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Deriving Value from Big Data Analytics in Healthcare: A Value-focused Thinking Approach

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Abstract:

With the potential to generate more insights from data than ever before, big data analytics has become highly valuable to many industries, especially healthcare. Big data analytics can make important contributions to many areas, such as enhancements in the quality of patient care and improvements in operational efficiencies. Big data analytics provides opportunities to address concerns such as disease diagnoses and prevention. However, it has posed challenges such as data security and privacy issues. Also, healthcare institutions have concerns about deriving the greatest benefit from their big data analytics endeavors. Therefore, identifying actionable objectives that can help healthcare organizations derive the maximum value from big data analytics is needed. Using the value-focused thinking (VFT) approach, we interviewed individuals associated with data analytics in healthcare to identify actionable objectives that one needs to consider to derive value from big data analytics, which practitioners can use for their own endeavors and provide opportunities for future research.

Keywords: Value-focused Thinking, Healthcare, Data Analytics, Big Data, Social Theory.

Gurpreet Dhillon was the accepting senior editor for this paper.

1 Introduction

Due to the vast amounts of data that they accumulate and acquire, healthcare institutions have an opportunity to develop better insights into many facets of their business with big data analytics. Big data repositories include various sources, such as electronic health records and health information exchanges (Guha & Kumar, 2018). Healthcare institutions have taken a prominent interest in using big data to improve their operations ranging from financial improvements to more effective patient care (Wang et al., 2018; Weerasinghe et al., 2018; Raghupathi & Raghupathi, 2014; Institute for Health Technology Transformation, 2013). Because these institutions have such extensive and varied opportunities, using big data to assist both healthcare professionals and administration presents ample possibilities (Weerasinghe et al., 2018). However, many organizations have faced various challenges in trying to realize the full benefits from these opportunities, such as insufficient training, difficulty in dealing with data intricacies, and the inability to show value from data (Appold, 2017). Multiple studies have focused on the benefits of using big data analytics in healthcare (e.g., Wang et al., 2018; Institute for Health Technology Transformation, 2013; Archenaa & Anita, 2015; Srinivasan & Abrunsalam, 2013), but none have focused on identifying the actionable objectives needed to realize its full potential. These objectives can benefit healthcare institutions by helping them to strategically plan and manage their big data analytics initiatives. Therefore, we propose the following research question:

RQ: What actionable objectives do healthcare institutions need to consider to derive value from big data analytics?

To identify these actionable objectives, we use a value-focused thinking (VFT) approach to identify the relevant values that can be transformed into actionable objectives (Keeney, 1992). Keeney (1992) proposes that values should drive decision making because values reflect what individuals desire to achieve. Grounded in these values, the objectives provide guidance and actionable insights that healthcare organizations need to consider to achieve the desired value. VFT has been used in other IS studies such as voice assistant adoption (Rzepka, 2019), information systems security (Dhillon & Torkzadeh, 2006), and mobile technology in an educational context (Sheng et al., 2010). Researchers have also used VFT in the context of big data strategic management, such as developing appropriate policies, in other domains (e.g., Coss et al., 2019). Therefore, we use VFT to identify objectives that healthcare institutions can employ to strategically manage big data analytics.

This paper is organized as follows. In Section 2, we present a review of the literature. In Section 3, we discuss social theory, which provides the study's theoretical foundation and, in Section 4, our research methodology. We then present the data collection and research results in Sections 5 and 6, respectively, followed by a discussion of the results in Section 7. In Section 8, we discuss the study's implications and limitations as well as note possibilities for future research directions before concluding the paper in Section 9.

2 Background and Literature Review

2.1 Big Data Analytics Uses and Opportunities

The healthcare industry has used a myriad of data for its analytic endeavors and for many aspects such as operational and clinical. Because of recent advancements in technology, the sources and structure of data used in analytics can be more expansive and diverse than previously possible (Appold, 2017; Wang et al., 2018). For example, data that organizations use for analytics purposes includes medical records, laboratory reports, and physician notes (Saggi & Jain, 2018; Archenaa & Anita, 2015). Also, the volume of data in the healthcare industry is expected to grow dramatically in the years to come (Institute for Health Technology Transformation, 2013). Organizations can analyze data from payers, clinics, and psycho-socioeconomic sources. With this growth in the volume of data, the healthcare industry has great potential to increase its operational efficiencies and effectiveness as well as improve patient care.

The insights derived from this data can lead to a variety of benefits, such as better healthcare quality, improvements in efficiency, as well as earlier disease detection and management (Institute for Health Technology Transformation, 2013; Archenaa & Anita, 2015; Noorbergen et al., 2021). Many organizations are leveraging big data analytic tools to determine the probability of patient readmission and identify patients at higher risk of developing certain diseases. For example, a physician can be notified if a patient has not refilled a medication. The physician can subsequently follow up with the patient to help prevent a readmission, which can provide health benefits to the patient and create operational efficiencies for both the physician and healthcare institution.

In addition, big data analytics provides immense potential to improve healthcare services. For instance, opportunities include reducing costs, predicting disease epidemics, improving medical diagnoses, and discovering trends associated with reactions to medicines (Weerasinghe et al., 2018; Guha & Kumar, 2018; Saggi & Jain, 2018; Alexandru et al., 2018). Healthcare models have evolved to create more personalized and proactive care, such as identifying categories of individuals with a similar biological basis for a disease such that better treatment plans can be developed (Whelan, 2018; Wu et al., 2017). Healthcare organizations have begun to leverage clinical data to gain better insight into a population's concerns and make more accurate predictions, as well as create opportunities to provide personalized medicine at a faster pace (Appold, 2017; Guha & Kumar, 2018). Therefore, big data analytics has the potential to provide improvements in treatment and subsequent outcomes, but organizations need guidance to assist in their related strategic planning efforts of it.

Big data analytics has shown the potential to improve healthcare facility operations, but organizations may need to adapt as it evolves. Big data analytics has created opportunities to reduce fraud, waste, and abuse related to insurance claims (Raghupathi & Raghupathi, 2014). From the administrative perspective, organizations can use big data analytics for charge capture, budgeting, continuous auditing/monitoring, and payment analysis (Appold, 2017; Alexandru et al., 2018; Raphael, 2017; Tschakert et al., 2016). However, the potential applications of big data analytics and its value continue to emerge. Therefore, clear objectives could greatly assist healthcare organizations in strategically managing big data analytics to realize its potential.

Previous research has focused on many facets of big data analytics in healthcare. Studies have explored areas such as improving models, enhancing the richness of the data, and identifying more optimal methods of processing data to improve hospital readmission predictive analytics (Zolbanin & Delen, 2018). Research has explored using multi-omic (e.g., genomic, metabolomic) and electronic health record data to facilitate precision medicine (Wu et al., 2017). In addition, research has focused on healthcare improvements such as quality of patient care (Wang et al., 2019) and disease diagnoses (Fawagreh & Gaber, 2020). Also, research has identified benefits that organizations can derive from big data analytics architectural components and capabilities (Wang & Hajli, 2017) as well as the creation of strategies to leverage big data (Institute for Health Technology Transformation, 2013). Research has proposed various frameworks, such as studying big data and business-IT alignment from a social dynamics perspective (Weerasinghe et al., 2018) but has not identified a comprehensive set of actionable objectives that organizations need to consider to strategically manage big data analytics and realize its full potential.

2.2 Big Data Analytics Challenges

2.2.1 Data Governance

Big data analytics in healthcare is not immune to challenges such as data governance concerns. For example, some data sets are currently fragmented and need to be integrated to enhance integrity and reduce costs (Appold, 2017; Saggi & Jain, 2018). Other data governance issues to address include the transmission, processing, and storage of data as well as the variations in types of data. For instance, types of data include both structured and unstructured (Saggi & Jain, 2018; Wu et al., 2017; Raghupathi & Raghupathi, 2014). Unstructured data, such as physician notes, can be problematic to analyze due to variations in formats, misspellings, and domain-specific acronyms. Data may come from various sources such as sensors, self-reported data, images, and videos (Saggi & Jain, 2018). In addition, data in the healthcare industry can vary in frequency (e.g., collected once during a genome test, collected periodically from a lab report, or collected continuously from a glucose monitor).

