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The Impact of Emerging Data Sources and Social Media on Decision Making: A Culturally Responsive Framework

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Abstract

Emerging data sources are gaining popularity because of their accessibility, pervasiveness, and enormous potential. Blogs, images, Twitter, Foursquare (location sharing), and Flickr (photography) are significant sources of information regarding human activities. There are several elements that influence decision making behavior at the individual, group, and organizational levels, including information technology and decision support systems. Recent advancements in user interfaces for social tools, in conjunction with an increase in the usage of mobile wireless computers, have resulted in the creation of social networks that are instantaneous, widely distributed, mostly unmanaged, and pervasive. The proliferation of information and communication technologies continues to open new doors. In the age of big data and new data sources, the challenge for modern businesses is to align their decision making and organizational processes with data that could help them make more informed decisions. The study also proposed a culturally responsive framework that entails emotioncy and cultuling analysis to support institutions in the process of decision making when using emerging data sources.

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1. Introduction

The growth of generating digital data is becoming widespread. Many governments and international organizations have started to control huge capacities of this data from uncountable business transactions and many other communication procedures. These data sources come from emerging data sources like the Internet and communication technologies (OECD, 2015). The widespread use of data has generated more emerging sources, meaning richer and more compound forms are available than ever before. So, this trend brings new opportunities to the commercial world and leads organizations in a successful direction (UK. Statistics, 2015). Emerging data sources are important because the need for accessing statistical information is ever-growing. Therefore, the emerging data is available online and is not expensive to collect (Struijs et al., 2014).

Work-group relationships evolve because of daily email exchanges, according to Zummo (2018), which in turn makes new communication styles conceivable and acceptable even in uneven professional exchanges. Using a self-compiled corpus of selected computer-mediated business emails written by five participants over the course of three months, the study focused on the (spoken) discourse aspects of email messages. Using English as a “Lingua Franca” (BELF) and computer-mediated communication, this “written dialogue” exchange mimics the characteristics of spoken discourse. It also involves non-native speakers of English (in particular, BELF). Researchers found that even though emails are the oldest computer-mediated technology, they are still a “not yet conventionalized” way of communicating affected by the push email system and offer a new (dynamic) way to talk.

In recent decades, most governments worldwide have been paying attention to the evolution of emerging data, especially in providing economic and social statistics, because these statistics provide a good understanding of society (Struijs et al., 2014). Large-scale data collection and analysis are becoming more difficult because of the proliferation of Big Data. In order to take full advantage of the opportunities presented by Big Data, however, a number of issues must first be resolved. This encourages greater cooperation between the National Statistical Institutes and big data owners, corporations, and institutions. This could lead to a shift in the role of statistical institutes in providing society with high-quality and objective statistical information. It was Struijs et al. (2014) who discussed how to interact in a changing situation. Collaboration with other parties requires each to draw on their unique skills in the process. The traditional strengths of national statistical agencies include their ability to collect and combine data sources with statistical outputs and their focus on quality, transparency, and good methodology. They have a unique understanding of official statistical production processes in the Big Data era of competing and expanding data sources. This unique position as a third party is due to their neutrality and respect for privacy as codified in law. Then they can make recommendations about the reliability and trustworthiness of various information sources. So, they will be able to play an important role as sources of information in a society that changes quickly.

Incorporating emerging sources into statistical processes may be more beneficial for making better national decisions than using traditional databases (UK.Statistics, 2015). One of the statisticians' primary goals is to integrate emerging data sources to enhance the quality of the population's statistics. So, statisticians are moving to the next stage of the data revolution, where this data is becoming available all the time (Raghunathan, 2015). To be more specific, scanning devices, sensors, mobile phones, satellites, social media, and other emerging data sources play an important role and have a direct impact on the output of statistics (UN.Statistic, 2016). However, having effective statistics needs strong tools to manage these emerging resources, as mentioned (UN. Statistics, 2016).

