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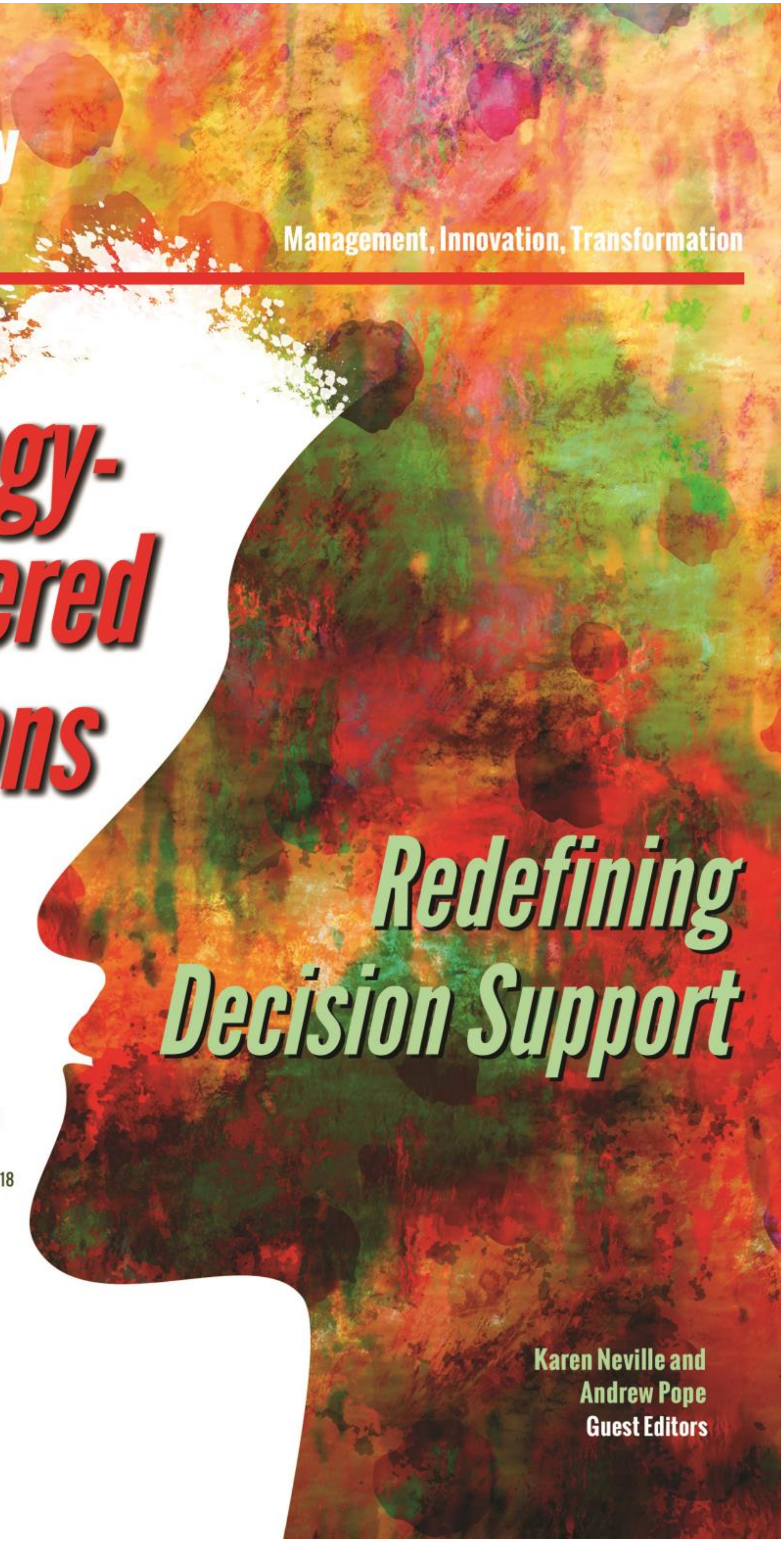

Redefining Decision Support

Karen Neville and
Andrew Pope
Guest Editors

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Opening Statement

by Karen Neville and Andrew Pope, Guest Editors

The origins of decision support systems (DSSs) can be traced back to the 1970s, when the promise of enhanced managerial decision making through the use of models and the data processing capabilities of computers were first touted. Some would argue that this history goes back even further. However, it is not our intention in this issue of *Cutter Business Technology Journal* (*CBTJ*) to review the entire DSS literature, as many others have done a fine job of this already.[1]

Over the last 50-plus years, DSSs have been applied in numerous settings — whether it be allocating resources during an emergency, predicting crime, improving medical outcomes in a hospital setting, or optimizing a company's supply chain. It could be argued that the evolution of DSSs is neither linear nor straightforward. Yet, despite fundamental changes to the underlying technology that drives DSSs, the discipline has thrived. Indeed, innovations in information and communications technology (ICT) have brought with them successive generations of DSSs. There will be many who argue that artificial intelligence (AI) and DSSs should not be grouped together; however, the expansion of DSSs and the influence of technically related disciplines has a historical precedent. Thus, we see DSSs playing a pivotal role as a reference discipline for advances in AI, big data, machine learning (ML), and data analytics.

The cutting edge of DSS development is that exciting intersection between DSSs and these new technologies. The human-centered lens of a DSS can provide a particularly advantageous perspective by promoting a people process and technology approach that goes beyond quantitative models alone. While AI research has attempted to *replace* the human decision maker, DSS researchers and practitioners have sought to *assist* the human decision maker. The next generation of DSSs must straddle these dual, often conflicting, purposes. Cloud-based storage and infrastructure-on-demand have removed many of the constraints traditionally associated with implementations, and advancements such as AI and ML have stretched the boundaries of what is possible. It is only natural, then, that such technology advances have engendered even greater optimism with regard to ICT-assisted decision making.

Our massive appetite for accumulating data is matched only by the inexorable advances in technologies that support the creation and storage of that data. However, it is through the analysis of such data that real value is derived. The positive impact of data-driven decision making on firm performance is well established. But big data, with its large volumes, high velocity, and variety, does not lend itself to the traditional analysis methods. A new breed of business analysts skilled in data science and Agile practices is crucial for the next wave of DSSs.

Lessons learned from data warehousing and online analytical processing systems can teach us how to glean insights from ever-increasing volumes of data. The application of quantitative data models and simulations to aid decision makers, as typified by model-driven DSSs, are more relevant than ever. Big data's Achilles' heel — the analysis of semistructured and unstructured data — is a well-trodden path in DSS research. Past research on dashboard design principles for data-driven DSSs can guide the data visualizations of tomorrow.

We can also learn from past mistakes unencumbered by the technical limitations of previous generations of DSSs. Previous work on group decision support systems, for example, quickly moved from systems that support colocated managers to systems that support geographically dispersed managers as communications technology improved. In the same way, the next wave of DSSs is evolving to incorporate data that is no longer restricted by geographic and organizational barriers. Social media activity; real-time, cloud-connected sensors; and virtual assistants are just some examples of the ever-growing sources of data. Identifying and prioritizing data sources of strategic value will be a crucial activity going forward.

For more than 50 years, the DSS discipline has evolved by incorporating the technological advances of the day. However, the longevity of DSSs is not due to technology alone. DSSs seek to leverage the insights and experience of users who interact with such systems. The discipline's enduring success has always relied heavily on humans' creativity and innovative capacity. As the field of DSSs has expanded to include other reference disciplines and technological advances, so too have the possibilities that such growth affords us.

Issues of values, trust, collaboration, and decision bias represent key challenges at the intersection between DSSs and AI. We contend that the practice of leveraging user insights and involving a wide variety of stakeholders in the collaborative design of DSSs is similarly prudent for AI and big data analytics projects. One only has to look at the example of the recent global financial crisis, and the subsequent rise of behavioral economics, to appreciate the limitations of quantitative models and the importance of unquantifiable insights. Deciding whom to rescue first in an emergency, for example, raises a dilemma that cannot be answered by technology alone. But technology can play a role by facilitating collaboration and communication between experts and leveraging past experience.

Hiring business analytics talent and leveraging skilled employees are key requirements for business intelligence (BI) success.[2] Beyond technical and modeling skills, ethical and aesthetic concerns are often nonquantifiable and require participation from a broad range of stakeholders. Issues such as trust, motivation, and conflict are poorly understood in the realm of big data.[3] Co-opting users into the design process may alleviate some of these concerns.

In This Issue

The challenge for this *CBTJ* issue was to accurately represent the diversity of research in the DSS arena while also giving a glimpse of the cutting-edge DSSs of tomorrow. As a starting point, Ciara Heavin and Daniel Power provide an overview of the design and development of modern BI and data-driven DSSs. They identify challenges and opportunities for managers and provide a sociotechnical view of DSSs by demonstrating practical guidelines for the people, process, and technology components of modern BI and data-driven DSSs.

The next two articles speak to the diversity of settings in applying DSSs. Both incorporate cautionary tales for practitioners tempered with practical solutions to address these concerns. Tom Butler and Leona O'Brien provide a timely perspective on AI in the financial industry. Their article provides a pragmatic perspective on the capabilities of AI and pours cold water on some of the hyperbolic claims made about AI and ML in the fintech and regtech space. The authors suggest a direction and guidelines for future research for AI to realize its potential in the financial services sector.

Next, Frederic Adam and Paidi O'Raghallaigh tackle the current healthcare crisis. They shine a light on the opportunities provided by medical decision support for clinicians and patients and identify a number of challenges to achieving connected health, which they define as "the use of technology-based solutions to deliver healthcare services remotely." The article proposes a connected health blueprint that may well pave the way for future connected health systems.

The next two articles focus on emergency management (EM), providing guidelines for the use of scientific modeling technologies in disaster management and for contact tracing of airline passengers during a biological outbreak. The aim is to improve disaster mitigation, preparedness, response, and recovery, leading to better economic and human outcomes.

Theresa Jefferson and Gloria Phillips-Wren discuss modeling for disaster response. This is vital for practitioner/manager decision making to reduce the impact of a natural or man-made disaster. The authors examine the concept of technology embeddedness, noting that emergency managers must trust the technology and show a preference to use it *prior* to an actual disaster; the time to integrate technology into disaster recovery operations is not *during* a disaster. They explain how to effectively appropriate, integrate, and use modeling technologies for disaster response and, therefore, recovery.

In our final article, Michael Gleeson discusses how public health agencies and emergency managers can leverage the digitization of contact tracing of airline

Upcoming Topics

Cutting-Edge Agile II
Alistair Cockburn

Industry 4.0
Keng Siau

Is Software Eating the World?
Greg Smith

passengers at risk from a biological outbreak. He outlines the increased risk of infection and spread, facilitated by the increased numbers of airline passengers globally. A global framework to prepare for and respond to a biological threat, natural or otherwise, spread via air travel, can be achieved through the digitization of contact tracing using a collaborative approach among the airline industry, public health agencies, and EM practitioners. Identifying and locating at-risk passengers in a fast and efficient manner is paramount to limiting contagion spread.

Looking Forward

Successive generations of DSSs have leveraged emerging technologies to enhance the breadth and scope of the domain. AI, ML, and data analytics will be the hallmarks of the next generation of technology-assisted DSSs. The articles in this issue highlight the technology that will drive the next generation of DSSs and illustrate the criticality of the *human* aspects of decision making. We advocate the importance of diverse stakeholder involvement in the analysis and design phases along with the use of technology to enhance collaboration and communication for distributed teams and improved decision making through training and simulation. Business analysts must augment traditional requirements-gathering techniques with data science skills. Project leaders must leverage their communication skills to champion new technologies and articulate the business value of AI-assisted decision support.

To learn about how new technologies will impact the traditional corporate environment, we need only look at users who experience needs similar to those of corporate users — but in extreme forms. Take, for example, cross-border or transboundary EM where multiple stakeholders often combine to make joint decisions irrespective of agency or geographic location. In such scenarios, strategic decision makers use complex data sets, risk models, and real-time sensor data while also leveraging the local insights of skilled decision makers. Decision making is enhanced by technology without ever being truly dependent on it. However, imagine a future where ML has the potential to enhance decision making by reducing cognitive bias and removing the stress associated with human decision making under duress.

From a societal perspective, dealing with large-scale issues such as connected healthcare and the prevention of pandemics will require a concerted effort from the private sector to cut across rivalries and administrative red tape. A more focused research approach is prescribed to meet the opportunities AI provides in the financial sector. There is also a huge opportunity for industry consortia to pave the way for the DSS/AI architecture of the future while also upholding ethical standards that adequately reflect wider societal values and morals. Each article in this issue provides practical insights for managers. In effect, we are not simply asking what the DSSs of the future can enable us to do. We are asking what we need to do to ensure the success of the next wave of DSSs.

