dependence** and ***low power*** in relationship κ)	Descriptive information. Potential of value construct (e.g. relationship between prices and social investment on recycling rates) could be developed	
		Residential and commercial suppliers require having solid waste removed from their sites, while IPCA needs quality supplies[a]. Certain corporates need high recycling rates as part of their CSR objectives. (**Medium dependence** and ***medium power*** in relationship χ)	Certain corporate clients require data on a monthly basis (**volumes**). At times, due to auditing requirements, specifics on quality of sorts, buyers, and end use of waste needs to be reported (**variety**)	**Resilience**–corporate clients remain and possibly get additional clients

Table 1 continued

Value stream	Environment	Degree of **Dependence** and ***Power*** on (**I**) by nodal actors	Big data (volume, velocity, variety, veracity, value)	Outcomes related to big data
		Government land. IPCA relies on the acreage provided by the state government to compost waste. Available land in large Indian cities is very limited, but the government officials are currently not very demanding[d] (**High dependence** and ***medium power*** in relationship π)	Periodically, based on political parties in power IPCA needs to provide visits and access (**variety**)	**Resilience—**retain the use of land
Education (E) and healthcare (H)	Limited resources in the education and healthcare value stream. Little competition in providing services to rag pickers. High uncertainty. High resource diversity	Overseas NGO's funding (γ) for a 3-year duration and covers approximately 90 % of the expenditures[e] IPCA provides access to the ragpicker communities. (**High dependence** and ***medium power*** in relationship γ)	High **volume** given educational and health data being collected on each child.[f] Health card created and diseases tracked. Attendance in schools tracked	Improve attendance (**deliverables**) with low cost (**pricing/cost**), and children stay longer in school (**lead-time**)

Table 1 continued

Value stream	Environment	Degree of **Dependence** and ***Power*** on (**I**) by nodal actors	Big data (volume, velocity, variety, veracity, value)	Outcomes related to big data
		Government schools—access for the ragpicker children in the network. Getting into government schools is critical in "mainstreaming" ragpicker children. Fortunately, IPCA has been able to place some 65 children in government schools[g] IPCA provides access to the ragpicker communities. (**High dependence** and ***medium power*** in relationship η)	High **veracity** in data is necessary as school officials need to trust birthdates provided and other data necessary for admission	**Resilience** and **deliverables**. Sixty-five children admitted into government school and the number is growing steadily
		Local donors provide material donations including medicines, clothes, books, etc. Furthermore they pay for rent of school buildings and health camps. IPCA is highly dependent on these resources[h] -(**High dependence** and ***medium power*** in relationship ι)	**Variety** of data is high due to health indicators being collected. High veracity in data is necessary to conduct health camps	**Resilience**. Funding continues and participation with other NGOs is forthcoming

[a] Primary data source: interview with the director of IPCA
[b] Primary data source: discussion with ragpicker union official, secondary: interview with the director of IPCA
[c] Primary data source: discussions with company officials, secondary: interview with the director of IPCA
[d] Primary data source: site visits
[e] Primary data source: expenditure reports provided by IPCA
[f] Primary data source: copy of health care card, secondary: interviews with IPCA officer
[g] Primary data source: interviews with IPCA officer, secondary: newsletter, tertiary: interview ragpickers
[h] Primary data source: interview with the Director of IPCA

Table 2 Hub-n'-Spoke (**H**) focal NGO: resource dependence and power, network actors, big data and humanitarian outcomes

Value stream	Environment	Degree of **Dependence** and ***Power*** on (**H**) by nodal actors	Big data (volume, velocity, variety, veracity, value)	Outcomes related to big data
Education (*E*)	Medium competition from state and private schools. Limited uncertainty	Highly dependent on overseas NGO funding[i] Link with government schools (η) is critical, and there is a necessity for buy-in from the local *panchayats* (φ). On the other hand, given the lack of regular attendance by some of the government teachers, the Hub-n'-Spoke teachers are valued by the community[j]. **High dependence** and ***medium power*** in relationships γ, η, φ)	High **volume** with marks provided on a quarterly basis for each subject for some 300 children in the network. BMI indices are also computed quarterly. Costing of the educational value stream reported on a monthly basis. Since the project has been collecting data for 8 years, **veracity** has been established. Variety and velocity are not critical. **Value** is being generated by conducting intra-hamlet comparisons and even correlating with cyclone impact. Data is being tracked between Hub-n'-Spoke as children progress from grades 1–5, grades 6–10, and beyond	**Deliverables** (average 87 % marks) with **low unit cost** (75$/child). **Resilience** as evidenced by continued funding and growth
Healthcare (*H*)	Little competition. High uncertainty	**High dependence** on government rural healthcare network (δ) and overseas NGO relationship (γ) in funding, but neither the government nor NGO is demanding information from nodal NGO given the ***low power*** being applied	Volume, veracity, variety, velocity, and value are limited as the overseas NGO is not demanding data	Project has yet to document significant outcomes

