Progress in Disaster Science 12 (2021) 100202

Contents lists available at ScienceDirect

Progress in Disaster Science

journal homepage: www.elsevier.com/locate/pdisas

The role of data and information quality during disaster response decision-making

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ARTICLE INFO

Article history:
Received 8 May 2021
Received in revised form 26 August 2021
Accepted 29 August 2021
Available online 30 August 2021

Keywords:
Disaster response
Decision making
Data and information quality

ABSTRACT

Massive amounts of data and information are exchanged during the response phase of disaster management. A large body of contemporary research has indicated that most of these data and information have severe quality related concerns, meaning that they may not be suitable for critical decision-making. The current paper addresses these issues by identifying how certain features of data and information quality function, to support specific, naturalistic decision-making processes during disaster response. These functions are used to revise and consolidate pre-existing definitions of data and information quality, for use in further disaster response research.

1. Introduction

The concept of data and information quality (DIQ) has existed for well over three decades [82]. Its management has long since matured into a professional discipline [60,99], through contributions from both research and practitioner communities. Academic researchers have explored DIQ from diverse perspectives ranging from technical to more administrative aspects of solutions to data quality issues [1,5,29,83,93,96]. Industry practitioners have also made a large volume of contributions to managing data quality problems [26,30,64,67,80], based on a wealth of experience-based knowledge.

Recent research by Moore [68] found that organizations believe that an average of $15 million per year is lost, due to poor decisions made using low quality data. This study emphasized the financial disadvantages of poor quality data in a commercial context. It is also worth investigating the multi-faceted costs of poor quality data in disaster management contexts. Prasanna et al. [76] and the Linked Open Data for Global Disaster Risk Research (LODGD) [61] task group have outlined how the quality of disaster-related data is a critical aspect of these contexts, determining the effectiveness of disaster management decisions. Many disaster management decisions involve life-threatening situations [75], meaning that the costs of poor-quality data are often not recoverable or able to be calculated in monetary terms. Furthermore, the diversity of disaster types, impacts, and of disaster management activities mean that the data associated with disaster management have a much broader scope than data used in domains such as business information systems. The current paper outlines a disaster-focused synthesis of a range of literature concerning DIQ. It provides a broad-based theoretical foundation for using DIQ-related concepts and criteria during disaster response in particular. As far as the current authors are aware, it is the first academic paper to do so.

Disaster risk reduction requires various timescales (i.e. short, medium, and long term) disaster management to meet relevant challenges. This is usually broken down into four different phases: *reduction* (reducing or eliminating risk of damage and disruption from future disasters), *readiness* (preparing for hazards that cannot be prevented or mitigated), *response* (responding to disasters that occur), and *recovery* (regeneration and enhancement of a community following a disaster) [77]; also known as *mitigation*, *preparedness*, *response*, and *recovery* [95]. Despite broad and extensive risk reduction efforts, such as the 1990–2000 International Decade for Natural Disaster Reduction and the 2005–2015 Hyogo Framework for Action, millions of people have still been affected, thousands have been killed, and catastrophic events have continued to cause substantially unmitigated human, property, economic and environmental losses every year [8]. These ongoing and multi-faceted disaster-related losses mean that the response phase of disaster management remains both crucial and critical [36,57].

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http://dx.doi.org/10.1016/j.pdisas.2021.100202

De Smet et al. [18] argued that there has nonetheless been a lack of in-depth research into disaster response. They outlined the need for fresh approaches to modelling response dynamics, and to better understand the multi-faceted and dynamic nature of this disaster management phase. Altay and Labonte [2] emphasized that quality information, reaching a greater number of humanitarian actors, would result in better coordination and better decision-making. According to Altay and Pal [3], this would improve their responses to beneficiaries' needs, while also improving agencies' financial accountability [3]. Current initiatives, such as the Natural Hazards Partnership (NHP) on producing impact-focused information through partnerships between public sector organizations [38], provide one such example of how managing and sharing quality information can improve disaster response activities.

Data analytics have become even more important since organizations recognized and leveraged the potential for big data analysis [13,69]. This includes the analysis of crowd-sourced data from platforms like Twitter and Facebook [9] which can help map disaster vulnerabilities, progressions and impacts [37], enhance the humanitarian supply chain [20,74], and inform a range of contingency planning [71] during disasters.

Tapia et al. [94] argued that crowd-sourced data may never meet the quality standards required for effective search and rescue operations. Among other challenges this may be because it shares the same three categories of: structured data, semi-structured data, and unstructured data [5]. Goodchild & Glennon [32] stated that relevant data quality issues need further research, after being relatively neglected. This call for further research has been re-emphasized by an international task group dedicated to the use of open data for disaster management [14].

The objectives of the current paper are to: (1) Summarize DIQ concepts and criteria which have been established for relatively generic purposes; (2) Characterize the distinct purposes of DIQ for disaster response; and (3) Determine how DIQ functions to improve the efficiency and effectiveness of relevant decision-making processes. Each of these objectives is addressed through a summary of relevant literature that collects, synthesizes, and assimilates findings from previous research and theoretical literature. As a whole, the current paper interrogates the use of data and information during disaster response, providing a robust conceptual foundation for further research.

The remainder of the paper is structured into seven more sections, beginning with a systematic definition of established DIQ dimensions, and an explanation of why these need to be adapted for disaster-response. Section 3 then outlines relevant decision-making processes which are affected by DIQ-related issues. This is followed by Section 4, which provides a more detailed explanation of how DIQ supports the same decision-making processes, known to occur during disaster response. The paper concludes with relevant recommendations for disaster response practice and outlines ongoing research in the same domain.

2. Data and information quality

Based on a traditional definition of *information* as processed data, Wang and Strong [97] stated that information is like a product while data is like the raw materials in a typical product manufacturing process. This relates to the well-established concepts of product quality control and quality management, where fitness for use [46] becomes the key criteria for data and information quality. ISO 9000:2015 is the most relevant, international standard for quality management systems. This standard defines quality in general as "a degree to which a set of inherent characteristics of an object fulfils requirements" ([43], p.1). In line with this general definition of quality, ISO 8000 [44] sets the standard for data quality and outlines the characteristics of data determining its quality.

The distinction between data and information is nonetheless part of a longstanding debate. Relevant literature has used the two terms *data quality* and *information quality* more or less interchangeably. For example, Madnick et al. [66] highlighted the minimal difference between the ways these terms are used. They outlined how there has been a tendency to use data quality to refer to technical issues and information quality to refer to nontechnical issues. For the sake of consistency and breadth, the current paper uses an overarching term: *data and information quality* (DIQ).

The following definitions of data and information quality have been provided by various authors:

- "High-quality data is data that is fit for use by data consumers" ([90], p.104).
- "Conformance to specification and as exceeding consumer expectations" ([47], p. 184).
- "To be of high value to its users" ([59], p. 88).
- "The degree to which information has content, form, and time characteristics which give it value to specific end users" ([72], p. 116).
- "The characteristic of information to meet the functional, technical, cognitive, and aesthetic requirements of information producers, administrators, consumers, and experts" ([24], p. 42).

The above definitions of DIQ demonstrate that the *characteristics* of data and information define their quality. It follows that a DIQ problem occurs when data and information do not adhere to characteristics expected and required by users. DIQ characteristics are therefore subject to the requirements of data and information users, while DIQ problems arise from data and information characteristics that do not match those requirements. The following sub-section discusses the broad range of applicable DIQ characteristics, and how they assemble into a compact set of eight dimensions.

2.1. Data and information quality characteristics and dimensions

Wang and Strong [97] stated that data need to have twenty characteristics to meet user expectations for performing tasks. Obvious characteristics, like accuracy, make up some of these dimensions but do not appear to account for all expectations held by data consumers. Other aspects, such as interpretability, ease of understanding, accessibility, timeliness, completeness, reputation, and objectivity, characterize data according to the expectations of data consumers. Researchers and practitioners have suggested further ways to classify data quality characteristics based on this fundamental framework, for example: Redman [81], Loshin [63], Price and Shanks [79], English [26], Stvilia et al. [91], and Lee [58].