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Implementing Modern Decision Support and BI

by Ciara Heavin and Daniel Power

Computerized decision support and business intelligence (BI) are necessary for organizations to compete successfully in many industries. Many first-level and middle managers routinely use performance dashboards, enterprise resource planning systems, forecasting and replenishment systems, and a plethora of other specialized decision support capabilities, and some senior managers use BI or data-driven decision support systems (DSSs). However, these legacy capabilities are from second- or third-technology generations. Today's managers need to invest in upgrading or replacing existing capabilities and thus make strategic investments in developing new decision support capabilities. The realm of decision tasks has greatly expanded.

> *There is no single, widely accepted approach or methodology to design and develop modern decision support or BI capabilities and tools.*

DSSs are interactive computer-based systems that help managers use computer communications, data, documents, knowledge, and models to solve problems and make decisions. Building data-driven decision support for BI, model-driven decision support for forecasting, and other decision support tools for human decision making requires complex, time-consuming design, development, and implementation tasks. Today's new technologies present opportunities for DSS developers to follow a more solutions-based approach to solving problems using artificial intelligence, machine learning, decision process support software, subjective and qualitative data analysis from social media and experts, or perhaps in some situations totally rethinking decision support.

Building decision support capabilities using new technologies certainly raises some familiar questions; however, the technology alternatives have vastly changed, and the possibilities have greatly expanded. For instance, revisiting earlier design and development decisions may show that factors from the past that constrained our choices no longer exist. Indeed, some decision support solutions considered and rejected may now be feasible. With the premise that modern decision support and BI are complex sociotechnical systems, this article explores issues and questions that are especially important to assess and evaluate prior to building new decision support capabilities. We cover various elements regarding implementation, including the design approach, requirements, appropriate technologies, and user knowledge/expertise.

Designing Modern Data-Driven DSSs and BI

There is no single, widely accepted approach or methodology to design and develop modern decision support or BI capabilities and tools. Broadly speaking, there are three main approaches to system design and development: (1) the traditional system development lifecycle approach; (2) rapid prototyping (aka Agile development); and (3) end-user development.[1] Each approach has its pros and cons, making it difficult to recommend the "best option" for modern decision support and BI. However, given the development of easy-to-customize tools, an Agile approach with rapid prototyping is often optimal.

In many cases, leaders and decision makers have only a general idea regarding the DSS and BI possibilities and the effort required to design and deploy a novel decision support capability. IT managers and developers may realize how complex business decision making surrounds the current disrupted business environment, but their understanding of how to improve and support decision making may be biased or incomplete and their ideas may be limited.

Establishing system requirements and user stories is easier when problems are routine and structured. The more unstructured the decision, the less knowledge there is available of what requirements will best serve the decision maker and the decision-making scenario.

Uncertainty about requirements should lead the way to using an Agile development approach. Managers can explain the current decision process, and developers can document that process and then work with participants to brainstorm problems and possible improvements.

Data-driven, model-driven, and knowledge-driven DSSs incorporate facts and past data along with observations into the respective systems. Although DSSs may quantify some intangible decision-relevant data and incorporate this data into analyses and models, decision makers must still assess the accuracy and relevance of the data and analyses provided in the system. Thus, soft, subjective data must be incorporated when relevant and deemed appropriate. It is important to remember that some data is difficult to capture and record, and some sentiments, values, and subjective data cannot be captured at all. Consequently, big data may or may not be useful for modern decision support and BI.

Decision makers may not recognize some assumptions used when building a DSS; that gap may then negatively influence analysis of a specific decision problem. Making decisions without considering assumptions implicit in using a decision support tool is a serious mistake. Decision makers must realize that computerized DSSs are merely support tools and are not infallible. Indeed, decision makers must recognize that a decision support result is nothing more than a recommendation.

Although recent advances in computing user interfaces for decision support tools make the tools much easier to learn, understand, and manipulate, some decision makers may be reluctant to adopt and use a new decision support tool. Potential users with greater IT knowledge and expertise often find it easier to learn new systems than those who are infrequent users and hence lack knowledge and expertise. Thus, developers should strive to build a decision support capability that targets potential users, matching the design to user needs, abilities, and skills.

In his book *Change by Design: How Design Thinking Transforms Organizations and Inspires Innovation,* IDEO CEO Tim Brown writes:

> A purely technocentric view of innovation is less sustainable now than ever, and a management philosophy based only on selecting from existing strategies is likely to be overwhelmed by new developments at home or abroad. What we need are new choices — new products that balance the needs of individuals and of society as a whole.[2]

New approaches to product and service design, such as design thinking, help understand complex user requirements and decision scenarios. Moving away from the analysis of historical data and an overemphasis on technology, a design thinking process is a creative approach to understanding existing user problems in order to better understand the future needs of decision makers. Therefore, decision support design should focus on: (1) viability, (2) feasibility, and (3) desirability. Human-centered design "brings together what is desirable from a human point of view with what is technologically feasible and economically viable."[3]

Design thinking promotes a human- or user-centered approach to understanding stakeholders' problems, contexts, lived experiences, and decision needs. Exploring the specific decision support needs of users as part of an ongoing design-build-evaluate approach will likely result in a DSS that fulfills users' needs. Furthermore, involving users early and often promotes engagement and ownership of the system with the aim of identifying and tackling the complexities and challenges of the decision scenario early in the design process. This approach is ideal for the development of decision support for complex decision scenarios; for example, it is widely used in the design and development of clinical DSSs. Pursuing an iterative, Agile, and incremental approach to DSS prototyping and evaluation will help DSS designers and developers, in collaboration with end users, create viable decision support capabilities that are usable, accessible, and fit for purpose.

Selecting Technology for Data-Based Decision Support

Information and decision support technologies are evolving. Technology selection is important, but not all decision support must be built using new technologies and unfamiliar software. Vendors constantly promote new products to managers and IT staff, but developers must carefully evaluate possibilities and inform managers about the tradeoffs associated with alternative technologies. Decision support "on the go" (or mobile decision support), for example, is expanding in terms of capabilities and ease of deployment. And managers are increasingly viewing off-premise BI — mobile BI or mobile intelligence — as necessary to compete. Mobile business analytics broadens the capabilities available to managers, sales staff, and anyone operating away from place-bound decision support. The opportunities for mobile BI and DSSs are many, and the trends toward self-service data analytics and visualization are both exciting and promising for data-driven organizations.

For instance, wireless networks have expanded in coverage and are ever-faster, which has facilitated the increased development of improved informational and decision support applications. Mobile analytics and BI use wireless devices to provide information transfer that enhances decision making, and, in general, mobile delivery platforms are a rapidly maturing decision support application area. Mobile BI applications exist for all mobile operating systems, with more applications becoming available from startups and traditional BI vendors for innovative dashboards, live reports, customer relationship management, and performance monitoring. There are many options in the increasingly competitive mobile DSS and BI market, and it is not easy to identify the optimum application(s). Market analyses are widely available comparing these technologies based on such factors as user feedback, developer feedback, application features, rate of adoption, price, and so forth. Managers must not only decide on a prioritized set of criteria for evaluating the available options but must also focus on selecting the most appropriate option with the aim of achieving a well-articulated business objective.

> *BI is no longer solely for senior managers and IT professionals, as the enhanced availability of self-service BI provides new opportunities to share data.*

Many organizations deliver mobile BI as a native application as well as providing mobile-responsive Web-based access. Given the demand for iOS mobile BI, many vendors start by offering native Apple applications for iPads and iPhones and then develop mobile BI for the other platforms. Mode of delivery is not hugely important to most mobile BI users; however, they are concerned with the accessibility of the data coupled with the analytical and visualization capabilities of the tool. Advances in mobile technology, networking infrastructure, and BI software have supported the opportunities for advancing mobile BI. However, the wide range of mobile devices in terms of screen size, processing, and storage capabilities makes the design and delivery of great mobile BI a challenge for BI designers and developers.

Today's increased availability and use of mobile technology and Web 2.0 technologies foster collaborative decision support. Consequently, BI is no longer solely for senior managers and IT professionals, as the enhanced availability of self-service BI provides new opportunities to share data, subsequently creating better opportunities for collaborative decision making. Furthermore, improvements in software facilitate new ways of embedding decision support features in existing software applications.

Mobile BI analytics, BI, and DSSs provide easy access to timely decision support. Successful implementations provide three major benefits:

1. Faster access to decision-relevant information
2. Anywhere, anytime access to decision support, improving operational and process efficiency
3. More widespread BI and DSS deployment, which can facilitate business expansion in the form of cross-selling and upselling opportunities

All this brings us to security. In modern organizations, data governance and security are important priorities that must be considered in parallel with BI, decision support, and analytics opportunities. While self-service BI using cloud-based data storage may offer benefits to individual users, realizing this level of flexibility and agility is challenging for many organizations, particularly in terms of security and maintaining data governance and data quality.[4] Ensuring data security while providing improved data access to a greater number of users with decision support needs is a challenge. Managers need to prioritize data security features when identifying and selecting/building mobile analytics/BI solutions. Further still, organizations need to implement new data security policies and strategies that address the needs of this new, mobile self-service workforce that align with government regulations (e.g., the European Union's General Data Protection Regulation).

Building Decision Support Solutions

Encouraging and developing data-based decision support is an organization-wide effort and requires many resources, including people, money, and technologies. Building an effective decision support capability can help improve decision making, but meeting that goal is a challenging task. Providing company-wide decision support requires creating a sophisticated IT architecture of computing assets as the foundation for data-based decision making and digital transformation. Data-based decision making benefits from computer-based support for collecting, analyzing, and sharing different types of data, keeping in mind that often relevant decision support information is derived from real-time and historical quantitative and qualitative data.

Creating and managing a modern computing architecture requires a mix of people skills, technologies, and managerial procedures that are often difficult to assemble and implement. Most companies need to purchase high-end servers with multiple processors; advanced database systems, including NoSQL databases; and translytical databases to support real-time transaction processing, data analytics, and big data storage capabilities. Importantly, managers need to understand the business use case before they can approve the appropriate mix of hardware and software. Moreover, highly skilled IT professionals with advanced database design and data management skills are required to implement a suitable, enterprise-wide decision support architecture.

5 Pivotal Questions for Senior Managers

So how can senior managers increase the chances of the successful implementation of an enterprise-wide data-based decision support, analytics, or BI project? The answers to the following five pivotal questions provide some insight:

1. **Who should be involved?** To get the project on the road to success from the start, identify an *influential, knowledgeable project champion* who must be a respected senior manager. A project champion can deal with political issues and help ensure that development participants realize that they are part of a cross-functional analytics and decision support team. The team may change over time, but it will include business analysts, software developers, data scientists, managers, and statisticians.

2. **What challenges will managers encounter?** Generally, the major challenge comes from *technology shortfalls*. Hardware and software problems are inevitable with enterprise-wide DSS/BI projects. Often, the technology to accomplish a desired decision support task is not currently available or not easily implemented. Unforeseen problems and frustrations will occur. Building any decision support capability, whether data-driven or model-driven, requires patience and perseverance. Thus, managers need to maintain their focus on decision support development goals that directly align to organizational objectives.

3. **What does management need to know about the new DSS/BI capability?** Managers need to *understand what is possible* for the new DSS capability. They need to be both ambitious and realistic in their expectations. Developers and the project champion must be clear about the costs of creating and using the proposed decision support capability. Managers need to know, for example, how much it costs to develop, access, and analyze decision support data.

4. **How does management ensure targeted users will adopt the new DSS/BI capability?** Key users need to be *involved in the design* of a new DSS capability. Given the number of off-the-shelf solutions available, most organizations consider buying before attempting to build their own DSS/BI capability. Typically, these applications require customization to support the needs of the organization. Such customization must be driven by the targeted users of the decision support application.

   Moreover, it is essential for organizations to put forth the appropriate level of investment in *training users*. Digital competence is no substitute for intensive professional training. Set aside adequate resources, both time and money, so users can learn to access and manipulate the data and capabilities in a new (or updated) data-driven DSS or BI system. From the start, encourage users to "test" routine, complex questions used for recurring decision support.

5. **How should the project champion share important information about the new DSS/BI tool?** The project champion must *market and promote* the new decision support capability using many channels, including face-to-face, videos, and small group meetings. Moreover, the project champion should provide incentives and motivation for appropriate use of the system.

Ongoing Challenges for Decision Support

Effective decision support requires ongoing innovation and refinement. As decisions become more complex and as data increases in quantity and variety, systems must undergo refinement and enhancement. Consequently, decision support requires a continuous and iterative design and development process.

Moreover, evidence suggests that many DSS/BI projects are still partial or near-complete failures (i.e., not meeting expectations). Why? The absence of a knowledgeable project sponsor who is not in the IT realm is often part of the problem. The sharing of a realistic vision is also crucial to success.