Table 2 continued

Value stream	Environment	Degree of **Dependence** and ***Power*** on (**H**) by nodal actors	Big data (volume, velocity, variety, veracity, value)	Outcomes related to big data
Agriculture (*A*)	Little competition. High uncertainty	**Medium dependence** on government institutions (relationship ϕ) in obtaining seed and soil testing with also a **high degree of dependence** on overseas NGO (γ) on account of funding[k] Currently, ***low power*** is being applied on focal NGO by nodal actors	New intervention, but with expectations from funding NGO (γ) to increase. Volume, velocity, variety, veracity, value are quite limited as of yet. Potential for high variety and high value (experimentation and segmentation of data)	Project has yet to document significant outcomes
Disaster relief (*DREL*)	High competition. High resource diversity	**High dependence** and ***medium power*** in relationships with overseas NGOs (relationship γ), local corporates, (relationship κ), and local donors (relationship λ). Overseas donors provided funding, while the local corporate and donors provided supplies. Focal NGO was highly dependent on supplies, but limited pressure was applied on the NGO by the respective donors[l]	Post-cyclone Hudhud relief had a sense of urgency. In spite of the disrupted communications, photos and write-ups were shared through email and social media. High degree of **velocity** and **variety** but with limited volume and veracity. Difficult to assess value	**Lead-time** and **resilience**. Delivery for supplies to remote areas hit hard by the cyclone. Reaching disaster-afflicted areas in 1–2 days
Disaster recovery (*RECO*)	High competition	**High dependence** and ***medium power*** in relationships with overseas NGOs (relationship γ), and local donors (relationship λ). Donors provided funding for recovery[m] efforts	**Veracity** of data provided after being asked by donors. Limited volume, variety, velocity or value documented	**Deliverables** Repairs in the hostel were completed

[i] Primary data source: expenditure reports provided by Hub-n'-Spoke Chief Operation Officer, secondary: annual salaries
[j] Primary data source: interview with Hub-n'-Spoke hamlet coordinator and teachers
[k] Primary data source: quarterly reports provided by Hub-n'-Spoke Chief Operation Officer
[l] Primary data source: emails and pictures, secondary: site visits
[m] Primary data source: expenditure report by Hub n' Spoke Chief Operation Officer

Table 3 Sodhana (**S**) focal NGO: resource dependence and power, network actors, big data and humanitarian outcomes

Value stream	Environment	Supply chain nodes (relationships with nodal NGO)	Big data (volume, velocity, variety, veracity, value)	Outcomes related to big data
Land (L) redistribution and agricultural support	Little competition. Low uncertainty. Low resource diversity	**Moderate dependence** on Self-Help Groups (relationship β) in order to have access to the communities, but the SHGs themselves have ***low power***[n]. Sodhana was **highly** dependent on the government registrar and court system (relationship π), and these entities hold considerable ***power*** (***high***) over the focal NGO in providing specific documentation[o]	**A high degree of volume** associated with some 500-600 land transfers. Due to legal matters, **veracity** was critical and involved tracking multiple sources of information across generations. Sodhana needed to provide a **variety** of data including deeds, records, and death certificates. The *dalits* (lower caste) gained tremendous **value** in obtaining title to land. Velocity was not critical as the Indian legal system takes years to issue judgments	**Deliverables** – transfers of land, long–term increased yields, and higher standard of living
Micro-credit (M)	Little competition. Low uncertainty. Low resource diversity	**Moderate dependence** on 200 Self-Help Groups (relationship β) with ***low power***[p] However, **high dependence** and ***high power*** was exerted by government bank (relationship μ) on Sodhana in terms of repayment, distribution/collection of funds, and documentation[q]	**Volume**—monthly updates of some 2,500 women in the network. Repayment data and proper supporting documentation is required. Over some 40 years, the **veracity** of the data becomes established. The SHGs need to provide moderately high **velocity** of data with monthly updates. The variety of data provided is quite narrow	**Resilience** of SHG, better returns (**costs**), shorter **lead-time** to implement, and improved operational outcomes were observed. A low default rate attracted future funding
Nutrition (N)	Limited resources Little competition	**High dependence** on overseas NGOs for funding, and they exert ***medium power*** (relationship γ) in terms of documentation[r]. Commercial suppliers of eggs as part of the nutritional support program have **low dependence** and ***low power*** (relationship χ) with Sodhana (**S**)	**Volume**—track 900 children's BMI. Survey households	**Improved deliverables** Reduction in malnutrition rate and at a **low unit cost** ($ 0.06/egg/child)

