Novel Systems for Rapidly Identifying Toxic Chemicals during Emergencies

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LIST OF TERMS AND ABBREVIATIONS

WISER	Wireless Information System for Emergency Responders
MAIDN	Mining and Interpretation of Diagnostic Networks

ABSTRACT

During chemical emergencies such as those resulting from plant explosions and bioterrorism, speed and accuracy in detecting unknown chemicals are critical for reducing injury and death of chemical workers, first responders, and the larger public. Unfortunately, less than 10% of toxic chemicals can be automatically identified through chemical detectors. Furthermore, current systems designed to help search toxic chemical databases currently use rudimentary search algorithms and interfaces, which require too many user inputs, do not guide users to select the most discriminatory inputs, and therefore do not facilitate an efficient response.

To address the above problems we conducted a feasibility study to design, implement, and evaluate novel algorithms and interfaces with the goal of helping first responders and plant safety managers to rapidly identify unknown toxic chemicals. This was achieved through three specific aims:

1. Quantify the complex relationship between chemicals and their symptoms/properties in well-known public health databases. This aim was achieved through the use of advanced bipartite network visualizations and quantitative analysis methods, and through the invention and use of three novel bipartite quantitative approaches to analyze the overlap of symptoms/properties across chemicals. The results revealed the precise nature of the overlap of symptoms/properties across chemicals in two large databases, which led to insights for efficient algorithms and interfaces to identify unknown toxic chemicals.

2. Identify the needs of first responders, and of safety managers at chemical plants. This aim was achieved through focused semi-structured interviews of 20 first-responders from Texas and Michigan, followed by a nation-wide survey. Our focused plus broad data collection of information/tool needs of first responders provided a detailed understanding of (a) the subpopulation of first responders who would most likely use advanced decision-support tools for toxic chemical identification, (b) the context in which such tools will be used, and (c) the specific interface features that are critical for decision-support tools.

3. Develop and evaluate novel algorithms and interfaces to aid in the rapid identification of toxic chemicals based on symptoms and properties. This aim was achieved by developing four novel algorithms designed to enable the rapid identification of (a) individual chemicals, (b) classes of chemicals, (c) combination of chemicals with different probabilities of occurring during any specific incident, and (d) individual chemicals that were robust under incorrect inputs. We also developed a prototype for a visual analytical decision-support system based on user needs, which provided a framework to enable the above algorithms to be useful and usable for first-responders on laptops, and mobile devices.

Our results, based on the integration of computational, cognitive, and contextual dimensions, have the potential to substantially reduce the time it takes to identify toxic chemicals during chemical incidents, and therefore reduce injury and death of workers in chemical plants, and first responders. The results have been published[1-9] in peer-reviewed national conferences and high-impact journals, has received a national poster award[2], received a student poster award, resulted in a US patent application (US 2013/0245959 A1), and has been applied in other biomedical domains[10-16].

SECTION 1

Motivation for Research. A key motivation of our research was the observation that there is a very high overlap of symptoms and properties across chemicals in public health chemical databases such as that used in the Wireless Information System for Emergency Responders (WISER)[17]. This high overlap of symptoms (also known as the non-specificity of symptoms) results in two problems for users such as first responders and plant managers: (1) Users have to enter many inputs to narrow down the number of possible chemicals. This puts a burden on the user during a chemical emergency. (2) Users do not know which symptoms are the most discriminatory and therefore have to rely on limited and often incorrect information available during a toxic chemical incident.

Significant (Key) Findings

1. Development and Use of Methods to Measure the Overlap of Symptoms across Chemicals.

To address the limitation of current tools, we analyzed the overlap of symptoms in two well-known toxic chemical databases (WISER and Haz-Map) as described below:

a. To comprehend the overlap of symptoms across chemicals, we represented the data using a bipartite network of toxic chemicals and symptoms. The analysis revealed a large number of chemicals that had many highly overlapped symptoms, a small number of chemicals that had many but a low overlap of symptoms, and a small number of chemicals that few symptoms with a low overlap.

b. To quantify the above complex patterns of overlap, we developed a new quantitative measure referred to as the ***Degree of Overlap*** curve. This curve characterizes the average number of chemicals that have an overlap for different set sizes of symptoms (pairs, triplets, etc.). For both databases we found that the symptom overlap was best characterized by an exponentially decaying curve (many chemicals that overlapped with about 10 symptoms, and few chemicals that overlapped with many symptoms), and in addition was significantly more overlapped compared to what could be expected by chance.

c. To estimate how many symptoms it would take to identify a toxic chemical using rudimentary search algorithms used in WISER and Haz-Map, we developed a second measure referred to as the ***Time to Diagnosis*** curve. This curve was generated by calculating the smallest number of symptoms to uniquely identify each chemical, and averaged this number across all chemicals. The results showed that both databases required an average of about 10-26 symptoms to identify an unknown chemical.

d. To further visualize the overlap of symptoms within sub-classes of chemicals, we developed a third approach referred to as the ***Module Imbalance*** algorithm (patent pending). Here we ranked individual symptoms based on how they were differentially caused by classes of chemicals (e.g., poisons vs. non poisons), and then dropped symptoms until distinct clusters in the network emerged. The application of this algorithm revealed the complex and high overlap of symptoms across chemical classes.

While each of the above approaches specifically contributed to our understanding of chemical-symptom relationships and resulting insights about algorithms, these approaches generalize to any database containing bipartite relationships.

2. Identification of the subpopulation and context of use for future decision-support systems.

While the analysis of symptom overlap provided insights for why current algorithms used in systems for toxic chemical identification are not efficient and how to improve them, such an analysis is not designed to reveal how to develop decision-support systems that are effective in the field. We therefore solicited information about tool use and context directly from first-responders:

a. To understand the cognitive and contextual dimensions for designing such systems, we conducted semi-structured interviews with 20 first responders (because they are high risk for injury and death due to toxic chemical exposure) in Texas and in Michigan. The interviews revealed three intersecting themes. (1) The **plurality of roles** that most first responders play during emergency response. (2) The **combination of assorted tools** used during most chemical incidents. (3) A **multiplicity of triggers** for using decision-support tools for toxic chemical identification such as WISER[17].These qualitative results provided a focused understanding of how and when decision-support tools are currently used, which provided a framework to understand how best to design future tools.

b. To solicit quantitative information from a broader population, we conducted a nation-wide survey of first responders. This survey, which had a high response rate (24%, n=139), revealed that compared to first responders from jurisdictions with smaller coverage combined (single and countywide), first responders from regional jurisdictions used significantly more detection technologies (e.g., radiation detectors), and used WISER significantly more often. This difference in WISER use is important because there was no significant difference in the number of chemicals identified by respondents in regional jurisdictions compared to the rest. Discussions with an expert first responder revealed that the difference in tool usage reflects the extra federal funding received by regional jurisdictions resulting in increased resources for investing in sophisticated systems. Furthermore, the significantly higher usage of the existing decision-support tools such as WISER in regional jurisdictions, suggests that they will be more frequent users of our proposed solutions.

3. Development and evaluation of algorithms and interfaces for decision-support systems that enable the rapid identification of toxic chemicals

Understanding the overlap of the symptoms across chemicals, and identifying the user needs and context of use, were incorporated into the design of algorithms and interfaces as described below:

a. To make the chemical identification process more efficient, we developed four algorithms which ranked symptoms and eliminated chemicals using different criteria. This was done by (i) individual chemicals, (ii) classes of chemicals, (iii) combination of chemicals with different probabilities of occurring during any specific incident, and (iv) individual chemicals that were robust under incorrect inputs.

b. To make such advanced algorithms useful and usable, we incorporated our understanding of symptom overlap and user needs to develop a prototype for a visual analytical decision-support system called MAIDN. The system was designed to guide the user in selecting the most appropriate algorithm for a specific task, and to guide the user in selecting symptoms or properties that were either present during the incident, or not present but equally important in rapidly reducing the number of candidate chemicals.

c. The prototype system was included as part of the nation-wide survey (described earlier) to solicit perceptions of its usefulness and usability. The results revealed that there were no significant differences between the regional jurisdictions and the rest in the perceived usefulness and usability of MAIDN. Finally, while the overall ratings were mostly positive, the usefulness scores were significantly lower compared to usability across all jurisdictions. Textual comments provided insights into how to improve the usefulness of MAIDN.

Translation of Findings

The findings from each of the three specific aims have the potential of developing in the future robust systems for rapidly identifying toxic chemicals, as described below:

a. The high overlap of symptoms should motivate the many developers of toxic chemical databases to develop advanced algorithms and interfaces to enable more efficient searches of their databases.

b. The difference in usage of decision-support tools across jurisdictions provides the basis for future studies that explore solutions that are specific to different jurisdictions.

c. The proof-of-concept provided by MAIDN, and its positive feedback nation-wide suggests that such a system when reprogrammed in a robust programming language, could be successfully deployed nation-wide.

Outcomes/Impact

MAIDN and the space of advanced algorithms that we have developed, provide the foundation for developing and testing the next generation of tools for the ever increasing range of toxic chemicals that provide an imminent threat to millions of workers world-wide.

SECTION 2

Scientific Report

1. Background

Despite major advances in occupational safety, numerous workers continue to be injured or killed due to exposure to toxic chemicals[18-20]. For example, in the US chemical industry alone, from mid-1994 to mid-1999, 1,205 US plants reported 1,970 accidents related to toxic chemical exposures, resulting in 2154 injuries, 32 deaths and more than 6000 individuals requiring some medical attention[21]. First responders (fire-fighters, law enforcement officers, and emergency medical technicians) have similarly high injuries and deaths due to work-related toxic exposures[22].

The above statistics are regularly played out around the world in familiar scenarios: (1) A **worker in a chemical plant** suddenly experiences unusual symptoms, including ringing in the ears and shivering. The safety manager needs to quickly identify what chemicals the worker has been exposed to, so that the first responders can prepare the proper treatment and locate the source of the chemical leak. (2) A **team of firefighters** is unconscious with burns after being exposed to brownish toxic fumes from an explosion. First responders from the local HazMat team need to identify the nature of the chemical exposure based on symptoms and properties to triage the victims and to issue neighborhood warnings.

In the above scenarios, the rapid identification of toxic chemicals is critical to providing proper medical treatment for the victims, and to mobilize containment and cleanup of the chemicals to prevent further injury. Unfortunately, there are two major reasons why rapid identification is currently difficult: (1) Only 10% of toxic chemicals can be identified using chemical detection devices[23], and (2) current systems like WISER[17] that are designed to help in toxic chemical identification, use very basic search algorithms that do not facilitate an efficient response.