Significant challenges for big data analytics include incomplete data, high costs, and extensive periods of time to generate a return on investment (Appold, 2017; Saggi & Jain, 2018). For example, in the context of predictive analytics, incomplete data can create difficulties when trying to apply data-driven insights to broader populations (Appold, 2017). Also, incorrect, heterogenous, or unlabeled data can impact the quality of data analytics (Grover et al., 2018; Wu et al., 2017). Smaller organizations have a disadvantage with data management and analytics as they lack the scale to make it cost effective (Appold, 2017). The uncertainty and time to generate a return on investment can also pose a significant challenge because organizations will need to make investments in developing their infrastructure, training employees, as well as collecting and licensing quality data (Weerasinghe et al., 2018; Grover et al., 2018). Therefore, big data analytics presents obstacles that organizations need to address to realize its full potential.

Many organizations are reluctant to share their data because they could lose a potential competitive advantage (Dash et al., 2019). If organizations are willing to share data, it is most likely not in a compatible format, making it difficult to fully analyze (Adarsha et al., 2019; Alexandru et al., 2018). Organizations will need to consider effective approaches to integrate big data analytics into their current IT infrastructures. Ideally, this integration entails the full utilization of the data and formatting it in a manner so it is useful to other organizations.

Other issues include security and privacy concerns (Guha & Kumar, 2018; Saggi & Jain, 2018; Alexandru et al., 2018). Healthcare organizations have the potential to acquire a significant amount of personal, financial, clinical, and behavioral information using big data analytics. Because some patients may receive care at multiple locations, organizations will have to consider issues of privacy and security of the data as it moves between various organizations or organizational divisions (Dash et al., 2019). They may need to adjust policies to ensure data flows optimally across their healthcare system in a manner that protects the privacy and security of their patients' data (Institute for Health Technology Transformation, 2013). To derive the greatest value from big data analytics while maintaining data privacy and security, healthcare organizations must design their systems in a way that minimizes the trade-off between privacy and performance (Burns et al., 2015). With a set of defined objectives, strategic planning that addresses these obstacles and concerns would greatly benefit healthcare institutions and their patients.

2.2.2 Adoption and Use

Adopting and using big data analytics provides additional challenges. For instance, some healthcare professionals may be averse to change (Weerasinghe et al., 2018). Inexperienced data analysts can also pose a significant challenge for big data analytics in healthcare. Analysts may need to adopt or create new ways of thinking. For example, predictive analytics may require new approaches to be effective and provide value (Saggi & Jain, 2018). However, data experts may not have the understanding of or capabilities to use new approaches that can turn data into valuable insights (Appold, 2017).

In addition, a disconnect between data experts who create the models and healthcare professionals who use the information can exist (Appold, 2017). In other words, the actors who create and use big data analytics can have different perspectives regarding how to realize value from big data analytics. Healthcare professionals also typically lack the time to participate in predictive model development and integrate these predictive models into their existing work routines. For some healthcare organizations, these challenges contribute to decision making not exhaustively leveraging the use of analytics (Wang et al., 2018). Hence, actionable objectives to help strategically manage big data can address these challenges and help organizations realize the value that big data analytics offers.

Organizational norms can emerge from these actionable objectives such that they guide individual behaviors and decision making. However, previous research has not identified these objectives in a comprehensive manner. We focus on filling this gap by identifying actionable objectives necessary to assist healthcare organizations overcome the challenges, strategically manage big data analytics, and realize its full potential. We do so by first identifying the value of big data analytics in healthcare to ensure we ground the actionable objectives on what truly matters.

Researchers have effectively used a value-focused thinking (VFT) approach in many areas, such as philosophy, internet commerce, and social media, to identify actionable objectives (Syed et al., 2019). However, VFT has not been fully utilized in a broad sense for healthcare organizations. To fully use the VFT approach, one needs to examine the many aspects of healthcare, such as management and community health, because the value of big data analytics can be intertwined among them. Therefore, we conducted a comprehensive study to bring the most benefit to healthcare and did so in consideration of this interconnectedness. For example, operational inefficiencies could negatively impact medical professionals' ability to provide the most effective treatment plan for their patients. These inefficiencies could lead to higher costs and dissatisfied medical professionals, which could cause a higher turnover and, ultimately, impact an organization's profitability. These same operational inefficiencies could negatively impact patients' treatment as well, which could result in less-than-desirable outcomes. Organizations may address these operational inefficiencies with big data analytics and create value for themselves and their patients. In other words, an important contribution can be made and a gap in the literature filled by utilizing a comprehensive approach to identify actionable objectives that healthcare organizations need to consider to strategically manage and derive the value they desire from big data analytics, which is the focus of this research.

3 Theoretical Foundation

3.1 Social Theory and Norms

In our study, we use social theory as the theoretical foundation. Researchers have argued that social theory presents a “theory about the working out of various rules within which sets of persons act” (Coleman, 1990, p. 11). The social theory conceptual framework comprises: 1) a social system’s effects on the actors within a system, 2) the actors’ actions, and 3) systemic behavior that results from these actions’ interacting and merging. Social systems contain social norms. Social norms arise when a need for effective norms exists and actors can fulfill that need.

Norms exist at an organizational level, which Coleman (1990) refers to as the “macrosocial level”, but direct behaviors at an individual level (e.g., employees). As Coleman notes (1990, p. 224), “norms are macro-level constructs, based on purposive actions at the micro level but coming into existence under certain conditions through a micro-to-macro transition”. Hence, norms are generated by the behaviors of individuals, reside at a system or organizational level, and influence individuals’ future behaviors. Social norms dictate the appropriateness or inappropriateness of an action. Individuals intentionally establish and maintain norms to obtain perceived benefits or avoid negative consequences. Norms influence the decisions that individuals make and the subsequent actions that they take. In other words, “persons whose actions are subject to norms…take into account the norms…not as absolute determinants of their actions, but as elements which affect their decisions about what actions it will be in their interests to carry out” (Coleman, 1990, p. 244). Hence, norms can guide the behaviors of individuals in healthcare institutions, which can result in generating value from data analytics endeavors.

3.2 Social Relationships and Professionalization

Information can drive actions (Coleman, 1990). However, acquiring information can require significant time and cost. An efficient and cost-effective means to acquire information involves using existing social relationships. An individual’s ability to use their social relationships to gain information depends on the individual’s expertise from whom they seek information. If the individual is considered a credible source, then one can consider the information reliable and it can enable action. To acquire information regarding appropriate actions to take when engaging in big data analytics endeavors and achieve the desired value, individuals in a healthcare institution may be able to rely on others in the institution who are knowledgeable of its organizational norms.

Professionalization establishes norms for individuals who share an occupation. Members of a profession establish procedures and structures for their work, requisite knowledge and skills for admittance into the profession, and “a cognitive base and legitimation for their occupational autonomy” (DiMaggio & Powell, 1983, p. 152). Norms associated with professionalization arise through formal education and professional networks. Professionals with similar training, positions, decision-making strategies, and inclinations can foster undifferentiated individuals. Professionals learn the norms and become socialized regarding the appropriate vernacular and acceptable behaviors. Hence, individuals associated with big data analytics in healthcare can adopt or share norms associated with the industry or their profession through professionalization. These norms can foster actions that result in maximizing the value of big data analytics.

3.3 Diversity and Development of Norms

Norms have diverse forms. Prescriptive norms encourage certain actions through positive feedback, while proscriptive norms discourage actions through negative feedback (Coleman, 1990). Conjoint norms target the actions of individuals or groups who also benefit from them, while disjoint norms target the actions of individuals or groups who do not benefit from them. Conjoint and disjoint norms represent the farthest opposing points on a continuum with other norms residing in between the two extremes. These norms can promote certain actions that can help healthcare organizations achieve the most value from big data analytics. Norms can benefit both healthcare institutions as well as the patients and communities that they serve.

