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Applications of artificial intelligence-guided clinical decision support in disaster medicine: an international Delphi study

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Background: Since the 1950/s, artificial intelligence (AI) technologies have been beyond the reach of most disaster medicine (DM) practitioners. With the introduction of ChatGPT in 2022, there has been a surge of proposed applications for AI in disaster medicine. However, AI development is largely guided by vendors in high-income countries, and little is known of the needs of practitioners. This study provides an international perspective on the clinical problems that DM practitioners would like to see addressed by AI.

Materials and methods: A three round online Delphi study was performed by 131 international DM experts. In round one, experts were asked: "What specific clinical questions or problems in Disaster Medicine would you like to see addressed by artificial intelligence guided clinical decision support?" Statements from the first round were analyzed and collated for subsequent rounds where participants rated statements on a 7-point linear scale for importance.

Results: In round one, 77 participants gave 539 proposed statements which were collated into 47 statements for subsequent rounds. In round two, 89 participants gave 3,008 ratings with no statements reaching consensus. In round three, 63 participants gave 2,942 ratings: five statements reached consensus: distribution of disaster patients within the hospital, estimating the size of the affected population, hazard vulnerability analysis, acquisition and distribution of resources, and transportation routing. Experts tended to disagree with the use of AI for ethics, mental health, cultural sensitivity, or difficult treatment decisions.

Conclusions: In this online Delphi study DM practitioners expressed a preference for AI tools that would help with the logistical support of their clinical responsibilities. Participants appeared to have much less support for the use of AI in making difficult or critical decisions. Development of AI for clinical decision support should focus on the needs of the users and be guided by an international perspective.

KEYWORDS

artificial intelligence, disaster medicine, clinical decision support, machine learning, Delphi, equity, diversity, inclusion

Introduction

Although artificial intelligence (AI) technologies have been in existence since the 1950s, they have largely remained beyond the reach of disaster medicine practitioners. However, with the public introduction of ChatGPT in November 2022, there has been a surge of proposed applications of these technologies in the field of disaster medicine. A recent bibliometric study mapped current research at the intersection of disaster medicine and AI (1). This included areas such as disaster monitoring and prediction, AI-based geospatial technology, decision support systems, social media analysis, machine learning algorithms for disaster risk reduction, and the utilization of big data and deep learning for disaster management.

However, there is limited knowledge of which applications are most valuable to clinical practitioners in disaster medicine. Currently, disaster medicine applications of AI are largely guided by vendors concentrated in high-income countries—in countries with robust information technology infrastructure and long histories of advancements in computing science. However, both natural and man-made disasters are global phenomena, where low and middle-income countries are often the most affected by these events. This makes it clear that when vendors independently decide which AI products to develop for disaster medicine, the resulting tools may not fully meet the needs of disaster medicine practitioners.

The goal of this study was to provide an international perspective on the clinical problems that disaster medicine practitioners would like to see addressed by artificial intelligence technologies. The primary outcome was a prioritized list of statements that reached consensus.

Materials and methods

Study design

The study was a three-round Delphi study administered electronically. Delphi studies are structured, iterative research methods in which a panel of selected experts anonymously responds to a series of questionnaires over multiple rounds, with

each round incorporating summarized feedback from the previous one, enabling participants to reconsider and refine their views until a stable consensus or clearly defined range of opinions is reached on a complex or uncertain topic (2).

The first round included open-ended and demographic questions. The second and third rounds included ratings of specific statements developed by the study team.

Study setting

The study was performed with an international group of expert panelists.

Participants and ethical review

From the onset, this study was envisioned as an international study emphasizing equity, diversity, and inclusion. The authorship team, composed of clinicians and researchers with recognized experience in disaster medicine, identified through professional networks and peer recognition, was specifically designed to ensure that all world regions were represented. A single author from each world region formed the authorship team, and each author was responsible for recruiting expert participants from their region.

Participant recruitment was performed in a three-step process. Firstly, each author was asked to identify potential participants who they believed were experts in disaster medicine. Authors were given freedom to use their own judgement in identifying and contacting the experts, which could include personal contacts or liaison with other institutions and organizations. No formal definition of criteria to classify as a disaster medicine expert was given. Identified experts within each world region were contacted by the author from that region and asked if they would be willing to participate. Those who agreed had their names forwarded to the study coordinator, MV. Secondly, the study coordinator sent an email to the potential participants, including the study information sheet and informed consent document. Those who consented proceeded to the third step, where they created a username and password on the study's electronic Delphi platform.

The study was approved by the Human Research Ethics Board of the University of Alberta under study ID PRO 00135232.

Abbreviations: AI, artificial intelligence, DM, disaster medicine, U/X, user experience.

Interventions

All Delphi rounds were conducted online using STAT59 (STAT59 Services Ltd, Edmonton, AB).

Outcome measures

The primary study outcome was a prioritized list of statements that reached consensus. Analysis included parametric statistics of mean and standard deviation (SD) as this analysis has been previously documented to be valid and reliable (3). Consensus—the degree to which experts agreed with one another—was defined *a-priori* as a SD of ≤ 1.0 on the 7-point linear scale. Statements were prioritized based on their mean score on the 7-point scale.

Data collection and analysis

During the first survey round, participants were asked several demographic questions including: country of origin, language used at home, region of residence, professional discipline, clinical work environment, sex at birth, gender identity, self-identification as a visual minority, self-identification as having a disability, years of practice in disaster medicine, and age.