To address such problems, the National Occupational Research Agenda[24] (NORA) designated Exposure Assessment Methods as a coordinated emphasis area[25], with one of its strategic goals being to develop or improve specific methods and tools to assess worker exposures to critical occupational agents and stressors. Our research directly targeted the need for developing novel computational tools to help safety managers (in the Manufacturing Sector) and first responders (in the Healthcare and Social Assistance Sector) to rapidly and accurately identify toxic chemicals based on worker symptoms and chemical properties during emergencies (in the Health Hazard Evaluation, and Emergency and Preparedness/Response Cross-Sectors).

Why is there a need to develop new methods to rapidly and accurately identify toxic chemicals? It is common knowledge there are numerous websites that help users search through large amounts of evidence-based data on toxic chemicals and their symptoms and properties, such as the Wireless Information System for Emergency Responders *(WISER* which helps to identify hazardous chemicals during emergencies[17]) and the *Haz-Map* (which helps users recognize and control occupational chemical hazards[26]). For example, as shown in Figure 1, the WISER mobile system is designed to help first responders identify toxic chemicals based on symptoms and properties during an emergency (e.g., an explosion in a chemical factory). Unfortunately, such systems use basic dictionary look-up approaches like Boolean queries that require a large number of symptom and property inputs in order to identify a chemical.

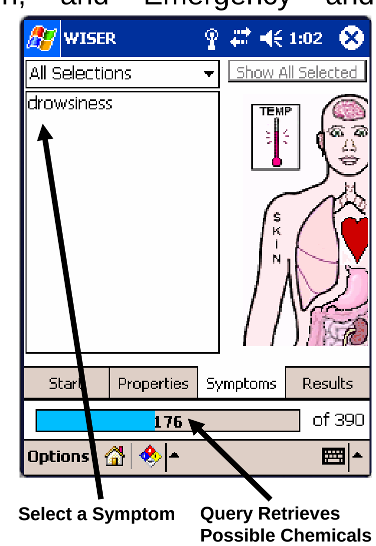


Figure 1. *The WISER system accepts symptoms and properties as inputs, and uses a database query to retrieve the set of chemicals that match those inputs.*

Our preliminary results[27] revealed that systems like WISER are impractical because they require a large number of inputs to identify a toxic chemical. Because the rapid identification of a toxic chemical is critical to saving workers from injury and death, there is a need for more efficient and effective search algorithms and user interfaces to aid in rapid and accurate toxic chemical identification. Unfortunately, there is no theoretical framework to guide the development of efficient and effective algorithms and interfaces for decision support systems such as WISER.

To address these challenges, this grant brought together an interdisciplinary team of researchers who used cutting-edge research in **Network Analysis** (to understand the complex relationship between chemicals and their symptoms and properties), used **Grounded Theory** and conducted a **National Survey** of first-responders (to understand the user needs and context of the end users), and developed **Algorithms** and **Interfaces** (to help in the rapid identification of toxic chemicals) with the goal of translating the research findings into practical systems to help exposure victims in the workplace.

2. Specific Aims

The grant conducted research based on the following three specific aims, which were unchanged from the submitted proposal:

Specific Aim 1. Quantify the complex relationship between chemicals and their symptoms/properties in well-known public health databases.

Specific Aim 2. Identify the needs of first responders and safety managers at chemical plants.

Specific Aim 3. Develop and evaluate novel algorithms and interfaces to help in the rapid identification of toxic chemicals based on symptoms and properties.

3. Methodology

Our methodology for each of the above specific aims is described below:

Method for Specific Aim 1

Network Analysis. Networks are increasingly being used in a wide range of domains[28] to analyze complex relationships between entities. In healthcare, they have been used to understand relationships between classes of information, such as between disorders and disease genes[29], and how healthcare facts are scattered across relevant webpages[30]. A network, or graph, consists of *nodes* and *edges*; nodes represent one or more types of entities (e.g., chemicals or symptoms), and edges between the nodes represent a specific relationship between the entities (e.g., a symptom is caused by a chemical). Figure 2 shows a sample bipartite network (where edges exist only between two different types of entities) of toxic chemicals and the symptoms they are known to cause.

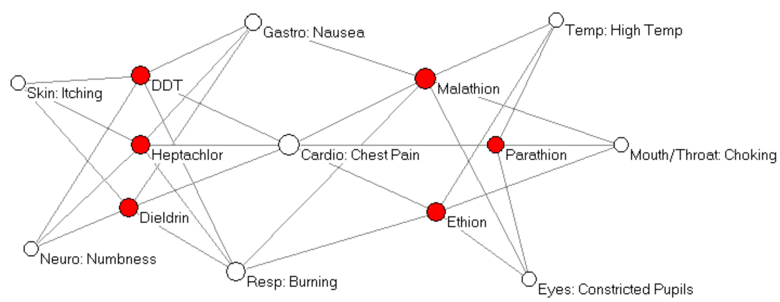


Figure 2. *A bipartite network visualization showing the relationship between chemicals (solid nodes) and their symptoms (white nodes).*

Networks have two advantages for analyzing complex relationships. (1) They represent explicitly the relationship between different nodes, which enable complex relationships to be described through quantitative network measures. (2) They can be rapidly visualized and analyzed using a toolbox of network analysis methods and visualization algorithms. For example, Figure 1 shows a *spring-embedding layout algorithm*[31] which helps to visualize the relationship between chemicals and symptoms. The algorithm simulates placing springs (attractive force) between connected nodes, and a weakly repulsive force between disconnected nodes. As shown, the result is that chemicals with similar symptoms (e.g., *DDT*, *Heptachlor*, and *Dieldrin* on the left) are placed close to each other and close to the symptoms that they cause.

We used the above bipartite network visualization method to analyze the WISER (415 chemicals, 79 symptoms), and the Haz-Map (240 chemicals, 90 symptoms) datasets. We also attempted to analyze the NIOSH Pocket Guide (720 chemicals, 96 symptoms), but unfortunately the data contained many natural language statements not contained in the dictionary of terms, requiring significant structuring of the database before it could be analyzed. We attempted to make these terms consistent for purposes of analysis using programmatic and manual methods. However, at each iteration we discovered more non-dictionary terms, and therefore were unable to fully structure the data. The problem was caused because this database had been originally constructed using handwritten notes, and transferred later to a Word document resulting in a large number of inconsistencies in vocabulary. We therefore focused instead on the WISER and Haz-Map datasets for our analysis both of which were well-structured and therefore more amenable to computational methods.

Because the overlap of symptoms across chemicals was high in both datasets, and existing network measures were not appropriate, we developed three new methods to quantify and visualize the overlap:

Degree of Overlap. To measure the overlap of symptoms over chemicals, we developed the Degree of Overlap curve which was generated by plotting the average number of chemicals that have an overlap for different set sizes of symptoms (pairs, triplets, etc.). We then measured whether the area under this curve was significantly higher compared to what could be expected by chance.

Time to Diagnosis. To estimate how many symptoms it would take to identify a toxic chemical using rudimentary search algorithms used in WISER and Haz-Map, we developed a second measure referred to as the Time to Diagnosis curve. This curve was generated by calculating the smallest number of symptoms to uniquely identify each chemical, averaging this number across all chemicals, and plotting the distribution.

Module Imbalance. Because the symptoms in both datasets had a very high overlap across the chemicals, in both cases the network visualization could not reveal whether there was a similar complex overlap of symptoms across classes of chemicals. We therefore developed a third method where we ranked individual symptoms based on how they were differentially caused by classes of chemicals (e.g., pesticides vs. non pesticides), and then dropped symptoms until distinct clusters (as measured by modularity) in the network emerged.

Method for Specific Aim 2

Identification of toxic chemicals during emergencies is a complex and stressful task that requires the use of a wide range of decision-support tools (e.g., WISER), resulting in critical decisions related to rescue, containment, and cleanup. Unfortunately, while there exist numerous prescriptions and policies for conducting such operations, few studies have probed the tasks and contexts in which such tools are used. A literature search of tools and their use by first-responders retrieved research related to architecture of systems for disaster response[32], communications patterns during an emergency[33], mobile tools to help in medical triage and mobile tools[34], and the design of GIS-based tools[35]. However, none of these studies provided us an understanding of the range of tools that first responders use during a toxic chemical emergency, and the context in which they are used. We therefore conducted semi-structured qualitative interviews and a national survey to understand the tasks, and contexts in which first-responders use current tools.

Semi-structured Interviews

Given the practical difficulties of directly observing toxic chemical incidents, we conducted semi-structured interviews with first responders experienced in identifying toxic chemicals during chemical emergencies. We used a snowball method to identify interview participants starting with an initial sample of first responders (provided by Chris Weber, expert first-responder on our team), who then identified additional participants to recruit in Texas and in Michigan. This method resulted in 20 first responders from fire departments, emergency management teams in hospitals, and chemical plants across the two US states.

The participants were asked to describe their role as first responders, and the context, tasks, and tools they used during a chemical incident which was potentially hazardous to humans. Appendix-1 shows the protocol for the semi-structured interviews. The interviews were audio-recorded, transcribed into 274 pages of text, and subsequently analyzed in two phases using methods from Grounded Theory[36]. To comprehend the complex flow of information during a toxic chemical incident, we used a directed bipartite network consisting of nodes representing the environment, actors, or tools, and directed edges between the nodes representing information flow. The interpretation of the results was verified by an expert first responder (CW).

Self-Administered Survey

Guided by the above qualitative study[2] of technology usage and context, we conducted a nation-wide online survey (see Appendix 2) consisting of 36 questions related to: (1) **demographics** (e.g., location and jurisdiction), (2) **tool usage** (e.g., frequency and type of tools used), and (3) **perceptions of the usefulness and usability** of a prototypical visual analytical system, using a validated instrument based on the technology acceptance model. The visual analytical system called MAIDN[1] (designed for reducing the number of user inputs required to rapidly identify a toxic chemical based on patient signs/symptoms and chemical properties) was demonstrated through an online video provided as part of the survey. The survey (which was made available online through Survey Monkey) was sent to 795 email addresses of first responders obtained from Chris Weber who has a company (Dr. Hazmat Inc.) that trains HAZMAT teams nation-wide in partnership with federal agencies, and therefore represented a wide cross-section of first responders. The results of the semi-structured interviews and the survey were reviewed and interpreted by Chris Weber, leading to an integrated understanding of the emergent themes from both studies.

Method for Specific Aim 3

We used our understanding of regularities underlying the databases (based on the network analysis in Specific Aim 1), and user needs (based on our interviews and survey described in Specific Aim 2), to design and evaluate **algorithms** and **search interfaces** with the goal of building a decision-support system. The goal of this development is to assist safety managers and first responders to speed up the search of existing toxic chemical databases.