Therefore, healthcare institutions can foster appropriate norms for deriving value from big data analytics and use them to guide individual actors in their data analytics endeavors. Healthcare institutions may develop these norms by implementing appropriate policies or procedures and by integrating them into their institutional goals and mission statements. Norms can guide future actions and decisions, which makes them advantageous when implemented in a manner consistent with the appropriate values. Therefore, as an initial task, one needs to identify what one values. These values can be transformed into actionable objectives that can then develop into organizational norms. To identify these values, we use the value-focused thinking (VFT) approach.

4 Research Methodology

4.1 Value-focused Thinking

To identify the actionable objectives associated with deriving value from big data analytics in healthcare, we used the value-focused thinking (VFT) approach. Keeney suggests that "values should be the driving force for our decisionmaking [sic]" (Keeney, 1992, p. 3) because values embody our critical concerns, which makes them of the utmost importance. However, utilizing values as an essential aspect of decision making does not necessarily occur. Decision making tends to occur by choosing among a set of alternatives, referred to as "alternative-focused thinking" (Keeney, 1996, p. 537). In other words, decision making tends to take place by identifying existing alternatives and selecting the best one. However, the gamut of potential alternatives tends to be narrow and less optimal when one pursues this approach. The approach promotes identifying alternatives *before* values and the associated objectives, which one needs to evaluate the alternatives (Smith & Dhillon, 2019). However, values should have a central role in decision making, and alternatives should constitute only a means to accomplishing what one values (Nah et al., 2005; Smith & Dhillon, 2019). When making a final decision to select an alternative, the values one possesses should drive the decision (Syed et al., 2019).

Therefore, when making decisions, one should commence by first identifying what one values. Values can be "ethics, desired traits, characteristics of consequences that matter, guidelines for action, priorities, value tradeoffs, and attitudes towards risk" (Keeney, 1992, p. 7). Value-focused thinking (VFT) focuses on determining what one wants to accomplish and the means to accomplish it (Keeney, 1992). Hence, VFT can assist individuals in making more effective decisions because it "has been designed to identify desirable decision opportunities based on the underlying values of those involved in the decision context" (Dhillon & Smith, 2019, p. 143). With VFT, individuals exert more effort on identifying what they value and using these values as the basis for making decisions. They can use these values to make appraisals or evaluations (e.g., evaluating potential outcomes).

Values may be difficult to discern and articulate (Keeney, 1992). VFT provides a process for identifying what one finds important and the means to attain it (Sheng et al., 2010). Although initially considering what one values can help identify conscientious values, VFT provides a means to identify subconscious values as well (Keeney, 1992). As Keeney (1992) states, VFT helps decision makers make values "explicit with objectives" (p. 33), which can subsequently direct actions.

4.2 Value Identification and Transformation

As we note in Section 3.3, organizational norms can emerge from actionable objectives, which are derived from values. In VFT, one first identifies values, which are then transformed into actionable objectives (Dhillon & Smith, 2019; Keeney, 1992). To do so, one conducts interviews and poses questions to help elicit these values (Dhillon & Smith, 2019; Keeney, 1996; Sheng et al., 2005). For our study, we posed questions such as "what would you like to achieve with big data analytics?" and "If there were no limitations with big data analytics, what value could be derived?" to our participants. In addition, we posed questions about goals, potential benefits, and issues with big data analytics in healthcare. Further, we asked them to create wish lists but not prioritize or rank any items on their list. We continued posing questions until no further values could be identified.

The values were then transformed into actionable objectives. Three features characterize objectives: "a decision context, an object, and a direction of preference" (Keeney, 1992, p. 34). The decision context "is most readily specified by the activity being contemplated" (Keeney, 1992, p. 35). As an example, an actionable objective related to deriving value from big data analytics in healthcare is "maximize quality of life and well-being". The decision context is deriving value from big data analytics in healthcare, the object is the patient quality of life and well-being, and the preference direction is to maximize. We derived this actionable objective from participants' value statements such as:

> *It's really coming down to…ultimately your [referring to a patient] quality of life…and your well-being will see a positive impact* and *lead a more productive…life…allows them to do what they want to be able to do.*

The next step entails "combining similar or component objectives under a common general objective" (Keeney, 1999, p. 536). The above objective was categorized with other similar objectives under the general or main objective "maximize individual patient health and well-being".

4.3 Organization of Objectives

The types of actionable objectives include fundamental and means objectives (Nah et al., 2005). Fundamental objectives are "an essential reason for interest in the decision situation" (Keeney, 1992, p. 34). These objectives elucidate the values of interest and focus on ends versus means (Keeney & McDaniels, 1992). Means objectives are necessary to attain the fundamental objectives or other means objectives (Keeney, 1992). To identify the fundamental from the means objectives, we asked participants the question "Why is this objective important?", referred to as the "WITI test", in the context of deriving the maximum value from big data analytics in healthcare (Dhillon & Smith, 2019; Keeney, 1992, p. 66). If the objective was important as an essential purpose for this decision context, it was classified as fundamental (e.g., "maximize quality of life and well-being" as we note above). If the objective was important because of its relevance to another objective, it was classified as a means objective.

For example, the participant whose value statement we refer to above also said "have the most appropriate treatment plan and not seeking unnecessary care" beforehand, which was converted to the means objective "maximize effectiveness of patient treatments and outcomes". As another example, the other participant that we quote above noted that "they will be able to…determine the most appropriate plan of care or plan of treatment on a very consistent basis, so consistently picking the correct plan of treatment…for every patient", which states the same value. As such, it was combined with the previous stated value. We repeated the WITI test until all objectives were identified as means or fundamental. A means-ends objectives network was derived based on the results of this test, which shows the means that help achieve other means or fundamental objectives (Dhillon & Smith, 2019). For instance, "maximize effectiveness of patient treatments and outcomes" could be one of the means objectives to achieve the fundamental objective "maximize quality of life and well-being". Therefore, means objectives have an essential role in a decision context and will help achieve fundamental objectives either directly or indirectly (Dhillon & Smith, 2019).

Because objectives are derived from stakeholders' values, one can use the network to derive fundamental principles for achieving the maximum value of big data analytics in healthcare. Healthcare institutions should be able to use the network to identify decision pathways to achieve the fundamental objectives that they desire. Institutions can consider alternate decision pathways that will be most feasible and effective to implement. These actionable objectives can emerge as organizational norms for that institution. Also, the norms can emerge in other institutions through mechanisms such as professionalization, as social theory suggests.

Because the goal of this research study is to identify actionable objectives associated with deriving value from big data analytics in healthcare, we consider VFT an appropriate method for identifying objectives associated with this endeavor. VFT offers a comprehensive approach to eliciting objectives (Dhillon & Torkzadeh, 2006). Other methods (e.g., surveys) may not allow one to identify a comprehensive set of objectives. One can use VFT to identify objectives that have a foundation in what one truly values. The steps we performed for the VFT process (see Figure 1) are noted in Table 1.