Then there is the training issue. Ultimately, we have lost sight of what training means for enterprise applications. Training differs when the targeted user group is 50-100 senior- and middle-level managers versus 500 store managers, or even 10,000 store employees. Computer literacy does not mean someone can learn on their own or with video on-demand training. People have never liked to read "manuals," whether printed or via online help or PDFs. One-on-one coaching is often the best approach.

In many cases, managers can be coached to perform their own self-service analyses. However, in some respects, supporting decision-making interaction between people and technology in workplaces remains extremely challenging. Thus, employing sociotechnical thinking can take into account both social and technical factors that influence the functionality and usage of computer-based DSSs.

Conclusion

New types of decision support such as mobile DSS and self-service BI provide a greater number of employees with analytics capabilities and promote enhanced interaction and collaboration among staff. However, it is important to keep the business use case at the center of an organization's strategy for the design and development of novel approaches to DSSs and BI. Figure 1 illustrates a modern user-centered approach to decision support design and development.

Focused on the actual, lived experiences and problems of targeted decision makers, Figure 1 emphasizes the need to understand decision-maker data, analysis, and visualization requirements for good DSS/BI design and development. Designers and developers can then identify the most appropriate hardware and software, including data storage, processing, and visualization capability. From a design and development perspective, few organizations develop modern DSS/BI solutions from "scratch"; rather, for most organizations, a new DSS/BI capability requires that an off-the-shelf software product be purchased, customized, and tailored to serve the needs of the intended users. For the decision support capability to be a success, the new solution must be promoted, and project champions must be incentivized to engage with each stage of design, development, and evaluation by providing valuable feedback on every iteration.

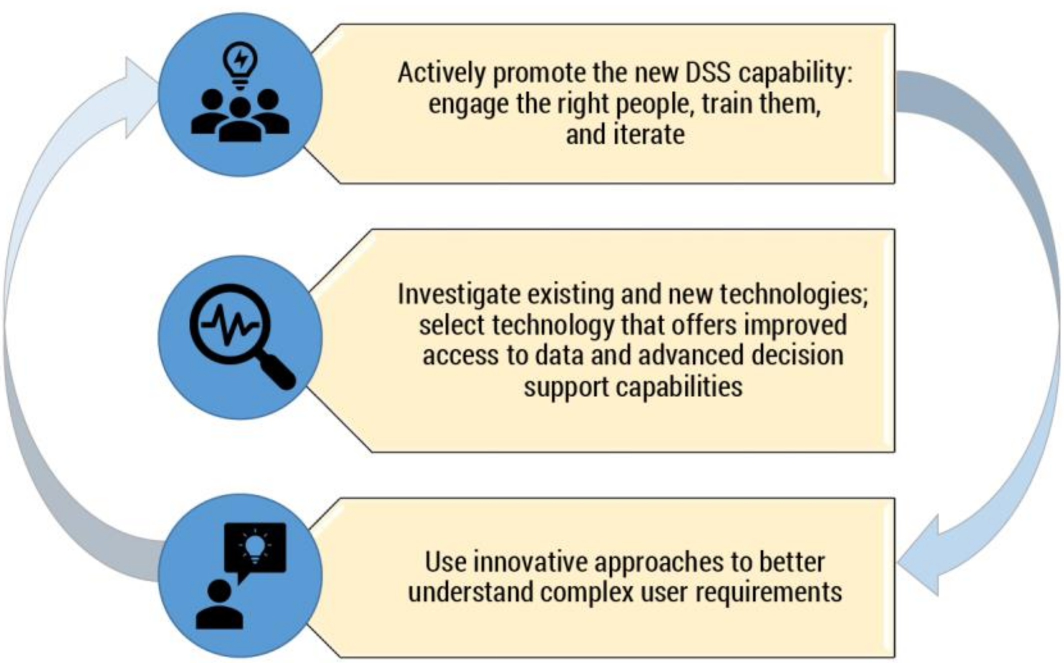

Figure 1 — Modern user-centered approach to decision support design and development.

Decision support and BI capabilities for managers are still evolving and are certainly not mature. Managers must review their current decision-making processes and identify the needs and hopes for more effective computerized assistance and then share that information with information and decision support professionals.

Much has changed in 70 years of decision support development, but major gaps of functionality likely remain. Following the prescriptions for successful implementation identified in our answers to the five pivotal questions may seem easy and straightforward, but too often implementation and deployment of decision support and BI is considered part of a "well-worn" path, and that perception is not true. Change is always challenging, and new paths are constantly tried. Both organizational practices and organizational culture must adapt to maximize benefits from modern decision support and BI.

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AI in the Financial Industry: A Pragmatic Perspective

by Tom Butler and Leona O'Brien

This article critically examines the promise and potential of artificial intelligence (AI) in the financial industry. Financial institutions have digitally transformed their business processes and products, creating vast sources of structured and unstructured data. AI offers the means to complete this transformation in radical ways — across the front, middle, and back offices, while also addressing the big data problem. In addition, AI is also shaping the fintech and regulation ("regtech") landscapes, particularly in addressing what has become known as "Big Regulation." However, AI's promise must be balanced with current limitations to the application of enabling technologies like machine learning (ML) and natural language processing (NLP). This article takes a pragmatic approach in explaining the promise, potential, and limitations of AI in the financial industry. It concludes by identifying how a combinatorial approach to the application of AI technologies, based on good data governance, can make the AI dream come true for financial institutions.

Smart machines with AI capabilities offer financial institutions the potential for greater automation, to better manage the digital world of big data, and to further transform banks to true digital enterprises. In assessing AI's general capabilities, Brynjolfsson et al. argue that AI "is a 'general-purpose technology,' like the steam engine and electricity, which spawns a plethora of additional innovations and capabilities."[1] However, it is clear from their analysis that AI's potential remains unclear, as does the answer to the question how best can AI be employed to reap the benefits of the digital transformation of financial enterprises through fintech and regtech?

The problem with AI is that its capabilities and application have generally failed to create business benefits over the past 62 years; nevertheless, some argue that AI may be at a tipping point.[2] Pragmatists argue, however, that AI will not achieve its potential "without a reengineering of how business organizations operate."[3] Nevertheless, many organizations have achieved success in the application of AI and are enthusiastic about its potential. Take, for example, Chevron CIO Bill Braun, who states: "It's springtime for AI, and we're anticipating a long summer."[4] However, there is the possibility of a "third AI Winter"; that is, the period of pessimism among researchers, the press, industry, and governments that followed the failure of AI to deliver on its promises in the 1970s and late 1980s/early 1990s.[5] Avoiding this outcome requires a pragmatic understanding of AI and the pragmatic integrative application of enabling technologies.

Understanding the Art of the Possible with AI

The concept of AI was first proposed by computer scientist John McCarthy during the Dartmouth Summer Research Project on Artificial Intelligence in 1956.[6] Indeed, it was the early computer scientists who recognized the potential of computers to perform logical and mathematical computations better, faster, and cheaper than humans and at greater scale. AI has been the subject of intensive government, business, and academic research since way back then, with mixed results. Researchers posit three possible types of AI:

1. **Weak AI or "narrow AI."** This non-sentient type of ML, the objective of current research, "is aimed at creating programs carrying out specific tasks like playing chess, diagnosing diseases, driving cars, and so forth."[7]

2. **Strong AI/artificial general intelligence (AGI) machines.** These AI types are hypothetical as of 2019. AGI machines will have the potential ability to apply intelligence to any problem, rather than just one specific domain and to "learn to solve new problems that they didn't know about at the time of their creation."[8]

3. **Super intelligence.** This area is also currently hypothetical. In this scheme, AI machines surpass human semantic, perceptual, and cognitive abilities.[9] Due to recursive self-improvement, super intelligence is expected to be a rapid outcome of creating AGI.

Weak or narrow AI may be all that is possible in the short term.[10] However, researchers assert that explainable AI (XAI) is required to achieve it. David Gunning of the US Department of Defense's Defense Advanced Research Projects Agency (DARPA) argues that:

> The current generation of AI systems offer tremendous benefits, but their effectiveness will be limited by the machine's inability to explain its decisions and actions to users. Explainable AI will be essential if users are to understand, appropriately trust, and effectively manage this incoming generation of artificially intelligent partners.[11]

Regulators in the financial industry, for example, are concerned about banks' use of virtual assistants or chatbots, which, for the most part, currently make unexplainable or black box decisions when providing consumer advice and choices. Concerns also exist around AI technology being used to manage risk and compliance. There are, however, other more fundamental problems and challenges to address, as the remainder of this article indicates.

The world of digital business is, in essence, a mirror image of the analogue commercial reality facing banks and other financial institutions. In the digitized world of financial data, there are truly enormous volumes of heterogeneous structured and unstructured data across siloed data stores. Managing such complexity is beyond human cognitive abilities or comprehension; hence, AI-based smart machines are required to assist human cognition and decision making.

The volume, velocity, and variety of laws and regulations since the global financial crisis resulted in what has become known colloquially in financial services in London as Big Regulation. Responding to this, the *Financial Times* in 2016 reported on the growth of the regtech market,[12] with AI technologies being employed to reduce the cost of regulatory compliance on the industry side and the cost of supervision on behalf of the regulatory side.[13] However, many argue that all AI currently does is "digital pattern matching."[14] This is sufficiently effective for a range of business and regulatory problems but comes with its limitations. These limitations arise because the low-hanging fruits of the ML approach predominate, at the expense of a combinatorial approach that involves knowledge representation, NLP, and ML.

Limited problem solving in narrow domains combined with digital pattern matching are currently all that AI is generally capable of achieving. A machine does not have a "mind" in the neurological sense. Human-created combinations of models, algorithms, and hardware are incapable of "knowing." Thus, financial, legal, and regulatory subject matter experts will remain in the loop for some time. That may not be a bad thing for society as it adjusts to the potential of AI's reshaping of the analogue world. Nothing stays the same, as Judea Pearl and Dana Mackenzie claim in the *Wall Street Journal*:

> When researchers combine data with causal reasoning, we expect to see a mini-revolution in AI, with systems that can plan actions without having seen such actions before; that apply what they have learned to new situations; and that can explain their actions in the native human language of cause and effect.[15]

However, to arrive at that point, the financial industry will need to undergo a paradigmatic transformation. We now turn to what is practically possible.

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Practical Application of AI in Fintech and Regtech

There are three general technological paradigms in AI: knowledge representation (KR) (capturing semantics in models such as ontologies and vocabularies), NLP, and ML. Deep learning (DL) is a sophisticated form of ML that employs artificial neural networks (ANNs). Collectively, they offer great promise in making AI a reality — at least weak AI. However, they are being employed individually, with ML the most widely used. For example, the Financial Stability Institute reports that AI-enabled supervisory technologies (a variant of regtech called "suptech") chiefly involve the application of ML (supervised and unsupervised learning and ANN) and NLP for data analytics.[16]

The Big Regulation and big data problem domains are not suited to traditional programming approaches that encode regulatory and business rules and logic into static programs.[17] Moreover, many extant software engineering approaches and practices that involve applying engineering solutions to complex problems are severely limited in their abilities to do so. Such practices have been the subject of significant criticism, and the software itself considered high risk,[18] as the recent Boeing 737 Max failures indicate.[19] This may be a serious issue for automating compliant financial processes, given the significant evidence that problems with dysfunctional approaches to software development contributed to the global financial crisis.[20]

The financial industry is currently focusing on AI solutions using ML and NLP technologies. Here, software, fintech, and regtech vendors are developing and improving models using data and supervised (training) and unsupervised learning. This proves more effective than previous AI approaches. In ML, a machine uses data and classifications provided by humans (algorithms and models on data patterns) to make predictions and decisions. With DL, a machine can autonomously learn in order to adapt to changing environments. However, while DL attempts to make manual software engineering more efficient, it is still too immature a technology. As ML and DL do not currently employ XAI, they would currently be unacceptable to regulators. On a practical note, as current software engineering practices lack sufficient rigor,[21] particularly where technologies of compliance are concerned,[22] all such models need stringent risk assessment.

Knowledge representation is a key element in semantic computing, which involves combining KR approaches such as semantic metadata models represented as ontologies and vocabularies with NLP to process unstructured data and then federate and integrate heterogeneous structured and unstructured data.[23] This approach models knowledge as machine-readable ontologies of concepts and their relationships. While data visualization is a basic application of ontologies, expressive and fully axiomatized ontologies can be used for inferencing and reasoning. Here is the powerful contribution that ontologies have made to AI. From a practical perspective, the EDM Council's Financial Industry Business Ontology (FIBO) is an open standard semantic metamodel developed by council member financial institutions to perform semantic computing.[24] FIBO represents knowledge of how financial instruments and business entities and processes work in the financial industry.[25] Semantic metadata models are relatively mature in several industries, and several large banks currently employ such models to perform semantic computing for operational risk.