Design and Evaluation of Algorithms

To make the chemical identification process more efficient, we developed four algorithms which ranked symptoms, and which eliminated chemicals using four strategies: (A) individual chemicals, (B) classes of chemicals, (C) individual chemicals that were robust under incorrect inputs, and (D) combination of chemicals with different probabilities of occurring during any specific incident.

Algorithm A and B were developed using a common coding-theoretic framework, and are based on reinterpretation of the standard binary search tree as a generalized form of Shannon-Fano coding. We first established an exact formula for the expected number of symptoms required to identify a chemical using an arbitrary decision tree, and showed that the binary search tree effectively performs a greedy, top-down optimization of this objective function. We then extended this formula to the case of chemical identification under unknown prior distribution and chemical class identification, and developed analogous greedy algorithms. Because our algorithms used greedy approaches, the obtained solution is not guaranteed to be optimal. However, we theoretically proved that the obtained solution is guaranteed to be near-optimal. Specifically, we developed a logarithmic approximation bound using the notion of sub-modularity.

Algorithm C and D were developed using a common decision-theoretic framework, where we modeled the problem as uncovering the value of a random vector using probability theory. For chemical identification under incorrect inputs, we proposed a novel rank-based approach where we outputted a ranked list of the chemicals based on their likelihood of being the underlying chemical given the inputs. We developed a greedy algorithm to select symptoms such that the expected rank of the true underlying chemical was minimized. Furthermore, the algorithm can be implemented without any knowledge of the underlying input noise distribution. Finally, we considered a more general setting of the above diagnosis problem where a combination of chemicals may occur. To address this issue, we proposed an extension to the above rank-based algorithm, where we selected symptoms such that the area under the ROC (receiver operating characteristic) curve was maximized. This measure therefore allowed us to make a simplifying assumption that significantly reduced the complexity of symptom selection when combinations of chemicals are present, with little or no compromise to performance.

The above algorithms were evaluated through extensive simulations on synthetic data and using the WISER database (version 4.21). In each case, the performance of the proposed algorithm was compared to baselines that included the standard binary search tree, and a random selection of symptoms.

Design and Evaluation of Interfaces

To make the above advanced algorithms useful and usable, we incorporated our understanding of symptom overlap, user needs, and context to develop a prototype for a visual analytical decision-support system called MAIDN. The system was designed to guide the user in selecting the most appropriate algorithm for a specific task, and to guide the user in selecting symptoms or properties that were either present during the incident, or not present but equally important in rapidly reducing the number of possible chemicals. We collaborated with experienced first responders from a local county hazardous materials response team to iteratively identify features required on the interface, and used guidelines (e.g., provide system feedback) from the *heuristic evaluation*[37] method to implement and refine the design

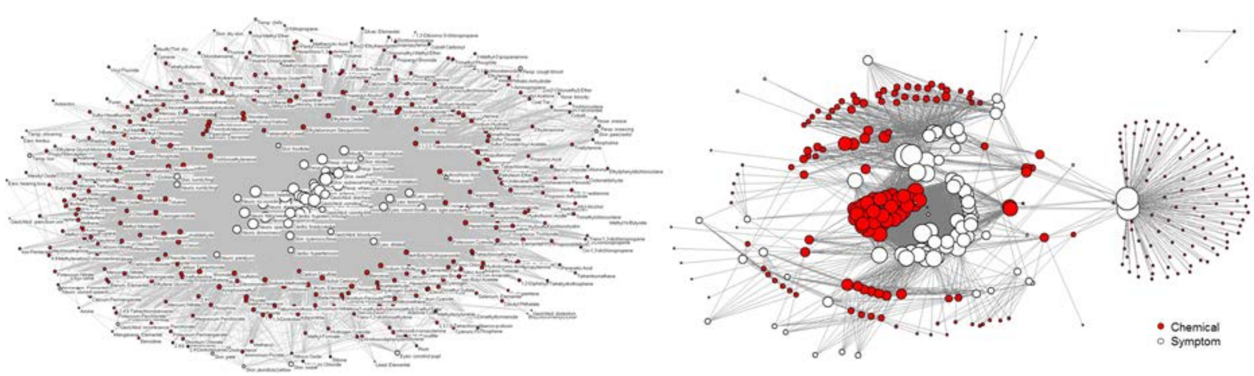
The MAIDN prototype was evaluated as part of the national survey described earlier. A link to a YouTube video of the MAIDN system was provided in the survey, and respondents were asked to watch the video and answer questions related to **perceptions of the usefulness and usability** of system, using a validated instrument based on the technology acceptance model (TAM)[38].

4. Results

Results for Specific Aim 1

Network Analysis

Figure 3 shows the results of the bipartite network analysis related to WISER and Haz-Map. As shown in Figure 3A, the bipartite network for WISER makes explicit the relationship between the 415 chemicals and the 79 symptoms they cause. Furthermore, besides showing the relationship between the chemicals and symptoms through the connecting edges, the size of a node is proportional to its *degree* (number of edges that connect to that node). Therefore, the larger a node, the more edges it shares with other nodes.



A. WISER B. Haz-Map

Figure 3. *Visualization of a bipartite network (automatically generated by the spring algorithm) showing the relationship between chemicals (solid nodes) and symptoms (white nodes) in (A) the WISER dataset, and (B) the Haz-Map dataset. The size of the nodes is proportional to the number of edges that connect to them. Therefore common symptoms have large nodes, whereas rare symptoms have smaller nodes.*

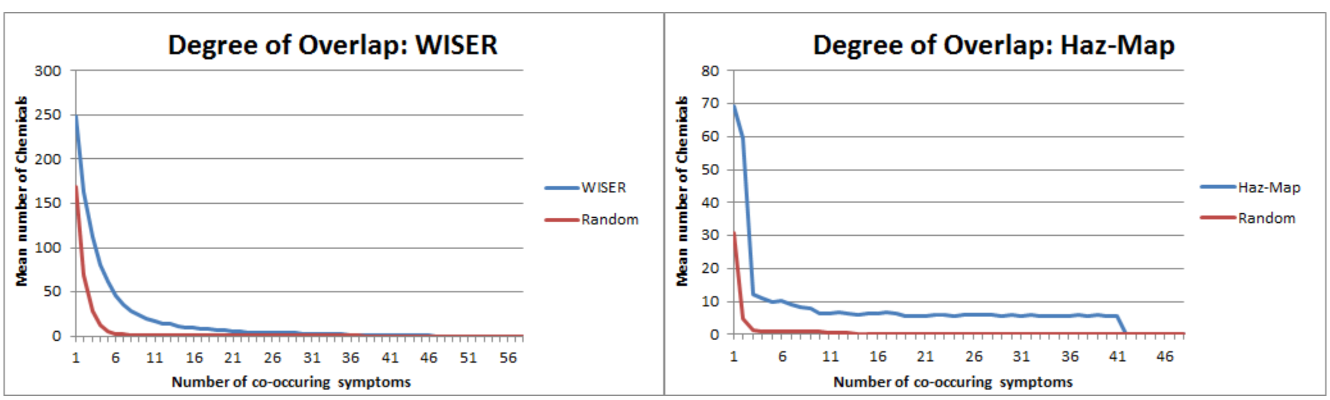
This network visualization revealed two critical patterns related to chemicals and symptoms: (1) There are 59 commonly occurring symptoms in the center of the network, while 20 rare symptoms are placed around the periphery. For example, Neuro: headache (a) is in the center of the network with 257 edges each connected to a chemical. In contrast Ear: hearing loss (b) is on the far left periphery with only 7 edges. This observation from the visualization was verified statistically: the mean degree of symptoms is large, and there is a large range in degrees (Mean = 155, SD = 107). (2) The chemicals form a ring around the 59 symptoms in the center. Chemicals close to the inner set of symptoms cause many symptoms compared to chemicals in the outer ring. For example, the chemical Hydrochloric Acid (c) has 47 symptoms, whereas the chemical Ethylphenyldichlorosilane (d) has 17 symptoms. This observation from the visualization was verified statistically: the mean degree of chemicals is small, and there is a small range in degrees when compared to symptoms (Mean = 31, SD = 11).

The above network topology in which there are many chemicals (in the ring) with similar degree, and a relatively smaller number of symptoms (in the center) with high degree, results in a high overlap in the number of symptoms for most chemicals. This can be seen in the high density of edges between the chemicals in the ring, and the symptoms in the center, resulting in a gray mass of indistinguishable edges. To measure this effect we calculated the network's edge density (number of actual edges / number of possible edges), which was 0.396. This value is high compared to the edge density of most large networks that have been analyzed[28], which typically ranges from almost zero to 0.1, with edge density for a fully connected network = 1.0. These results suggest an extremely high overlap of symptoms across chemicals.

In contrast to the WISER network which shows the association between chemicals and acute symptoms, the Haz-Map network represents the association between chemicals and symptoms caused by chronic diseases such as lung cancer. Perhaps because of this difference in the nature of symptoms, there is strong clustering of chemicals (red nodes) with modularity of the chemicals at 0.36 (>0.3 is considered to be substantial clustering[28]). As shown, while there are distinct clusters of chemicals, there is relatively less differentiation in the symptoms, suggesting that they highly overlap across the clusters of chemicals.

While edge density provided a measure of overlap, it is neither designed to reveal the range of overlap, nor the average number of symptoms it would take to identify a chemical. We therefore used the **Degree of Overlap** and **Time to Diagnosis** curves to more precisely measure the overlap and its outcome to diagnosis. As shown in Figure 4A and 4B, both networks had symptoms that were significantly (WISER area under curve=980.83, $p<0.01$; Haz-Map area under curve=382.94; $p<0.01$) more overlapped compared to random networks of the same size. Next, using the Time to Diagnosis curve, we calculated the average number of symptoms required to diagnose a chemical in each database. The results showed that the average number of symptoms was higher for WISER compared to Haz-Map (WISER mean = 26.66, SD = 11.31; Haz-Map mean=10.18, SD=13.89). This suggested that in the Haz-Map dataset, although the overall symptoms were highly overlapped across the chemicals (as shown in Figure 4B and similar to WISER), clusters of chemicals shared similar symptoms, and therefore entire clusters of chemicals could be eliminated even if a few symptoms did not match. This on average, results in a smaller number of symptoms required for diagnosing a chemical.

While the above analysis focused on the overlap of symptoms across individual chemicals, we also wished to understand whether there was a similar complex overlap of symptoms across *classes* of



A. WISER B. Haz-Map

Figure 4. *Degree of Overlap curves for (A) WISER, and (B) Haz-Map. In both cases the symptom are significantly more overlapped compared to what can be expected by chance.*

chemicals. To visualize this complex overlap, we used the Module Imbalance algorithm, which requires as input an *a priori* classification of chemicals consisting of two or more classes (e.g., poisons vs. non-poisons), ranks individual symptoms based on how they were differentially caused by the inputted classes of chemicals, and then progressively drops symptoms until the best clusters (as measured by modularity) in the network emerge.