Individuals, groups, and entire organizations all continue to have new chances to change how they make decisions because of advancements in information technology. The emergence of social media and technologies based on Web 3.0 are two changes that are tied to one another (Power et al., 2011). The third generation of internet services for websites and applications is known as Web 3.0. The primary goal of Web 3.0 is to deliver a data-driven and semantic web by utilizing a machine's ability to analyze data. Web 3.0 is the third generation of internet services. The end goal of Web 3.0 is to develop websites that are smarter, better-linked, and more accessible to users. Because Web 3.0 has not yet been fully implemented, there is no clear definition for it at this time. It took more than ten years to migrate from the first version of the web, known as Web 1.0, to Web 2.0, and it is anticipated that it will take at least as long, if not longer, to fully deploy and restructure the web using Web 3.0 (Yen et al., 2015). On the other hand, the technological advancements that some experts feel will ultimately constitute and characterize Web 3.0 are currently in the process of being developed. Two instances that demonstrate how Web 3.0 is already having an impact on technology are the use of wireless networks by smart home appliances and the Internet of Things (IoT).

These technologies have the potential to have both a positive and a negative impact on the rationality and efficiency of decision-making. For instance, adjustments that assist marketing managers in altering the decision-making behavior of consumers may result in customers making decisions that are of poorer quality. Additionally, managers that make judgments by largely relying on social networks rather than expert opinion or facts run the risk of making decisions that are skewed. Several hypotheses can shed light on the ways in which social media may influence decision-making and the outcomes of those decisions (Power et al., 2011).

The evolution of social media can be attributed to advances in technology. These more recent technologies enable users to quickly disseminate content that they have created themselves. It is simple for people to integrate stuff, edit it, and archive it. Thoughts and opinions that are put out into the world are not reviewed, censored, or checked for quality in any way. The emerging data sources inherently transmit emotions (Schreiner et al., 2021), language (Barrot, 2021), and culture (Marbun et al., 2020), which have a great potential to influence the decision making process. Even though several theoretical frameworks have been introduced to analyze emerging data sources for achieving more informed organizational decisions, little research has been conducted about proposing a culturally responsive framework. Therefore, this study aims to discuss social media effects and emerging data sources and classify them according to their importance and usage. It also wants to talk about how they are used in decision-making and suggest a framework that takes culture into account.

2. The Classification of Emerging Data Sources

Digital data has been actively utilized by populations originating from a variety of places across the globe (Alisjahbana, 2012). In March 2014, the UN Statistical Commission established a worldwide working group mandated to provide strategic vision, direction, and coordination of a global project on Big Data for official statistics, signaling the community's formal recognition of Big Data's potential. The goal of the GWG is to solve the problems caused by Big Data by using it in real life, building up people's skills, and sharing their own experiences (The UN Statistical Commission, 2004).

According to what is highlighted in the document titled “Information Economy Strategy”, data is produced in order to get data value for the economy (Garifovam, 2015). Collecting official statistics through emerging data sources can assist statisticians and analysts in making more informed decisions based on the facts (UN.Statistic, 2016). They can utilize them on their own or in conjunction with other more conventional methods, such as conducting sample surveys (Alisjahbana, 1966). Figure 1 illustrates the four main categories of digital data sources: social media, transaction/business data, administrative/ government data, and mobile data. Even though technological progress has led to a wide range of digital data sources, this is still the case.

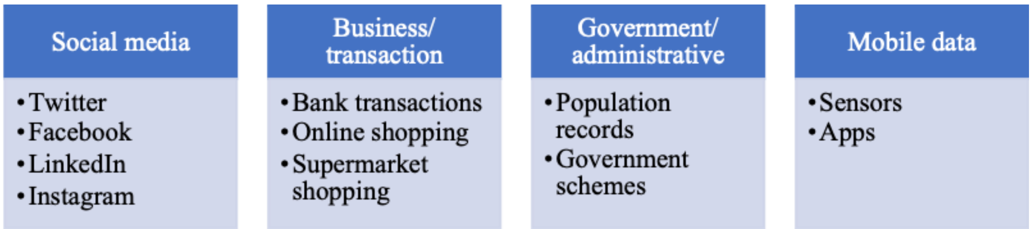

Figure 1
Emerging Data Sources

2.1. Social Media

The idea behind social media, also known as social networks, is that individuals can share their goals with other people in a variety of settings (Couper, 2013). The widespread adoption of social media platforms has made it possible for citizens and government agencies to communicate with one another in a way that is both more productive and, ultimately, more satisfying (Knowles, 2016). For example, many researchers in Indonesia used social media such as Twitter and blogs two years ago to analyze the price and quantity of food to understand capacity, affection, mood, and geographic basis. So then, they can make assumptions and compare the results to official government statistics (Alisjahbana, 1966). Furthermore, Facebook data has been used in Indonesia to develop strong estimates for its official statistics, especially regarding the inflation of food prices (Landefeld, 2014). According to Chunara et al. (2012), using social media such as Heath Map and Twitter, which are available online in real-time, provides a good correlation between the trend in data volume over the time used by social media and the trend in volume used by official reported cases (Chunara et al., 2012). On the other hand, the biggest problem with the rise of social media is that it may give information about a population's preferences, feelings, or ideas, but it may not take into account the behaviors that go along with those views (Couper, 2013).