Table 3 continued

Value stream	Environment	Supply chain nodes (relationships with nodal NGO)	Big data (volume, velocity, variety, veracity, value)	Outcomes related to big data
Limited resources	Low uncertainty		**Veracity**—Entered into households to see actual food consumption	
	Low resource diversity		**Velocity**—Annual report	
			Variety—Standard survey form	
			Value—Based on data (patterns), Sodhana makes suggestions to families in terms of increasing food intake and quality	
Education (E)	Limited resources. Little competition	**Moderate dependence** on local donors (relationship λ) and Self-Help Groups (relationship β) with ***low power***. **High dependence** but ***moderate power*** of government schools in providing access for children in the network (relationship η)[s]	Limited data is being collected. For example, for the 900 children in Sodhana's schools, marks are not being recorded	Improved **deliverables** (attendance)
	High uncertainty			**Resilience** other schools in the district have adopted Sodhana program and training is being provided to other government schools
	High resource diversity			

[n] Primary data source: interview with Self-Help Group members
[o] Primary data source: interview with Sodhana's Chief Operation Officer
[p] Primary data source: interview with Self-Help Group members
[q] Primary data source: interview with Sodhana's Chief Operation Officer, secondary: local bank official
[r] Primary data source: report created by Sodhana for India Development Service
[s] Primary data source: site visits to schools

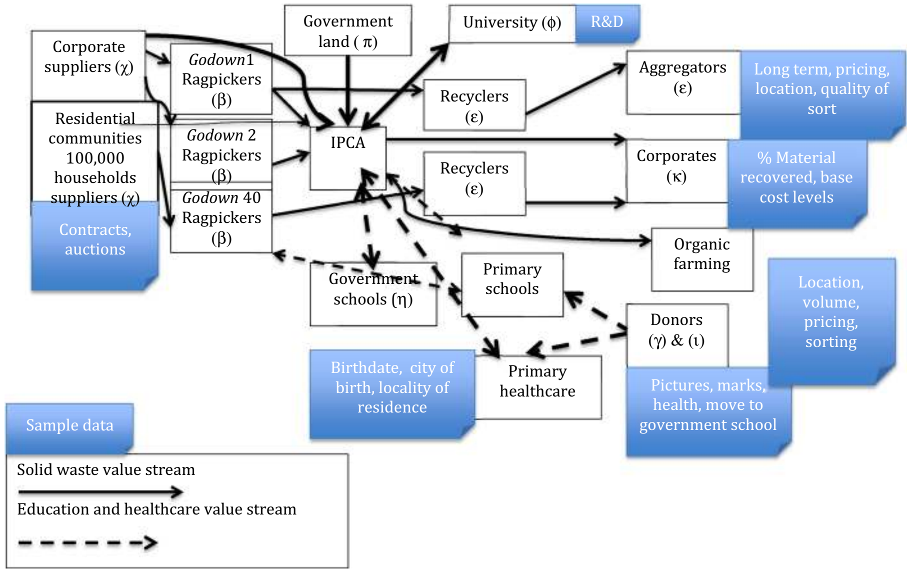

Fig. 1 IPCA (focal NGO) supply chain network, nodal actors, and relationships between actors

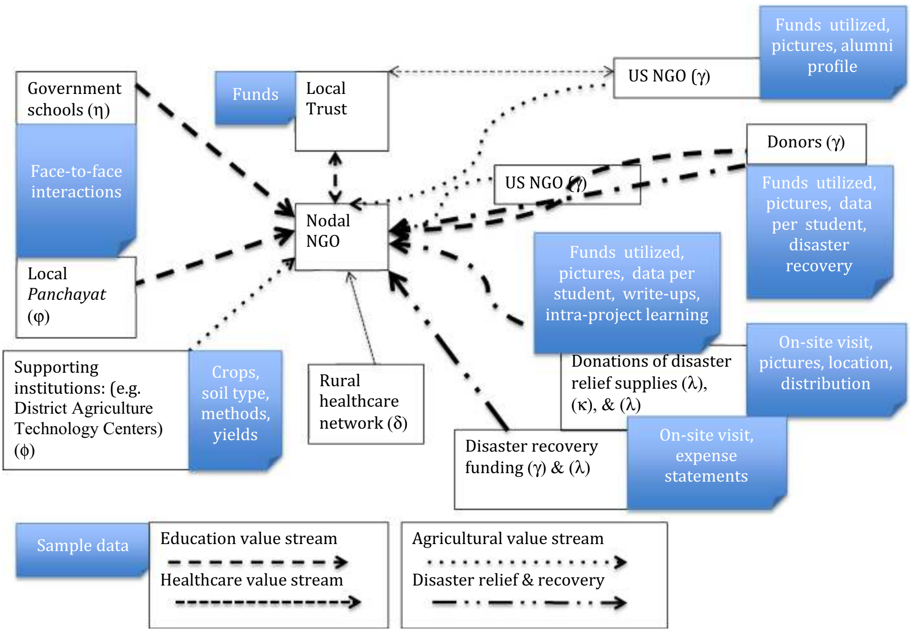

Fig. 2 Hub n' Spoke (focal NGO) supply chain network, nodal actors, and relationships between actors