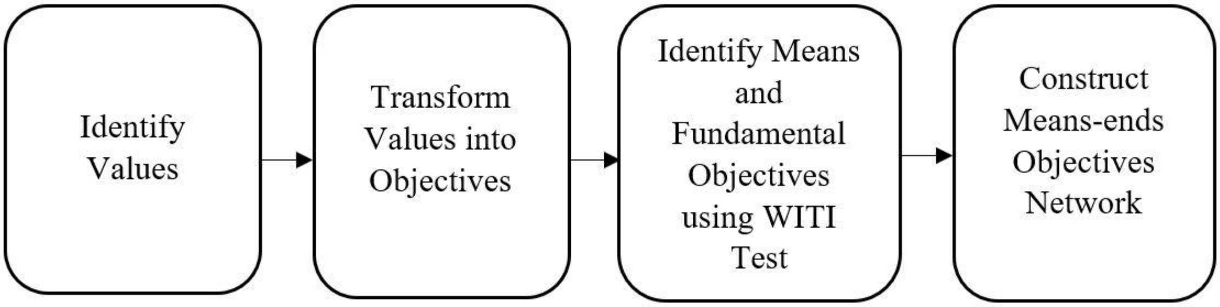

Figure 1. Value-focused Thinking Process (Dhillon & Smith, 2019; Keeney, 1996; Sheng et al., 2005)

Table 1. Steps in Value-focused Thinking Process (Dhillon & Smith, 2019; Keeney, 1996; Sheng et al., 2005)

Step	Procedure
1	To generate a comprehensive list of values for this particular decision context, we asked participants a series of questions. We initially asked them "What would you like to achieve with big data analytics?" to derive the value of big data analytics in healthcare. We then asked them questions about the goals, potential benefits, and issues with using big data analytics in healthcare. We asked them to create wish lists with no ranking or prioritizing as well. Other probing questions included "If there were no limitations with big data analytics, what value could be derived?". We continued asking questions until no additional values could be identified. The values identified in this step were then transformed into a common form as actionable objectives.
2	For each actionable objective that we identified in the first step, we asked the participant "Why is this objective important" in the context of deriving the maximum value from big data analytics in healthcare to distinguish means from fundamental objectives (Dhillon & Smith, 2019; Keeney, 1992, p. 66). If the response indicated that the objective was important because it represents "the essential reasons for interest in the situation" (Keeney, 1992, p. 34), then it was classified as a fundamental objective. If the response indicated that the objective was important to achieve other means or a fundamental objective, then it was classified as a means objective. We continued to ask the question "Why is this important?" to identify additional means objectives or a fundamental objective. The probing continued until the fundamental objective was identified.
3	A means-ends objectives network was created based on the results that we derived from the previous step. The network represents the means and fundamental objectives, as well as the relationships among them.

5 Data Collection and Analysis

We interviewed 10 data analysts or individuals associated with data analytics in healthcare for our study. We took notes during the interviews and recorded all sessions. On average, participants had over 11 years of experience with data analytics and over 16 years of experience in the healthcare industry (see Table 2 for demographic information). Our participants included individuals with Master in Healthcare Informatics and Nursing Informatics degrees, directors of informatics departments, decision support and data analysts, and data scientists. Eight participants had worked for more than one organization. For the two who worked for only one organization, they worked in other positions within their current organization. Some examples of the languages and applications they used include RStudio, Python, Allscripts, SQL, Epic, and Crimson.

Table 2. Demographic Information

	Minimum	Maximum	Mean
Work experience—data analytics	1	30	11.29
Work experience—healthcare (years)	2.5	34	16.65
No. of employees in organization	100	16,000	5,426

Interviews lasted from 45 minutes to one-and-a-half hours. The number of interviews that are conducted in VFT studies varies, but interviews should continue until the point of saturation is reached, which evolves naturally with the VFT process (Dhillon & Smith, 2019; Nah et al., 2005; Smith et al., 2018). The point of saturation was reached after the fifth participant. With 10 interviews in total conducted, the saturation point was adequately reached, and the additional interviews enhanced the validity of our findings.

5.1 Validation of Results

Similar to Dhillon and Torkzadeh (2006), we used a panel of experts to validate our findings. We selected five panelists based on their domain of interest being big data analytics in healthcare and their job responsibilities. Their educational backgrounds included doctorates in health services research and master's degrees in fields such as information science and technology. The panelists had responsibilities for data analysis and research in healthcare. Their work experiences included healthcare data analytics and management positions overseeing healthcare data analytics.

We asked the panelists to review the fundamental and means objectives and assess their relevance for the given decision context before we met with them. We asked them to assess the extent to which the objectives pertained to the decision context (i.e., limited relevance, somewhat relevant, relevant). In addition, we asked the panelists to provide feedback on the WITI test results that identified means and fundamental objectives. After doing so, we then asked the panelists if any other objectives should be included. The meetings ranged from approximately 25 to 75 minutes except for one individual who preferred to communicate via email. For those we met with, we recorded the meetings and took notes. After we revised the objectives and network based on the panelists' suggestions, we shared the revised results with the panelists and requested additional feedback via email. We note the results in Section 6.

6 Research Results

From the initial interviews with data analysts or the individuals associated with data analytics in healthcare, 26 general or main objectives were derived. Among these 26 objectives, nine were identified as fundamental objectives and 17 as means objectives. In validating the results, the panel of experts indicated that all the existing objectives and relationships were relevant and provided suggestions for additional means objectives (resulting in four additional general or main objectives being added). The additional main objectives included "maximize data availability and customization", "minimize workload/burden", "maximize viable programs/policies", and "maximize informing guidelines".

Examples of expert comments that resulted in the means objective "maximize clinical data available to provider (internal and external)" include "a patient sees somebody else…have no idea…prescribing them something that's going to create problems…patient record and interaction with all of their providers…trying to make that available". Another example includes "the data should be really tailored to what's needed at the point of care", which was converted to the objective "maximize customization of data to meet provider's needs". These objectives were categorized under the main objective "maximize data availability and customization".

Other examples of expert comments include:

> *Relieving the administrative burden on the providers…often complain that they can't find the stuff they need…now I got 50 pages of stuff to look through, I just need to know this, this, and this – that's all I need. Why can't I surface that and get what I need right away.*
>
> *Regulatory reporting…reducing the provider burden…only get data within your healthcare system…patient can go elsewhere… so if there is way to receive data outside their healthcare system.*

These comments were included in the means objectives "minimize workload/burden of analyzing data on provider" and "minimize workload/burden of regulatory reporting on provider", respectively. These objectives are categorized under the main objective "minimize workload/burden".

The experts suggested some modifications to the existing objectives. For example, the experts suggested replacing "growth" with "viability" for the fundamental objective "maximize organization's growth". As another example, they suggested rewording "maximize non-data resource utilization" to "maximize efficiency and effectiveness of healthcare resource utilization". We adopted the recommendations from the experts accordingly. The final main and component objectives are listed in Tables 3 (fundamental) and 4 (means) and the means-end objective network is presented in Figure 2. Similar to other studies (e.g., Keeney, 1999), we include only the object for each objective in Figure 2 for tidiness purposes. The fundamental objectives are listed on the right with the overall objective being maximizing the value of big data analytics in healthcare.

The means objectives are shown on the left and represent the various categories that healthcare institutions can pursue to achieve the fundamental objective desired either directly or indirectly through other means objectives.

Table 3. Fundamental Objectives Related to Big Data Analytics in Healthcare

Maximize organization's reputation • Maximize brand reputation • Maximize reputation as well-regarded	**Maximize data utilization and derived benefits** • Maximize use of data in healthcare • Maximize benefits big data can provide in healthcare • Maximize return on investment in data analytics through continued use
Maximize organization's strategic success • Maximize success of long-term strategy • Maximize accomplishment of strategic objectives • Maximize ability to compete	**Maximize financial outcomes and stability** • Maximize financial outcomes (short-term) • Maximize long-term financial stability
Maximize organization's viability • Maximize viability of organization • Maximize capital investments for future to expand and stay current	**Maximize organization's healthcare services success** • Maximize healthcare improvements • Maximize performance of organization through optimized healthcare • Maximize ability to continuously provide patient services
Maximize individual patient health and well-being • Maximize patient health • Maximize ability to lead a healthy lifestyle • Maximize quality of life and well-being	**Maximize community health and well-being** • Maximize health of community • Maximize population quality of life
Maximize efficiency and effectiveness of healthcare resource utilization • Maximize effectiveness of resources and time • Maximize facility/providers (with established relationships) being available to patients • Maximize use of caregivers' time and address shortage of number of caregivers	