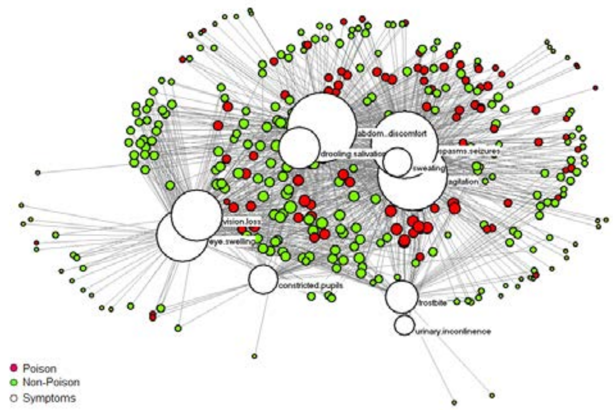


Figure 5. *Application of the Module Imbalance algorithm revealed that the overlap of symptoms across the largest class of chemicals (poisons) in WISER and the rest of the classes was complex resulting in a maximum modularity of chemicals to be at 0.16.*

As shown in Figure 5, the results showed that even when we considered the largest class of chemicals (poisons), and compared it to the rest of the classes combined, the maximum modularity of the network was 0.16 and never reached a high modularity (defined as >0.3). The analysis therefore revealed a complex and high overlap of symptoms across the two chemical classes. Although we intend to use this approach to analyze other granularities of chemical classes, this method provided the motivation for developing an efficient algorithm to help first responders rapidly identify classes of chemicals in situations where the identity of a specific chemical is not as important as the chemical class.

The overall results from Specific Aim 1 suggest that current toxic chemical databases have a high and complex overlap of symptoms, and understanding the nature of that overlap can lead to insights for developing more powerful algorithms to make the toxic chemical identification process more efficient.

Results for Specific Aim 2

Semi-structured Interviews

Analyses of the transcripts from the semi-structured interviews[1-3] helped to identify three intersecting themes.

(1) **Plurality of roles.** Most first responders reported that they played multiple roles during toxic chemical emergencies. For example, a hazmat technician stated:

> *"Basically, we set up training, we respond, look at needs of the team, help out…help supervise an incident, possibly, or different parts of an incident… We do a little bit of everything whenever we need to fill in."*

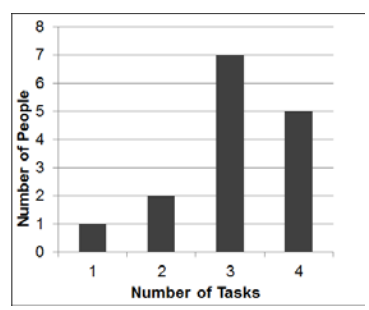


Figure 6. *Most respondents in the interviews played between 3 and 4 roles during toxic chemical emergencies.*

Analysis of the rest of the data helped to identify 11 different roles (Scene Response, Medical Response, Truck Operation, Incident Paperwork, Hazmat Training, Safety Compliance, Investigative Response, Rescue and Transport, Equipment Maintenance, Team Leadership, Training). Furthermore, as shown in Figure 6, most respondents reported playing between 3-4 roles during toxic chemical emergencies.

(2) **Combination of tools.** Most first responders reported using a combination of tools to identify an unknown toxic chemical. For example, a first responder stated:

> *"…if it's just a quick, simple, identify a chemical, we'll use WISER, HAZMATID, First Defender, a PID at a minimum, an UltraRadiac for radiation, pH paper, uh…sometimes a spill fighter…"*

Figure 7 shows the use of a combustible gas indicator, a pH meter, and tools in a lab to assist human judgment in determining the nature of a liquid in an abandoned truck. Analysis of the rest of the data revealed a total of 7 monitoring tools (PI Detector, pH Strip, Hazmat ID, Biological Detector, Chemical

Lab, Radiation Monitor, and Thermal Imaging), and 7 diagnostic tools (Emergency Response Guide book, NIOSH Handbook MSDS, WISER, CAMEO, COBRA, and HAZMAT IQ) used across the respondents.

(3) A **multiplicity of triggers** for using decision-support tools for toxic chemical identification such as WISER. For example, a first responder stated:

> *"…when I do my research in CAMEO first and foremost, and then back it up with the information from WISER ..."*

Analysis of the rest of the data helped to identify 7 possible triggers (Hazmat ID not available, public safety/scene control, absence of sample, possible error of ID systems, absence of reliable symptoms, and high percentage of sample with same symptom) across all the participants in the study.

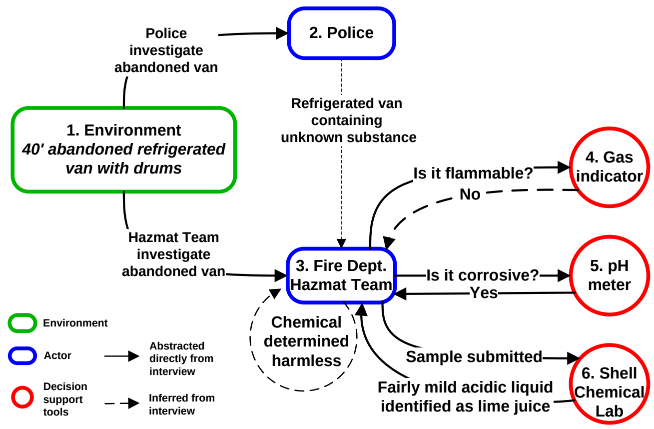


***Figure 7**. A directed network showing how information flowed between the environment, actors, and decision-support tools during a chemical incident of a suspicious liquid in an abandoned truck.*

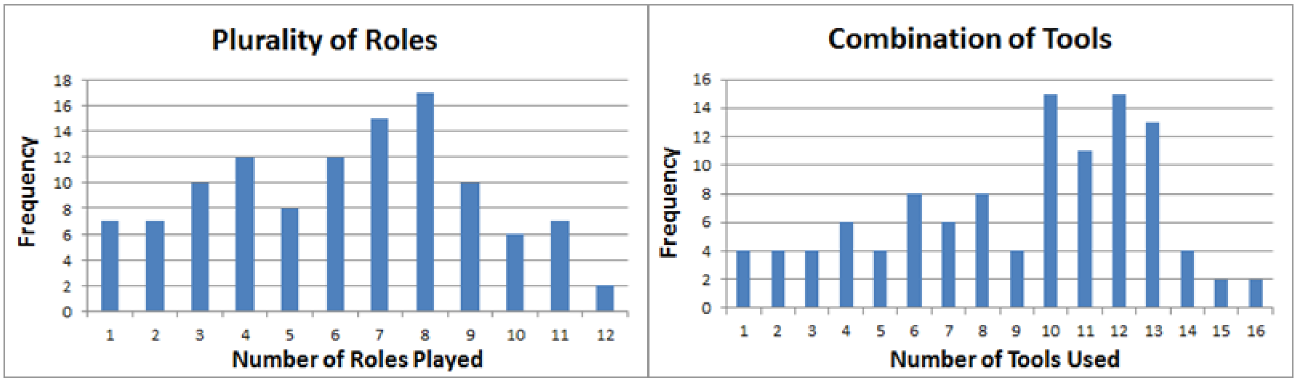
Overarching Themes. We conducted 3 additional interviews with an expert first responder to whom we presented the above themes with the goal of verifying and deepening our understanding of the results. These interviews revealed two overarching explanations for the emergent themes: (1) Hazmat teams that have smaller budgets can afford fewer instruments which detect and/or identify chemicals, and therefore possibly rely more heavily on decision-support tools such as WISER. Such teams also tend to play more roles compared to teams with larger budgets that have more specialists. (2) Some Hazmat teams minimize risk to their first responders by collecting substantial information from different decision-support tools before entering a hot zone with an unknown chemical; others make calculated risks based on the potential harm the delay could cause to victims and the environment. The triggers for tool use are therefore contingent on the outcomes of such trade-offs.

This emergent grounded theory therefore provides a nuanced understanding of how culture, context, and cognition mediate behavior during an emergency incident. The team economics, and risk trade-offs explain the critical dimensions by which decision-support tools for emergency response are different from those used by clinicians, and provide implications for the development of decision-support tools that are targeted to different types of team sizes and decision-making processes, with the goal of enabling more effective responses during emergencies. These results therefore helped to define the space of possible combinations of roles, tools, and triggers, which could guide the design of future decision-support tools[27].

Self-administered Survey

The understanding of tool usage and context through interviews of 20 first responders provided the motivation to conduct a nation-wide survey of first-responders. Unlike a qualitative interview, surveys tend to be more structured, and therefore we used the survey to collect demographic and tool usage, and perceptions of the usefulness and usability of those tools based on the technology acceptance model theory.

The survey yielded 191 responses (24% response rate) from 27 states, with 139 who completed all questions, and who were chosen for analysis. The analysis revealed a significant stratification of tool usage based on jurisdiction (response coverage). Compared to respondents from jurisdictions with smaller coverage combined (single and countywide), respondents from regional jurisdictions used significantly more (U=843.5, p<.001, two-tailed test) detection technologies (e.g., radiation detectors), and used WISER (a decision-support system) significantly more often (U=1185.0, p<.01, two-tailed test). This difference in WISER use is important because there was no significant difference in the number of chemicals identified by respondents in regional jurisdictions compared to the rest. As shown in Figures 8A and 8B, the survey confirmed our results from the semi-structured interviews, that first responders across many states also played multiple roles, and used a wide range of tools.



A B

***Figure 8**. First responders play multiple roles and use a combination of tools.*

Discussion of these results with an expert first responder revealed that the difference in tool usage reflects the extra federal funding received by regional jurisdictions and their increased usage of WISER suggests that they will be more frequent users of future decision-support tools.

Results for Specific Aim 3

Each of the four algorithms for toxic chemical identification based on symptoms that were described in the method section, were implemented in Matlab, and evaluated by comparison to random selections of symptoms.