Figure 1 captures the current state of practice in the financial industry's application of AI. It indicates the potential of models, algorithms, and applications when applied to practical use cases through smart machines in the financial industry to automate and informate business processes and ensure financial compliance.[26]

It is important to note that the financial industry currently depends heavily on ML approaches. These include regression (statistical models), support-vector machine, graph theory, Bayesian (Bayesian belief network, Gaussian naive Bayes), decision trees, ensemble, clustering, and rule-based system models and algorithms. Software houses, IT departments, and fintech/regtech vendors that use an ML approach aim to reduce development costs and time (to market), a goal that involves a significant move from designing traditional program-based applications and is not

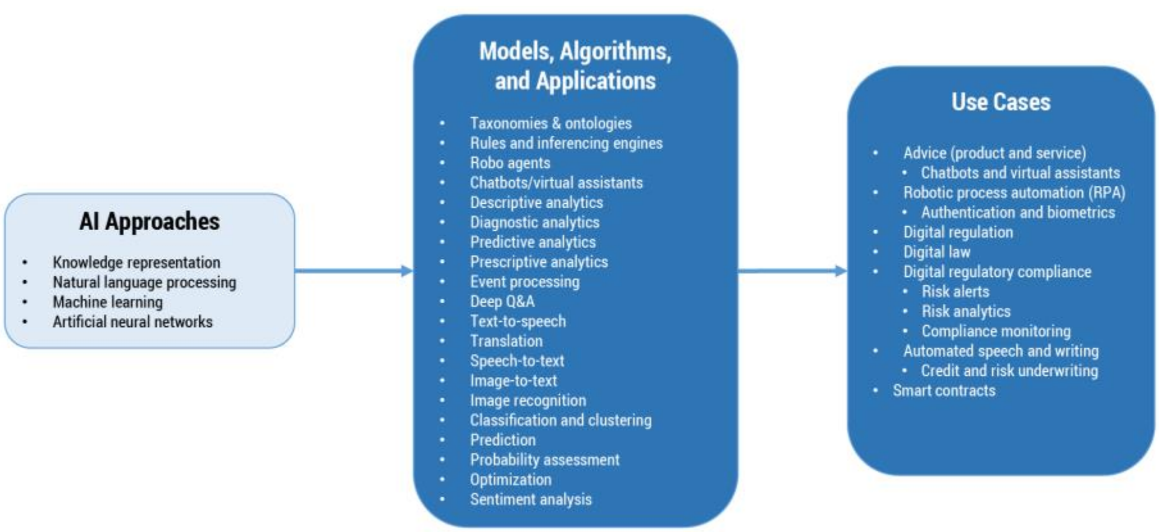

Figure 1 — AI approaches, models, and use cases in the financial industry.

risk-free. ML approaches employ ensemble models and learning algorithms integrated into software-as-a-service applications. Much human input is required for the development of all AI approaches, particularly engineering and subject matter expertise from knowledge and software engineers; computer scientists; mathematicians; linguists; cognitive psychologists; and financial, legal, and risk professionals with legal, business, compliance, and risk knowledge.

State of Practice 2019

Many large financial institutions have AI R&D programs in place. These are either in-house (e.g., JP Morgan Chase, Goldman Sachs, HSBC, Bank of America), where adequate IT resources and capabilities exist or can be acquired, or involve collaborating with startup companies through accelerator programs, or pilots. A recent *Financial Times* article provides balanced insights into current thinking across the industry, with an analysis of 30 of the world's largest banks revealing that robotic algorithms, ML, and NLP are being employed for the following purposes:[27]

- Chatbots and virtual personal assistants
- Customer profiling
- Automating and streamlining processes
- Data analytics and spotting patterns in data
- Risk management, chiefly through de-risking first-line business processes in the front, middle, and back offices

Amazon, Google, Apple, Facebook, Microsoft, and IBM are all investing heavily in AI R&D.[28] Financial institutions, fintechs, and regtechs are doing likewise.[29] Google has invested more than other Big Techs, with US $3.9 billion invested, the majority of which was spent in its 2014 acquisition of Nest Labs ($3.2 billion).[30] However, this investment pales in comparison to that of IBM, which, between 2010-2015, invested $15 billion in cognitive computing and, since 2015, an additional $5 billion in acquisitions.[31] This amount dwarfs that of the other top 10 tech companies whose collective investment is estimated at $8.5 billion. Notably, IBM Watson Financial Services is leading the way in the application of AI in digitizing financial services and for regulatory compliance.[32]

Furthermore, potential competitors to banks are investing heavily in AI, with Apple and Amazon spending $786 million and $871 million, respectively.[33] Across the world's top 30 banks, the total amount being invested is at least $90 million and at most $400 million. So the entire financial industry is, on lower estimates, investing 11.45% of Apple's investment and at best a bit over 50% of Amazon's. But, if one takes IBM's total spend as approximately $20 billion, we get a sense of how unprepared the banking sector is, and, indeed, how vulnerable it is to Big Tech players extending their focus from payments into other banking and insurance services.

It is imperative for the financial industry, particularly dominant players, to keep pace with digital innovation, including AI. This means applying a critical perspective to question the AI hype and educate senior executives on AI's practical limitations. To be sure, significant strategic, tactical, and operational advantages can accrue from the application of AI. However, as we have previously argued, current AI-based approaches based on ML and NLP alone limit the potential contribution of AI.[34] This is particularly relevant given predications that AI will benefit financial institutions with $1 trillion in savings by 2030.[35] In addition, the front, middle, and back offices will see a gain in productivity of 20%-40% as firms switch from humans to bots, with the front office saving $490 billion; the middle office $350 billion, and the back office $200 billion. This translates to $450 billion in cost reduction for banking and $400 billion in cost reduction for insurance. Risks include the operational risk of AI software failure and regulatory risk.[36]

Conclusion

According to Foteini Agrafioti, head of Royal Bank of Canada's AI research arm Borealis:

> There are too many people making these statements [about big cost and job impacts]. The problems we have solved are very narrow. The misconception is that humans and machines can perform at the same level. There's still a long way to go and many challenges we need to solve before a machine can operate [at a level] even near the human mind.[37]

Agrafioti is clearly of the opinion that the benefits of AI, as they currently exist, are being hyped. Given our knowledge of the market and engagement with regtech vendors and financial institutions, what people say they are doing with AI and what they are actually doing are often poles apart. IBM Watson has come under specific criticism in this regard.[38] We believe that if AI is to achieve its promise, financial institutions are going to have to address a range of challenges.

Based on our previous research,[39] we posit the following. The primary challenge for firms applying AI is data access and quality, specifically access to, and the quality of, heterogeneous data spread across internal and external silos. Firms will need to focus on data identification, enrichment, and integration before pattern recognition and intelligent response using AI solutions will be possible. However, semantics and KR approaches provide an ideal approach to virtualize data.[40] Knowledge engineering and semantic computing approaches will, we believe, be key.

Our research indicates a clear shortage of experienced knowledge engineers and computer and data scientists, particularly as concerns ML, NLP, ANNs, and KR. This talent shortage will act to constrain many AI initiatives.

Chief risk officers and regulators will require XAI, as black box AI-ML solutions will become controversial. How an AI-ML-ANN application arrives at decisions and the impact of those decisions on clients will need to be transparent. Likewise, any AI-ML-ANN application used for risk mitigation and risk data aggregation will come under similar scrutiny. Research by DARPA identifies AI technologies that have the potential to provide XAI.[41] The need for human subject matter experts to be "in the loop" will become the norm as the limitations of AI become apparent.

Our research on semantic technologies indicates that if AI is to realize its potential, the industry will also need to focus on semantic KR and machine reasoning — this is semantic computing. The industry is currently focusing on what is known as perceptual computing, enabled by the ML paradigm and NLP. To be truly effective, albeit as weak AI, hybrid approaches involving semantic KR, machine reasoning, and ML/DL technologies are required. Furthermore, these will need to be based on open standards–based technologies and models. This approach offers the optimal route to sustainably leveraging the many benefits of AI.

The rationale behind this argument is straightforward. Over the past five years, we have observed in our field research that practically all financial institutions have problems with data federation and integration. The root cause is a lack of investment in information architecture and adequate data governance. These problems have been underlined by CDOs (corporate data officers) and CIOs at major conferences.[42] The bigger the bank, the bigger the problem with "spaghetti pots" of systems and data. The absence of common business and data taxonomies and vocabularies within and across organizations is therefore a significant problem that hinders the potential of current ML/NLP.[43]

Thus, semantic metadata models that represent business and regulatory knowledge about data are required. Standards-based ontologies that express common business and data concepts, such as the EDM Council's FIBO, are required. The first and most practical use case for such models is to virtualize structured and unstructured data, enabling access, whether in production data stores or data lakes. The second is to create new knowledge based on reasoning and inferencing over internal and external structured and unstructured data to identify unknown relationships. Reasoning and inferencing engines are mature technologies that offer complementary predictive, prescriptive, and descriptive analytics capabilities to extant ML and DL approaches. However, we argue that to make AI work, there must first be a return to the rough ground of information architecture. Only then will a combinatorial approach using KR, ML, and NLP realize the potential benefits of AI in the financial industry.

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Smarter Medical Decision Support:

The Case for Connected Health

by Frederic Adam and Paidi O'Raghallaigh

A Healthcare Sector in Crisis

While life expectancy has continued to increase in most places in the world over recent decades, it seems the concept of *healthy life expectancy* is not keeping up. As life expectancy lengthens, so does the prevalence of several chronic conditions, such as obesity, diabetes, and elevated blood pressure (BP), which dramatically affect the lives of portions of the population.

As well as being responsible for a significant number of early deaths, chronic conditions reduce the quality of life for many adults and represent a substantial financial cost to patients, insurers, and the health and social care systems. In recent times, the number of people seeking care for such conditions has increased at the same time that there is a growing shortage of healthcare professionals in both the primary and secondary care areas of many health systems. In fact, the demand for services is growing at such a rate that our reliance on face-to-face interactions for the delivery of care is compromised and the healthcare systems of many countries are faced with the medical equivalent of a "perfect storm."

One striking aspect of this evolution is that both developing and developed countries are facing the same crisis, although in different shapes and with different degrees of urgency. Crucially, the medical area is one that illustrates very well that developing countries should no longer try to follow the same slow stages of development developed countries have used. Where there is a new technological frontier, developing countries should strive to leapfrog evolutionary steps and catch up to the latest advances.

Because it is light in infrastructure, connected health — the use of technology-based solutions to deliver healthcare services remotely — can be the next step in the development of healthcare systems the world over. For instance, many African countries have mobile telecom networks on a par with those of the most advanced European countries, providing a great opportunity for them to catch up to developed countries in a number of domains, including mobile healthcare.

The current healthcare crisis is here to stay, however, at least in the medium term. It is resulting in lengthening waiting lists, reduced attention to individual patients, overworked medical staff, and even closure of medical facilities as operating units cannot be staffed adequately. All this is against the backdrop of significant budgetary constraints. These crisis impacts conspire to reduce the effectiveness of the healthcare system and negatively affect the patient experience, making it impossible to maintain patient safety and adhere to quality standards.

The Burden of Chronic Conditions

A substantial contributory factor in the current evolution of healthcare is the rise of chronic conditions. Some chronic conditions are genetic and can be found in relatively stable conditions in all countries. Other chronic conditions are related to unhealthy sedentary lifestyles and other factors, such as a poor diet and poor sleep hygiene. Diabetes and hypertension, for example, are reaching epidemic proportion and, although they were initially considered to be developed world illnesses, there are signs that they are becoming issues in the developing world as well. Insofar as these are essentially conditions caused by behavioral factors, they cannot be adequately managed through medical intervention alone. Management requires sustained changes in an individual's lifestyle and behavior, meaning that the focus for caregivers must switch from treating an individual once he or she has developed a chronic condition to keeping that person healthy in the first place. The scale of the current development of these conditions leaves no margin for error: action is urgently required.

Given the increasingly early age at which some of these conditions appear (obesity, for instance), it is essential to educate individuals from an early age to develop their commitment to looking after themselves. This crisis is systemic; many societal factors have combined to bring it about and continue to exacerbate it. Very difficult-to-control factors, such as consumerism, advertising, and social media, are all contributors. The solution is also systemic and will involve many actors in society, including the medical insurance systems (health practitioners, insurance providers) and education systems (schools, teachers, sports coaches, as well as parents and the individuals themselves), among others.