Hilte et al. (2018) examined the non-standard writing patterns of Flemish adolescents in a large social media corpus (2.9 million tokens) in search of connections with the social class of the adolescents. The students' educational track, parental profession, and home language were all included in their study. For this reason, they combined these two variables into a single social class designation. The varied language practices that emerged from the analyses showed that social class significantly impacts adolescent online writing. They also showed that working-class kids had a significant link to the online writing culture, or “new vernacular”, which contradicts traditional findings on working-class adherence to the “old vernacular”. And finally, they showed how complicated this variable is by showing how social class interacts with gender and age, as well as by studying groups of teenagers whose social backgrounds were unclear and, as a result, hard to measure.

2.2. Business/Transaction Data

Credit cards, loyalty cards, phone records, and browsing behavior are some examples of transaction data (Couper, 2013). Since the increase in services paid and the owners' official identifiers connected to their paying processes, transaction data plays a vital role in providing detailed information for effective statistics. This data has been available for a long time (Nordbotten, 2010). Long-term trend indicators for credit and cash use can benefit from transaction data. Without developing these indicators, measuring short-term (monthly and quarterly) processes will be difficult. According to Landefeld (2014), transaction data is the most important data source that helps improve the efficacy of official statistics (Landefeld, 2014). Transaction data, on the other hand, just reveal what people do—that is, people's behaviors—but not the reasons why they are doing such an activity or what they are capable of doing in the future. This makes this type of data frequently inaccurate (Couper, 2013).

2.3. Government/Administrative Data

Administrative data is delivered by individuals or organizations for different government activities (Couper, 2013). It is gathered mainly for non-statistical objectives and is assumed for use in producing statistics. Nordbotten (2010) reported in his study some examples of statistics relying on administrative data: census statistics, population statistics, foreign trade statistics, income statistics, social statistics, health statistics, etc. A significant portion of official statistics output is now generated using administrative data, either directly or indirectly. These datasets necessitated the creation of new methods for the transmission and editing of data, as well as for the estimation and quality evaluation of statistical products for their effective usage. Credit card use, electronic tickets, traffic surveillance, and the radio frequency identification of commodities, among other things, all generate enormous volumes of data that could serve as administrative data for official statistics in the future. According to current technology developments, large amounts of administrative data will be generated by implanted and embedded electronic chips in the near future. If private information is to be included in official statistics, it needs to be thought about, talked about, and carefully planned and put into place. Administrative data provides proper statistical overviews for better decision making. It also improves the statistical collection frames (Nordbotten, 2010) and the accuracy of these statistics (Landefeld, 2014). Moreover, administrative data provides high-quality data and a long-term survey structure (Einav & Levin, 2014).

2.4. Mobile Data

Individuals collect mobile data from mobile sensors, data extracted from the Internet, and released data from the government (Arribas-Bel, 2014). To better comprehend cities, Arribas-Bel (2014) looked at three new data sources that have recently emerged, as well as the opportunities and problems these new data sources present for regional science. Individuals' mobile sensors provide the data, while corporations' internet activities provide the data, and government data are both released in open formats. They all came into being as a side of their respective functions, but their popularity, pervasiveness, and ease of access have made them attractive alternatives for scholars to investigate. These new possible information sources were shown through projects and activities that already exist and fit into each category. Furthermore, mobile data can refer to mobile devices used for interviewing, such as smartphones, tablets, and mobile web (Couper, 2013).