recovery (*RECO*), only overseas NGOs (relationship γ),and local donors (relationship λ) were a key source of funding.

Sodhana Charitable Trust (**S**) has been operating in around 40 villages in and around Cheepurupalli, Andhra Pradesh, with a focus on *dalits*, children, women, and the elderly poor. Currently, they run a network of around 10 primary schools and 200+ Self-Help Groups (SHG) for women. The schools educate (E) and feed (N) some 578 children. Each SHG group consists of 10–12 members and is organized to support micro-credit (M) initiatives to alleviate poverty. Earlier, one of Sodhana Charitable Trust (**S**)'s interventions also focused on land distribution and agricultural support (L). In Table 3, we identify important nodal actors, data expectations, and outcomes for Sodhana's value streams. The land distribution and agricultural support (L) required working with the registrar and court system (relationship π) to ensure that villagers (relationship β) received land allocated by the government. The micro-credit (M) value stream entailed working with around 200 women's Self-Help Groups (relationship β) to ensure the delivery of funds from a local government bank (relationship μ) and monitor repayment of loans. In addition, Sodhana Charitable Trust (**S**) provides valuable group networking and training exercises. In our data analysis, we also found that Sodhana Charitable Trust (**S**) depends upon an overseas NGO for funding (relationship γ) and a commercial supplier for eggs (relationship χ) for the nutritional supplement value stream. Finally, the educational (E) value stream is dependent on local donors (relationship λ) and access to government schools (relationship η).

4.3 Resource dependence and power along humanitarian supply chains

NGOs that work in the field operate in a unique environment whereby they are dependent on resources of donors, volunteers, communities, government entities, and even other NGOs for their funding, operations and, consequently, for their outcomes. The cases demonstrate that the degree of dependence and power exerted by external nodes varies.

In Table 1, the degree of dependence of the focal NGO (**I**) on the external nodes is identified. Thus, for the solid waste value stream (W) the focal NGO (**I**) appears to have a relatively low-to-medium level of dependence on buyers of aggregated waste (relationship ε), rag-picker communities (relationship β), and corporate supporters (relationship κ). Furthermore, these external entities do not have the necessary resource dependence surplus or choose not to exert their power on the focal NGO (**I**) for big data. However, in the case of certain commercial suppliers (relationship χ), access to government land (relationship π), and universities (relationship ϕ), there is a high-to-medium level of dependence with a corresponding medium level of power exertion to demand big data in terms of volume, variety, and value. For the healthcare (H) and education (E) value stream, there is a high degree of dependence on external nodes (relationships γ, η, ι) with a moderate level of power applied to demand big data, specifically in terms of value, veracity, and variety.

In the case of the education (E) value stream of the Hub-n'-Spoke (**H**) intervention, the focal NGO has a high degree of dependence on relationships γ, η, and φ, with a medium level of power applied to demand volume, veracity, and value of data (Table 2). In the case of the healthcare value stream (H), although the dependence on the rural healthcare network (δ) and overseas NGO relationship (γ) is high, little pressure is being applied by the actors in demanding big data. Similarly, for the agricultural value stream (A), there is a medium-to-high level of dependence (relationships ϕ and γ, respectively), but a low degree of power applied in demanding big data. Finally, in the case of disaster relief (*DREL*) and disaster recovery (*RECO*), there is a high degree of dependence but a medium exertion of power.

In the case of Sodhana Charitable Trust (**S**), the land distribution value stream (L) has a high degree of dependence on the government registrar and court system (relationship π), and power is exerted to demand big data in terms of volume, variety, veracity, and value. For the micro-credit value stream (M), there is a high degree of dependence and a corresponding use of power by the government bank (relationship μ); as such, the focal NGO (**S**) needs