Yet, conventional fee-for-service reimbursement models discourage preventive technologies and services that would keep people healthy and out of the hospital. We must realize, however, that this is the only sustainable way to provide more effective healthcare while also reducing costs within the context of healthcare systems that are nearly bankrupt due to double-figure annual inflation in medical costs. New approaches, enabled by emerging technologies, can allow individuals to become more aware of their health status, to take greater responsibility for their lifestyle, and to make knowledgeable decisions about their behaviors. In this context, knowledgeable means data-driven and evidence-based, in a landscape where too many people — notably teenagers — are exposed through social media to low-quality (and often incomplete) advice about many aspects of their lives. The pressures they face or that they put on themselves (e.g., to maintain or achieve a certain appearance) are often conflicting and their attention is pulled in many different directions. Individuals are often presented with complex lifestyle choices, many of which are in direct competition with a healthy lifestyle. Some young people might feel inadequate physically, for example, and may be enticed to rely on training regimens and alimentary supplements that are inappropriate (and sometimes dangerous). They might also be tempted to adopt dietary advice that is dangerous to their well-being.

A Solution for the Future

The growing prevalence of the Internet of Things, together with plummeting component costs, has made it possible to connect just about anything, from the very simple to the very complex, and to offer remote access, sensing, control, and monitoring. These technologies make it possible for healthcare providers and patients to work together to improve health in novel ways that were previously unimaginable. A critical element in this new model is that focusing on what is happening with the patient when they are *not* in front of a health professional, using sensors to deliver remote monitoring and a more complete picture of an individual's health, is more likely to have an impact than focusing on the brief amount of time spent during in-person medical visits. Joseph Kvedar, MD, suggests that the healthcare industry should focus more on what is happening with the patient during the 99% of time the patient is not in front of the health professional.[1]

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Sensors are one way for healthcare to move beyond face-to-face engagements with health professionals, providing a more complete picture of an individual's health through remote monitoring and self-generated data. Crucially, this approach does not have the elevated costs associated with face-to-face care. The technology is there to digitally empower individuals to conveniently and unobtrusively take care of their health either themselves or as part of a monitoring service moderated by a health professional (e.g., a remote monitoring system for BP and weight that can provide nurses with automatic alerts). Patients can monitor their own health status, and at the same time, there is an escalation path whereby nurses can review patient data each day and communicate with only the highest-risk patients and, when appropriate, alert their doctors.

The adoption of these technologies, however, requires patient engagement. Studies have shown that activity trackers are very popular — one out of five people over the age of 18 owns an activity tracker[2] — and surveys have found that about 33% of the population have a health-tracking application of some sort.[3] However, a French study reported a slow exponential decay of Fitbit Zip device usage, with 25% of users dropping out after three months and only 16% still using their tracker after 12 months. The average duration of usage in this study was 129 days, which indicates people's limited attention span for such devices.[4] Individuals want to do what is best for their health, but they struggle to jump from good intentions to good behavior. New technologies that are now available must be rolled out on a wide scale to empower individuals to change their behaviors to become healthier and to manage their chronic conditions. The goal of connected health must go beyond merely *collecting* data and toward "nudging" individuals from an early age into healthy behaviors that stick over time.

Wirelessly connected sensors can enable feedback loops, which feed personal health data from devices back to individuals, raising awareness and offering everyday support and solutions. In combination with social media, where individuals post their everyday results, achievements, and problems,[5] proactive prevention rather than reactive care can be achieved for all individuals, through a certain level of peer pressure to perform and positive reinforcement when things go well.

> *Connected health methods, by providing technology-based solutions, can alleviate or eliminate problems across many healthcare domains.*

Thus, research investment must be directed toward exploring the use of personalized, motivational, engaging interventions for individuals to help them improve health and sustain behavioral change. Such interventions will entail incentivizing patients to engage with change programs and adhere to the recommendations given to them. Incentives can take the shape of rewards, reduced premiums (as is the case for drivers who accept having their cars fitted with trackers in exchange for discounted insurance premiums), and/or priority access to faster or more complete services.

An Architecture for Connected Health

Connected health methods, by providing technology-based solutions, can alleviate or eliminate problems across many healthcare domains. Figure 1, based on research carried out at the INFANT research center, University College Cork, Ireland,[6] formally exposes this broad principle. It indicates four domains for connecting health methods:

1. **Home-based solutions** — allow people to be monitored from their own home, without the need to travel to hospitals or clinics. Home-based solutions offer the promise of round-the-clock interventions embedded in the places where people live.

2. **Community-based solutions** — allow patients to receive the same level of service they would typically only be able to receive in a hospital in their community: in primary care centers, general practitioners' practices, and so on. Community-based solutions afford a unique opportunity to accelerate the integration of all care that patients must access and to provide a much more holistic system of care reliant on a much higher level of data sharing among healthcare specialists. This integration is critical in the case of multiple illnesses; particularly chronic illnesses that increasingly are present together (e.g., diabetes and elevated BP). Integration can also greatly increase the speed at which patients can access key services.

3. **Ward-based solutions** — patients are automatically monitored in real time while in the hospital using an array of wireless and wired sensors. As an example, a patient's vitals may be collected at regular intervals and stored on a dedicated platform. Ward-based solutions offer the potential to increase the frequency of monitoring without any increase in workload, allowing staff to concentrate on treating patients rather than taking BP readings and writing them down every hour or so. Ward-based solutions can boost the implementation of electronic early-warning scorecards, which compute patients' health status scores in near real time, particularly in intensive care wards where the frequency of monitoring directly correlates with the speed of identifying patient deterioration and implementing escalation paths.

4. **Low-resource settings** — for conditions that, in the Western world, are usually treatable but still potentially lethal. This special case has enormous potential in terms of improvements to the health outcomes of patients in these settings. These improvements are both critical and broad ranging — from access to information and services, to diagnosis and treatment, to disease surveillance and general population health — and carry a far more affordable transaction cost than that of a traditional system of care.

Figure 1 illustrates a generalized typical architecture for the delivery of a connected health service. In part, the required architecture will already be in place yet will require dedicated investment and development. At the bottom of the diagram, the cloud-based area of the solution includes an electronic health record (EHR), which is now an industry standard in some healthcare

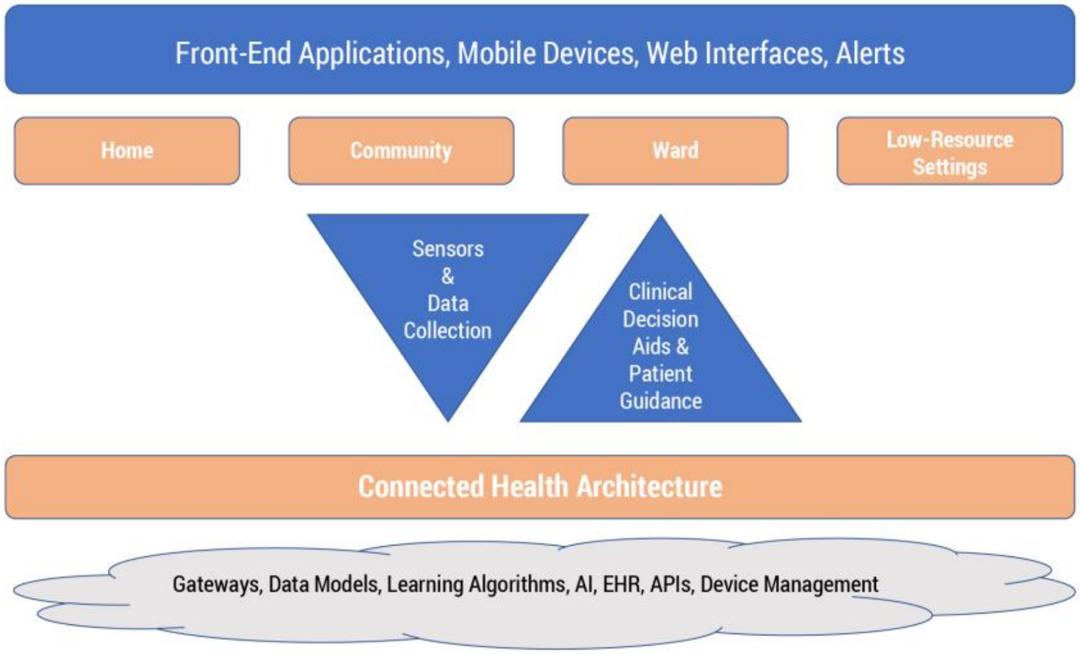

Figure 1 — An architecture for connected health solutions.

systems, including those of Estonia and Australia, and an ambition in others. An EHR is the basis for the systematic collection of all relevant patient data across time and across interventions. The existence of a national EHR is the basis for sharing data between medical staff and for the continuity of care.

Achieving the implementation of such a national data architecture is in itself a challenge that requires difficult decisions and the leadership to drive change and uniformizing of practices in healthcare. Many countries are not yet at that stage, and even the basic concept of sharing medical data between the different elements of the healthcare system causes legal issues. These challenges explain why, initially, data sharing is likely to be limited to national entities — sharing medical data on a global scale will be a challenge for a future century.

The bottom layer in the architecture also includes dedicated services for device management, to recognize the data uploaded by the different sensors used throughout the healthcare system and properly assign the data received to each patient/user. Any artificial intelligence (AI) system or set of algorithms would also be stored there, where it could be invoked by users to analyze the data, either automatically in real time — raising alerts in case of health deterioration (e.g., on an intensive care ward) — or on demand, when a clinician is trying to diagnose a set of specific symptoms.

The top layer of the diagram shows the front-end applications, running on the phones of the patients, on the tablets of the clinicians, or on the desktops of the hospital administrators. These applications all contribute to various aspects of the solution: data collection, remote patient monitoring, note-taking, provision of advice and instructions to patients, and so on.

The middle layer shows the flows of data — running from the front end to the back in the case of data collected, and from the back end to the front when it comes to the decision support provided to clinicians or the advice sent to the patient.

We can consider the architecture shown in Figure 1 as a template for a broad range of connected health applications. The case of low-resource settings deserves some additional observations: in this scenario, countries may have organized their healthcare systems around a small number of large hospitals serving as centers of excellence. Large proportions of the population, however, may reside in remote areas and have limited means to travel to these hospitals. Their health needs are served primarily by conveniently located local dispensaries, which may be staffed by nonmedical staff under the supervision of one generalist nurse.

While local dispensaries are effective for many illnesses, the type of interventions that can be undertaken locally is limited, and an escalation of care often requires traveling to one of the large hospitals. The use of remote monitoring devices can increase the range of locally viable interventions by allowing a remote consultation with a specialist and triage of patients, with the result that only a small number of patients, instead of all of them, still need to travel to the hospital.

Given the scale of the challenges facing us, and the potential scale of connected health solutions, we have little choice but to "byte" the connected health bullet, because it is the only chance to break the vicious cycle of rising workloads, long waiting lists, and inadequate budgets.

WHO and UNICEF are promoting country-specific guidelines to better support healthcare workers in these settings in order to provide targeted health information (e.g., to expectant mothers); to run immunization clinics; and to assess, diagnose, and treat prevalent illnesses such as malaria.[7] These guidelines are ripe for digitization, which could be the basis for the development of a program of targeted interventions, leading to customizable, personalized support service, and, more importantly, to large-scale preventive services that target large portions of the population before anyone becomes a patient. Such large-scale interventions are currently totally impossible in a traditional healthcare delivery scenario.

The connected health scenario lends itself to the acquisition of large volumes of health data and its analysis, which facilitates the development of learning algorithms and other AI artifacts that can guide doctors toward correct treatment, based on a faster recognition of symptoms. The area of hypertension in pregnancy and, particularly, the early diagnosis of pre-eclampsia in pregnant women, is an example of a pathology where the collection of large-scale data and its systematic exploration using deep learning techniques has the potential to greatly consolidate diagnosis, accelerate the identification of at-risk cases, and reduce the number of false positives. Given the nature of BP as an indicator of health status, false negatives are not very likely unless devices are faulty but may be a critical consideration in the case of other connected health applications. Thus, device management will remain a challenge, even in a connected health scenario.

Conclusion

While healthcare systems around the world are clearly facing enormous challenges from medical inflation, tight budgets, and the increasing burdens of chronic diseases and an aging population, technology-based solutions are coming down the track under the dynamic banner of connected health. The new challenge will be to properly select the applications that have greater potential and to deploy them safely across regions, nations, and continents. In certain areas, it is already apparent that this new challenge is changing shape and has shifted toward the need to "connect the system back to itself." The proliferation of independent siloed systems will not amount to overall improvements in healthcare service but will only widen the gap between centers of excellence and the dark ages of healthcare provision.