Table 4. Means Objectives Related to Big Data Analytics in Healthcare

Maximize security and privacy • Maximize data security • Maximize privacy protection • Minimize adverse effects of sensitive data • Minimize harm to individuals	**Maximize data availability and customization** • Maximize clinical data available to provider (internal and external) • Maximize non-clinical data available (e.g., socioeconomic aspects including ability to afford medications) • Maximize customization of data to meet provider's needs
Minimize workload/burden • Minimize workload/burden of analyzing data on provider • Minimize workload/burden of regulatory reporting on provider	**Maximize optimal use of data** • Maximize optimization of data usage at point of care • Maximize optimal data use
Maximize confidence/trust in data • Maximize trust in data • Minimize time convincing accuracy/reliability of data • Maximize confidence of stakeholders	**Maximize viable programs/policies** • Maximize viable programs/policies available for specific healthcare needs and costs • Maximize viable programs/policies available to address gaps in care • Maximize access to healthcare

Table 4. Means Objectives Related to Big Data Analytics in Healthcare

Maximize patient health and personal needs • Maximize patient's management of care/condition • Maximize identification and understanding of patient needs and resources • Minimize risk of failure points • Minimize financial resources spent (patient's financial resources)	**Maximize quality of care** • Maximize quality of patient care • Maximize effectiveness of patient treatments and outcomes • Maximize patient safety (e.g., infection prevention practices)
Maximize sharing, access, and leveraging data • Maximize sharing of data • Maximize data accessibility • Maximize leveraging power of big data	**Maximize organization's productivity** • Maximize organizational performance (more efficient) • Maximize productivity • Maximize initiative (e.g., physicians driving change/championing process improvements) • Maximize collaboration (e.g., facilitate greater collaboration between clinical and financial professionals)
Maximize efficiency and effectiveness of data analysis • Minimize data overload/data paralysis • Maximize ability to interpret the data • Maximize efficiency and effectiveness of analysis • Maximize insights of data (e.g., identify trends, opportunities for improvement)	**Minimize challenges associated with data & data analysis** • Maximize ease of use/simplicity • Minimize natural challenges of big data (e.g., pace of data, volume) • Maximize data governance (e.g., maintenance, integrity, accuracy, standardization) • Maximize relevancy of data (e.g., right level of data) • Maximize data consistency (e.g., querying data in same way) • Minimize misinterpretations of data • Minimize risks associated with data & data analysis • Minimize user biases
Maximize agility and risk & cost management • Maximize ability to adapt to changes in healthcare • Maximize ability to manage risk • Maximize driving change to understand, manage, and minimize costs • Maximize efficiency in patient care leading to cost savings	**Maximize operational and strategic objectives** • Maximize improvements in operational performance • Maximize impactful action plans • Maximize driving strategies • Maximize partnerships (e.g., community, universities)
Maximize internal satisfaction and retention • Maximize retention of medical professional • Maximize employee satisfaction • Maximize engagement of employees	**Maximize communication and understanding of data analysis** • Maximize understanding of data to make it valuable to user • Maximize communication of results (e.g., non-data analysts)
Maximize quality of decisions • Maximize decision-making effectiveness • Maximize ability to make objective decisions based on data • Maximize accuracy in decision making • Maximize adoption of decisions	**Maximize organization's financial health and growth** • Maximize short-term financial well-being • Maximize long-term financial health • Minimize outmigration • Maximize organizational continuity • Maximize institutional growth
Maximize perceptions and patient experience • Maximize patient engagement • Maximize patient loyalty • Maximize patient satisfaction • Maximize patient perception of quality • Maximize external perceptions of organization (e.g., distinguishable)	**Maximize informing guidelines** • Maximize informing evidence-based guidelines • Maximize informing clinical practice guidelines

Table 4. Means Objectives Related to Big Data Analytics in Healthcare

Maximize innovations • Maximize innovative service offerings • Maximize innovations to improve patient care • Maximize innovation of payment models • Maximize innovation focused on health of the population

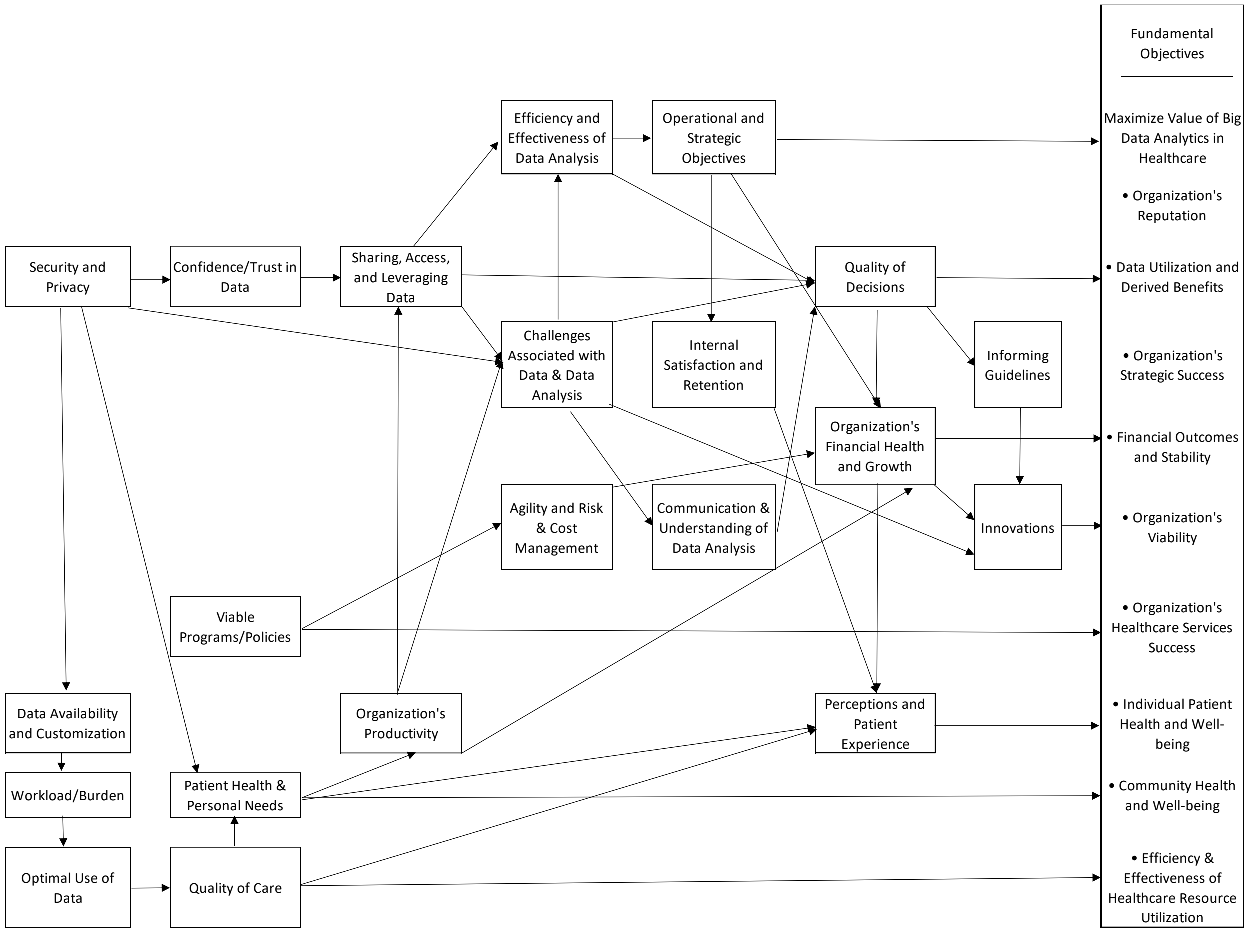

Figure 2. Means-ends Objectives Network

7 Discussion

7.1 Fundamental Objectives

In healthcare, the overarching goal is to maximize the value of big data analytics. In this context, we identified nine fundamental objectives:

1) "Maximize organization's reputation"
2) "Maximize data utilization and derived benefits"
3) "Maximize organization's strategic success"
4) "Maximize financial outcomes and stability"
5) "Maximize organization's viability"
6) "Maximize organization's healthcare services success"
7) "Maximize individual patient health and well-being"
8) "Maximize community health and well-being", and
9) "Maximize efficiency and effectiveness of healthcare resource utilization".

These objectives represent “the essential reasons for interest in the situation” (Keeney, 1992, p. 34).