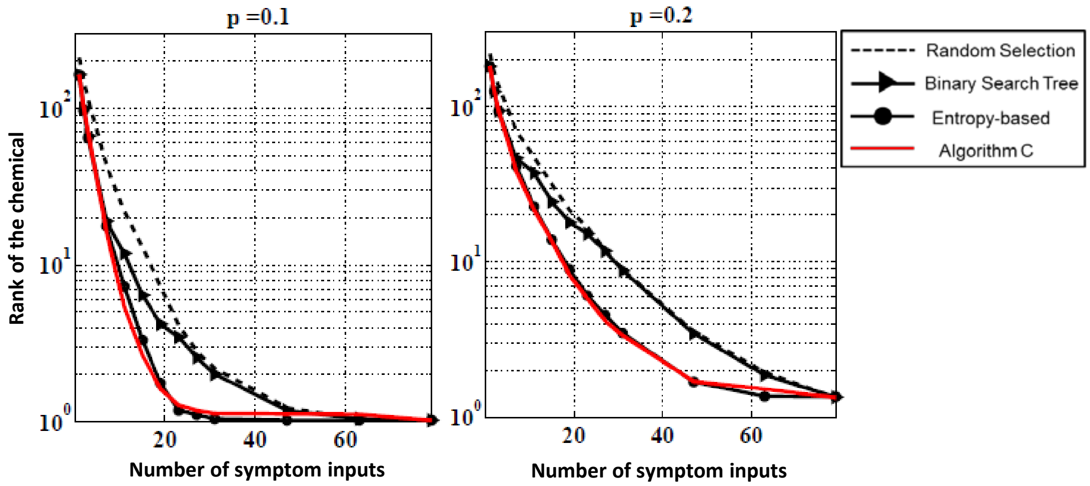
Algorithm A. This algorithm was designed to identify individual chemicals by enabling users to select from a ranked list of symptoms. The ranking was based on the binary search tree algorithm, where the symptoms are ranked according to their split ratio. The split ratio for a symptom is defined to be the minimum between the fraction of chemicals that exhibit the given symptom, and the fraction of chemicals that do not exhibit that symptom. Symptoms with a split ratio close to 0.5 are ranked higher in the ranked list. Our evaluation of this algorithm showed that Algorithm A takes significantly fewer symptoms (mean = 8.29, SD = 0.45) to identify a chemical, as compared to Boolean search (mean = 26.66, SD = 11.31), which is the algorithm typically used in chemical databases such as WISER.

Algorithm B. This algorithm was designed to help identify classes of chemicals (e.g., poisons) by enabling users to select from a ranked list of symptoms[5,9]. We evaluated this algorithm by calculating the average number of symptoms required to narrow down the categories to one based on 2000 simulations. This was compared to the standard binary search tree algorithm (Algorithm A), and to randomly selecting symptoms, as shown in Table 1. However, the reduction in the number of symptoms required to identify the chemical class using Algorithm B is only marginal. This is due to the non-specificity of the symptoms in the WISER database. More specifically, in the WISER database, chemicals in the same group tend to have different symptomologies while chemicals in different groups exhibit similar symptomologies.

Algorithm	Average number of symptoms
Algorithm B	7.29 ± 0.001
Binary Search tree	7.95 ± 0.003
Random Selection	16.33 ± 0.177

***Table 1.** Average number of symptoms required to identify the chemical class.*

Algorithm C. This algorithm was designed to help identify individual chemicals by enabling users to select from a ranked list of symptoms, but under incorrect inputs[6,10]. Figure 9 compares the performance of Algorithm C to the binary search tree algorithm, and random selection of symptoms under two different noise models. Figure 9A corresponds to a noise probability of 0.1, where 10% of the inputs are incorrect, while Figure 9B corresponds to a noise probability of 0.2. The standard binary search tree and random selection algorithms serve as baselines and are not expected to perform well since the binary search tree does not account for noise, and the random selection algorithm just selects symptoms at random. Figure 9 shows the rank of the true chemical based on the symptoms selected using the different approaches. Each curve in this figure is averaged over 1000 random simulations, where each simulation corresponds



A. Noise Probability = 0.1 **B. Noise Probability = 0.2**

Figure 8. *Expected rank of the chemical as a function of the number of symptom inputs, under (A) Noise probability = 0.1, and (B) Noise probability = 0.2. In both cases, Algorithm C requires less number of symptoms as compared to the binary search tree and random selection algorithms.*

to a random selection of a chemical, and a random set of symptom responses inverted (corresponds to incorrect inputs). Note from this figure that the rank of the true chemical converges to "1" using very few queries with the proposed approach as compared to both the binary search tree and the random selection.

Algorithm D. This algorithm was designed to help identify a combination of chemicals by enabling users to select from a ranked list of symptoms, but under incorrect inputs[8,10]. Figure 10 compares the performance of Algorithm D to identify a combination of chemicals under incorrect inputs, on a synthetic dataset. We compared the proposed solution with binary search tree and random selection that serve as baselines, as well as with an optimal solution that has an exponential complexity and hence cannot be implemented in practice. Figure 12 compares their performance measured using the area under the ROC curve, as a function of the number of symptom responses inputted. Each curve in this figure is averaged over 1000 random simulations, where each simulation corresponds to a random combination of chemicals and random set of symptom responses inverted (corresponds to incorrect inputs). This figure corresponds to a noise probability of 0.1. Note from this figure that the proposed solution performs significantly better than both the binary search tree and random selection. At the same time, the proposed solution also performs comparable to the optimal solution while having a computational complexity that is orders less than that of the optimal solution.

Design and Evaluation of Interface

Design. In response to the results from the semi-structured interviews and the survey, we were motivated to develop a system which directly addressed the overloading of short term memory. Such memory overload is the direct result of contexts where users play multiple roles and perform multiple tasks on different tools in response to the emergency situation. Our focus on reducing short term memory load led us to develop a visual analytical system which on the one hand helped to rapidly identify chemicals through more efficient algorithms, and on the other hand enabled users to comprehend at a glance, the symptoms or properties that had been progressively entered, and the

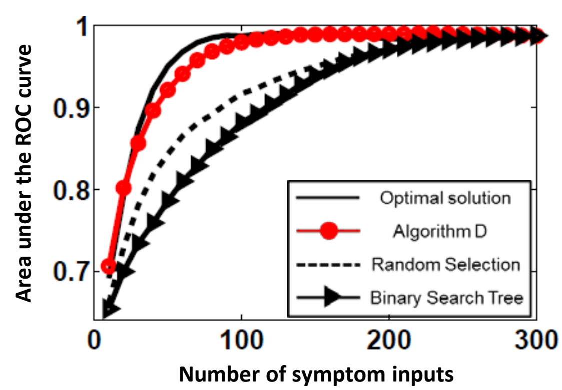


Figure 10. *Area under the ROC curve as a function of number of symptom inputs. Algorithm D requires less number of symptoms to discover all the chemicals.*

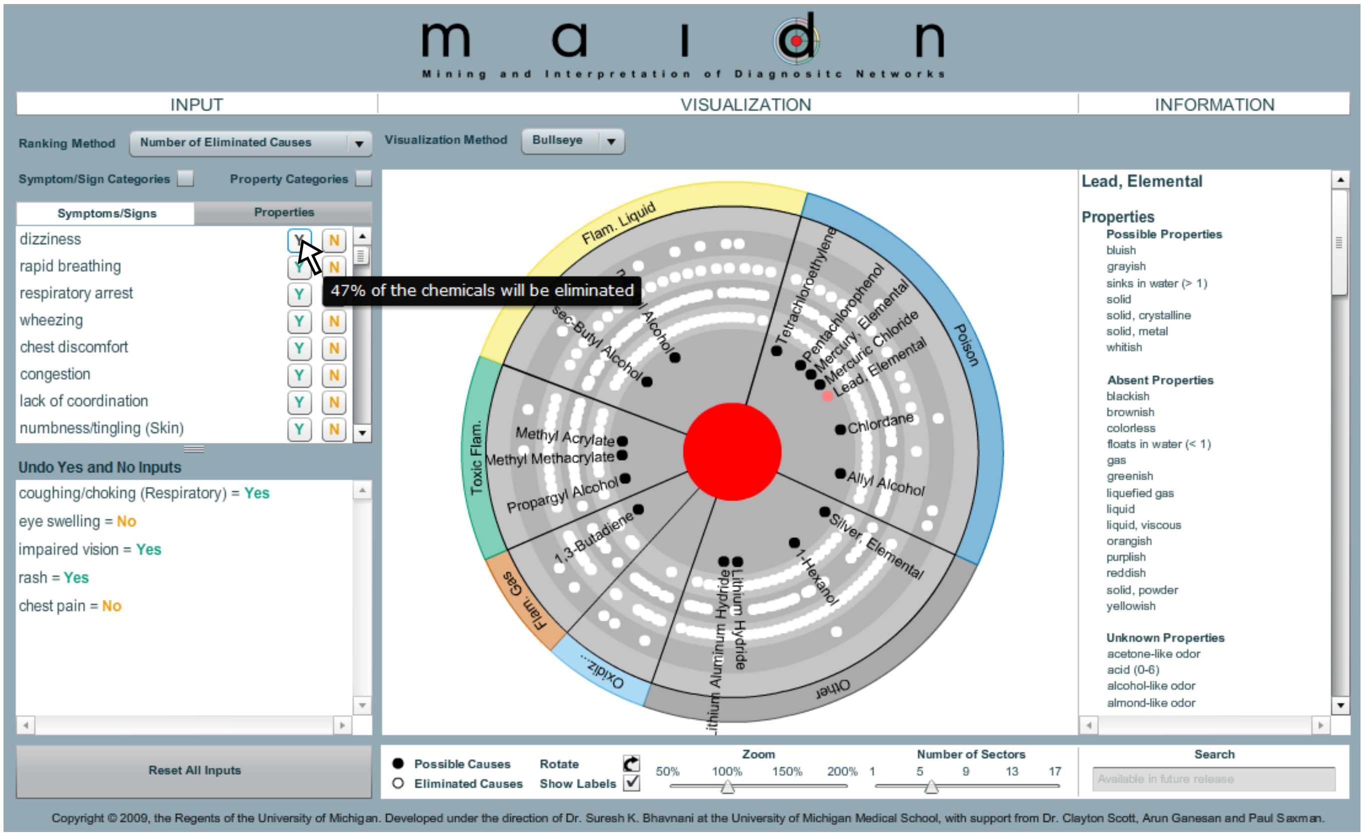


***Figure 11**. The MAIDN prototype integrates an algorithm which guides users to consider the most discriminating symptoms (upper left pane), and a visualization (center) that provides "at-a-glance" how the symptom selections reduce the candidate chemicals (black dots moving to the center), which are categorized by their chemical properties (sectors).*

result it had on the elimination of chemicals. By reducing short-term memory loads in the decision making process, we aimed to reduce errors in input and judgment.