The need for using mobile data is important to resolve some statistical issues such as privacy and controlling private data, community opinion regarding mobile data use, and technical problems concerning mobile data usage and access. By including mobile data with official statistical processes, many organizations can provide applicable, accurate, and timely data for their customers. There is a good summary of big data and how it is used in official statistics by Landefeld (2014). Non-statistical use of commercial and administrative government data is not a new phenomenon, despite recent developments in information technology, data sources, and procedures. Statistically speaking, it is not going to be a silver bullet for agencies struggling to meet increasing demands for better, faster, and more comprehensive data. Big data can help improve the accuracy, timeliness, and usefulness of economic statistics at a lower cost than adding more data to existing collections, as long as incentives are carefully thought out, privacy is protected by data protocols, and there are agreements to work together.

3. The Use of Emerging Data Sources for Decision Making

Every second, companies, agencies, and organizations generate a massive amount of data. They can aid in the improvement of the official airline, investment, and institute data, among other things (Khan & Al-Badi, 2020; Landefeld, 2014). Many government services, such as registering addresses, medical services, income statements, and social benefits, are now available via the Internet. These services save time by eliminating the need to enter all of the relevant data, resulting in cost and time savings for users' statistics when compared to traditional service delivery methods. The opportunity to improve services will grow (Nordbotten, 2010). Banks and insurance businesses, for example, are among the commercial entities that choose to exploit developing data sources (Nordbotten, 2010). In the private sector, the manner in which this massive amount of data is collected is changing. The general press got the information from companies like Google and Facebook that do business on the Internet.

Furthermore, economic companies tend to collect data on individuals' spending and financial transactions by using data from customers' businesses, banks, credit card companies, etc. (Einav & Levin, 2014). Transparency between the government's official statistics and the business owner will be fulfilled and can help in estimating new methods to produce high-quality data (Landefeld, 2014). Also, data availability is expanding, which leads to it being the foundation of business models (Struijs et al., 2014).

There are a variety of technologies that are utilized in traffic management. These technologies are categorized into sensors and include the following: point (Inductive loop detectors, Radar/Infrared/Microwave/Acoustic/ Ultrasonic/Sensors, Video image detection systems, Weigh-in-motion (WIM) systems), point-to-point (Automated Vehicle Identification (AVI) systems, Vehicle identification without driver “cooperation”, License plate recognition), and area-wide (Cell phones (Antoniou et al., 2011)). The newly developed technologies for data sources have advantages in terms of the availability, storage, and accessibility of data, as well as in terms of comprehending the health problems of patients (Asghar et al., 2017). The new data source may be put to use in the administration and preparation of road networks (Antoniou et al., 2011).

Traffic control and prediction are achievable with automatic vehicle recognition systems and probing vehicles (Antoniou et al., 2006). A significant volume of data is collected on health through doctors, patients, and pharmacists (Trifirò et al., 2018). Twitter, Facebook, Instagram, Doximity, and LinkedIn should be used by urologists in decision making (El-Bakri & Larré, 2017). The additional data sources are mobile sensors, internet enterprises, and government data (Arribas-Bel, 2014). Table 1 demonstrates emerging data sources in decision making.

Table 1
Emerging Data Sources and Corresponding Decision Making

Researcher	Emerging data source	Decisions
(Antoniou et al., 2011)	Automated vehicle identification data	Traffic management
(Ma & Koutsopoulos, 2008)	Plate matching system with video cameras	Prediction and estimation of travel times in urban areas
(Park et al., 1999)	Automated vehicle identification data	Prediction and estimation of travel times
(Mishalani et al., 2002)	Video cameras	Real-time traffic management
(Dixon & Rilett, 2000)	Automated vehicle identification data	Real-time traffic management
(Arribas-Bel, 2014)	Mobile sensors, online businesses, and government data	Regional and urban analysis
(Overman, 2010)	Geographical information systems (GIS)	Statistical or econometric analysis
(El-Bakri & Larré, 2017)	Twitter	Urologic oncology and biomedical research
(F. E. A. Horita et al., 2016)	Observation-aware Decision Model and Notation with social media integration	Disaster management
(F. E. Horita et al., 2017)	Model-based framework with smartphones, social media platforms, and wearable technologies	Disaster management
(Trifirò et al., 2018)	Big data	Drug safety

4. Proposed Framework and Modelling Process

The culturally responsive framework entails emerging data sources, emotioncy, and cultuling analysis (CA). Using emerging data sources for decision-making can be effectively informed through the above two constructs.