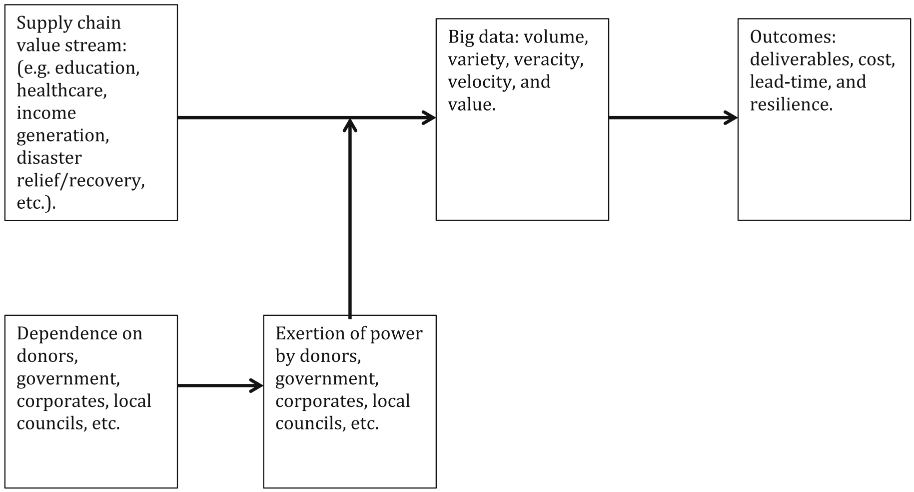

Fig. 3 Proposed model

to provide sufficient value, veracity, and velocity in the data provided. In the case of the nutritional supplement value stream (N), a high degree of dependence on overseas NGOs is present (relationship γ), with a medium level of power applied. Consequently, the focal NGO (**S**) delivers big data with attributes including volume, veracity, and value. Finally, in the case of the education (E) value stream, there is a medium-to-high degree of dependence on external nodes but a medium-to-low power being applied. Limited data is, hence, being generated.

From this data analysis, it can be concluded that the degree of dependence serves a critical role in generating the power asymmetries between the focal NGO and external nodes. However, this happens only when the external nodes choose to exert their power. It is also important to note that the power asymmetries demand that big data be forthcoming from the focal NGOs (see Fig. 3). The type of big data attributes generated would, of course, reflect the needs of the respective value streams. Next, we will explain in further detail how the relationship between the various value streams relates to the types of data attributes being generated.

4.4 Five big data attributes in the context of the humanitarian sector in the developing world

The five main attributes of big data include: volume, variety, velocity, veracity, and value (Wamba et al. 2015). Our cases confirm the relevance of these data attributes in the developmental sector. However, we find that the conceptualization of these attributes may need to be adjusted to be generalized to our research context.

In the corporate sector, *volume* might be measured in terms of terabytes. For NGOs, the size of data files might be smaller due to stakeholder expectations and operational differences. Nonetheless, volume is found to be a critical dimension in the developmental sector. For example, Indian Pollution Control Association (**I**) started its operations with a single corporate entity but is now a service provider to over 100,000 households and a host of corporate entities. Thus, the number of records Indian Pollution Control Association (**I**) needs to track has grown exponentially. In addition, as NGOs grow more sophisticated, they start collecting additional fields of data. For example, the Hub-n'-Spoke intervention started with recording only student names in each hamlet, but it now tracks students' grades and malnutrition levels as well. The scale, scope, and sophistication in data collection all contribute to the increased volume of data being generated.

In the developmental sector, *variety* should not be confined simply to the electronic media. In an emerging country such as India, there are a variety of language/dialects coupled with pockets of illiteracy. Thus, variety could range from items such as drawings, pictures, and even verbal and informal communications all the way to electronic forms such as text messages, spreadsheets, written reports, and so on.

In the development sector,*velocity* is a function of the demands placed by the respective network nodes. For example, while working with land redistribution issues, Sodhana Charitable Trust (**S**) was at the mercy of the government judiciary and registrar, where the flow of data may take years. At the other extreme, in order to take advantage of a life insurance scheme offered by a government bank, Sodhana had to provide a death certificate and *Aadhaar* card (unique identity card) within a matter of hours of an SHG member passing away.

Veracity of data is particularly critical in humanitarian supply chains. Our research found that veracity requires the cross-validation of the primary data being collected. Focal NGOs operate differently as a function of pressure exerted outside the nodal expectations. Thus, Sodhana Charitable Trust (**S**) needs to provide data with a high degree of veracity to ensure continued micro-credit support of their SHGs, while Indian Pollution Control Association (**I**) has to ensure the accuracy of birthdate records in order to admit children in government schools. In addition, given the demands from overseas and local donors, the focal organization of the Hub-n'-Spoke network provides detailed expenditure records for disaster recovery in the aftermath of cyclone Hudhud.

Value has the potential to play a very important role in humanitarian supply chains. In this research, we found evidence of the following dimensions defined by Wamba et al. (2015): (1) creating transparency, (2) enabling experimentation, (3) segmenting population, and (4) innovative new business models, products, and services.