Given the scale of the challenges facing us, however, and the potential scale of connected health solutions, we have little choice but to "byte" the connected health bullet, because it is the only chance to break the vicious cycle of rising workloads, long waiting lists, and inadequate budgets. The scale of investment required will mean resources must be set aside to fast-track the development and implementation of the architecture illustrated in Figure 1 on a large scale. In many countries where the state does not have the financial capacity to front such investment, collaboration from industry will be required. Some large players, notably in the high-tech industries, are getting ready to face up to the challenge, with IBM and Microsoft, for instance, committing to invest billions of dollars in healthcare in years to come. For areas of the world such as Africa, collaboration with these large players will be critical to leapfrog experimentation stages and move rapidly toward an efficient digital healthcare system.

The technical challenge of assembling the multidisciplinary teams required to properly specify and develop the applications that will realize the potential of connected health must be met head-on. Technologists, application developers, cloud services providers, medical experts, insurance providers, policy makers, parliamentarians, and, of course, patients will need to come together and undertake the vast technology assessment exercise[8] that must underpin a rigorous and harmonious evolution from the current healthcare systems of the world to a global connected architecture that will provide the ability to look after everyone equitably, in a distant and perhaps somewhat utopian future.

Developing the decision support layer of the connected health architecture we have discussed in this article, and, in particular, harvesting and leveraging the vast volumes of data that connected health applications will generate — from home, from the community, or from hospital wards — will require an even broader range of rare skills. Successful connected health solutions will rely on data scientists and AI experts, as well as leading-edge medical experts with the foresight to understand what data to use for early detection of chronic conditions and the ability to design prospective studies to determine which lifestyle changes can keep these chronic conditions at bay. One current example of such development is underway at the INFANT research center, where a team of neonathologists and health information systems specialists focus on how to collect and leverage data on "the first 15 minutes of life" in order to better care for the small proportion of babies that are born before 32 weeks of gestation (about 1.5% of all births) and are at significant risk of a range of permanent injuries, particularly brain injuries.

The development of fully connected platforms for national — and, even more so, global — connected healthcare will require much more, including the coordination and harmonization of access to services, which, at the moment, is well beyond reach. It is sufficient to consider the vast differences in equitable access to health in different countries and the different level of resources committed across the world to realize how far we are from anything that resembles a global system of healthcare.

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The Search for Embeddedness: Leveraging Scientific-Based Modeling in Disaster Response

by Theresa Jefferson and Gloria Phillips-Wren

Numerous studies concerning the response to extreme events demonstrate serious management, coordination, and problem-solving issues that diminish the ability to minimize human suffering. Yet there is a plethora of scientific modeling technologies available today to aid in both the planning for and response to disasters. In fact, the availability of scientific models is accelerating — but adoption of such technology has shown a much slower growth pattern.

This article focuses on determining ways of appropriating, integrating, and using scientific modeling technologies to improve disaster response efforts. In addition, we uncover key reasons that scientific models are currently underutilized in disaster operations. Our goal is to provide guidance to increase the use and assessment of modeling technologies for disaster response using the concept of technology embeddedness. A key takeaway is that the time to introduce technology into disaster management is *not* during the response phase; rather, practitioners must introduce and utilize these aids during the mitigation and planning phases, before an actual event occurs.

The Challenges of Disaster Preparedness

Scientific-based modeling systems contain extraordinary amounts of data and produce mountains of output. These systems offer almost limitless options for providing the user with informed knowledge. In emergency management (EM), in particular, geographic information systems (GISs) that incorporate scientific models are widely employed for running hazard simulations in support of planning and mitigation efforts.[1] However, a study by the US National Academy of Sciences found that numerous geospatial information tools were being effectively used in emergency planning, but very few were being used for emergency response activities.[2] This article seeks to use the concept of *technology embeddedness* to delineate factors that are prohibiting emergency managers from harnessing the capability of scientific modeling systems when responding to disasters.

In disaster response, emergency managers need sound situational awareness to support critical decision making. Situational awareness gives context to the information needs required for effective operations. Sound situational awareness is necessary to estimate the physical impacts of a disaster. Estimates of the physical impacts can then be used to derive the requirements for disaster response, such as water, food, and shelter, as well as the need for medical, evacuation, and rescue support. Unfortunately, emergency managers often do not have the information they need to obtain sound situational awareness following a disaster, resulting in a less than optimal response strategy. Further still, in major disasters, communication systems are often damaged, making it difficult to obtain information concerning overall damages and impacts in the disaster area.[3] Discerning relevant from nonrelevant information, especially during the first few hours of response, presents a huge challenge to decision makers. This is extremely problematic at a time when confusion is high, the common operating picture is vague, and communication is limited.

A key element of the common operating picture is disaster assessment. In today's environment, scientific models often incorporate a GIS interface, which offers a computer visualization of various types of data related to positions on the earth's surface. A GIS interface can display information based on actual data and data produced by scientific models. GIS-driven maps are in high demand when initiating a response effort, due to their ability to combine layers of data. The most useful maps show the impact area with damage information, the population locations within the impact area, the locations of assets and resources, expedient repair materials for shoring and patching, medical supplies, generators, power outages, and road and bridge closures.[4] After data has been verified as accurate, a

GIS allows the responder to view relationships between relevant components and make informed decisions.

Over the past decade, geospatial data and tools have proven invaluable in disaster operations. Emergency responders have used such tools to save lives, limit damages, and reduce costs associated with emergencies. Despite these benefits, there is still an underutilization of geospatial data and tools. This lack of adoption primarily stems from a lack of time and personnel to devote to the understanding of new types of tools and data sets.[5] Moreover, communities and local governments affected by the disaster could utilize these tools to make informed decisions or form disaster assessments. However, they currently lack the knowledge and training to do so.

Considering damages to communication networks, it may take hours, and possibly days, to generate accurate geospatial information. Thus, although many consider real-time GISs as the gold standard in disaster response, data and information required for the system are not readily available, and responders must fall back on traditional communication networks, such as radios and expert opinion. What is often overlooked in the search for real-time information is the use of scientific-based modeling using scenario analysis. Using these models can help narrow the gap between known information and required information.

There are many applications of scientific models in emergency management. Operations research has produced scientific and decision support models in emergency planning and response; recent studies have branched out along homeland security themes in the areas of border and transportation security, critical infrastructure, cybersecurity, emergency preparedness and response, and threat analysis.[6] In addition, policy and EM literature describe a common operating picture as the key to success for emergency response.

A lack of modeling and simulation tools is not the problem; as one survey of emergency managers pointed out, the response community often feels "inundated" with information on "new" modeling applications. However, existence is not the same thing as adoption. Many responders elect not to use these tools because they perceive their current environment as being too "low-threat" to justify model adoption. Some responders stated that they have concerns about the "experts" who have developed the models, and others believe that the models would be too hard to customize to fit their requirements. Some reported concerns that a model might diminish the role of interpersonal communication.[7]

Therefore, although there are many scientific models available, adoption has been hampered by the poor fit between the task of emergency response and the technology. Issues such as interoperability between organizations, poor communication, lack of real-time data, unclear leadership, lack of trusted data, distrust of the technology, and time lag are impediments to technology adoption. Technology needs to be embedded with the user so that it is a trusted, natural extension to the responder's decision making. In the sections that follow, we explore modeling and the EM lifecycle, and then apply the concept of technology embeddedness to assess how well the technology integrates into decision making for disaster response.

> *Issues such as interoperability between organizations, poor communication, lack of real-time data, unclear leadership, lack of trusted data, distrust of the technology, and time lag are impediments to adoption.*

Modeling and the EM Lifecycle

We can view the EM lifecycle as four interconnected phases: mitigation, preparedness, response, and recovery.[8] *Mitigation* includes activities that minimize the effects of a disaster. *Preparedness* comprises planning, training, or other activities that seek to improve the capability to respond to a disaster. The *response* phase includes actions taken during and in the immediate aftermath of a disaster to save lives and/or property. The *recovery* phase encompasses those activities that enable communities to return to a normal state. Due to their interconnected nature, occurrences in one phase can have a positive or negative impact on occurrences in other phases.[9] Therefore, implementing the correct measures in the preparedness phase can significantly minimize harmful effects during a disaster and, in turn, lead to a more successful response and recovery.[10]

In the discussion of scientific modeling that follows, we focus on the response phase. However, the models can (and should) be used for mitigation and preparedness. In fact, a necessary condition to effective use of scientific models during response is the familiarity of responders with the aids. Emergency responders must be comfortable with using decision aids before they need them under conditions of confusion and stress in an actual emergency or disaster.

Much of the literature on policy and emergency response challenges supports focus on early response actions, catastrophic disasters, and the immediate needs of victims. In Figure 1, the influence diagram illustrates the basic decision environment of the research problem and the fundamental goal of completing the response initiation and mobilization. The rectangles are derived from questions presented within the description of response activities in the US Federal Emergency Management Agency's (FEMA) National Response Framework (NRF), which provides guidance for communities in responding to disasters and emergencies. It describes the "principles, roles, and responsibilities, and coordinating structures" for delivering the "core capabilities required to respond to an incident and describes how response efforts integrate with those of the other mission areas."[11] The end state represented by the diamond in Figure 1 indicates the first stage of emergency response.

One technique used by national, state, and local EM organizations to better plan and prepare for catastrophic disasters within the US is scenario-based planning. This method starts with the development of a threat-specific scenario. Next, computer-based modeling determines the physical losses and social impacts. Then, response requirements, along with appropriate courses of action, are determined from analyzing the impacts.[12] As seen when studying past disasters, a critical success factor for disaster response is the creation of response plans
based upon realistic scenarios.[13]

Scientific-Based Models

Models have been developed to estimate the impacts to the population under various disaster situations. For example, RimSim is a simulation system developed by Bruce Campbell and Konrad Schroder to train medical logistics personnel to respond to an earthquake.[14] Unreal Triage is a "game" in which a player uses data transmitted from sensors located on "victims" to allocate victims into different triage categories.[15] A number of other scenario-based modeling efforts have focused on supply chains, logistics, and evacuation support.

In the US, the Emergency Support Function Leader Group (ESFLG) has catalogued scientific-based models.[16] ESFLG is composed of US federal agencies and departments designated as coordinators for emergency support functions or coordinating agencies for other NRF annexes. FEMA leads ESFLG and is responsible for helping the group jointly address such topics as policies, preparedness, and training. Under the direction of ESFLG, FEMA and its Modeling and Data Working Group led a federal interagency effort to develop an inventory of scientific-based models for

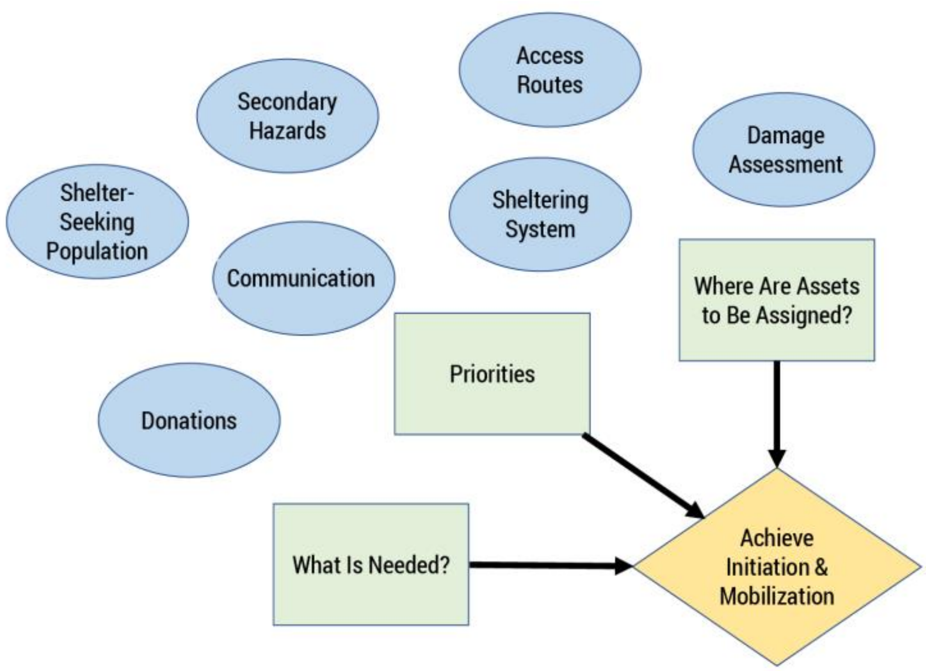

Figure 1 — General influence diagram of initial emergency response. (Adapted from US Department of Homeland Security.)

supporting operational decision making in the context of emergency management. Many of these models incorporate GIS interfaces. ESFLG developed a framework to illustrate the ways in which data and models can be used to assist all EM phases. As shown in Figure 2, this framework distinguishes between data sources (circles) and data processing tools (rectangles). The figure illustrates the relationships between the data and the tools. Data is processed by models (black arrows). Models produce data (dashed arrows) and this data is then used to refine previous data sets (gray arrows).