4.1. Emotioncy

The role of emotion in social media is the subject of a burgeoning body of research. For example, social media status updates most likely reflect individual emotional life. Emerging data sources demonstrate a greater degree of emotions, such as alertness by activation status. In contrast, a lower degree of emotions, including the feeling of indifference and drowsiness, is related to deactivation (Panger, 2017). Emotions could also be manifested by various body or facial expressions and physiological changes (Tracy, 2014). According to Fredrickson (2001), sense-induced emotions are related to a particular action inclination, for instance, passion for having a commodity with a longing to buy it. Individuals who love to buy a favorite item would mobilize the necessary materials and psychological capital to conduct the behavior and take decisive action.

In essence, emotion plays a pivotal role in making judgments and defining how it is demonstrated via language in terms of biases (e.g., Keltner & Lerner, 2010). Emotionality is also a predictor factor for linguistic biases manifested in an individual's speech patterns (Pishghadam & Abbasnejad, 2017). The concept of emotioncy was coined by Pishghadam et al. (2013) to accentuate the role of emotion in language education. Individuals maintain varying emotions, loaded by their senses, toward different concepts and lexicons. "Emotioncy" is a combination of human emotion and frequency (Miri & Pishghadam, 2021). It entails a process in which a person's distinctive worldview through his senses can be defined and assessed. It also incorporates emotions, senses, and sensory engagement, which may give rise to emotional responses (Pishghadam et al., 2016) and revitalize cognition (Pishghadam et al., 2013). Emotioncy has a hierarchical model that includes four main levels: Avolvement, exvolvement, involvement, and metavolvement. Avolvement, which is a null form of emotioncy, refers to a status in which the individual did not experience or has no knowledge about a particular concept. However, the individuals engage audio, visual, and kinesthetic senses to learn and share a concept at exvolvement level. At the involvement level, the individuals have directly experienced the concept. Ultimately, at the metavolvement level, individuals engage their senses and cognition to a greater degree to create something new, for instance, designing a model to arrive at a well-informed decision. Pishghadam et al. (2016) also proposed an emotioncy scale that measures both emotion and frequency simultaneously. On this scale, the emotion construct could fall into three levels, including positive, neutral, and negative. Similarly, Pishghadam, Ebrahimi, and Bigdeli (2020) argued that individuals' emtioncy profiles could influence their individual and social attitudes. Such sense-induced emotions and underlying attitudes exponentially influence individual and collective decisions, judgments, and behavioral patterns (Van der Pligt, 2015).

Introducing emotioncy as an invisible controlling force for casual decisions, Pishghadam and Abbasinejad (2017) argued that the increase in 'involved' individuals' emotioncy level results in ascribing reasons to external/situational factors, which are contextual features, such as the degree of difficulty in performing a task, yet the exvolved individuals attribute reasons to internal/dispositional factors, which are the qualities driven by one's nature, attitude, and personality. Similarly, in investigating the relationship between emotioncy and prejudice, Pishghadam and Abbasnejad (2017) argued that there is a negative reciprocal relationship between individuals' emotioncy and bias level, indicating that as emotioncy develops to the next level, the bias level drops. This means "involvement slides people toward being less judgmental and thus less biased in language, while exvolvement leads people toward using more abstract words, and therefore more biased language" (p. 293). According to Barret (2009), individuals undergo induced senses once they construe their inner state regarding their context (social media). Barret (2009) also argued that since human psychological tensions are comprehensive in nature, several sense-induced emotions could be identifiable across various languages and cultures. However, different cultures may recognize and attach meanings to different senses. By looking at how these emotions are caused by the senses, corporations could make better decisions.

4.2. Culturing Analysis

Wardhaugh (2010) perceived culture as a tool to communicate and facilitate significant interactions among community members. Moreover, cultural analysis demonstrates individuals' perceptions, paradigms of thinking, values, and lifestyles. Derakhshan (2018) stated that these attributes are conveyed through language, which is an indispensable constituent of a culture. In a similar vein, emerging data sources inherently embed a culture that influences individuals' thoughts and mindsets through language. In other words, people (re)shape their surrounding context via their language (Pishghadam, Ebrahimi, & Bigdeli, 2020).

Pishghadam (2013) combined the two constructs of culture and language to coin and develop the 'cultuling' concept, which refers to the reciprocal relationship between culture and language. This concept includes expressions and structures inherent to a language that provide evidence of a nation's cultural history. Pishghadam, Ebrahimi, and Bigdeli (2020) stated that cultuling is covert in language expressions that are employed by users in their routine interactions. As a result, the study of cultuling can reveal hidden cultural patterns and ideologies, as well as provide insights into how to modify inappropriate cultural memes and habits.