The multiple classifications of DIQ characteristics that resulted from these efforts made it difficult to determine a consensus. This situation led Jayawardene [45] to analyze sixteen classifications of DIQ characteristics in multiple contexts such as government administration, healthcare, banking, and manufacturing sectors. This study identified 189 distinct DIQ characteristics, across a range of literature. Most of the definitions had similar themes but also had minor distinctions depending on the context. Themes were analyzed to identify thirty-three distinct DIQ characteristics and categorize them into eight main clusters, grouped by similarities. These clusters were named *DIQ dimensions* and provide a higher level of description rather than an extensive range of potential characteristics. The eight DIQ dimensions identified by Jayawardene [45] were: completeness, validity, reliability and credibility, accuracy, currency, availability and accessibility, usability and interpretability, and consistency – as outlined in Table 1.

2.2. The contextual nature of DIQ dimensions

It is important to understand that DIQ dimensions are a relative, rather than an absolute, set of concepts. They almost entirely depend on data users' requirements, which can change depending on their task environment or on the wider context in which they operate. Like classifications from Wang and Strong [97], the categorization shown in Table 1 was developed for commercial business information systems. It is therefore questionable whether the same DIQ dimensions and characteristics are applicable to data and information in a disaster response context. The entire framework needs to be adapted and better defined, for the purposes of diverse disaster response tasks and relevant operating contexts.

The *completeness* of data is one definition which may or may not fit an operating context. It is a requirement for many organizations, who may use one or more definitions, including that completeness determines "the

Table 1
DIQ dimensions and characteristics. Adapted from *A Pattern Based Approach for Data Quality Requirements* (p. 64) by W. Jayawardene [45], Brisbane, Australia: University of Queensland. Copyright by W. Jayawardene.

Completeness	Validity	
• Completeness of mandatory attributes • Completeness of optional attributes • Completeness of records • Data volume	• Business rules compliance • Meta-data compliance • Standards and regulatory compliance • Data standards • Statistical validity	
Reliability & Credibility	Accuracy	Currency
• Source quality • Objectivity • Traceability	• Accuracy to reference source • Accuracy to reality • Precision	• Data timeliness • Data freshness
Availability & Accessibility	Usability & Interpretability	Consistency
• Continuity of data access • Data punctuality • Data maintainability • Data awareness • Ease of data access • Data access control	• Usefulness and relevance • Understandability • Appropriate presentation • Interpretability • Information value	• Uniqueness • Redundancy • Semantic consistency • Value consistency • Format consistency • Referential integrity

extent to which data is not missing. For example, an order is not complete without a price and quantity" ([31], p. 334). This aspect of completeness is required where usage becomes meaningless without a defined set of mandatory data elements. Data can also be defined as complete "…if no piece of information is missing, Anti-example: The Beatles were John Lennon, George Harrison, and Ringo Starr" ([48], p. 186). This aspect of completeness emerges when there is a clear set of data that users need to know about, when performing a relevant task. For example, a customer register should contain all the organization's customers, and the asset register should contain all the organization's assets. Data completeness can also be defined in terms of *comprehensiveness*, for example: "…a measure of the availability and comprehensiveness of data compared to the total data universe" ([67], p. 128). Like many statistical analyses, this aspect of DIQ requires a particularly numerous and comprehensive sample of data.

The *accuracy* of data and information may be more intuitive at first glance. However, "A measure of the correctness of the content of the data which requires an authoritative source of reference to be identified and accessible" ([67], p.127) is only one of many definitions. This particular definition focuses on how databases represent and match data in the wider world. Accuracy can also be defined as: "…if it conveys a lexically, syntactically and semantically correct statement" ([48], p. 186), i.e. whether the text-based formulation of data and information can be correctly understood. Likewise: "Data values are correct to the right level of detail or granularity" ([26], p. 181). Prices can be specified to the nearest cent and weight to the nearest gram, but this level of specification would not be required for even moderate sums of money (in dollars) or very large weights (in tons).

Like other dimensions, these definitions of accuracy highlight how DIQ dimensions depend on intended use. It follows that DIQ dimensions defined in other domains are unlikely to suit the purposes of disaster response. For example, the magnitude of an earthquake can be reported as 7.1 when the geologists have determined it was 7.3. The question is whether this difference is important for disaster response tasks. For Gatling et al. ([31] p. 334), the accuracy of data "…determines the extent to which data objects correctly represent the real-world values for which they were designed". Slight differences between original and reported magnitude data may or may not matter for carrying out the response operations, depending on the way an information context has been designed. The same can be said for the completeness of data, because sensor networks can often fail during disasters, and large quantities of sensor data may be missing. The available data may nonetheless be used to successfully perform disaster response tasks, depending on the way that information systems have been designed and the way that decision-makers can handle incomplete information.

The *validity* of data is another aspect that signifies whether they are acceptable or legitimate for desired tasks, defined as "a valid value or within a specified range of valid values for this data element" ([26], p. 181). Data values sitting outside of the acceptable range are not retained for performing a particular task. Validity can also be defined as "…whether physical instances of data are in record with their formats" ([81], p. 146). This dictates that valid data formats are required for performing particular tasks. *Coherence* is another consideration, in terms of whether data and information can be "…reliably combined in different ways and for various uses" ([65], p. 83).

The key question becomes: What DIQ dimensions are required to support data users' requirements during disaster response? DIQ for this operating context is still in its infancy and there have only been a few studies published at the time of writing. Initial research, by Seppänen and Virrantaus [88], provides one example which will be discussed in the remainder of this paper. It is therefore necessary to characterize how data and information are used in the disaster response domain, and to articulate all DIQ dimensions that apply. The following section interrogates the use of data and information during disaster response in particular. The intended purposes of using these data and information during disaster response help to understand associated user expectations. This leads into a specific set of DIQ dimensions, and their defining characteristics.

2.3. Information for disaster response

As outlined above and by Jayawardene [45], DIQ has been well established for organizational settings such as government administration, healthcare, banking, and manufacturing. However, DIQ for disaster response is fundamentally distinct from these enterprise-based antecedents. The distinct nature of data and information used during disaster response has been recognized by the Committee on Data (CODATA) for the International Science Council (ICSU) as part of their Decadal Programme for using data across domains [15], and through a task group focused on the findability, accessibility, interoperability, and reusability (FAIR) of data for disaster risk reduction [16]. Several reasons for this distinction, between disaster response and enterprise-related data and information, are outlined below.

Disaster response information is heterogeneous because it is both structurally and semantically diverse [33]. It may consist of: (i) incident action plans and situation reports; (ii) damage analysis reports; (iii) geographic data and the operating status of roads, bridges and other infrastructure, including key buildings; (iv) logistical data about vehicles, supplies and delivery times; (v) general communications; (vi) financial data, including the collection and distribution of funding; and/or (vii) internet hosted information [34,70]. Relevant data is received in very different formats, including structured, semi-structured and unstructured data, and in types of media that include text, images, and videos. These formats and types further increase the heterogeneity of relevant data and information.

Disaster response data is received in large volumes from sensor networks, satellites, social media servers, cell phones and other multimedia devices. This typically creates what the Harvard Humanitarian Initiative [37] called a *raging river* of high-volume information. The massive amount of crowd-sourced information exchanged in social media during disasters are a recent addition which can be harnessed for detecting events and even clarifying event locations [78].

The heterogeneity of disaster management extends to varying time-related and topographical characteristics. According to Hristidis et al. [34], this results in three different types of relevant data: Spatial, temporal, and spatio-temporal. Generation of spatio-temporal data requires real-time data integration, for example: between heterogeneous, archived information and other data streams used to support response operations. Relevant data is typically produced and received in a relatively short period of time. This constitutes another aspect of a raging river, characterized by high velocities of data and information.