In Fig. 1 we see that the different forms of value stream affect the data attributes. This relationship is moderated by the power exerted by external nodes on the focal NGO. More importantly, a few relationship patterns become discernable with respect to the types of value stream and the forms of data attributes based upon our case study.

Table 4 was developed by classifying the type of data attributes by value stream in Tables 1, 2, and 3 and adding data obtained from content analysis of the various cases. Thus, in Table 1, we see in IPCA's big data column that volume, variety, and values (in bold) appear to be significant outcomes of the solid waste income stream. Likewise, in Tables 1 and 2, for the educational value stream, we note that volume, veracity, and value are significant. Hence, we can make a number of propositions. In the informal solid waste value stream (S), we see that volume, variety, and value play a relatively important role. In education (E), healthcare (H), and nutrition (N), the necessary data attributes are volume, variety, veracity and value. Disaster relief (*DREL*) is associated with variety and velocity attributes, while disaster recovery needs veracity of data. Focal NGOs working on land distribution (L) need to focus on volume, variety, veracity, and value, but when working on micro-credit support (M), volume and veracity are important. Consistent with RDT predictions, these findings show that power-based relationships among focal NGOs and their nodal actors influence the propensity of big data use.

Table 4 Humanitarian value supply chain, focal NGO, network actors and data attributes

Value stream	Data attributes (focal NGO with the respective network actors)				
Solid Waste	Volume	Variety	Velocity	Veracity	Value
Education E	**IPCA (I)** Attendance in informal schools and government schools tracked for overseas donors (γ)			**IPCA (I)** needs to provide documents (birthdates and residency) that government school (η) officials can rely upon. For the **Hub-n'-Spoke (H)** intervention data has been systematically collected and verified for the last 8 years as per the overseas donors' (γ) requirements	**Hub-n'-Spoke (H)** Government schools (η) and *panchayats*/local council (φ) expect improvement in grades. Data is being tracked between Hub-n'-Spoke as children progress from grades 1–5, grades 6–10, and beyond to predict performance. Intra-hamlet comparisons and correlation with cyclone impact documented to analyze resilience
	Hub-n'-Spoke (H) marks are provided quarterly in each subject area for some 300 children. Also, educational performance is tracked as the children move from the hamlets into the hub hostel				
Health-care H and Nutrition N	**IPCA (I)** Health card for each child created and diseases tracked. **Sodhana (S)** currently tracks 900 children's BMIs for overseas donors (γ). **Hub-n'-Spoke (H)** BMI measures computed quarterly. Costing of the educational value stream reported on a monthly basis for overseas donors (γ)	**IPCA (I)** provides a range of health indicators tracked on the health cards for local corporate donors (ι). Includes medical and dental examination records		**Sodhana (S)** entered households to assess actual food consumption as per overseas donors (γ) questions. For the health camps run by **IPCA** and supported by local doctor group (ι) require veracity of data in the children's health cards	Based on data (patterns), **Sodhana (S)** made suggestion to families in terms of increasing caloric intake and quality of nutrition as per overseas donors' (γ) questions

Table 4 continued

Values stream	Data attributes (focal NGO with the respective network actors)				
	Volume	Variety	Velocity	Veracity	Value
Disaster Relief DREL		**Hub-n'-Spoke** provided photos and write-ups through email and social media with overseas donors (γ), government entities (κ), and local donors (λ)	**Hub-n'-Spoke** shared information quickly with overseas donors (γ), government entities (κ), and local donors (λ)		
Disaster Recovery DREC				**Hub-n'-Spoke** needed to provide verifiable data as requested by overseas donors (γ). This data includes contractor names, work done, amount disbursed, and check numbers	
Land Redistribution L	**Sodhana** works with Self-Help Groups (β) to procure data for 500-600 land transfers	**Sodhana** procures deeds, records, death certificates as per government requirements (π)		**Sodhana** is tracking multiple sources of information across generations to ensure proper documentation as per the requirements of various government entities (π)	**Sodhana** transfer of land to *dalits* (lower caste) (β)
Micro-Credit Support M	**Sodhana** monitors and collects monthly updates from over 2,000 women in the Self-Help Group (β) network			**Sodhana** is required to assemble and procure verifiable documentation for government bank (μ) generated by the Self-Help Groups (β)	

4.5 Big data and outcomes

Based on Tables 1, 2, and 3, we can also identify possible relationships between the type of data attributes and the outcomes (Table 5). For example, in Tables 1, 2, and 3, we note that volume is associated with educational deliverables for IPCA (**I**) and Hub-n'-Spoke (**H**) interventions, while in the case of Sodhana Charitable Trust (**S**), volume is associated with land distribution, (mal)nutrition, and micro-credit deliverables. Specifically, the volume of data potentially helps in increasing the deliverables (e.g. improved attendance, better grades, reduction in malnutrition, and so on), reducing costs, adding to the resilience of the operations and, in some instances, reducing lead-times. Velocity of data is important in certain situations (e.g. disaster relief or obtaining death benefits). Velocity also has an important role to play in obtaining future funding (i.e., resilience), especially when dealing with disaster relief. Variety of data can also be useful in terms of reducing lead-times (faster release of funds) and adding to resilience of the operations. Veracity is an important attribute as it affects deliverables, costs, lead-time, and resilience. Finally, we see value is primarily associated with deliverables and to some degree with cost and resilience.