CA can be considered an analytical approach to reconstructing an inclusive understanding of cultural memes and patterns inherent in language expressions within a community. In CA, the context, social conditions, media of communication, and relationships among members of groups in society that affect the construction of cultulings play a crucial role. According to Pishghadam, Ebrahimi, and Derakhshan (2020),"the overt collective features, frequently characterizing people's behaviors and discourse, can be considered as a cultuling which can be represented through specific words" (p. 22).

Pishghadam, Ebrahimi, and Derakhshan (2020) proposed a model for CA that entails three underlying factors: emotioncy, linguistic, and cultural differences. The context in which individuals live, whether it is physical or cyberspace, influences CA. It creates cultuling differences and determines the level of emotioncy, linguistic and cultural discrepancies which could be a rich source for making informed decisions. For instance, in an affluent environment, a person demonstrates a varying level of emotioncy through expressions (avolvement, exvolvement, involvement, and metavolvement) on social media compared to one in an under-resourced context. These emotioncy differences serve as a source and even an algorithm to predict individuals' behavioral patterns. Environmental factors also create linguistic differences. People living in the southern part of a country with hot tropical conditions construct and reconstruct different lexicons in cyberspace compared to those who reside in the northern part of the country. These linguistic differences also function as a source to shape various cultuling and predict individuals' behaviors. They are the results of cultural differences. Ultimately, individuals who socially interact in an environment, either physical or virtual, replicate a set of various cultural memes demonstrated in the words they use in daily communication. These cultural differences provide in-depth information on how people act and behave. For instance, collectivist and individualistic cultural disparities can influence the decision-making process. In a collective culture, people prioritize "we" and "us" instead of "I". Such an inclination is demonstrated through their language and narratives. Their behaviors and decisions are defined by the values they share in the group. However, in an individualistic culture, people have more freedom to make personal choices and emphasize personal preferences rather than collective values (Shulruf et al., 2007). In other words, collectivists strive for advice and harmony, yet individualists demonstrate personal peculiarities such as task-orientedness, responsibility, competitiveness, and uniqueness (LeFebvre & Franke, 2013). Taken together, emotioncy, linguistic, and cultural differences as factors in CA can support more culturally-responsive organizational decisions.

5. Discussion

This emerging data has many opportunities for improved performance, calibration, transportation management applications, and data surveillance. The emerging technology data sources in healthcare consist of patient-generated health data, consumer device data, wearable health and fitness data, and data from social media (Asghar et al., 2017). The emerging data source revolution provides critical opportunities for improving the quality of official statistics, but they must be supported by appropriate methods and procedures (UK. Statistics, 2015). So in our research, we need to understand the impact of emerging data on official statistics.