Relevant data and information can be therefore classified as *big data*, characterized by high levels of volume, velocity, and by uncertain verity [50]. The lack of uniform quality definitions or criteria for big data [12] creates further challenges for disaster response, especially for response-related decision making. The following section outlines decision-making processes which are affected by these data-, and information-, -related challenges.

3. Naturalistic decision making in disaster response

Decision makers in more standard business organizations or public administration departments tend to use relatively rational decision-making processes [27]. These processes involve the systematic analysis of well-structured data with a step-by-step process to choose between alternative options. This has resulted in a rational decision-making model that tends to assume that decision-makers have full or perfect information about their decision-making context, and that they also have the time, cognitive capacities, and resources to evaluate one known set of choices against one another [92]. Disaster-response contexts do not usually provide the luxury of full and perfect information. Decision-makers in these contexts are typically pressured for time and by demanding conditions that tend to diminish their cognitive capabilities [77]. Furthermore, disaster contexts often evolve from the rapid interaction of diverse natural and social dynamics, which further challenge cognition at the individual level [40]. As a result of such a challenging operating environment, rational decision-making processes are not usually viable [51,54,73,77].

This is one of several domains where rational decision-making is not usually a viable option, and where naturalistic decision making (NDM) has become a preferred alternative for studying and supporting operational decisions. Other domains include military and aviation-related decision-making contexts [22,51,54], where decision-making rationality is complicated by the impact of substantial stressors [101] in addition to time pressure [89]. Both types of factors limit information processing, the quality of received information, and overall decision-making performance [102]. Rather than taking a more analytical approach, decision makers attempt to follow the course of action that most closely fits their job role, their experience, and the situation at hand [51,54,73,77].

Over the last four decades, a well-developed body of NDM research by Dreyfus [19], Klein [52], Endsley [22,23], Salas et al. [84], and others has looked at this kind of decision-making under pressure. These authors have established how experts make rapid but generally effective decisions using a holistic process involving situation recognition and pattern matching. Their findings are particularly relevant for disaster response, where the failure to make and implement a rapid decision can have much worse consequences than making a timely but sub-optimal decision [6]. Individual situation awareness (SA) in these kinds of contexts characterizes how data and information form an important aspect of relevant decision-making processes.

3.1. Level 1 SA – Perception

Endsley [23] developed an SA-based model to explain certain NDM processes, which has since become very widely accepted. In Endsley's [23] model, decision-makers use *mental models*, otherwise known as schemas or internal representations, of the situation they are dealing with. These mental models are based on past experience, meaning that decision-makers classify and categorize available information according to both current objectives and pre-existing experience.

A well-developed mental model will provide: (1) Knowledge of relevant system elements, that, used for directing attention and classifying perceived information (Level 1 SA); (2) A means of integrating elements in a way that helps understand their meaning in context (level 2 SA); and (3) A mechanism for predicting future system states, based on both the current state and an understanding of relevant dynamics (level 3 SA) [22]. Once a high level of SA has been achieved, the same mental model will prescribe subsequent decisions and actions. This formulation of SA makes classifying and mapping perceived information onto existing mental models a very important part of NDM.

As a whole, SA is defined as “The perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future” ([21], p.1). In order to develop a high degree of SA, data and information should be provided both effectively and efficiently, to support all three levels of knowledge. For disaster response, this allows incident commanders to plan and carry out rescue and other response operations. In order to develop each level of knowledge, data and information are usually analyzed and visualised through an emergency management information system (EMIS) [76], or through a combination of other information systems and more ad hoc tools [41].

Situation awareness research and theory by Endsley [21–23] are mainly based on military scenarios and fire response incidents. Research by Ashish et al. [4], Beatson et al. [7], and Schoenharl et al. [85], among many other authors, nonetheless highlights how the same principles can apply to a broad range of incidents and disasters such as terrorism, earthquakes, flooding, storms, and earthquakes. More recent research, by Huggins and Prasanna [41] highlights the relevance of SA research and theory to the wide range of disasters managed by emergency response Controllers in Aotearoa New Zealand.

The first step in developing SA is to perceive the status, attributes, and dynamics of relevant elements in the environment. The raw data and information relevant to the situation are often summarized and organized to facilitate human awareness. This is done with the help of information system interfaces, which support an end-user to maintain their awareness of elements that are relevant to a particular job role, as a response situation progresses [100]. For example, dashboards like the one shown in Fig. 1 contain data including temperature, water levels, and traffic conditions. Together, these elements support basic awareness of a fire response incident. By changing the type of incident data and geographic scale, the displays discussed below could also be applied to other types of disaster scenarios - such as industrial explosions, chemical leaks, flooding, or even earthquakes and storms.

3.2. Level 2 SA – Comprehension

Comprehension is achieved by synthesizing previously disjointed elements of a situation, perceived at Level 1. This second level of SA goes beyond simply being aware of current elements, to understanding their goal-orientated significance. Level 1 data is combined to form a holistic picture of the environment, including the relative significance of each object and event. Rather than presenting sets of un-related information, like the numbers and text shown in Fig. 1, Fig. 2 shows how graphical representations can integrate dynamic and static information, to improve the user's overall SA. It is important to note that novices and more-experienced decision-makers may be capable of achieving a similar degree of level 1 SA. However, especially in the absence of an appropriate information interface, they may struggle to integrate various data elements along with pertinent goals, to effectively comprehend the response situation.

3.3. Level 3 SA – Projection

The ability to predict potential changes in situational elements forms the third and highest level of SA. This level is achieved through a more comprehensive awareness of elements' status and the dynamics affecting that status. Fig. 3 displays an interface supporting this third level of data and information synthesis. It can help responders to make difficult predictions with higher levels of confidence, including the implications of choosing particular alternatives.

Disaster-related data can have diverse spatial characteristics and this becomes particularly important during disaster response [100]. Geographical information system (GIS) technology provides an important way to map and analyze multiple hazard types and to visualize their spatial distribution. GIS integration means that EMIS systems can generate interactive maps of