7.1.1 Maximize Organization’s Reputation

In healthcare, reputation is an important success factor. Participants noted that brand reputation is key and the necessity for healthcare organizations to be highly regarded. One participant noted the need for “well-regarded and nationally recognized” institutions that establish themselves as “regionally or nationally recognized healthcare institution[s]” and generate “a positive brand reputation”. Another participant noted the importance of having patients “like [institution name] brand as much as possible.”

Healthcare institutions have emphasized the need to manage their names as though they constituted a brand (Argenti & Druckenmiller, 2004). An organization’s reputation can be a key determinant in maintaining its competitive edge and achieving its goals. In environments in which patients have provider choices, a healthcare institution’s brand can be a valuable asset. Brands establish expectations in patients’ minds about what the healthcare institution can provide. The ability to meet those expectations can then benefit the institution’s reputation.

7.1.2 Maximize Data Utilization and Derived Benefits

To benefit from data analytics, healthcare organizations need to maximize the extent to which they use data analytics. Participants noted data as essential. Therefore, healthcare organizations need to continuously use data analytics to maximize the return on their investment. For instance, one participant stated: “I’ve seen many organizations dump lots of money into analytics only to have the program abandoned after about three months and they’ve spent thousands and thousands of dollars”.

Big data analytics enables evidence-based decision making (Wang et al., 2018). One can use various analytical techniques, such as data mining and predictive analytics, to analyze unstructured data (e.g., medical images) and documents (e.g., medical professional’s notes). Benefits from these tools include improvements in patient care and financial performance. Previous research has identified potential benefits such as IT infrastructure (e.g., decreasing redundancy in systems and IT costs), operations (e.g., improvements in the precision of patient treatment), as well as organizational and managerial (e.g., rapid identification of interoperability issues or changes in healthcare trends) (Wang et al., 2018). Hence, big data analytics can provide benefits in both organizational and clinical operations.

7.1.3 Maximize Organization’s Strategic Success

Healthcare institutions need to achieve their strategic objectives. Participants noted a need to not only be able to achieve success in long-term strategies but also the ability to position themselves to be competitive. One participant noted: “the ultimate goal….is to drive organizational strategy”. The participant additionally stated: “We can use data to…point us in the right direction…it will help drive your strategy.”

Previous studies have identified the strategic benefits that healthcare institutions can garner from using big data analytics (Wang et al., 2018). With big data analytics, healthcare institutions can gain a more insightful perspective on future healthcare service needs. For example, an organization can use big data analytics to discover a new market trend to help drive its strategy (Tschakert et al., 2016). By leveraging big data analytics, institutions can make more informed decisions resulting in more effective decision making (e.g., decisions pertaining to growth strategies). Thus, the use of big data analytics can help institutions better compete through their healthcare service offerings.

7.1.4 Maximize Financial Outcomes and Stability

Successful financial outcomes and stability are essential to healthcare institutions. Successful financial outcomes can include better operating margins and reduced costs. A participant noted the importance of “financial positives…better operational margins”. Another participant noted “better financial outcomes and…financial health of the organization”.

Healthcare institutions’ operating margins are one aspect of concern when assessing their financial health. In 2019, hospitals experienced a 21 and 15 percent decline in their operating margins and earnings before interest, taxes, depreciation, and amortization (EBITDA), respectively (Daly, 2020). Drivers of these results included higher than anticipated costs and lower patient revenues. Big data analytics is one potential solution to help healthcare institutions control costs by identifying issues such as fraud and errors (Malik et al., 2018; Srinivasan & Abrunasalam, 2013). When analyzing various patient treatment options, institutions can analyze data to determine the best and the most cost-effective course of treatment (Raghupathi & Raghupathi, 2014).

Not only are immediate financial outcomes important but the ability to maintain financial stability in the long term. For example, participants noted:

> *Develop long-term approach…to [ensure the] financial success of [the] hospital….*

> *The end all be all is your bottom line. You have to…stay financially solvent to continue to…stay in this business. Healthcare is not an easy one to stay in.*

Healthcare institutions face increasing financial challenges such as rising human resource and technology costs (Abrams & Kuchenreuther, 2017). To stem declining revenues and profits, healthcare institutions will need to effectively use big data analytics (Raghupathi & Raghupathi, 2014). For instance, they can use analytics to identify patients who will have elective surgery. By identifying needed service offerings with analytics, institutions can expand revenue streams.

7.1.5 Maximize Organization's Viability

Healthcare institutions need to expand and stay current, which includes viability considerations. They must consider their capital investments that will contribute to these endeavors. One participant noted "capital investments for the future to expand and update and stay current".

Being able to assess one's potential for growth will be essential for healthcare institutions' viability. Healthcare system consolidations have increased at a rapid pace (Abrams & Kuchenreuther, 2017). Mergers and acquisitions have facilitated opportunities for healthcare institutions to extend their service offerings to new markets. To successfully do so, healthcare institutions will need to have insights into potential changes in the markets' demographics and healthcare needs. They will also need to assess their competition and healthcare professionals' availability. Hence, big data analytics will be important for gaining such insights.

7.1.6 Maximize Organization's Healthcare Services Success

Healthcare organizations desire to optimize healthcare. Thus, they focus on both continually providing healthcare services and making improvements in the services they provide. One participant who noted investments in programs (e.g., providing care for uninsured, research and development) stated "advancing healthcare overall". Another participant stated that "the more exact we can get everything down to in our system, the less errors there will be and in turn the most optimized our healthcare will be in our system".

Big data analytics provides many opportunities to improve the success of healthcare services. For instance, healthcare institutions are mining data to diagnose and develop treatment plans, manage diseases, predict cardiovascular events, assess acuity levels, and identify at-risk populations (Malik et al., 2018). They have also used text mining with pharmaceutical information to facilitate accurate administration. Patient treatment outcomes may benefit from the use of predictive modeling at the point of care. Healthcare institutions have also applied big data analytics to predict patient safety events, length of hospital stay, probability of a patient's appearance at an appointment, and healthcare service delivery time.

7.1.7 Maximize Individual Patient Health and Well-being

Healthcare institutions ultimately want to assist their patients to achieve healthy and productive lives and, thus, seek the best quality patient outcomes. One participant noted the importance of "patients…to lead safer, healthier, more productive lives". Another participant noted that, when patients can achieve the best level of independence possible and do not have to be institutionalized, it "ensures the best possible quality of life for that patient and that in and of itself is probably the most important".

Big data analytics can assist healthcare providers and patients in their decision-making processes when assessing the best treatment plan for an individual (Raghupathi & Raghupathi, 2014). By analyzing immense quantities of medical records and data, healthcare providers can better understand treatment outcomes and apply them to individual patients' care plans. Analytics can help determine if a patient is more likely to experience complications from a surgery and derive less benefit from it as well. Big data analytics can help providers make complex diagnoses and, ultimately, provide more personalized and proactive patient care (Guha & Kumar, 2018; Whelan, 2018; Wu et al., 2017).

7.1.8 Maximize Community Health and Well-being

Healthcare institutions aspire to maximize their contributions to society. They have a keen focus on community health. In the context of high-risk patient populations, a participant noted:

> *It's the typical adage of the ounce of prevention is worth a pound of cure…if you are able to head off…chronic illnesses…if you're able to catch those diseases earlier on…by doing that more predictive look you're able to kind of head-off those…also start feeling better…. So that's what it kind of is, you want to improve the health of the population…. They don't feel crummy…[and] they have a better quality of life in essence because they feel healthier and they are able to do more."*

Healthcare institutions and providers can use big data analytics for early diagnosis and preventative care. For example, they can use big data analytics to identify factors associated with disease patterns and progressions or at-risk populations (Raghupathi & Raghupathi, 2014). Analytics can help them provide actionable insights to identify needed services or to predict/circumvent crises. Detecting vulnerabilities among the population can help healthcare institutions and providers better manage the population's health such as during disease outbreaks.