As shown in Figure 11, we used this approach to develop a prototype using the *Adobe Flash* platform with the *ActionScript* scripting language (which is browser-compatible and therefore accessible on desktop and mobile devices), called *Mining And Interpretation of Diagnostic Networks* (MAIDN). The prototype integrates search and visual analytics in a flat interface (requiring few pull-down menu selections), which was accepted by first responders as appropriate for use in stressful and time critical situations. The top left pane provides a dynamically generated list of symptoms ranked by their ability to eliminate close to half of the remaining chemicals. This corresponds to Algorithm A described earlier. For example, the top-ranked symptom (*Dizziness*) in the figure will eliminate 47% of the chemicals (as shown by the pop-up box) if it's yes option ("Y") is selected, and about the same if the ("N") option is chosen. In the middle pane, the visualization provides "at-a-glance" the chemical that are eliminated (white dots), and candidate chemicals (black dots with labels) which progressively move into smaller rings towards the inner red circle. When no more symptoms are available to distinguish between chemicals, the final candidate chemicals move into the inner red circle (the "bullseye"). The system therefore guides the user towards considering symptoms that eliminate many chemicals, and simultaneously provides visual feedback on the effects of different inputs to help make a rapid decision. Furthermore, MAIDN enables the selection of different algorithms, and therefore provides an extensible interface framework for adding other experimental algorithms.

Evaluation. The ranking algorithm was evaluated by 2000 simulations of a user diagnosing a chemical exposure using either WISER or our prototype. Significantly fewer symptoms were needed to uniquely identify a chemical using our prototype (mean=8.29, SD=0.45) compared to WISER (mean=26.66, SD=11.31, p<.01 two-tailed t-test). The design therefore should be effective in the rapid identification of toxic chemical during emergencies.

The system was also evaluated through an online survey discussed earlier. Although we had originally planned to do a pilot usability evaluation with a few local responders, we decided it would be more informative to get feedback about MAIDN from a broad population of first-responders across the nation. This decision was additionally useful as it made many more first responders across the US aware of the developmental efforts to improve toxic chemical identification through more advanced algorithms and interfaces.

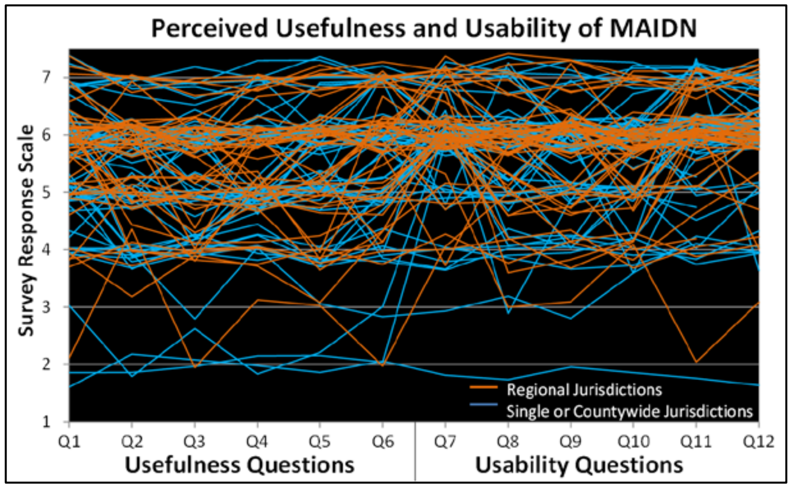


***Figure 12**. How 139 first responders across regional versus smaller jurisdictions perceived the usefulness and usability of MAIDN.*

As discussed earlier, the survey results showed that compared to respondents from jurisdictions with smaller coverage combined (single and countywide), respondents from regional jurisdictions used significantly more detection technologies (e.g., radiation detectors), and used WISER (a decision-support system) significantly more often. This difference in WISER use is important because there was no significant difference in the number of chemicals identified by respondents in regional jurisdictions compared to the rest. However, as shown in Figure 11, despite the above differences in tool use, there were no significant differences between the two jurisdiction groups (U=1584.5, p=0.24, two-tailed test) in the 12 questions about the perceived usefulness and usability of MAIDN. Finally, while the overall ratings were mostly positive (higher score=more positive), the usefulness scores were significantly lower compared to usability across all jurisdictions.

In addition to the quantitative scales, the respondents were given the option to select from a set of desired features for MAIDN, and to type in new features. As shown in Figure 13, the most common desired features included that MAIDN should be made available on the smart phone or tablet, and should be low or no cost. Other selections suggested that MAIDN could benefit from additional functionality such as inter-operability with other technologies used during chemical identification. The combined results from the prior qualitative study, and the quantitative survey therefore deepened and broadened our understanding for improving the overall usefulness of MAIDN.

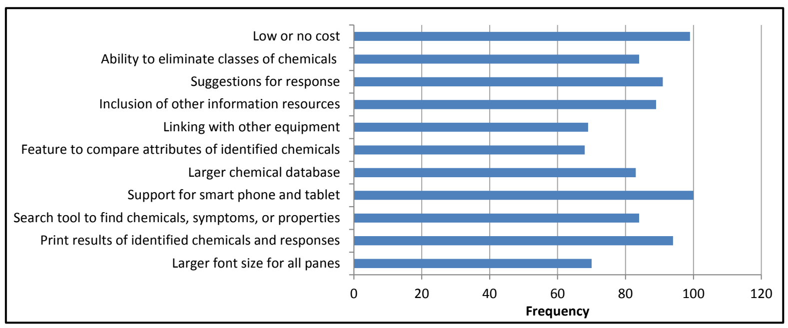


***Figure 13**. Ranked list of additional features requested by respondents to national survey.*

The MAIDN application and source code have been made publically available at the following link: <http://skbhavnani.com/DIVA/MAIDN.html>[39].

5. Discussion and Conclusion

Before we began our research on this grant, there was little published literature to guide our analysis and design of systems for first responders. We found no systematic analysis of the relationships between toxic chemicals and symptoms in publicly available databases, few studies of first responders in terms of the tools they used, and the context in which they are used, and few algorithms and interfaces that were designed to directly target those needs. Our research in analyzing relationships hidden in toxic chemical databases, and the user needs and context revealed complexities that we only vaguely knew of before the project commenced.

Our analysis progressively revealed details related to two types of complexities: (1) **Data complexity**, and (2) **Usage complexity**. Data complexity related to the high overlap of symptoms across chemicals, and across classes of chemicals, and its repercussions for rapidly diagnosing a chemical during an emergency. Comprehending data complexity motivated us to invent new analytical methods to measure and visualize the overlap, and new algorithms and interfaces to help first responders to navigate the overlap with the goal of rapidly identifying toxic chemicals.

In contrast to data complexity, usage complexity related to the multiple roles played, and tools used by first responders during a chemical incident, and the triggers that motivated them to use decision-support tools. Comprehending usage complexity motivated us to develop a visual analytical interface that directly addressed the overloading of short term memory common in a context where users play multiple roles and perform multiple tasks on different tools in response to the emergency situation.

Although this document is structured sequentially by specific aims, like any complex design process the design and implementation of MAIDN evolved iteratively. This was made possible because the usability and algorithm teams worked in parallel, and because we had ready access to an expert first responder that was committed throughout the project to give us feedback on the evolving design. Each time we had a new insight into the data or usage complexity, we were able to get immediate informal feedback on those insights. We believe this iterative informal feedback was crucial for the overall success of the project, and which was confirmed and deepened through the formal data collection and evaluation that the grant enabled.

Despite our new insights through this feasibility study, and positive reviews for MAIDN, we believe there are several steps required before our prototype is ready for the field. This will require reprogramming the prototype in a more robust programming language, and conducting large scale systematic usability studies that were beyond the scope of this project. In that respect, we believe the results of this R21 can form the preliminary results for a future RO1 that directly addresses the above issues, and leads to the translational goal of reducing harm to workers that are exposed to toxic chemicals during emergencies.

Inclusion Enrollment Report - Semi-Structured Interviews

This report format should NOT be used for data collection from study participants.

Study Title: Novel Systems for Rapidly Identifying Toxic Chemicals During Emergencies: Semi-Structured Interviews

Total Enrollment: 20 **Protocol Number:** PAR-06-552

Grant Number: IR210H009441-01A2

PART A. TOTAL ENROLLMENT REPORT: Number of Subjects Enrolled to Date (Cumulative) by Ethnicity and Race

Ethnic Category	Females	Males	Sex/Gender Unknown or Not Reported	Total	
Hispanic or Latino	1	0	0	1	**
Not Hispanic or Latino	0	16	0	16	
Unknown (individuals not reporting ethnicity)	1	1	1	3	
Ethnic Category: Total of All Subjects*	2	17	1	20	*
Racial Categories					
American Indian/Alaska Native	0	0	0	0	
Asian	0	0	0	0	
Native Hawaiian or Other Pacific Islander	0	0	0	0	
Black or African American	0	1	0	1	
White	0	15	0	15	
More Than One Race	1	0	0	1	
Unknown or Not Reported	1	1	1	3	
Racial Categories: Total of All Subjects*	2	17	1	20	*

PART B. HISPANIC ENROLLMENT REPORT: Number of Hispanics or Latinos Enrolled to Date (Cumulative)

Racial Categories	Females	Males	Sex/Gender Unknown or Not Reported	Total	
American Indian or Alaska Native	0	0	0	0	
Asian	0	0	0	0	
Native Hawaiian or Other Pacific Islander	0	0	0	**0**	
Black or African American	0	0	0	0	
White	0	0	0	0	
More Than One Race	1	0	0	1	
Unknown or Not Reported	0	0	0	0	
Racial Categories: Total of Hispanics or Latinos**	1	0	0	1	**

* These totals must agree.
** These totals must agree.

Program Director/Principal Investigator (Last, First, Middle): Bhavnani, Suresh

Inclusion Enrollment Report - Survey

This report format should NOT be used for data collection from study participants.

Study Title: Novel Systems for Rapidly Identifying Toxic Chemicals During Emergencies: Self-Administered Survey

Total Enrollment: 139 **Protocol Number:** PAR-06-552

Grant Number: IR210H009441-01A2

PART A. TOTAL ENROLLMENT REPORT: Number of Subjects Enrolled to Date (Cumulative) by Ethnicity and Race					
Ethnic Category	**Females**	**Males**	**Sex/Gender Unknown or Not Reported**	**Total**	
Hispanic or Latino	0	0	0	0	**
Not Hispanic or Latino	0	0	0	0	
Unknown (individuals not reporting ethnicity)	0	0	139	139	
Ethnic Category: Total of All Subjects*	0	0	139	139	*
Racial Categories					
American Indian/Alaska Native	0	0	0	0	
Asian	0	0	0	0	
Native Hawaiian or Other Pacific Islander	0	0	0	0	
Black or African American	0	0	0	0	
White	0	0	0	0	
More Than One Race	0	0	0	0	
Unknown or Not Reported	0	0	139	139	
Racial Categories: Total of All Subjects*	0	0	139	139	*

PART B. HISPANIC ENROLLMENT REPORT: Number of Hispanics or Latinos Enrolled to Date (Cumulative)					
Racial Categories	**Females**	**Males**	**Sex/Gender Unknown or Not Reported**	**Total**	
American Indian or Alaska Native	0	0	0	0	
Asian	**0**	0	0	0	
Native Hawaiian or Other Pacific Islander	0	0	0	**0**	
Black or African American	0	0	0	0	
White	0	0	0	0	
More Than One Race	0	0	0	0	
Unknown or Not Reported	0	0	0	0	
Racial Categories: Total of Hispanics or Latinos**	0	0	0	0	**

* These totals must agree.
** These totals must agree.