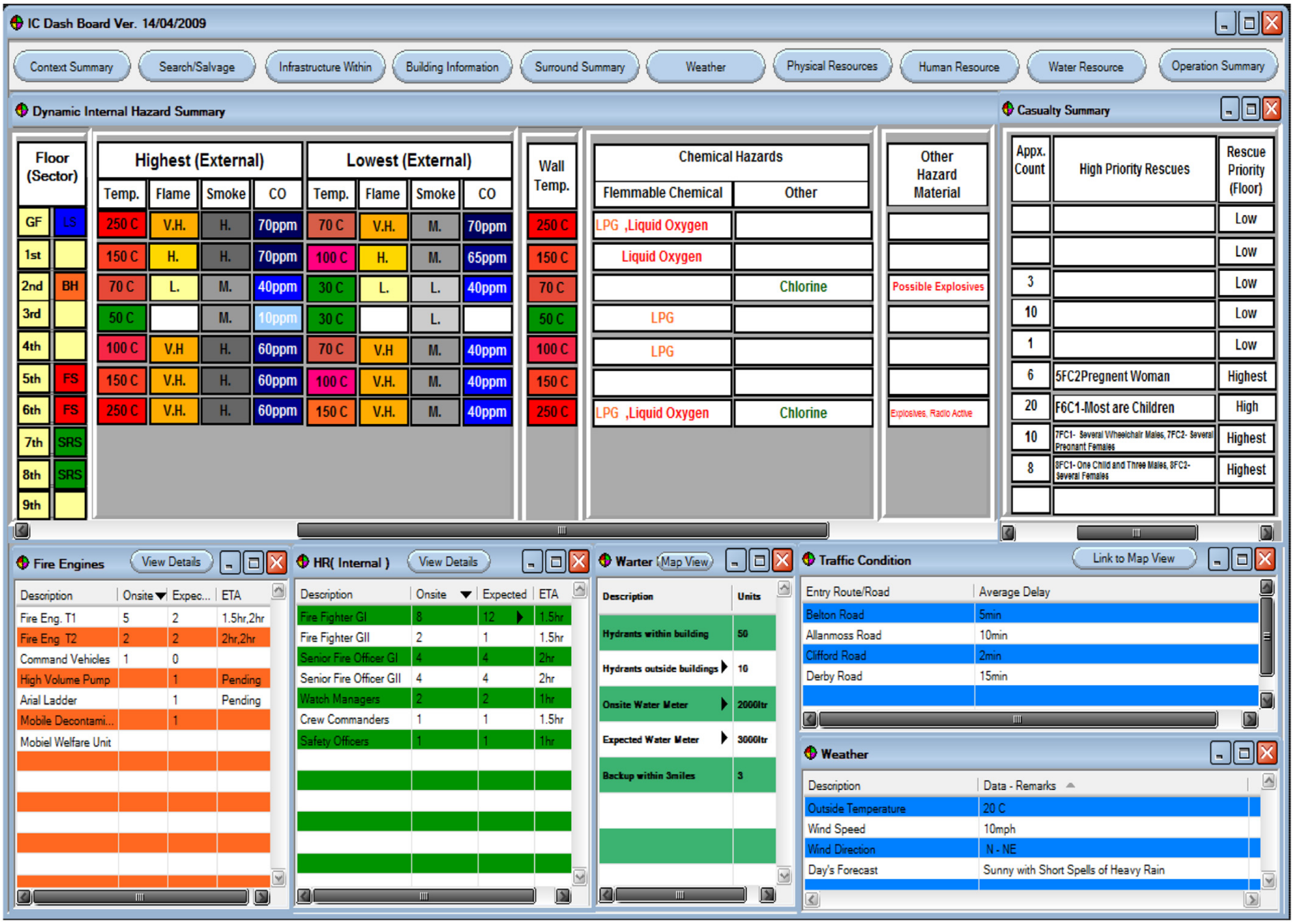

Fig. 1. Data analysis supporting Level 1 SA. From *Information Systems for Supporting Fire Emergency Response. A Doctoral Thesis Submitted in partial fulfilment of the requirements for the award of the degree of Doctor of Philosophy of Loughborough University* (p. 174) by R. Prasanna [77]. Copyright 2010 by R. Prasanna. Reprinted with permission.

vulnerability, operations, logistics, transportation and even incident predictions for use during a disaster response. These maps can incorporate vital information about trapped persons, medical resources, damaged buildings, closed roads, and the location of specific resources such as food, water, and shelter [7]. This level of synthesis support the projection of future states, by highlighting the dynamics that affect those states.

Level 3 SA is also supported through the analysis of highly dynamic, crowd-sourced information during a disaster response. The emergence of web 2.0 tools like Twitter, Facebook and YouTube, has led to the exchange of a massive amount of disaster-related data and information [9]. Although this can include information from a range of organizations, the majority of is generated by the public [37]. Subject to ensuring the quality of this information, it can nonetheless be used to develop real-time maps, representing an almost panoptic perspective of complex and rapidly changing response environments [7].

Although a higher level of SA allows an individual decision maker to function in a more timely and effective manner [22], disaster management as a whole will usually require team-level decision making. This involves shared situational awareness (SSA), which is developed between multiple team members and even between multiple stake holder groups [88]. For the sake of brevity, the current paper nonetheless focuses on an individual's decision-making process, while performing discrete disaster response tasks. As outlined by Kozlowski and Chow [56], these individual decision-making processes are a necessary component of broader levels of cognition, referred to as *macrocognition*. The next section focuses on this, relatively fundamental approach, to decision-making under time and other resource constraints.

3.4. Recognition-primed decision making

An alternative, and more specific, model of NDM processes was introduced by Klein [52] for the purposes of fire response. This model is referred to as Recognition Primed Decision Making (RPD) and is summarized in Fig. 4. Like Endsley's [22,23] SA formulation, the RPD model has three distinct levels. Rather than being distinguished by SA levels, the three types of RPD are distinguished by the cognitive complexity of a particular decision-making context. Each RPD level nonetheless arrives at a predictive level (level 3) of SA. As shown in Fig. 4, the RPD model accounts for how familiar information is mapped onto pre-existing mental models. This relates to information perception (SA level 1) and comprehension (SA level 2), even though these levels of NDM are not typically used to describe RPD processes.

The RPD model shows how firefighters apply distinct levels of cognitive processing to assess and classify a response scenario. Once they have recognized a particular type of event, firefighters typically know which type of response is required [103]. However, and as shown in Fig. 4, more complex and less familiar situations require more cognitive processing. The resulting decision making processes have also been observed in neonatal intensive care [104], chess [105], platoon-level command [106], and higher levels of military command and control [107].

As shown in Fig. 4, the simple RPD process (A) occurs when a situation is recognized and matched with an obvious reaction, which is then implemented. A slightly more extended process (B) occurs when the decision-maker consciously evaluates their reaction before implementing it. This involves mental simulation and modifications prior to acting. Expert decision

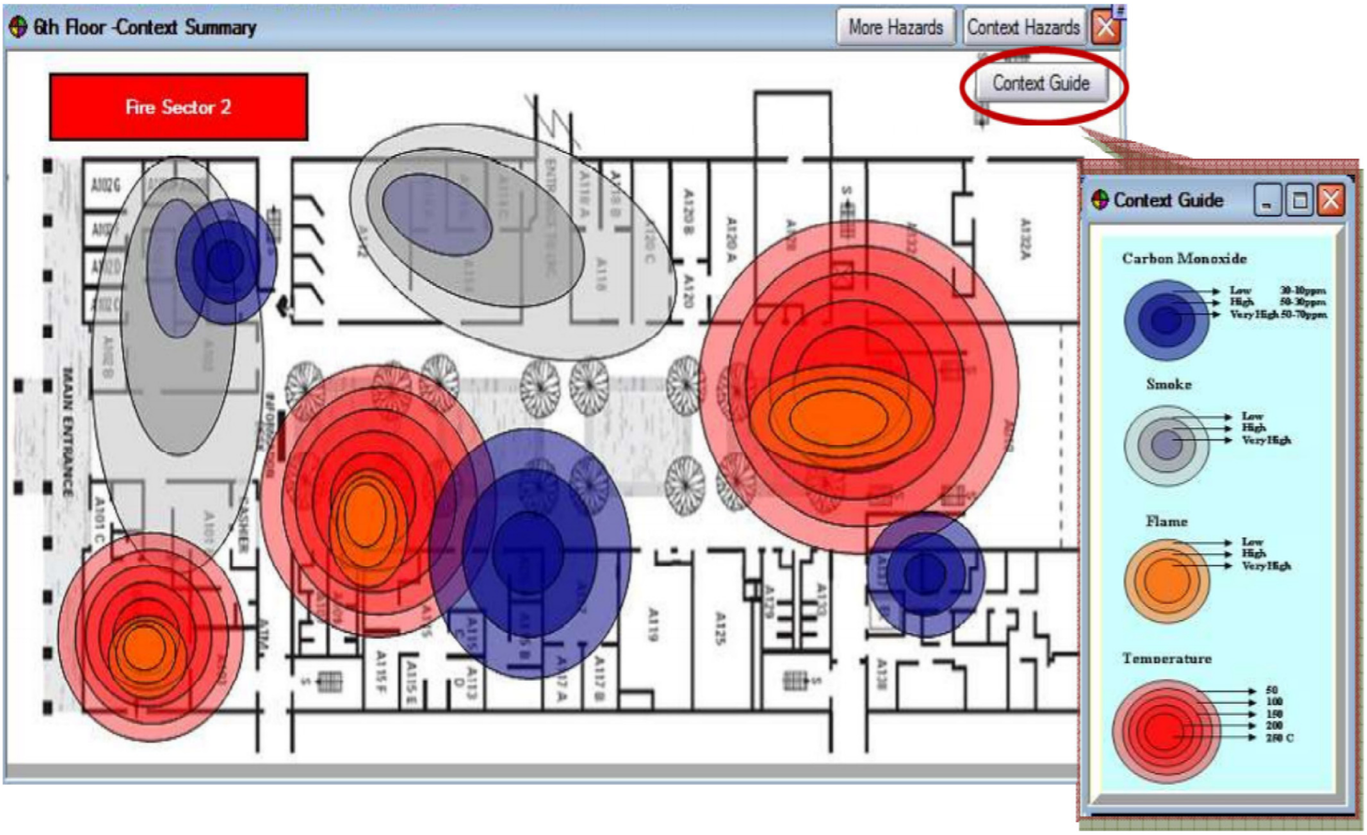

Fig. 2. Data analysis supporting Level 2 SA. From *Information Systems for Supporting Fire Emergency Response. A Doctoral Thesis Submitted in partial fulfilment of the requirements for the award of the degree of Doctor of Philosophy of Loughborough University* (p. 182) by R. Prasanna [77]. Copyright 2010 by R. Prasanna. Reprinted with permission.

makers commonly use these processes when responding to familiar situations, which they have previously experienced through operational practice or through training [51].