In Figure 2, *raw data* refers to data that is not processed and depicts the current state. It includes, for example, locations of fault lines, seismic activity, and weather conditions, among other data. Raw data is used as inputs to event characterization models and analysis tools that assist in defining or predicting events such as floods, earthquakes, and weather forecasts. When the raw data is processed through models for analysis, the output is called *situational awareness data*. Individuals can use situational awareness data to determine the state of the environment. Consequence models use situational awareness data to determine the impacts to society as well as the built environment. Consequence models produce outputs called *impact estimates*, which decision support tools can use. The outputs of decision support tools are *mission-specific requirements*, such as the personnel and resources needed to respond to the event.

The models and data that ESFLG has identified can assist in providing the timely and accurate information required for effective disaster management. The intent of this interactive inventory is to allow emergency managers to identify and incorporate data sets and models into operations plans. In an effort to encourage adoption of the available tools, ESFLG provides information to support the use of models and data sets during normal operations. Responders will only use tools with which they are already familiar once an actual emergency occurs. It is therefore necessary for potential users first to become familiar with the tools during normal operations.

Technology Embeddedness

Technology embeddedness is a concept that arises from an ideal world in which no boundary exists between the user and the technology. There is seamless integration between the two, and the technology is viewed as an extension of one's self. To instantiate this concept so that we can assess the degree of technology embeddedness, we utilize a theory about economic exchanges in which firms, and the people in them — operating within a *context* — form different types of relationships, some strong and some arm's-length. Turning to the relationship between the user and the technology, we want to describe characteristics that can be measured and that are indicative of the strength of the relationship. Borrowing from economic theory, we call this *technology embeddedness*.

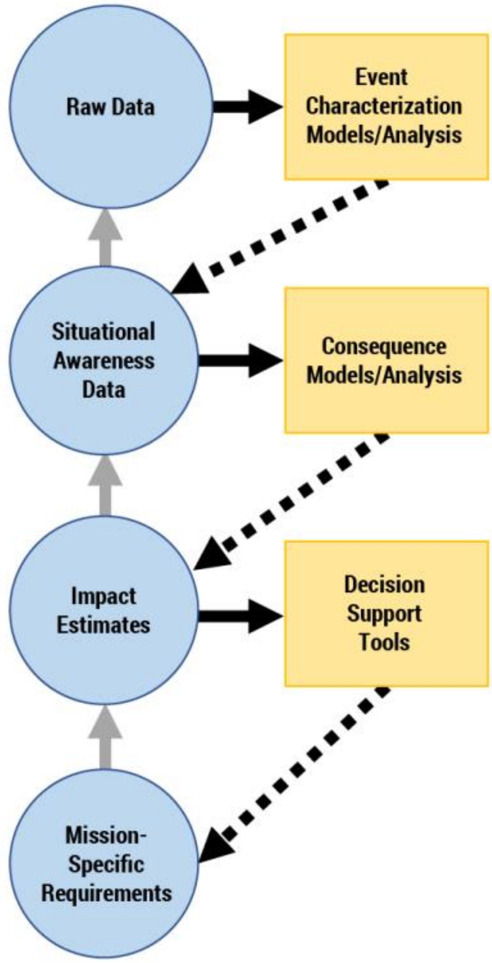

Figure 2 — ESFLG framework: an inventory of data and scientific-based models that support all phases of the EM lifecycle.

To measure the strength of technology embeddedness, we again borrow from economic theory and assess technology embeddedness in terms of two measurable characteristics: (1) *utilization* of the technology and (2) *preference* for the technology. On one hand, utilization expresses the frequency of use of the technology to accomplish the task. That is, how often do disaster responders actually use the technology to accomplish their tasks? On the other hand, preference describes the degree of users' desire to employ the technology to accomplish their tasks. That is, do disaster responders prefer to use the technology compared to alternatives? Preference implicitly includes trust in the technology, an essential factor in deciding to use technology for disaster response. Therefore, preference is a manifestation of user understanding of — and trust in — the technology. In preparing for and responding to an extreme event, disaster responders and the scientific-based modeling technology must work together to determine the appropriate response. The event itself, together with the user and the technology, form the context for the relationship. Context is then a precondition to embeddedness and describes the conditions in using the technology.[17]

We now need to describe the context for technology used in disaster management. Many previous studies of technology adoption in various settings have focused on tasks that individuals need to accomplish (i.e., *task characteristics*) and on characteristics of the technology (i.e., *technology characteristics*). In our studies of medical decision making under stressful conditions, we found that individual differences between users, such as experience level or familiarity with the technology, must be recognized as part of the context (i.e., *individual user characteristics).* In addition, local conditions such as time pressure or uncertainty provide another construct for context (i.e., *environmental characteristics*). The model for technology embeddedness is shown in Figure 3.

As an example, we apply these constructs to a context of the decisions regarding mass care. Mass care includes sheltering, feeding operations, emergency first aid, and bulk distribution of emergency items. *Task characteristics* concern the capacity of the modeling technology to align with the tasks required as part of the response effort. For example, consider a decision regarding sheltering: does the technology facilitate an assessment of sheltering facilities, such as the probability of physical damages and capacity? *Technology characteristics* concern the reliability of the software/hardware, availability, flexibility to accomplish the task, and ease of use. Technology characteristics are critical in the often-chaotic environment of emergency response. If the technology is not working as anticipated, and/or has reliability issues, the responders will develop a workaround.

Individual user characteristics concern individuals' willingness to use the technology and their knowledge concerning appropriate usage. As stated earlier, in

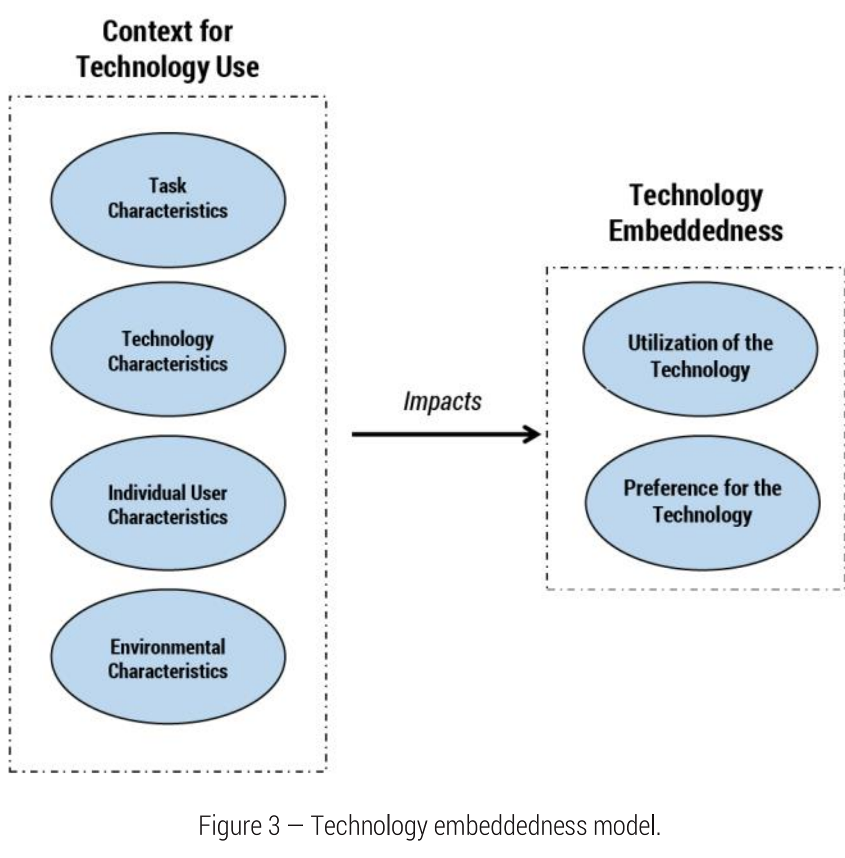

Figure 3 — Technology embeddedness model.

order for individuals to be willing to use a tool during response, they must first be comfortable with using it under normal operating conditions. During a disaster is not the time to learn a new technology.

The construct of *environmental characteristics* refers to appropriate support, organizational adoption, and culture concerning the use of scientific modeling technologies. Environmental characteristics can vary widely between organizations, specifically between countries, federal, state, military, nongovernmental organizations, and private corporations. Context will impact *utilization of the technology* and *preference for the technology*, which together provide a measure of technology embeddedness.

We believe that the model provides a way to quantify and assess the strength of the relationship between users and the technology and to investigate the underlying causes of any weaknesses. Structural equation modeling is well suited for this type of model exploration, as it provides for the modeling of complex dependencies and latent variables. The model also offers the opportunity to investigate the factors that lead to technology adoption or dissuade users from its use.

Summary

During the first few hours of disaster response, confusion is at its highest, the common operational picture is most vague, communication is limited, and information overload is common. Discerning relevant from nonrelevant information presents a huge challenge to decision makers. While the top priority at this time is obtaining accurate situational awareness, this is not an easy task, due perhaps to damages to infrastructure and the complexity of the event. Using existing modeling technologies can help by providing an initial model of the event that can then be updated as more accurate information becomes available. However, to many emergency managers, the thought of adding more, not necessarily accurate, information into the chaotic response environment is undesirable. Their unfamiliarity with the technology tools adds to their skepticism.

This article investigates the reasons that emergency managers in disaster response environments underutilize scientific modeling technologies. The goal is to provide guidance to increase the utilization of these technologies by developing a model using concepts of embeddedness and technology adoption.

We employ four contextual constructs (task characteristics, technology characteristics, individual user preferences, and environmental characteristics) to describe the context of system characteristics needed to support decisions on the use of scientific modeling technology during the emergency planning and response. Context is a precondition to embeddedness, and embeddedness of the technology is measured by utilization and preference. Utilization is the degree to which the technology is used to accomplish a goal. For emergency managers to rely on scientific-based modeling in a disaster environment, they must first trust the technology. Trust can be described as closeness or personal familiarity. We conceptualize trust, and the closeness between the emergency manager and the technology, as preference. Preference portrays the emergency manager's desire to use the technology to undertake a task and includes the emergency manager's feelings of trust and personal familiarity with the scientific modeling software. In our concept, the emergency manager and the scientific-based modeling technology cooperate to respond to the disaster.

Our model indicates that context is a precondition to embeddedness. Emergency managers focus on making decisions to minimize the impacts of a disaster on both the human and built environments, particularly on decisions regarding mass care. Therefore, the task characteristics involve the ability of the modeling technology to support the decision-making activities regarding mass care and to contribute in a meaningful way toward the accomplishment of response efforts. Technology characteristics concern the reliability of the software/hardware, availability, flexibility to accomplish the task, and ease of use. Individual user preferences concern individuals' willingness to use the technology and their knowledge concerning appropriate usage. Environmental characteristics refer to appropriate training, organizational adoption, and culture concerning the use of scientific modeling technologies.

Related but more detailed questions that can be extracted from exploration of the embeddedness model include:

- What causes emergency managers to reject the use of scientific-based modeling technologies?
- What are the impediments to emergency managers' use of scientific-based modeling technologies for disaster response?

- What are the characteristics of the disaster context that influence the use of scientific-based modeling technologies for disaster response?

The objective is to provide insights that will allow emergency managers to harness the capability that scientific-based modeling technology provides to improve decision making in the complex and chaotic disaster response environment.

The focus of this article is not on developing new technology but instead on determining methods for appropriating, integrating, and using candidate technologies to respond to an extreme event. Scientific modeling technologies can enable the decision making necessary in this often-chaotic environment. We believe that the effective use of modeling technologies will improve disaster mitigation, preparedness, response, and recovery, leading to better economic and human outcomes. The challenge for disaster response managers is how to better integrate technology into their operations and how to lead others to use it effectively.

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The Digitalization of Infectious Disease:
Preventing Biological Threats in the Sky

by Michael Gleeson

With the ever-increasing reach and speed of the global aviation network, contagion can spread anywhere in the world within 24 hours. As a result, the potential risk of introducing and spreading infectious disease is on the rise. This article explores the digitization of contact tracing of at-risk airline passengers in the event of a biological threat. With more than 4 billion airline passengers in 2017 and over 7 billion expected by 2036,[1] the possible transmission in flight of infectious diseases is of the utmost concern to global health authorities. In fact, in 2003, the emergence of severe acute respiratory syndrome (SARS) showed the potential of a contagion to emerge, spread, and affect the health and social and economic life of people across the world.[2]

The Air Travel Reality

People's increased mobility, facilitated by air travel, has resulted in the increased spread of contagion across geopolitical boundaries.[3] A growing awareness that bioterrorism agents could spread in the same way has raised the level of concern even more. Many practitioners and researchers agree that contact tracing, which is the identification and locating of people who may have been in contact with an infected person, represents an important factor in mitigating the spread of a pandemic.[4]

Transport networks, whether in the air, at sea, or on land, are continually expanding in terms of distance covered, speed of travel, and the volume of both passengers and goods carried. The increasing use and affordability of passenger air travel has contributed not only to people's growing mobility, but also to the increased transmission of infectious diseases, such as influenza,[5] tuberculosis (TB),[6] and SARS,[7] as well as a multitude of zoonotic diseases. In addition, the increased awareness of bioterrorism agents and their potential spread via air travel has caused public health agencies (PHAs) to reevaluate the potential spread in flight of these agents.[8]

According to the World Health Organization (WHO), air transport presents a key challenge to preventing the international spread of health risks.[9] In Europe in the 1300s, it took more than 10 years for the deadly Bubonic plaque to spread. Today, a person can travel almost anywhere in the world in a day, and a passenger can carry a fatal strain of avian flu from China to Europe within 24 hours. Indeed, the European Centre for Disease Prevention and Control (ECDC) has stated that air travel was behind the introduction of the influenza A (H1N1) strain into countries that had not been primarily affected previously. Moreover, airlines will likely be a major component when, not if, the next pandemic occurs.