7.1.9 Maximize Efficiency and Effectiveness of Healthcare Resource Utilization

Healthcare institutions desire to maximize resources other than just data. For instance, they want to maximize their employees' time as well as providers' and facilities' availability for patient care. Considering the current shortage of caregivers, this issue has become even more urgent. One participant particularly noted:

> *Makes them much more efficient in their practice…. [You] can have more focused interventions because you have a more complete picture on them [referring to the patient] then you can technically see and…. [You can] care for more people because instead of spending 45 minutes trying to figure out what's going wrong with the patient you have the full picture you can make an intervention in 15 minutes, okay now I can fit three people in whereas before I could only do one…. You are reducing some of that burden because you're using those providers to their greatest capability that they can be doing…. We have a massive shortage of caregivers.*

Researchers have applied big data analytics in various contexts such as workforce planning and patient care pathways (Malik et al., 2018). Variations can occur among healthcare institutions and providers in the delivery of services (Noon et al., 2003). Variations can occur in the care they provide to patients as well. Influential factors include specific service delivery time, the severity of the patient's condition, and the patient's current health. Other considerations include services that can vary in allowable delays of treatment (e.g., patient with a life-threatening injury versus requiring cataract surgery) and healthcare resources required to provide the service.

Challenges occur with services and utilization rates that can be random (e.g., number of patients and dates of service for a neonatal intensive care unit) (Noon et al., 2003). Healthcare institutions can analyze the relationships between the range of healthcare services they provide and the variations between them. Utilization rates can be lower for departments that have more unpredictable demand for their services, while those with more predictable demand can have higher utilization. Also, healthcare institutions can consider combining resources or having flexible resources (i.e., on-call professionals and staff reassignments).

7.1.10 Summary

Two main themes emerged from the fundamental objectives: 1) maximizing organizational success and 2) maximizing patient and community health as well as the services provided to them. Organizations desire to be successful strategically and financially. They endeavor to successfully leverage data and achieve the maximum benefits from it. They desire to have continuity in their services and growth, as well as for people to have positive perceptions of them. They aspire to be successful in their healthcare services offerings and successfully use their healthcare resources. Healthcare institutions care about enhancing the quality of health well-being of their patients and the communities they serve.

7.2 Means-ends Objectives Network

Means objectives allow one to achieve fundamental objectives or other means objectives (Dhillon & Smith, 2019). Some means directly affect fundamental objectives, while others do so indirectly through other means objectives. We identified 21 general or main means objectives in this study. From the relationships or pathways in the means-ends objective network diagram (see Figure 2), underlying principles can be derived to achieve these fundamental objectives. Because the means and fundamental objectives have their foundations in the values that were previously identified, these principles can be used to foster the desired organizational norms associated with deriving value from big data analytics for various stakeholders (i.e., patients, community, and organizations), and provide guidance to individuals in their data analytics endeavors. Healthcare institutions can consider developing policies, procedures, goals and mission statements, or general guidelines with these underlying principles.

For example, if an organization focuses on the patient stakeholder and aspires to maximize a patient's health (i.e., fundamental objective "maximize patient health") to derive the maximum value from big data analytics, one input is to lessen the workload or burden on healthcare providers associated with analyzing data and reporting (i.e., means objectives "minimize workload/burden of analyzing data on provider" and "minimize workload/burden of regulatory reporting on provider"). Minimizing these workloads/burdens can lead to optimizing the use of data at the point of care (i.e., means objective "maximize optimization of data usage at point of care"), which can help an organization provide high-quality care and services (i.e., means objective "maximize quality of patient care") and achieve the best possible results in patient's treatments (i.e., means objective "maximize effectiveness of patient treatments and outcomes").

As another example, if an organization desires to maximize its healthcare services success (i.e., fundamental objective "maximize performance of organization through optimized healthcare") to derive the maximum value from big data analytics, one input would be to address challenges associated with data and data analysis such as addressing inherent velocity and volume issues, as well as risks associated with data analysis and interpretations [i.e., means objectives "minimize natural challenges of big data (e.g., pace of data, volume)" and "minimize risks associated with data & data analysis"] and design effective data governance policies and procedures (i.e., means objective "maximize data governance (e.g., maintenance, integrity, accuracy, standardization)"). Minimizing these challenges and risks associated with the data as well as maximizing data governance can lead to maximizing innovations that can be offered to enhance patient care (i.e., means objective "maximize innovations to improve patient care") and provide cutting-edge services (i.e., means objective "maximize innovative service offerings"). Another input to maximizing organization's healthcare services success could be maximizing sharing and access to data (i.e., means objective "maximize sharing of data" and "maximize data accessibility"). Maximizing sharing of and accessibility to data can support decision quality enhancements such as maximizing accurate and effective decisions (i.e., "maximize accuracy in decision making" and "maximize decision-making effectiveness").

From a community stakeholder perspective, organizations may aspire to maximize opportunities to improve an entire community's health (i.e., fundamental objective "maximize health of community") to derive the maximum value from big data analytics. To do so, they can consider the programs and policies they have established that address specific healthcare needs or socioeconomic statuses as well as enhance healthcare's accessibility (i.e., means objective "maximize viable programs/policies available for specific healthcare needs and costs" and "maximize access to healthcare"). Maximizing programs/policies and access to healthcare can lead to organizational efforts to foster changes that reduce costs and enhance adaptability to changes in healthcare (i.e., means objectives "maximize driving change to understand, manage, and minimize costs" and "maximize ability to adapt to changes in healthcare"). A focus on becoming financially stable and continuously developing can further drive such efforts (i.e., means objectives "maximize long-term financial health" and "maximize institutional growth"). Maximizing long-term financial health and growth can help support organizational innovativeness in the areas that benefit population health and the services being available (i.e., means objectives "maximize innovation focused on health of the population" and "maximize innovative service offerings").

If one views a healthcare organization as a stakeholder and the organization desires to maximize its viability (i.e., fundamental objective "maximize viability of organization") to derive the maximum value from big data analytics, one input could be a focus on employee satisfaction and retention (i.e., means objectives "maximize employee satisfaction" and "maximize retention of medical professional"). Maximizing employee satisfaction and medical professional retention can lead to maximizing external perceptions and patient experience, such as satisfaction and loyalty (i.e., means objectives "maximize external perceptions of organization (e.g., distinguishable)", "maximize patient satisfaction", and "maximize patient loyalty").

8 Implications, Future Research Directions, and Limitations

Big data analytics has the potential to contribute substantially to patient treatment, community health and well-being, and institutional success. To do so, healthcare organizations need to consider the relevant actionable objectives and foster appropriate norms that will guide actions, behaviors, and decision making. Therefore, healthcare organizations need to ensure that these norms properly align with values associated with big data analytics in healthcare. In this study, we use value-focused thinking to identify these values by interviewing individuals associated with data analytics in healthcare and validating the findings with a panel of experts. The values were transformed into actionable objectives that can contribute to this endeavor. Healthcare institutions can use these objectives and the relationships among them as principles and guidance as they consider the organizational norms that they want to foster. These can be taken into consideration when developing and adopting mechanisms such as social relationships, institutional policies and procedures, as well as goals and mission statements.

For example, organizations will want to invest resources in reducing risks associated with security and privacy, which can reduce harm to individuals and foster users' trust and confidence in the data. Healthcare systems have advanced in leveraging technology to provide greater access to data while also generating issues and concerns regarding privacy and security (Esposito et al., 2017). Protection of private information is an important concern for many. Healthcare institutions can take a proactive stance on privacy and security issues by considering the appropriate procedures and policies needed for the entire lifecycle of health information.

Also, as one expert panel participant noted, fostering greater confidence and trust in the data can occur through continued use of the data. More specifically, referring to the means objectives "maximize confidence/trust in data" and "maximize sharing, access, and leveraging data", the participant noted: "I think on a lot of days you can think about it being bi-directional. The more you use it, the more trusted…it can also improve the trust". Hence, healthcare institutions' efforts to continually improve users' confidence and trust in the data can promote greater data usage which, consequently, promotes additional trust in the data they use.