In the most elaborate RPD process (C), a decision-maker evaluates the mental model used to recognize and categorize situational elements. This evaluation can reveal flaws in the way a situation has been recognized, leading the decision-maker to reassess the situation and search for additional information. Once expectations are no longer violated, the most obvious course of action is evaluated and modified until it seems workable. If modifications are unable to achieve feasibility, this course of action is discarded in favor of the next most obvious action, and so on. If a decision-maker is unable to mentally simulate a successful response, they will typically return to their initial situational assessment – as shown to the far right of Fig. 4.

Both SA and RPD models of NDM depend on pre-established schemas, or mental models. These mental models are a predominant factor for classifying situational data and information in highly dynamic and demanding decision-making contexts such as disaster response. The next section discusses how mental models and other factors affect NDM effectiveness.

3.5. Factors impacting NDM effectiveness

According to Endsley's [23] model, two types of factors affect the decision-making process: (1) *Individual factors* including abilities, experience, training, goals and objectives, preconceptions, information processing mechanisms, long-term memory stores, and automaticity; (2) *System factors* including system capability, interface design, stress and workload, complexity, automation. This distinction, between individual and system factors is comparable to the difference between individual and external stresses, outlined by Wickens [102] and Sinha and Chandrakasan [89].

Endsley's [23] model of situation awareness states that the mental models available in a decision maker's memory depend on experience of the decision-maker. In terms of individual factors, this means that an experienced disaster responder has well-developed mental models, which help decision-makers to categorize situational information both effectively and efficiently. Well-trained and experienced decision-makers can therefore acquire a higher level of SA, compared to novices.

The RPD model and associated research further demonstrates the importance of decision-maker experience [51]. A decision maker with prior experience of similar incidents will identify the solution via the most simple RPD process (A). Less experienced decision makers need to go through much more complex RPD processes (B,C). For example, an incident commander who has faced 100's of flooding events is much more likely to have a pre-existing mental model that fits new flooding incidents, compared to a novice disaster responder. This advantage reinforces the value of training and simulation, for improving decision-making capabilities. In the modern world, such training and simulation can performed using advanced technology platforms [10,98], rather than waiting for decision-makers to acquire many decades of disaster response experience.

Klein [51] and Prasanna [77] outlined how decision-centered design improves system factors and improves NDM processes. Decision-centered design refers to the use of decision requirements for designing information systems and human-system interfaces, for example: dashboards and automated data analysis. Fan et al. [28] highlighted how software tools, also referred to as *cognitive agents*, can reduce the cognitive demands faced by decision-makers. This improves the NDM process by off-loading some of these demands onto information system capacities.

More recent research suggests that automated planning tools provide distinctly proactive information to support decision-making in disaster situations [49,87]. This improves SA by providing the most relevant information, as a disaster response scenario progresses. For a counter-example, important information about fire safety deficiencies was not available to crews responding to the Grenfell Tower fire. The preliminary review of this disaster ([62], p.30) stated that there was “no system to ensure

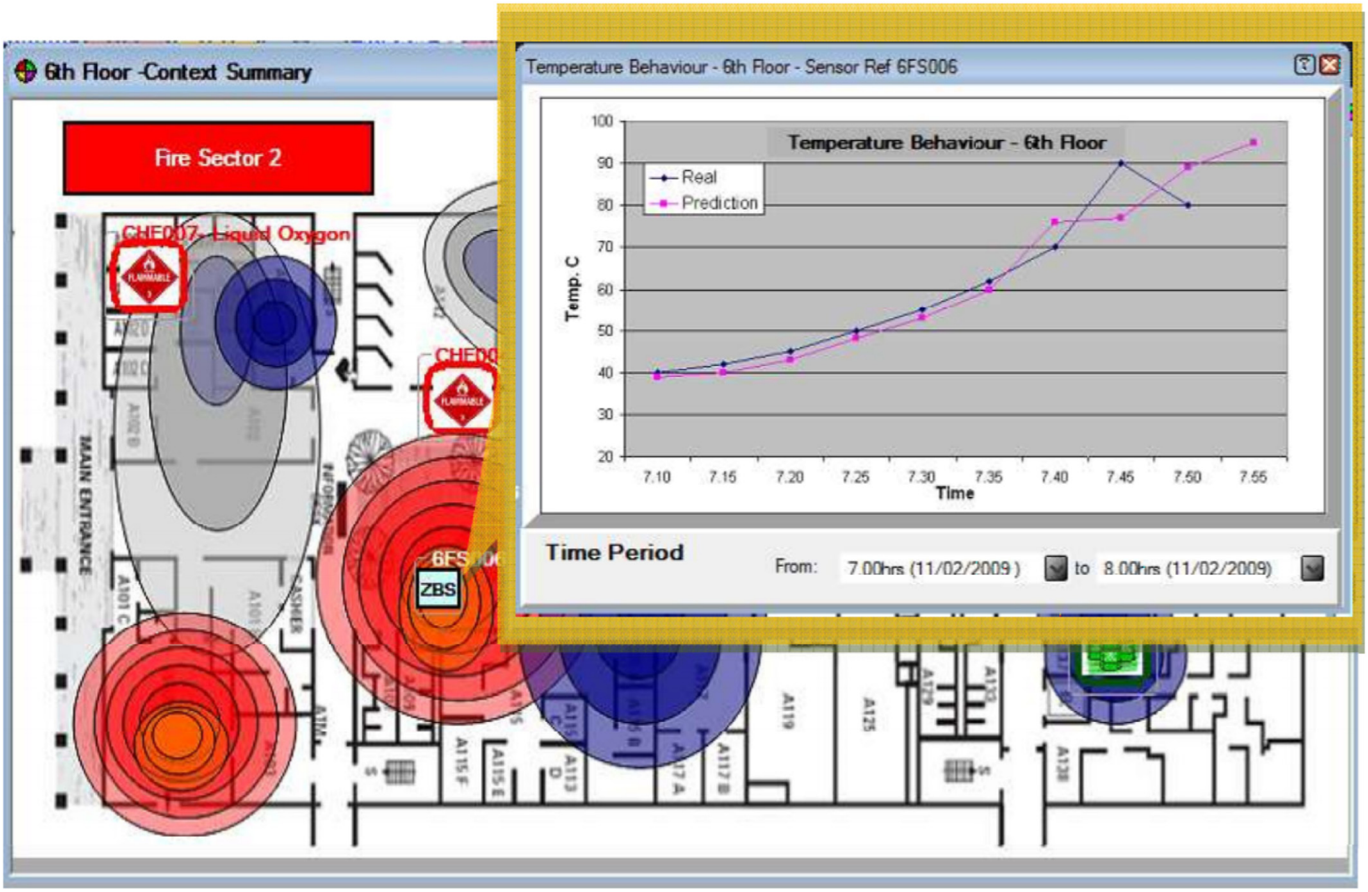

Fig. 3. Data analysis supporting Level 3 SA. From *Information Systems for Supporting Fire Emergency Response. A Doctoral Thesis Submitted in partial fulfilment of the requirements for the award of the degree of Doctor of Philosophy of Loughborough University* (p. 183) by R. Prasanna [77]. Copyright 2010 by R. Prasanna. Reprinted with permission.