5 Discussion

In this research, we demonstrate the applicability of big data analytics in the humanitarian supply chain context, extending the generalizability of resource dependency theory. Our findings have important policy implications and provide insights for future research.

5.1 Applicability of big data analytics in the humanitarian supply chain context

Based on the analyses conducted across the multiple value streams of the respective cases, it becomes clear that big data analytics is a critical strategic driver in creating humanitarian services.

In our case analysis,we find that the various data attributes (value, volume, veracity, variety, and velocity) are applicable to humanitarian services in the developing world context and that outcomes can be classified in terms of deliverables, lead-times, costs, and resilience. Furthermore, we have been able to develop a model (Fig. 3) that specifies how data attributes vary by the type of value stream, the role of dependency on data attributes and finally, the ways in which data attributes affect outcomes.

5.1.1 Value stream and data attribute

Multiple forms of humanitarian supply chain value streams (e.g. education, healthcare, disaster relief, etc.) are found to be associated with different mix of data attributes (e.g., volume, variety, velocity, veracity, and value) (Table 4). For example, value streams of humanitarian networks focused upon education (E) and healthcare (H) tend to demand volume, while disaster relief (*DREL*) streams are found to be more oriented towards velocity.

5.1.2 Resource, power and data attributes

Through our analysis,we are able to demonstrate the role of supply chain actors affecting the relative power on the focal NGO; this power is derived based upon the resources being provided by the various supply chain actors (nodes). The power can be utilized in order to

Table 5 Data attributes, focal NGO, value stream, network actors and types of outcomes

Data attributes	Types of outcomes			
	Deliverables	Cost	Lead-time	Resilience
Volume	Volume of data is correlated with improved attendance and better grades (**IPCA** and **Hub n' Spoke**) as expected by overseas donors (γ). Volume of data was also associated with Self-Help Groups (β) working with government entities (π) in gaining land title transfers (**Sodhana**). The flow of data from some 2,500 women was essential to the success of the micro-credit program supported by the government bank (μ)	Data is collected on the educational value stream allowing **IPCA** to monitor costs on a per unit (child) basis for overseas donors (γ). The large flow of micro-credit data from Self-Help Groups (β) managed by **Sodhana** to the government bank (μ) allows for a low default rate and greater profitability. **Sodhana** also provides monthly cost data on egg purchases as per the nutritional value stream	The volume of data is correlated with length of time children remain in ragpicker schools run by **IPCA**	The large volume of data ensures the growth and propagation of relationship between **IPCA** and some of its commercial suppliers (χ). The volume of data provided by **Sodhana** to the government bank (μ) ensures the continued loan scheme provided to the Self-Help Groups (β)
Velocity			High velocity of data provided by **Hub-n'-Spoke** for disaster relief was accompanied by quick disbursement of resources by the overseas (γ), local (κ), and corporate (λ) donors	High velocity of data provided by **Hub-n'-Spoke** for disaster relief was associated with long-term funding by overseas (γ), local (κ), and corporate (λ) donors
Variety			High variety of data provided by **Hub-n'-Spoke**for disaster relief *was* accompanied by quick disbursement of resources by overseas (γ), local (κ), and corporate (λ) donors	High variety of data generated by **IPCA** in the health cards provides long-term relationship potential with local corporate donors (ι) and admittance into government school (η). High variety of data provided by **Hub-n'-Spoke** for *disaster relief* was associated with long-term funding by overseas (γ), local (κ), and corporate (λ) donors. In IPCA's *solid waste income stream*, a high variety of data was correlated with long-term commercial suppliers' (χ) contracts and access to government land (π)