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What Is Contact Tracing?

As a means of controlling pandemics, the WHO has laid down guidelines to assist public health agencies in tracing airline passengers. As a background to this process, consider that if a PHA receives a report of a person suffering from an infectious disease, it is the responsibility of the PHA to perform a risk assessment to determine whether any other people are at risk of acquiring the disease due to contact with the infected person and to perform "contact tracing" if needed.

Contact tracing is defined, by the ECDC's "Risk Assessment Guidance for Infectious Diseases Transmitted on Aircraft" guideline, as "an investigation procedure aimed at acquiring contact information in order to approach contacts that were potentially exposed to pathogens,"[10] and by the European Parliament as "measures implemented in order to trace persons who have been exposed to a source of a serious cross-border threat to health, and who are in danger of developing or have developed a disease."[11]

The contact tracing of infected or at-risk airline passengers falls under the remit of PHAs that are, in turn, guided by emergency management (EM) practitioners. The current process is that data collection is facilitated by EM practitioners and subsequently collated by PHAs. The EM lifecycle consists of four phases: mitigation, preparedness, response, and recovery. Contact tracing pertains to at least two of those phases: preparedness and response. During the preparedness phase, it is incumbent on PHAs to have the necessary protocols in place to quickly identify an at-risk passenger. Once a threat has been identified, these protocols are acted upon during the response phase.

> *Public health and aviation sectors, together with other stakeholders, must manage public health events in air transport to avoid the international spread of disease.*

Information systems, normally complex and multifaceted, have a critical role in EM.[12] Such systems consist of multiple stakeholders and require decisions to be made under pressure, in a timely manner, and with valid information.[13] To aid this critical role in EM processes, information system tools have been developed to facilitate decision making and are used by emergency responders and decision makers during the phases of the EM lifecycle.[14] These tools are paving the way for a digital version of contact tracing to be used as a decision-making tool.

What Can Be Done?

Because of the multifaceted response to an infectious disease outbreak and the possible political, economic, social, and healthcare impacts of an outbreak, it is vital that resources are appropriately allocated, in parallel with the timely dissemination of consistent information.[15] The digitization of contact tracing can play a significant role in providing information for identifying and locating passengers at risk from a biological threat, in a timely manner, and using valid data.

In general, PHAs require quick access to passenger data, which means without any significant time delay. The time slot open to initiate and perform contact tracing depends on the incubation period of the specific disease involved and the time left to apply public health measures. For most infectious diseases, the incubation period and the time left to apply such measures is short, further underscoring the need for prompt and accurate contact information. Public health and aviation sectors, together with other stakeholders, must manage public health events in air transport to avoid the international spread of disease.

To assist with contact tracing, WHO developed a ''passenger locator form'' (PLF),[16] which currently exists in paper format. The UN's International Civil Aviation Organization's "Guidelines for States Concerning the Management of Communicable Disease Posing a Serious Public Health Risk"[17] states that the PLF "provides an appropriate method of rapidly collecting passenger contact information: aircraft operators should determine if the PLFs will be kept on board, or at all destination airports. Depending on the specific hazard, the number of PLFs needed may vary, from a few to one for each passenger." The inference here is that paper copies of the PLF should be kept at airports and on airplanes, to be prepared if and when they are needed. It may be necessary to acquire the data of only a small number of passengers (those in an at-risk area of the airplane), or it may be that the data of all passengers onboard needs to be captured.

In most cases, once a public health threat has been identified, the airline involved would be asked for its passenger manifest, which is collected in a digital format, to aid with the contact tracing of the passengers on that flight. The passenger manifest usually consists of a shortened version of the passenger name record (PNR), and includes the passenger's name, seat number, and dietary requirements. It can take a few hours to a few days to receive this information, which then needs to be analyzed, leading to a delay in effectively identifying those at risk from a biological threat.

A PNR consists of information provided by passengers and collected by air carriers during reservation and check-in procedures. Noncarrier economic operators, such as travel agencies and tour operators that sell package tours making use of charter flights, also collect and process PNR data. PNR data may include several different types of information, such as travel dates, travel itinerary, ticket information, contact details, baggage information, and payment information. The PNR data is collected for the sole use of the airline, and in many cases lacks vital contact information, including addresses and contact telephone numbers.

In many cases, the only data from PNRs that is of use to public health authorities will be names and nationality information. Many countries do not have the ability to acquire contact information for passengers from passport numbers. Although a telephone number is often requested in the context of the flight booking procedure, this is not a requirement, and the accuracy of the provided information is unknown. It is therefore often problematic to trace passengers using the PNR information alone.

Delays in effective and efficient contact tracing result in the need for a significant increase in resources, such as vaccines and human resources, as EM practitioners must deal with a larger geographical spread (as those potentially exposed continue to travel) and an increase in the number of people potentially exposed. Delays can also result in increased socioeconomic costs, such as increased demand on public health due to retrospective identification of at-risk passengers. In the worst case, delays can potentially result in an increased loss of life.

The quality of the passenger data collected for analysis, from both the PLF and PNR, also poses challenges. More often than not, the data is inaccurate and incomplete, which frequently leads to delays in identification and incomplete tracing of potentially at-risk contacts. Identifying and locating exposed persons through contact tracing is an important procedure during the containment phase of an emerging communicable disease, which forms part of the EM response phase.

Barriers to the identification of at-risk passengers include the current paper-based process, noncollaboration between the airline industry and PHAs, questionable data validity, and privacy laws in multiple jurisdictions. The digitization of this process will allow for an enhanced digital version of contact tracing that will have the capability to be linked to both airline data systems and to public health data systems. Digitization, along with the necessary legislation, should greatly reduce, if not negate, these current barriers.

Where to Now?

PHAs and EM practitioners have indicated that a digital method of contact tracing is preferable to the existing paper-based method (Figure 1 illustrates a prototype digital form). The existing methods (PLF combined with PNR) require greater time to collate and analyze than would a digital version. Thus, locating the "index"

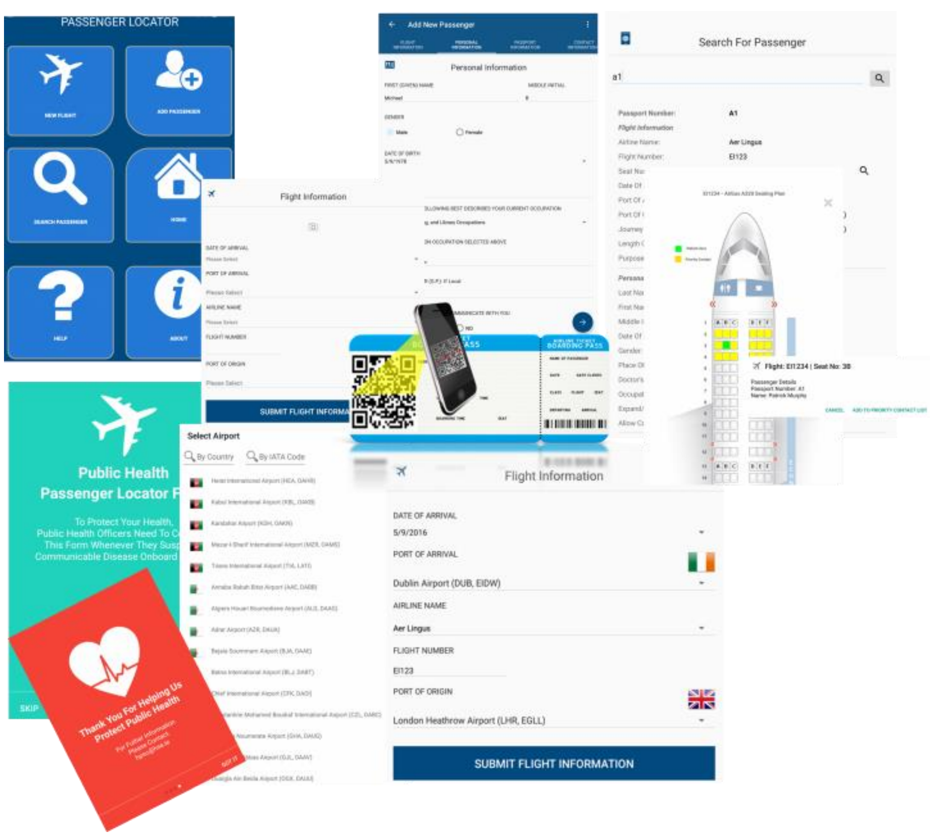

Figure 1 — Prototype digital contact tracing system.

passenger (the infected person) on an aircraft, along with the passengers in the "at-risk" vicinity, requires a considerable amount of time and effort from the public health agency. Digitizing contact tracing would provide an appropriate method of rapidly collecting passenger contact information, including:

- Flight information, including the flight and seat number
- Personal information
- Passport information
- Permanent and temporary address and contact information
- Emergency contact information
- Travel companions' information, both family and non-family

> *Collaboration between the airline industry, EM personnel, and public health agencies would greatly improve the ability to successfully identify an at-risk airline passenger.*

Passengers would fill in a digital form onboard the flight via hand-held devices linked to a database that would auto-populate certain fields of data (collected via the PNR) pertaining to the seat number or boarding card, such as name, home address, contact number, and so on.

EM practitioners and PHAs consider it important to capture additional data, which does not currently form part of the PLF, including:

- Passenger's doctor's name (this information would allow a health practice to be rapidly informed of a potential threat, possibly to be introduced by an existing patient, for passengers local to the port of arrival)
- Passenger's occupation
- Expanded details of the passenger's occupation (e.g., a person with the occupation of "education" poses a very different contagion risk depending on whether the work environment is independent [a writer or researcher] or is in a school [a primary school teacher has the potential to expose hundreds of children to an infectious disease])
- Passport issue and expiration dates, which may provide an indication of future travel plans
- Comment section for PHA members to record details on and tag the recorded passenger

Collaboration between the airline industry, EM personnel, and public health agencies would greatly improve the ability to successfully identify an at-risk airline passenger. A shared, up-to-date digital record of passenger data would almost certainly remove the challenges of collecting and analyzing passenger data. The digital collection makes it easier to verify that each passenger has completed a form and supplied all the information requested. This, in turn, enables digital analysis of the data, which can be carried out quickly and efficiently.

The digital format of the contact tracing system should have the functionality to interact with both airline and PHA systems to enable the collation of passenger information. This cooperation and digitization would certainly require that legislation and agreed service-level agreements be put in place. A European Commission PNR directive has been adopted that obliges airlines to hand EU countries airline passenger data for the prevention, detection, investigation, and prosecution of terrorist offences and serious crime;[18] however, it can be argued that this obligatory cooperation could also aid in contact tracing of passengers infected by disease.

Although PNRs currently frequently lack certain passenger data, as discussed earlier, the use of a revised version of the PNR will greatly aid the collection process of passenger data for contact tracing purposes by auto-populating a greater number of fields of data, limiting the time required to collate and locate passengers at risk of exposure and potentially carrying an infectious disease. It is envisaged that digitization would have the capability to auto-populate certain fields of passenger data, via use of the PNR, along with controlling the input of data by the passenger to ensure complete and correct data capture. Digital input can be controlled by limiting the available options to the passenger; for example, not allowing the passenger to input text into a number input or not allowing the passenger to input a return date that is in the past, and by auto-populating certain fields, such as seat number, or by auto-populating an address based on zip code. Uncovering the required data of an at-risk passenger in an efficient manner and without unnecessary use of valuable resources would require such a digitized system.

The digitization of contact tracing, including the involvement of and collaboration with multiple stakeholders, such as the airline industry, EM practitioners, PHAs (through their respective governments), and digital development experts, can provide an effective global framework to prepare for and respond to a biological threat, natural or otherwise, spread via air travel.

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