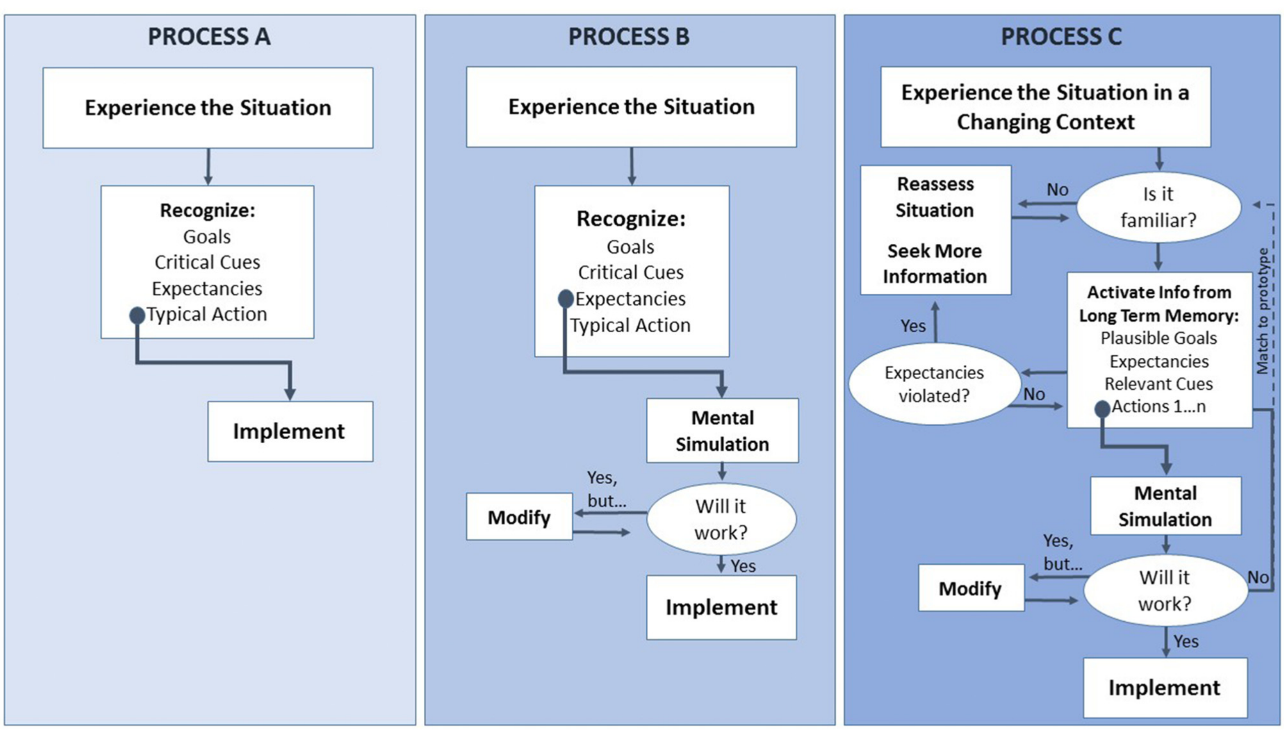

Fig. 4. Recognition-primed Decision Model. Adapted from *Naturalistic Decision Making* (p. 18) by G. Klein [55], *Gateway*, *2*, pp. 16–19. Copyright 1991 by Human Systems IAC.

information about any identified deficiencies in the fire safety provisions in a premises are available to all operational crews that may be required to provide an operational response". This meant that key decisions relied on reactive and substantially incomplete updates about the progression of a rapid and highly complex fire [62]. Considering that that cladding and other safety features became such important factors, better building-related information would have supported a more predictive level (3) of SA, supporting much more pro-active and effective decision-making.

It is clear that simulation and training and information system design can have highly positive impacts on NDM during disaster response. However, both the SA and RPD models of NDM may have neglected related impacts of data and information quality. Seppanan and Virrantaus [88] have discussed DIQ during disaster response, but did not account for the nature and purpose of relevant information as part of NDM. As a result, their extant concept of DIQ for disaster response do not align with NDM fundamentals. The following section addresses this disconnect through a more fundamental approach to identifying the role of DIQ as part of NDM during disaster response. Both SA and RPD models of NDM are discussed with a focus on data and information requirements, towards better understanding the specific value of DIQ for disaster response decision-making.

4. Data and information analysis in NDM

The two models of NDM processes outlined in Section 3 outline how NDM is a cognitive process that uses data and information from the environment, in relation to decision makers' mental models. The former model, from Endsley [22,23] outlines how three levels of SA are achieved by analyzing data and information to arrive at goal-directed decisions. Klein's [52] RPD model provides another view of NDM processes, accounting for different levels of expertize and scenario familiarity. Both SA and RPD models outline processes for using data and information to make decisions under demanding disaster response conditions.

The process-orientated views of NDM, outlined in Section 4, can be elaborated by considering how data and information impact effective decision making under disaster response conditions. This helps addresses the type and quality of information needed for effectively responding to a disaster. To theoretically formulate how data and information analysis form part of disaster response decision-making processes, Fig. 5 adds a data and information layer to the most elaborate RPD process (level C). SA model components, which usually form an implicit aspect of the RPD model, have also been specified.

4.1. Data and information at SA level 1

According to Endsley [23], the first step in the NDM process is to achieve level 1 SA. This relates to the initial RPD processes, shown to the top of Fig. 5. These processes involve the combination of mental models accessed from a decision-makers' memory with current data and information from the disaster response environment, e.g.: initial reports, communications and environmental cues. To account for the way that different types of information are involved in NDM, the current model refers to dynamic data and information from scenario environments as *external information*. This external information effectively stimulates the human brain to select from various mental models stored in LTM [11].

In this way, the external information assumes a mental model stimulus function, or *stimulus* function for brevity. This function, among others, is shown on Fig. 6. Together, they detail which aspect of RPD is primarily improved through DIQ. At Level 1 SA, the stimulus function addresses the need for initial information that is timely and accurate. This highlights how a high level of DIQ helps ensure that decision makers perceive highly decision-relevant aspects of a disaster situation. A low level of DIQ would mean that disaster alerts and other initial information mislead or distract a decision maker, leading them to select an erroneous mental model.

At the same initial level of SA, the *training* function helps ensure that decision makers possess a much more relevant mental model. A well-trained decision-maker will have more developed mental models, avoiding the need for large quantities of additional information under time and other resource constraints. By contrast, a poorly trained decision-maker will lack relevant LTM structures. Their available mental models will make a poor fit with available data and information, and will therefore require large amounts of additional information, to resolve the crisis in question. It follows that higher quality data and information provided during training will lead to more relevant and efficiently usable mental models.

4.2. Data and information at SA level 2

Level 2 SA mainly involves a process of categorization and pattern matching. This occurs when external information is categorized into categories within the selected mental model. The decision-maker identifies patterns of key information from the environment that match key information in a decision maker's mental model. Endsley [23] stated that this process is almost instantaneous, due to the superior abilities of humans to use pattern-matching mechanisms. For this stage, the *curation* function of well-structured data and information helps ensure the fit between external information and the internal information structured within a decision-maker's mental model. This supports level 2 SA, through a more comprehensible, and therefore useful, representation of a disaster response scenario.

At this intermediate level of SA, the training function that supported level 1 SA has also improves the suitability of default information stored in decision makers' LTM - where the suitability of default information is characterized by plausible goals and actions for addressing a particular situation [51]. The best fitting mental model will therefore provide a set of plausible goals and prescribed actions to achieve particular response goals. This constitutes another aspect Endsley's [23] definition of default information in SA. Prasanna [77] highlighted that both this default information and relevant goals are highly influenced by specific responder roles. It follows that, once goals and prescribed actions have been identified, they are much more easily prioritized by disaster response decision-makers who can delegate courses of action dictated by specific response roles.