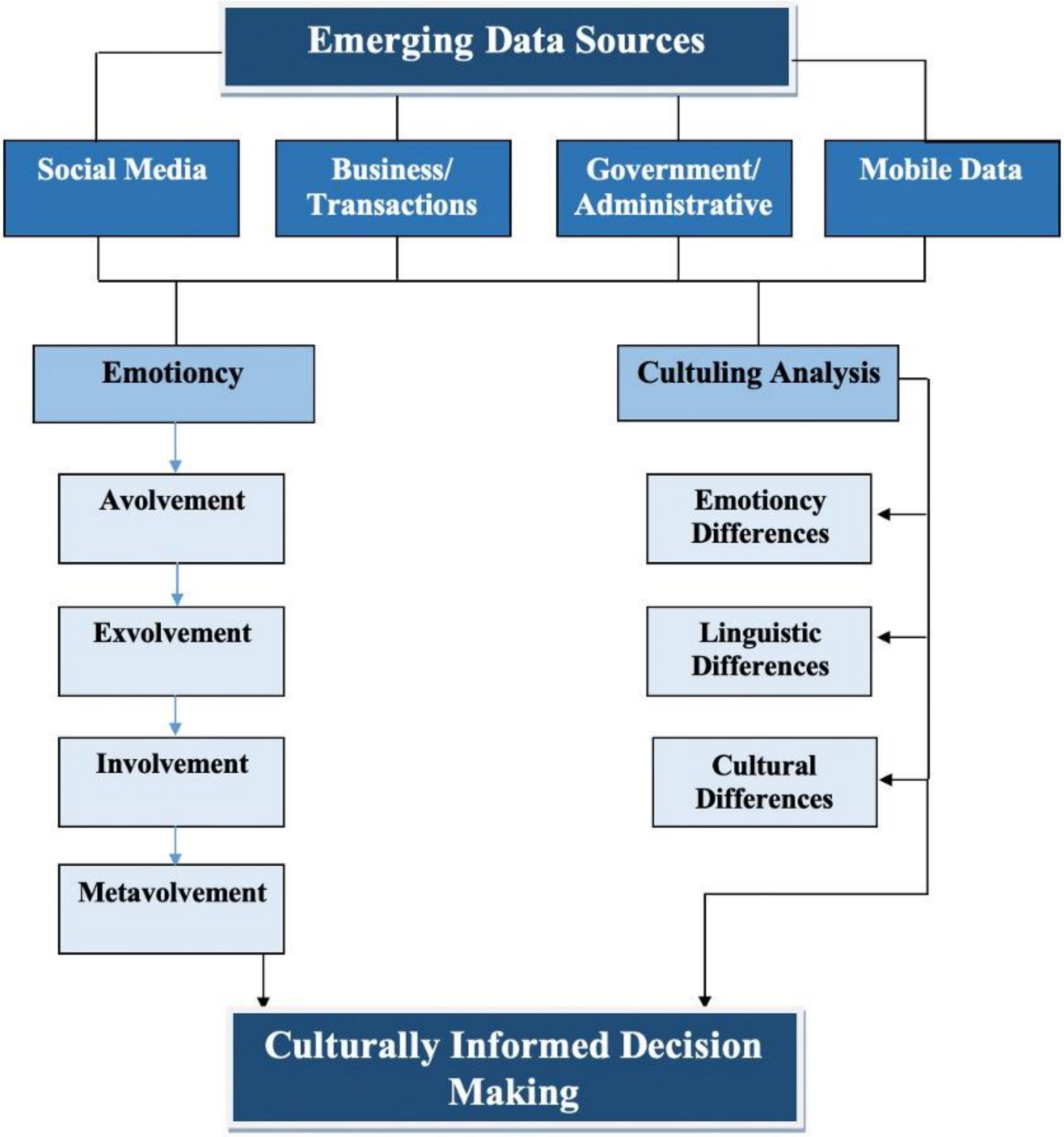

Figure 2
Emerging Data Sources Culturally Responsive Framework for Decision Making

In addition to boosting government performance and policymaking, official statistics also serve society as a whole. The expanding data sources provide academics, analysts, and public organizations with vital data to supplement official statistics. In addition, developing data provides a foundation for making smarter judgments within and beyond the government (UK.Statistics, 2015). Many organizations utilize developing data sources to satisfy societal expectations and improve the efficacy of official statistics (UN.Statistic, 2016). Emerging data assists in accelerating the production of official statistics and enhancing their consistency (The UN Statistical Commission, 2004). Emerging data sources provide accurate information on individuals and populations serviced by service centers, such as digital data to enhance health service management and public health (Institute of Medicine, 2011). Societies that rely on official statistics can benefit from the potential of emerging data sources (Alisjahbana, 1966). Businesses can also benefit from the use of digital data (emerging data sources) because it lowers the cost of storing data and makes it easy and quick to access capacity (Garifovam, 2015).

Combining emerging data from more than one source makes the information provided for official statistics more valuable (Struijs et al., 2014) since this data can be inexpensive, faster, and more comprehensive than a traditional sampling of official statistics (Alisjahbana, 1966). Also, emerging data sources are helping to illuminate the possible control over risk, but it is vital to realize that not all data sources are produced to provide equal use. Instead, they can bring important strengths as well as weaknesses to official statistics (Klinger, 2015). The idea that emerging data sources are essential to developing the statistics industry has enabled organizations to stay competitive with other emerging sources if the value of official statistics is recognized by governments (The UN Statistical Commission, 2004).