Publications

Publications (CDC/NIOSH acknowledged)

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Appendix-1. Semi-Structured Interview Instrument

Demographic and Prior Experience Survey

1. Participant ID _______
2. Age ___
3. Female ___ Male ___
4. Ethnicity _______________________

1. Please describe your current job title or role in Hazardous Materials Identification.	
2. What is your highest level of hazardous materials training.	Awareness ❍ / Operations ❍ / Technician ❍ / Specialist ❍ / N/A Comments:
3. Please indicate how many years you have worked as a first-responder.	Never ❍ / Less than 1 year ❍ / 1-5 years ❍ / 6-10 years ❍ / More than 10 times ❍ / N/A Comments:
4. Please indicate how many times in the last 5 years you have identified a toxic chemical during a chemical incident involving harmful human exposure.	Never ❍ / 1-5 times ❍ / 6-10 times ❍ / 10-15 times ❍ / More than 15 times ❍ / N/A Comments:
5. Please enter which system you use most often to help you identify a toxic chemical during a chemical incident.	
6. Please indicate how many times in the last 1 year you have used the WISER database and system to identify a toxic chemical during a chemical incident involving harmful human exposure.	Never ❍ / 1-5 times ❍ / 6-10 times ❍ / 10-15 times ❍ / More than 15 times ❍ / N/A Comments:
7. Please indicate what computer hardware you use most often when attempting to identify a toxic chemical during a chemical incident.	Laptop ❍ / Personal Digital Assistant (PDA) ❍ / Smart Phone ❍ / Other (Please explain) ❍ / N/A Comments:

Introduction and Consent

Thank you very much for your time today. I am XXX from XXX. We are interested in developing computer systems that help you during toxic chemical emergencies, and therefore would like to understand the different activities you do during a toxic chemical incident. Do we have your permission to record this session, as we would like to analyze it at a later time?

Background and Role

Question-1: Can you please describe your role in this department?

Possible Probes:

- When did you come to this department? Are you a volunteer? Where is your full time job?
- When and where did you get your highest level of training?
- Approximately how much time do you spend performing different duties such as response, training and administrative duties?

Tasks

Question-2: We would like to know the process of how you respond to a toxic chemical emergency. Can you please describe the most significant incident involving harmful human exposure, and the steps you and your colleagues took to address the problem?

Possible Probes:

- Can you please describe the specific tasks you did with respect to understanding and responding to the toxic chemicals such as chemical identification or chemical reactions?
- Can you please describe how you worked as a team during the toxic chemical emergency?

Tools

Question-3: Can you please describe the tools you used in the incident that you described? (Please include specific names.)

Possible Probes:

- Did you use a laptop, smart phone, or a PDA? Did you use them in combination?
- How did you get access to these tools?
- What difficulties do you have using these tools?
- Can you please describe how you use WISER?
- What improvements would you suggest for WISER?
- **How do you resolve the situation when two chemicals have exactly the same symptoms?**

Context

Question-4: Can you please describe the context in which you performed your tasks?

Possible Probes:

In what context did you use WISER?

- What was the atmosphere? What time did the incident occur and last?

Demo

We would like your feedback on a prototype system designed for the rapid identification of toxic chemicals during emergencies.

Appendix-2. Online Survey Instrument

First Responder Survey

1. Background, Tasks, and Tool Use

Instructions: Thank you for agreeing to take this survey. The goal of this survey is to understand your background, the tasks you perform as a first-responder, and to obtain your feedback on computer tools for toxic chemical identification so that we can improve them to better support your job. The survey consists of 36 questions divided into two parts, which should take approximately 15 minutes to complete.

The first part of the survey consists of 16 questions related to your background, and your impression of computer features in a toxic chemical identification system that you currently use. Please read each statement and select the appropriate response. If a statement does not apply to you, please select N/A if that option is available. You can also enter comments to elaborate your answers.

***1. Please select all the job responsibilities you have performed in the last year.**

- ☐ Hotzone Entry
- ☐ Chemical/Container Research & Assessment
- ☐ Medical Response
- ☐ Transport /Rescue Patients
- ☐ Engineer/Operator
- ☐ Equipment Maintenance
- ☐ Incident Paperwork
- ☐ Incident Command
- ☐ Hazmat Training
- ☐ Safety Officer
- ☐ Decontamination
- ☐ Other (Please specify in comments)

Comments

***2. Please enter your current job title.**

3. Please enter the location and size of your HAZMAT team.

State:

County:

Size of Department:

No. of People Served:

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First Responder Survey

4. Please indicate your HAZMAT team's jurisdiction.

- ◯ Absence of technician level HAZMAT team
- ◯ Part of a single department only
- ◯ Countywide
- ◯ Regional

***5. In the last 5 years, approximately how many times have you identified a toxic chemical during a chemical incident?**

- ◯ Never
- ◯ 1-5 times
- ◯ 5-10 times
- ◯ 10-15 times
- ◯ More than 15 times

First Responder Survey

1. Background, Tasks, and Tool Use

6. In the last year, which computer hardware did you use most often when attempting to identify a toxic chemical during a chemical incident?

- ◯ Laptop
- ◯ Personal Digital Assistant (PDA)
- ◯ Smart phone
- ◯ Tablet
- ◯ Other (please specify below)

7. In the last year, which computer hardware would you have preferred to use the most when attempting to identify a toxic chemical during a chemical incident?

- ◯ Laptop
- ◯ Personal Digital Assistant (PDA)
- ◯ Smart phone
- ◯ Tablet
- ◯ Other (please specify below)

First Responder Survey

8. Please indicate all detection equipment that you use to help you identify a toxic chemical d chemical incident.

- [ ] Radiation detector
- [ ] pH paper
- [ ] KI-starch paper
- [ ] F paper
- [ ] M8 paper
- [ ] Oxygen sensor
- [ ] Combustible gas indicator (e.g., CGI)
- [ ] Electrochemical sensors
- [ ] Photoionization detector (e.g., PID)
- [ ] Colorimetric tubes
- [ ] IMS (e.g., LCD or SABRE)
- [ ] ChemPro
- [ ] FTIR (e.g., HazMatID or TruDefender)
- [ ] Raman (e.g., RespondeR or FirstDefender)
- [ ] GC/MS (e.g., GUARDION or HAPSITE)
- [ ] Other (please specify below)

***9. Which software program do you use most often to help you identify a toxic chemical during a toxic chemical incident?**

- ○ Computer-Aided Management of Emergency Operations (**CAMEO**)
- ○ Wireless Information System for Emergency Responders (**WISER**)
- ○ Palmtop Emergency Action for Chemicals (**PEAC**)
- ○ CoBRA
- ○ HazMasterG3
- ○ None of the above

10. In the last year, how many times have you used the WISER system and database to identify a toxic chemical during a chemical incident?

- ○ Never
- ○ 1-5 times
- ○ 5-10 times
- ○ 10-15 times
- ○ More than 15 times

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First Responder Survey

1. Background, Tasks, and Tool Use

You previously indicated the system that you use most often to identify a toxic chemical. Please indicate the extent to which you find the system easy to use or useful.

11. I find the method for entering symptoms and properties in the [Q9] system easy to use.

Extremely easy	Very easy	Somewhat easy	Not very easy	Not at all easy
○	○	○	○	○

12. I find the display of identified toxic chemical results, based on my inputs into the [Q9] system easy to use.

Extremely easy	Very easy	Somewhat easy	Not very easy	Not at all easy
○	○	○	○	○

13. I find the display of response suggestions to toxic chemical exposure in the [Q9] system easy to use.

Extremely easy	Very easy	Somewhat easy	Not very easy	Not at all easy
○	○	○	○	○

14. Overall, I find the [Q9] system useful in my job.

Extremely useful	Very useful	Somewhat useful	Not very useful	Not at all useful
○	○	○	○	○

15. Overall, I find the [Q9] system easy to use.

Extremely easy	Very easy	Somewhat easy	Not very easy	Not at all easy
○	○	○	○	○

16. Please describe features of a toxic chemical identification system that are missing in the current system you use, and which you desire to exist in a future system that will improve your ability to identify toxic chemicals during a chemical incident:

Desired Feature 1: ______

Desired Feature 2: ______

Desired Feature 3: ______

Desired Feature 4: ______

Please enter more features: ______

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First Responder Survey

Demonstration of MAIDN

Instructions: We would like your feedback for a new prototype system called MAIDN. This system has been developed to help first responders rapidly identify toxic chemicals during chemical emergencies. Please watch the following video, which provides a brief overview of the features provided by MAIDN.

The video (5:28 minutes in length) contains audio (so please turn on the sound on your computer), and uses the YouTube video player (which requires the Adobe Flash Player). The video can be viewed in full screen mode by selecting the icon in the lower right hand corner of the video frame. When in full screen mode, please hit the escape key on your keyboard to return to the survey.

After watching the video, please select the next button below to continue with the last page of the survey.

If the video does not load, please click on the following link to watch the video on YouTube, and then resume the survey: http://www.youtube.com/watch?v=POFmlmuhpNM&feature=youtu.be&hd=1

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First Responder Survey

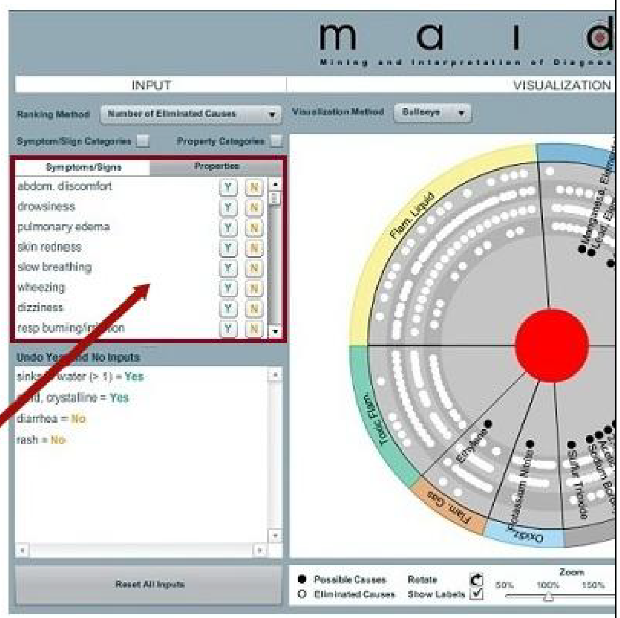
2. Feedback on the MAIDN system

Instructions: Thank you for watching the video on MAIDN. This part of the survey requests your feedback on individual components of the MAIDN system, and then the system as a whole. Please read each statement and indicate the extent to which you would find the system useful and easy to use.