4.3. Data and information at SA level 3

Default information embedded in a well-selected mental model is also relevant to the next level of SA. According to Endsley [23], this default information is the best source for generating SA level 3 projections, concerning the outcomes of particular responses. For example, a decision-maker may predict how far a fire will spread within the next few minutes, given a certain fire intensity combined with surrounding environmental conditions. More importantly, default information means that some aspects of level 3 SA can be achieved without the need for more detailed data analysis, within a decision-making scenario that is already highly demanding.

It is important to remember that time pressure typically means that multiple responses are not typically evaluated against each other within the RPD process [51]. Decision-makers will usually select the first workable course of action determined by their mental models, so long there are no critical cues to do otherwise [51]. The predominance of default approaches highlight the importance of ensuring that goals and actions acquired and reinforced during training amount to some kind of best, or evidence-informed, practice. In the absence of training functionality, the failure to provide high quality information during training can mean that decision makers acquire counter-productive reactions to situations requiring a much more robust skill set and knowledge base.

Where possible, each SA level 3 prediction should include some indication of how certain or uncertain the predicted outcomes are. The need to specify uncertainty, and especially compounding uncertainty, has been highlighted in a large-scale review of relevant literature by Hudson Doyle et al. [39]. The endemic uncertainty of many disaster response scenarios also creates the need for a *monitoring* function, concerning specific aspects of a disaster progression. A very high level of monitoring functionality will mean that decision-makers are informed of the results of implementing certain courses of action. Many of these results can be unanticipated and will require minor adaptations in situ. Highly unanticipated results will

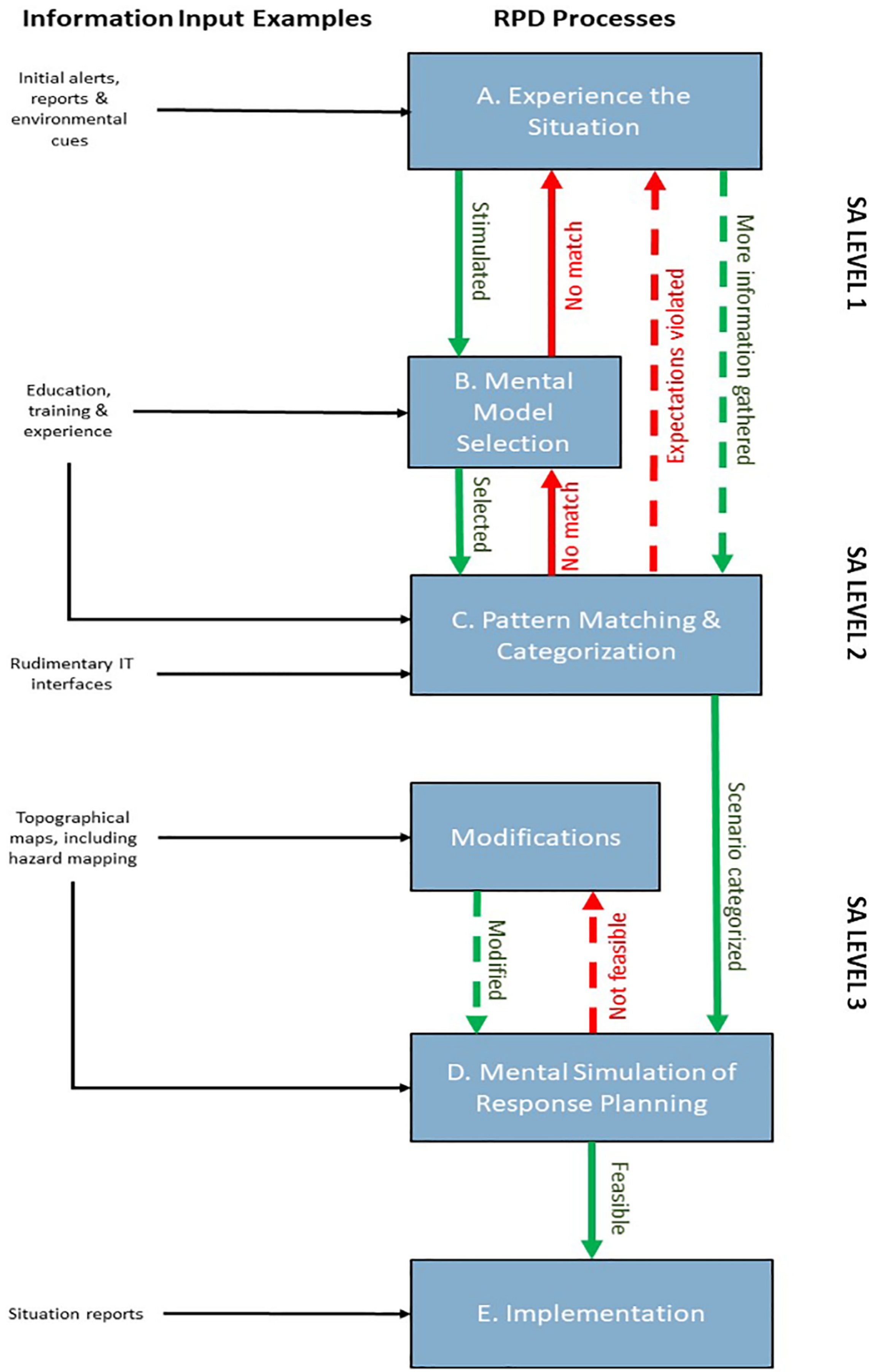

Fig. 5. RPD process incorporating external data and information.