Table 5 continued

Data attributes	Types of outcomes			
	Deliverables	Cost	Lead-time	Resilience
Veracity	The veracity of data is critical for educational, nutritional, micro-credit, and healthcare value streams. In the **Hub-n'-Spoke** educational intervention proper data allows for exams to be administered. Also, **IPCA** found that reliable records are necessary for access to government schools and hospitals (η)	**Sodhana's** ability to provide data with a degree of veracity has allowed micro-credit Self-Help Groups (β) access to low-cost loans	**Sodhana's** ability to provide data with a degree of veracity has allowed micro-credit support Self- Help Groups (β) faster access to loans. The veracity of data allows for the rapid disbursement of funds for the nutritional support by overseas donors (γ)	In the educational value stream, **IPCA** veracity in data has allowed some 65 children to move from the informal ragpicker schools to the formal government schools (η). Likewise, in the **Hub-n'-Spoke** intervention, the veracity of the data ensure long-term overseas donations (γ). **Sodhana's** ability to provide a high degree of veracity in income generation data allows for the long-term partnership between Self-Help Groups (β) and the government bank (μ). Also, for the nutrition support, the veracity of data led to *a* new health care initiative funded by overseas donors (γ)

demand big data from the focal NGO. Such pressure, if applied, can trigger the requisite data stream, which can then be used to facilitate superior project outcomes (i.e., in terms of the quality of deliverables, lead-times, cost, resilience).

5.1.3 Data attributes and outcomes

In our case study we also found that certain types of data attributes are associated with different types of outcomes (Table 5). For example, volume tends to positively affect the quality of deliverables, reduce costs, and shorten lead-times, while velocity and veracity influence efficiency in terms of lead-times and increase resilience. Veracity is also found to be positively related to deliverables, reduced costs, shorter lead-times, and increased resilience.

5.2 Policy implications

The proposed model provides a basis for focal NGOs, donors, and developmental agencies in designing humanitarian interventions and specifying big data expectations. Specifically, prior to a proposed intervention, the focal NGO and important stakeholders need to identify the respective critical data attributes (i.e., value, velocity, veracity, volume, or variety) that need to be generated for that type of intervention. Furthermore, there needs to be an understanding of the types of expected outcomes (e.g., deliverables, costs, lead-times, resilience) which would be forthcoming based on the attributes. Finally, the critical resource providers need to apply pressure to ensure that the focal NGO indeed creates the specified data attributes to produce superior humanitarian outcomes.

Based upon our case study analysis, the value attribute seems to have an effect primarily on the deliverables but potentially plays an important role in improving the humanitarian supply chain through data extraction and transformation. From our analysis, it is obvious that many NGOs are responsible for multiple value streams. The potential of data extraction and transformation actually lies in inter-value stream analysis. For example, the Hub-n'-Spoke intervention looked at the correlation between malnutrition (Body Mass Index, or BMI) and educational performance and found limited patterns intra-village but more nuanced inter-village correlations. However, this analysis could be taken a step further; the influence of malnutrition and education levels could be analyzed in the context of resilience to calamities (e.g., Cyclone Hudhud). Prescriptions from the analysis could then be used as a basis for long-term investments in communities and decisions about which value stream activities to promote. Big data analytics (especially the value attribute) requires a degree of information technology and statistical sophistication that many NGO personnel may not possess; for that reason, they may find it difficult to generate the necessary data streams required by the respective nodal actors. Perhaps training programs and educational modules can be created to provide NGO staff with the needed skill set.

5.3 Future research

The existing research in big data analytics does not clearly identify stages in data attributes. However, through our analysis, we note the potential of a life cycle approach in humanitarian supply chains. It is possible that there could be stages in data attribute flow, beginning with velocity and variety. The second stage could possibly be volume and veracity and, finally, the third stage might be value. Logically, we can derive sufficient value only when we have sufficient volume, variety, veracity, and velocity of data. Of course, additional research would be necessary to explore the possibility of such a pattern within the humanitarian supply chain context.

RDT has been studied primarily in the context of dyadic relationships or, in limited cases, linear two-tiered supply chains. However, in the humanitarian context, the resources—and hence the distribution of power—would be reflective of a distributed network. Furthermore, the relationships between the various nodal actors would not necessarily always traverse though the nodal NGO; inter-nodal pressures could also exist (see Figs. 1, 2). Future studies may examine realistic scenarios of non-linear patterns emanating from distributed supply chain networks as they relate to resources, power imbalance, data, and outcomes.

5.4 Conclusion

In this research, we apply resource dependence theory (RDT) to explain the relationship between supply chain actors and focal NGOs. We contribute to RDT by demonstrating how distributed supply chain partners affect the relative power balance vis-à-vis the focal NGO in generating big data. In addition, we add to the literature by showing how power needs to be applied in order to execute sufficient data streams (value, velocity, variety, volume, veracity), which ultimately affect outcomes. In addition, in our research we find that there are often multiple nodal partners simultaneously exerting pressure on the power relationships. Finally, the proposed model provides a road map for a focal NGO to create the necessary data attributes to produce superior humanitarian outcomes.

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