There are lots of opportunities that can be shown if we combine different emerging data sources to enhance the quality of official statistics, such as complementing the existing statistics, compensating citizens and companies for survey fatigue, reducing costs, optimizing production practices, etc. (Kitchin, 2015). Merging surveys (traditional datasets) and non-survey data (emerging data) offers unique opportunities to cover the usefulness of each data source and overcome challenges (Raghunathan, 2015). In his study, Couper (2013) stated that “big data is case rich but variable poor, whereas survey data is variable rich but case poor” (Couper, 2013). This means that although the growth of emerging data sources changes the context in which official statistics are produced and creates new opportunities, many challenges have to be mentioned. Controlling data quality, for example, can be lost; data accessibility can be inconsistent; individuals or organizations may face privacy and security challenges, and the reputation of emerging and public trust in this data can be harmed (Kitchin, 2015). If any government agency or company decides that they need to collect different data or for some business reason to stop their data collection, there will be no leverage by official statisticians to avoid the loss of such data (Landefeld, 2014).

For government agencies, there is a greater requirement to adopt new technologies in their business processes in order to improve new capabilities and translate them into valuable information (Alisjahbana, 1966). By offering effective services to citizens, government entities can gain a great deal from utilizing developing data sources. In Qatar, for example, the Ministry of Information and Communication Technology has set up a team to analyze large amounts of data from social media sources like Twitter, Facebook, blogs, and online forums so that decision-makers can get up-to-date and complete information about Internet-related issues (Chunara et al., 2012).

The significance of developing data sources has allowed government agencies to make adequate use of this data to enhance their operations and get a competitive edge over their business rivals (Jetzek et al., 2014). According to the IBM Center for Business and Government, Josh Helms (2016) provided instances of examining growing data sources in government organizations (Helms, 2016). For instance, the U.S. Social Security Administration uses emerging data to analyze and assess vast quantities of data (Helms, 2016). In addition, the Federal Housing Administration (FHA) is utilizing new data to improve its ability to forecast various rates, such as repayment and claim rates. According to Josh Helms (2016), the United States Department of Education is harnessing emerging data sources to improve and assess the teaching and learning process (Helms, 2016). Healthcare data privacy is a problem in New Zealand, Australia, the European Union, and the United States (Asghar et al., 2017). However, the data is often not utilized for its intended purpose. Emerging data sources also show users' feelings (Schreiner et al., 2021), language (Barrot, 2021), and culture (Marbun et al., 2020), all of which affect how people act.

Despite the fact that culture plays a significant influence in human development, determining whether a culture is healthy or ill is critical to influencing individuals' actions. A person must first identify the cultural memes ingrained in linguistic terms before evaluating what is acceptable or unacceptable in any given situation. A society's culturing can be seen in the linguistic features that come from memes. To uncover the cults, some language dissection strategies must be used. These tools are essential for analyzing language from a social, emotional, and sensory standpoint. It has been proposed to examine cultivations using a new, all-inclusive model developed to achieve this goal. Pishghadam, Ebrahimi, and Derakhshan (2020) proposed a conceptual model for cultuling analysis based on the premise that cultural practices should be recognized and validated. An analysis of language in these three ways is the goal of the conceptual model. Speaking and emotions can be used to identify cults, and cultural models can be used to explain the findings. With this new type of analysis, we hope to give policymakers and planners more of the information they need to make the world a better place for everyone.

The expansion of emerging data sources modifies the organizational structures for creating official statistics. Emerging data sources also generate opportunities for organizations to maximize their performance by making informed decisions. It requires a high level of collaboration among national statistics centers, individuals, businesses, and other parties. It also may change the role of statistical centers in producing high-quality statistical information for society. The study discussed the evolution of emerging data sources (social media, transaction data, administrative data, mobile data, etc.), the extent government agencies are currently using emerging data sources, opportunities and challenges associated with "Government Official Statistics", and the role of private sectors that may change the context of the information provided for official statistics. Emerging data can also help to improve the official statistics in Oman. Moreover, they need to be viewed through emotioncy and cultuling analysis models. Therefore, the proposed culturally responsive framework for emerging data sources can also support policymakers in making informed decisions. This study also proposes some implications for further research. Scholars could add other dimensions to this proposed framework to make it more inclusive, for example, Hofstede's (2011) culture dimensions. Moreover, scholars could conduct field research to operationalize this framework, examine how an organization could use emerging data sources considering the framework to make decisions, and investigate its impacts on overall organizational performance.

This study was also subject to some limitations. The researchers had difficulty obtaining local articles that represented the Omani context. The authors also had limited access to certain databases that included highly relevant articles on emerging data sources.

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