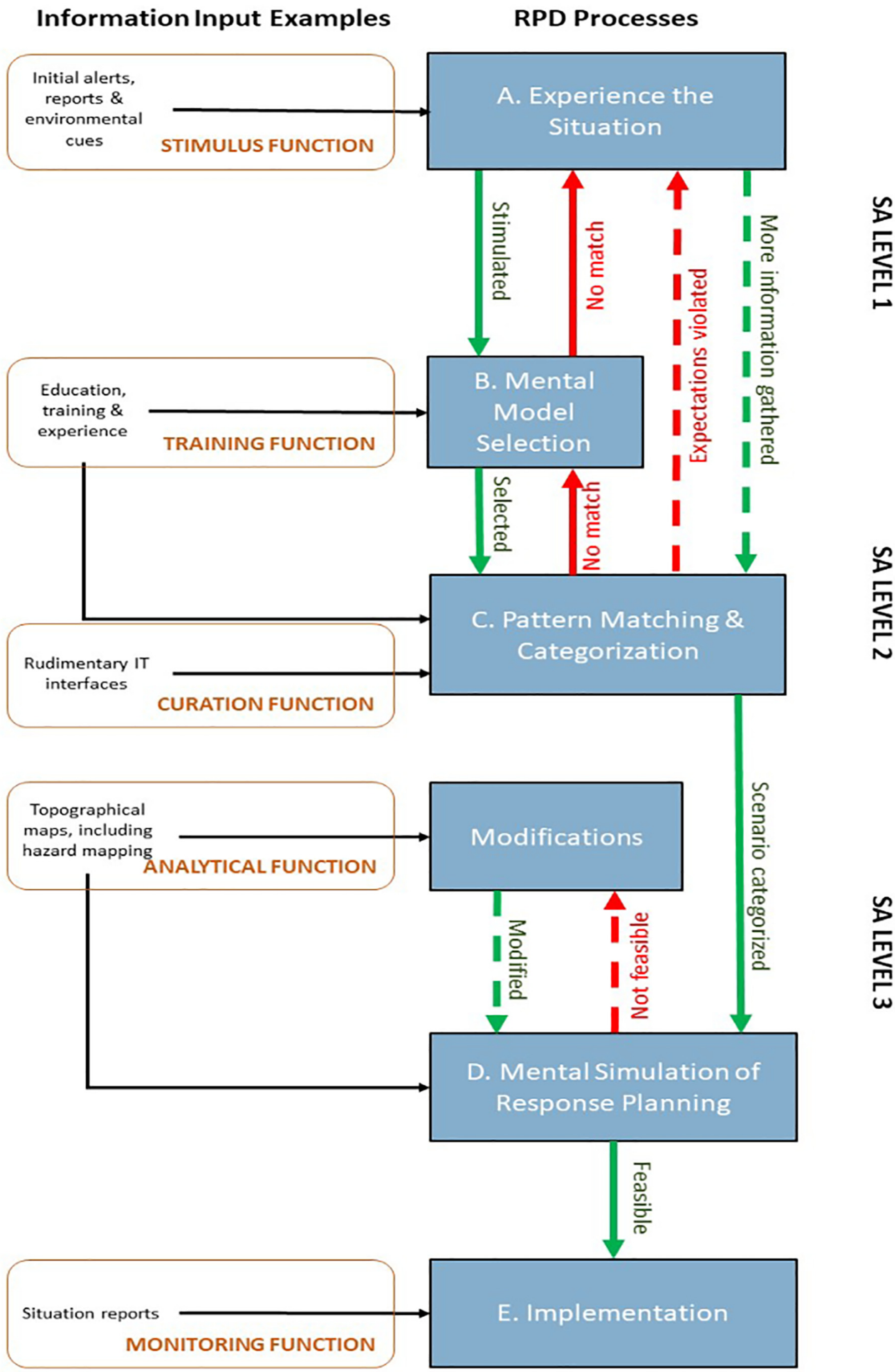

Fig. 6. Data and information quality view of NDM specifying DIQ Functions.

require a return to earlier stages of the RPD process, including: B. Mental Model Selection; C. Pattern Matching and Categorization; and D. Mental Simulation of Response Planning. In sum, DIQ can deliver a high degree of monitoring functionality, to help decision-makers determine whether to continue, modify, or more critically evaluate implemented courses of action.

Results and even entire events are much harder to anticipate when two or more types of hazards interact with one another. Relevant scenarios include: compound disasters, involving a linear chain of events caused by an initial hazard trigger [17]; cascading disasters, which involve the propagation of impacts and triggers through complex casual pathways and networks [42]; and complex disasters, where natural hazard and other types of hazard events coincide with armed conflict [17]. Other disaster scenarios do not readily fit these classifications. For example, the need for flood evacuations can conflict with the need to control pandemic infections in the affected population. Each scenario type exemplifies the dynamic complexity of interacting systems outlined by Huggins et al. [40], requiring very high levels of DIQ to support effective decision-making.

4.4. Key DIQ dimensions

Sections 4.1 to 4.3 highlight the major impacts of DIQ, on several components and levels of NDM. The summaries provided include a slightly simplified set of RPD components: A. Experience the Situation; B. Mental Model Selection; C. Pattern Matching and Categorization; D. Mental Simulation of Response Planning; and E. Implementation. Sections 4.1 to 4.3 also outlines how DIQ impacts all three levels of SA: 1. Perception; 2. Comprehension; and 3. Projection.

Table 2 builds on Figs. 5 and 6 by outlining data and information sources for each DIQ function. These categories have been related to specific DIQ dimensions from Section 2.1 of the current paper. For example, the stimulus function of initial alerts, reports and environment cues can be evaluated in terms of validity, reliability, credibility, accuracy, currency, availability, and accessibility. Deficiencies in any one of these dimensions mean that initial alerts, for example, will not efficiently and effectively stimulate relevant mental models held in a decision-maker's LTM.

5. Conclusion

High stakes decision-making during disaster response is constrained by substantial time and other resource limitations. It nonetheless depends on large quantities of rapidly changing and often unreliable information, concerning disaster scenarios that can include complex, compounding and cascading dynamics. These scenario and information characteristics mean that decision-making during disaster response is distinct from decision-making under more standard conditions, such as business decisions in an enterprise environment. This has created the need to define what DIQ means for disaster response decisions, in particular.

5.1. Summary

The current paper has outlined the importance of particular DIQ dimensions, for a range of decision-making contexts. It has also outlined the nature of DIQ for disaster response, for supporting decisions made under severe constraints on time and other resources. Effective decisions in these scenarios depend on attaining a high level of SA, where decision-makers can project the implications of taking certain courses of action. The current paper has outlined how this high level of SA is developed through the course of an RPD process, where decision-makers: A. Experience the situation; B. Select a mental model; C. Engage in categorization and pattern matching; D. Simulate and modify response planning; and E. Implement their chosen course of action.

Pre-existing SA and RPD approaches to NDM have been summarized and adapted, to determine the specific relevance of more generic DIQ dimensions: Completeness, validity, reliability and credibility, accuracy, currency, availability and accessibility, usability and interpretability, and consistency. The current paper has outlined how specific sets of these dimensions improve how data and information functions within an overall RPD process. As a result, DIQ dimensions have been systematically adapted and associated with specific aspects of disaster response decision-making, and their outcomes. As outlined below, this provides an initial conceptual foundation for future research, rather than a complete or all-encompassing set of findings.

5.2. Future research

The current paper provides a conceptual foundation for a broad range of future research into DIQ during disaster response. For example, DIQ for disaster response can be extended to address group-level macrocognition, where decision-making adapts to scenario complexity by engaging the capabilities and capacities of several decision-makers. Other relevant decisions can be made using more fluid interactions between humans and information systems, such as decision-making via augmented reality. It is hoped that both human-centric and technological approaches to macrocognition will improve responses to interacting, disaster-related dynamics within complex and highly interconnected human-environmental systems. Even though these topics are beyond the scope of the current paper, the same set of DIQ-related concepts are highly relevant for making progress on addressing them. Ongoing research will focus on more specific definitions for each DIQ dimension outlined in the current paper. Efforts are also being made to validate and refine each DIQ function, in terms of how DIQ supports specific RPD dynamics and helps to mitigate errors made during disaster response tasks.

At the time of writing, relevant research is also underway to develop processes and criteria for the effective fusion of multiple data and information types and their multiple sources. This research has the potential to improve the reliability and credibility of certain information types and

Table 2
Proposed DIQ functions, RPD processes and information examples.

DIQ Function	RPD Tasks	Data and Information Examples	Key DIQ Dimensions
Stimulus	Experience the Situation	Initial alerts, reports & environmental cues	Validity, Reliability & Credibility, Accuracy, Currency, Availability & Accessibility
Training	Mental Model Selection	Education, training and experience	Completeness, Validity, Reliability & Credibility, Accuracy, Currency, Usability & Interpretability, Consistency
	Pattern Matching & Categorization	Education, training and experience	Validity, Accuracy, Currency, Usability & Interpretability, Consistency
Curation	Pattern Matching & Categorization	Rudimentary IT interfaces	Completeness, Validity, Reliability & Credibility, Accuracy, Currency, Availability & Accessibility, Usability & Interpretability, Consistency
Analytical	Mental Simulation of Response Planning	Topographical maps, including hazard maps	Completeness, Validity, Reliability & Credibility, Accuracy, Currency, Availability & Accessibility, Usability & Interpretability, Consistency
	Modifications	Topographical maps, including hazard maps	Completeness, Currency, Availability & Accessibility, Usability & Interpretability
Monitoring	Implementation	Situation reports	Validity, Reliability & Credibility, Accuracy, Currency, Availability & Accessibility, Usability & Interpretability

sources, together with other DIQ-related benefits. Additional research will focus on specific DIQ dimensions for various disaster response roles and for specific disaster contexts such as fire, earthquake, or flood. The resulting definitions and information architectures will support response agencies to manage DIQ in acutely practical settings.

Funding

All of the sources of funding for the work described in this publication are acknowledged below:

BNU-HKBU United International College, Project No. R72021103.

Massey University Research Fund (MURF).

Declaration of Competing Interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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