==

The Input Pane

As described in the video, the Input Pane enables you to select from a ranked list of symptoms or properties based on their ability to eliminate close to half of the remaining symptoms, whether you answer yes or no. This is designed to help you reduce the number of inputs during the chemical identification process. Please give us feedback on the usefulness and ease of use of this feature.



17. I would find the ranked list in the Input Pane for selecting symptoms and/or properties in MAIDN useful in my job.

Extremely likely	Quite likely	Slightly likely	Neutral	Slightly unlikely	Quite unlikely	Extremely unlikely
◯	◯	◯	◯	◯	◯	◯

18. I would find the ranked list in the Input Pane for selecting symptoms and/or properties in MAIDN easy to use.

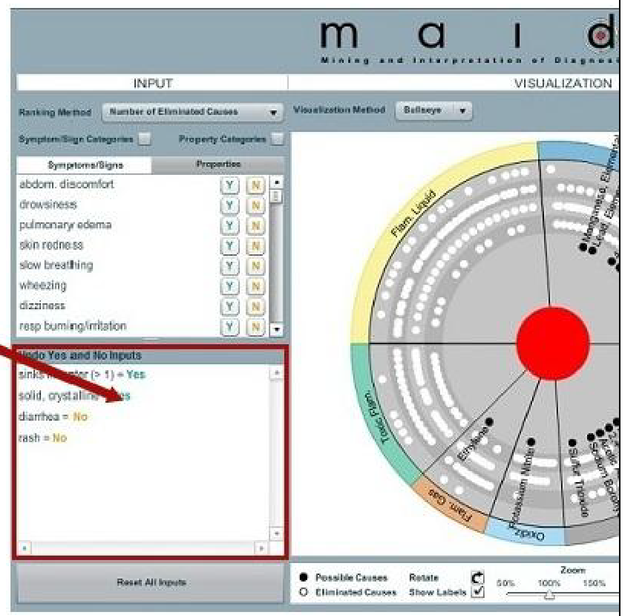
Extremely likely	Quite likely	Slightly likely	Neutral	Slightly unlikely	Quite unlikely	Extremely unlikely
◯	◯	◯	◯	◯	◯	◯

First Responder Survey

==

The Undo Pane

As described in the video, the Undo Pane enables you to change the currently selected inputs by clicking on a symptom or property in the Undo Pane, which will move the selected item back to the Input Pane. Please give us feedback on the usefulness and ease of use of this feature.



19. I would find the feature for undoing a selection in the Undo Pane in MAIDN useful in my job.

Extremely likely	Quite likely	Slightly likely	Neutral	Slightly unlikely	Quite unlikely	Extremely unlikely
◯	◯	◯	◯	◯	◯	◯

20. I would find the feature for undoing a selection in the Undo Pane in MAIDN easy to use.

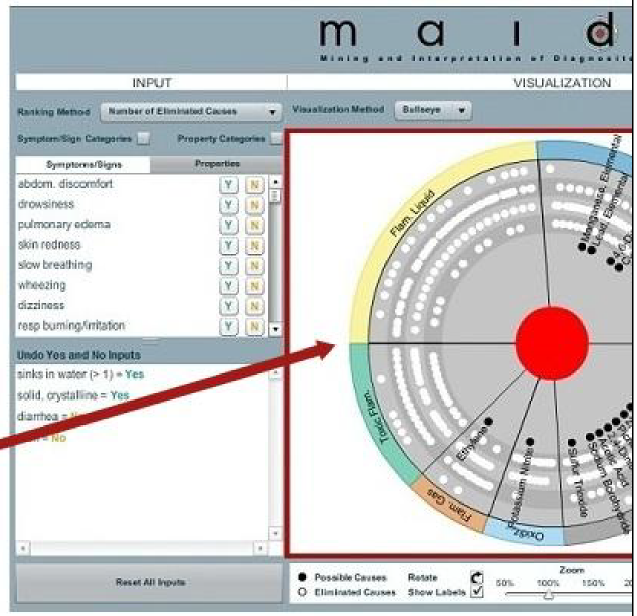
Extremely likely	Quite likely	Slightly likely	Neutral	Slightly unlikely	Quite unlikely	Extremely unlikely
◯	◯	◯	◯	◯	◯	◯

==

First Responder Survey

The Visualization Pane

As described in the video, the <u>Visualization Pane</u> enables you to inspect the number and categories of chemicals that have been eliminated (white dots), or are remaining candidates (black dots). Clicking on the chemicals displays more information about that chemical in the Information Pane. Please give us feedback about the usefulness and ease of use of this feature.



21. I would find the <u>Visualization Pane</u> that displays toxic chemicals results in MAIDN <u>useful</u> in my job.

Extremely likely	Quite likely	Slightly likely	Neutral	Slightly unlikely	Quite unlikely	Extremely unlikely
○	○	○	○	○	○	○

22. I would find the <u>Visualization Pane</u> that displays toxic chemicals results in MAIDN <u>easy to use</u>.

Extremely likely	Quite likely	Slightly likely	Neutral	Slightly unlikely	Quite unlikely	Extremely unlikely
○	○	○	○	○	○	○

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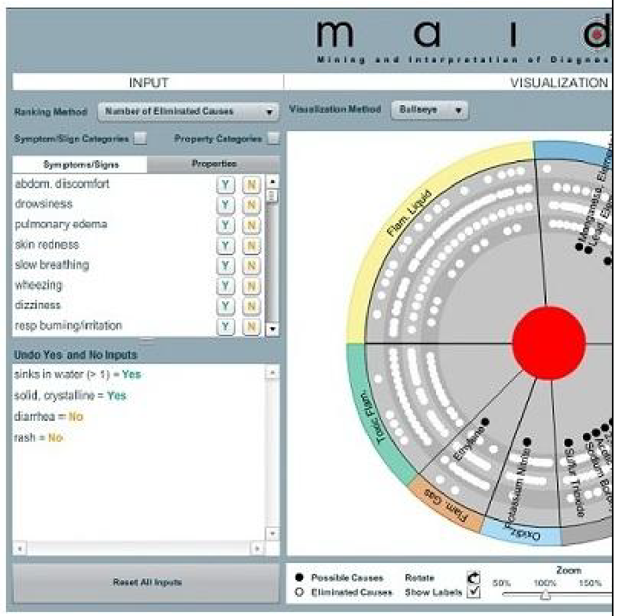
First Responder Survey

2. Feedback on the MAIDN system

The MAIDN System

As described in the video, the overall MAIDN system is designed to enable you to (1) rapidly identify toxic chemicals by reducing the number of inputs, (2) comprehend the effect of the selections through the visualization, (3) change inputs, and (4) display different types of information about the chemicals. Please give us feedback about the overall MAIDN system.



23. Using the MAIDN system in my job would enable me to accomplish tasks more quickly.

Extremely likely	Quite likely	Slightly likely	Neutral	Slightly unlikely	Quite unlikely	Extremely unlikely
○	○	○	○	○	○	○

24. Using the MAIDN system would improve my job performance.

Extremely likely	Quite likely	Slightly likely	Neutral	Slightly unlikely	Quite unlikely	Extremely unlikely
○	○	○	○	○	○	○

25. Using the MAIDN system would increase my productivity.

Extremely likely	Quite likely	Slightly likely	Neutral	Slightly unlikely	Quite unlikely	Extremely unlikely
○	○	○	○	○	○	○

26. Using the MAIDN system would enhance my effectiveness on the job.

Extremely likely	Quite likely	Slightly likely	Neutral	Slightly unlikely	Quite unlikely	Extremely unlikely
○	○	○	○	○	○	○

First Responder Survey

27. Using the MAIDN system would make it easier to do my job.

Extremely likely	Quite likely	Slightly likely	Neutral	Slightly unlikely	Quite unlikely	Extremely unlikely
○	○	○	○	○	○	○

28. I would find the MAIDN system useful in my job.

Extremely likely	Quite likely	Slightly likely	Neutral	Slightly unlikely	Quite unlikely	Extremely unlikely
○	○	○	○	○	○	○

==

29. Learning to operate the MAIDN system would be easy for me.

Extremely likely	Quite likely	Slightly likely	Neutral	Slightly unlikely	Quite unlikely	Extremely unlikely
○	○	○	○	○	○	○

30. I would find it easy to get the MAIDN system to do what I want it to do.

Extremely likely	Quite likely	Slightly likely	Neutral	Slightly unlikely	Quite unlikely	Extremely unlikely
○	○	○	○	○	○	○

31. My interaction with the MAIDN system would be clear and understandable.

Extremely likely	Quite likely	Slightly likely	Neutral	Slightly unlikely	Quite unlikely	Extremely unlikely
○	○	○	○	○	○	○

32. I would find the MAIDN system to be flexible to interact with.

Extremely likely	Quite likely	Slightly likely	Neutral	Slightly unlikely	Quite unlikely	Extremely unlikely
○	○	○	○	○	○	○

33. It would be easy for me to become skillful at using the MAIDN system.

Extremely likely	Quite likely	Slightly likely	Neutral	Slightly unlikely	Quite unlikely	Extremely unlikely
○	○	○	○	○	○	○

34. I would find the MAIDN system easy to use.

Extremely likely	Quite likely	Slightly likely	Neutral	Slightly unlikely	Quite unlikely	Extremely unlikely
○	○	○	○	○	○	○

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First Responder Survey

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35. Please indicate which additional features you desire for this system:

	Yes
Larger font size for all panes	☐
Print results of identified chemicals and responses	☐
Search tool to find chemicals, symptoms, or properties in interface	☐
Support for smart phone and tablet	☐
Larger chemical database	☐
Feature to compare attributes of identified chemicals	☐
Linking with other equipment (e.g., HAZMATID, PIDs)	☐
Inclusion of other information resources (e.g., MSDS sheets, NIOSH pocket guide)	☐
Suggestions for response (e.g., medical response, suit selection, etc.)	☐
Ability to eliminate classes of chemicals (e.g., poison, flammable liquids, etc.)	☐
Low or no cost	☐

Comments

36. Please provide below any additional comments about the system:

Materials Available for Other Investigators

1. The MAIDN application can be publically accessed online using any major web browser, such as Internet Explorer 9+, Chrome, Firefox, and Safari. The link and downloadable source code is available at: <http://skbhavnani.com/DIVA/MAIDN.html>.