Healthcare institutions should ensure their data is accessible and easily shared. Issues such as diversity in data syntax and semantics can constrain data sharing (Wimmer et al., 2016). Apprehensions regarding violations of privacy can present a barrier to data sharing as well. Therefore, healthcare institutions may consider multi-agent systems with privacy adherence capabilities that address both data heterogeneity and privacy issues.

Also, data integration can enhance the accuracy of predictive models used by healthcare professionals in their diagnostic processes (Wimmer et al., 2016). When considering the data to be shared, two different categories of data flows exist: primary and secondary (Esposito et al., 2017). Primary data flows refer to health information that healthcare professionals and patients share to assist with patient treatment. Secondary data flows refer to health information that individuals who are not directly related to patient treatment access (e.g., administrators and researchers). Healthcare institutions can take both data flows into consideration to develop effective data governance and maintenance programs.

Our findings suggest that healthcare institutions should provide adequate training such that users can understand, interpret, and develop an awareness of potential biases. Engaging employees in fully using big data analytics will be important such that employees are initiating its utilization so the data is fully leveraged. With big data analytics, one can analyze vast amounts of data to identify associations and patterns (Wang et al., 2018). Such analyses can prove beneficial in supporting evidence-based medicine, addressing hospital readmissions, customizing patient treatment plans, and detecting diseases. Therefore, healthcare institutions need to have employees with not only the requisite competencies but also the ability to communicate and collaborate with others from diverse backgrounds (e.g., medical professionals with data scientists). Healthcare institutions that lack effective communication and collaboration may face challenges in framing key questions and comprehending outcomes. Also, fostering employees' satisfaction and retention can, in turn, influence patients' perceptions of one's institution. Hence, healthcare institutions will want to constantly monitor employee and patient satisfaction, as well as turnover rates.

As healthcare institutions focus on patient health as well as community health and well-being, they need to ensure equitable access to quality healthcare services. To do so, they can use big data analytics to identify gaps in care, quality of care, and safety measures such that appropriate programs and policies are established. Big data analytics can help healthcare institutions monitor the effectiveness of treatments and their outcomes, patients' health management and engagement, and reductions in patients' risks and financial costs. For instance, healthcare data has expanded to semi-structured (e.g., wireless devices) and unstructured (e.g., transcription notes) data, and big data analytics tools are providing the capability to analyze these data sets (Wang et al., 2018). In this regard, one healthcare institution used natural language processing to identify efficiency and cost-reduction opportunities in treatment services and diagnostic tests.

Implementing control measures and maintenance procedures will be pivotal to ensure that healthcare institutions overcome data-related challenges, such as inaccurate and irrelevant data, to maximize data integrity. For decision making to be effective and the implementation of decisions successful, decisions will need to be accurate and of the highest quality. Therefore, healthcare institutions may consider reward systems for employees who successfully achieve data and decision quality objectives. Considering healthcare institutions are concerned about maximizing the innovations that they offer to patients and improving the quality of care, they can consider incentive structures to promote innovation or possibly implement gamification systems to foster innovative efforts.

Researchers have proposed gamification as applicable to various work contexts, such as implementation, training, acceptance, and continued enterprise system usage (Nah et al., 2019). For instance, if enterprise system implementation or usage issues arise, one can use gamification principles, such as social connectivity, to create teams to develop innovative solutions. Also, one can leverage the principle of competition and have teams compete to develop the most innovative solution. Healthcare organizations could also apply these principles. For example, they could create teams of healthcare professionals and administrative personnel who develop innovative service offerings for patients or solutions to improve the quality of care.

One expert in our validation panel noted the need for feedback mechanisms and adequate time provided for the change to be palpable. The participant noted:

> *Introduce a change and it takes a while for that change to take affect and sometimes conditions continue to worsening and after you intervene and then people want to try something else…. Take into account the sequence in which things occur, the expected lags, and have built-in feedback loops…. This is a time where you want to wait a little bit for this affect to take place...could lead people to think that they were on the wrong path and sort of derail them.*

Hence, healthcare organizations need to persevere in implementing these actionable objectives and obtaining feedback. Organizations may consider system archetypes that may impact their endeavors (Sales & Barbalho, 2020). Previous research has identified issues such as short-term vision being an impediment to realizing value from one's programs.

Organizations will want to consider measuring their progress towards achieving these actionable objectives and leverage this progress to widen their market reach. As one participant stated:

> *How are those attributes going to be measured, how well will that measurement be able to be, from an organization's point of view, be able to be translated into terms that consumers might use to say hey this organization really has it together and is doing a better job of keeping my costs down and improving my health so that they could use it to have patients sort of vote with their feet and…getting a larger market share.*

Hence, healthcare organizations' accomplishments of these actionable objectives can be used in their promotions and potentially contribute to the success of their future endeavors.

From a research perspective, we used the value-focused thinking (VFT) approach in this study. Previous research has successfully utilized this approach in other contexts (e.g., Keeney, 1999; Dhillon & Torkzadeh, 2006), and we extend its application to the context of big data analytics in healthcare. Also, we took a comprehensive approach to identify value that can be derived from big data analytics. Future studies can focus on more specific areas, such as administrative or patient treatment.

The actionable objectives identified in this study provide a myriad of future research directions. For instance, maximizing confidence and trust in the data was identified as an actionable objective that future research could examine. For instance, researchers could conduct Delphi studies to identify why distrust currently exists and what elements contribute to distrust. Participants also noted the need to minimize issues such as user bias. Accordingly, future research could identify methods to reduce bias. As another example, participants noted sharing data as being important. Future research could conduct experiments or surveys to identify important variables that contribute to the propensity to share or not share data. In addition, participants emphasized the need to reduce the workload and burden on healthcare providers. Future research may use action research or case studies to identify opportunities to reduce these burdens.

Future research may consider exploratory studies regarding the actionable objectives “maximize leveraging power of big data” and “maximize collaboration (e.g., facilitate greater collaboration between clinical and financial professionals)”. For instance, previous research has studied systems of representation in the context of systems implementation in healthcare (Ross et al., 2012). Future studies may consider extending this focus to participation in big data analytics projects and initiatives.

Future research could also explore the relationships between the means objectives or between the means and fundamental objectives, as well as the principles that were derived. For example, future studies could examine interventions that improve or increase employees’ satisfaction and the resultant effect on patients’ perceptions of the healthcare institution and their loyalty. The actionable objectives “maximize ease of use/simplicity” and “minimize data overload/data paralysis” were also derived from participants’ comments. Future research can use interventions to simplify the use of big data, as well as the associated analytics, and evaluate the resulting impact on reducing issues such as data overload, especially among non-data analysts.

As with any study, there are some limitations. A potential limitation of this research is its application to other domains. Although issues such as security and privacy impact many industries and domains, issues such as patient safety and satisfaction, quality of care, and community health and well-being pertain uniquely to the healthcare industry. Hence, the generalizability of our findings will need to be explored. Also, the actionable objectives were derived from the knowledge and perspective of individuals associated with data analytics in healthcare. Future research could identify actionable objectives from the knowledge and perspective of others such as payers and healthcare professionals.

9 Conclusion

Big data analytics has had a notable impact on many industries and created substantial opportunities (Lehto et al., 2012). In the healthcare industry, data analytics has significant potential to, for example, improve healthcare services, reduce operating costs, better diagnose and treat diseases, and enhance individuals’ and communities’ lives and well-being. Using a value-focused thinking approach, the actionable objectives that healthcare organizations need to consider to derive value from big data analytics in healthcare were identified. Our findings provide guidance and principles for practitioners to strategically manage and, ultimately, realize the maximum value from their big data analytics endeavors. More specifically, the actionable objectives that healthcare organizations need to consider to achieve the desired ends or value from big data analytics were identified and can be fostered as organizational norms. Our findings present new avenues for future research, such as studying mechanisms that will instill user trust and confidence in data. Overall, big data analytics has the potential to make a substantial contribution to healthcare, which makes it vitally important to identify the actionable objectives needed to achieve this goal.

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