In addition, the first round asked a single content related question: “What specific clinical questions or problems in Disaster Medicine would you like to see addressed by artificial intelligence guided clinical decision support?” Each participant was requested to provide a minimum of 10 and a maximum of 30 proposed statements. This survey round was conducted from March 19 to July 24, 2024.

Following the first (open) round of the Delphi study, proposals were analyzed by a subset of the study team (JMF, MV, and MC). This analysis was assisted by the AI-guided technology of the STAT59 software. During this analysis, proposed statements were checked for compliance with the initial goals of the study. Additionally, proposals were grouped when repeated proposals were received from multiple study members, and any proposals that did not meet the original research question were removed from subsequent rounds. Following this analysis, statements were moved on to the second Delphi round.

During the second round of the Delphi analysis, participants were again invited to return to the STAT59 platform. They were asked to rate each of the statements on the final statement list from the first round using a linear scale from one to seven, with one being “not at all important” and seven being “very important.”

Following the second round, the statements were analyzed again. Any statements with a standard deviation of less than or equal to 1.0 were considered to have reached consensus and were dropped from the third round. In the third round, participants were once again invited to the STAT59 platform to rate the remaining statements on the same one-to-seven scale. This time, they were shown their own previous rating from round two, as well as the mean rating from all other experts. After the completion of round three, the statements that reached consensus, with a standard

deviation of less than or equal to 1.0, were ranked based on their mean score. This ranked list formed the results of the study.

Of note, no demographic questions were mandatory. Furthermore, participants were able to skip rating any specific statement if they desired.

Sample size

No formal sample size calculation is known for Delphi studies. Generally, Delphi studies of more than 8–10 participants are known to provide statistically precise estimates when using a 7-point linear scale (3). However, the number of participants in this study was much larger to promote best practices of diversity and inclusion. Since the primary goal was to ensure a large enough number of experts to provide a global opinion on the research question, a target of 10–20 experts per world region was initially set.

Results

The final expert panel consisted of 131 participants who were recruited from 38 different countries (Table 1). Of note, not all experts completed every round of the study. In addition, not all experts answered all demographic questions. Of the 77 participants who answered the demographic questions, 29 (37.7%) were female and 48 (62.3%) were male. Participant age ranged from 30 to 73 (mean 46.6). Two participants (2.6%) self-identified as having a disability. Eleven participants (14.3%) self-identified as a visible minority.

Practitioners came from 15 different disciplines including physicians (46; 48.4%), nurses (25; 26.3%), paramedics (10; 10.5%), and others (10; 10.5%).

The mean number of years of experience as a disaster medicine specialist was 19.2 (range <1–34 years).

Participants were well-distributed across all seven world regions (Figure 1). The majority of participants were from Europe and Central Asia, East Asia and the Pacific, and North America.

Most participants (39; 50.7%) gave English as their primary language spoken at home. However, 20 other languages were also represented (Table 2).

In the initial round (round one), 77 participants gave 539 proposed statements (Supplemental File S1). During the analysis, these statements were collated into 47 unique statements, which were advanced to the subsequent rounds.

In round two, 89 participants rated 47 statements for a total of 3,008 ratings. No statements reached consensus in round two.

Because no statements reached consensus in round two, round three also consisted of 47 statements. In round three, 63 participants gave 2,942 ratings. Five statements reached consensus (Table 3). The mean score on the one-to-seven scale for these statements ranged between 5.9 and 6.1. The standard deviation ranged from 0.9 to 1.0. Two statements tied for scoring with the highest overall rating (mean 6.1/7): use of AI for estimating the size of an affected population at risk, and use of AI for hazard vulnerability analysis. Two statements tied for scoring with the second highest overall rating (6.0/7): use of AI to coordinate acquisition and distribution of resources, and use of AI in the

TABLE 1 Country of origin of experts.

	Country	Count	Percent
1	Argentina	1	1.3
2	Australia	12	15.58
3	Belgium	2	2.6
4	Bulgaria	1	1.3
5	Canada	6	7.79
6	Denmark	1	1.3
7	Egypt	2	2.6
8	El Salvador	1	1.3
9	France	1	1.3
10	Ghana	2	2.6
11	Greece	1	1.3
12	Hong Kong	2	2.6
13	India	1	1.3
14	Italy	1	1.3
15	Japan	3	3.9
16	Jordan	4	5.19
17	Kenya	1	1.3
18	Mexico	1	1.3
19	New Zealand	1	1.3
20	Norway	2	2.6
21	Panama	1	1.3
22	Papua New Guinea	1	1.3
23	Philippines	2	2.6
24	Poland	1	1.3
25	Portugal	1	1.3
26	Romania	1	1.3
27	Saudi Arabia	1	1.3
28	Singapore	1	1.3
29	Slovenia	1	1.3
30	South Africa	2	2.6
31	Spain	2	2.6
32	Switzerland	1	1.3
33	Sweden	3	3.9
34	Turkiye	1	1.3
35	United Arab Emirates	2	2.6
36	United Kingdom	1	1.3
37	United States	8	10.39
38	Zambia	1	1.3

Experts were not required to answer all demographic questions, so total count may not be equal to the total number of experts.

prehospital disaster setting to guide transportation routing. A fifth statement reached consensus with a mean of 5.9/7: use of

AI to optimize the distribution of disaster patients within the hospital. Forty-two statements did not reach consensus after round 3 (Table 4).

Of the five highest-ranking statements that did not reach consensus (Table 4), all had a mean of 5.7 or above, and their standard deviation ranged from 1.1 to 1.3.

Of the five lowest-ranking statements (Table 4) the mean score of importance ranged from 3.1 to 4.3. Of note, none of the lower ranking statements reached consensus.

Discussion

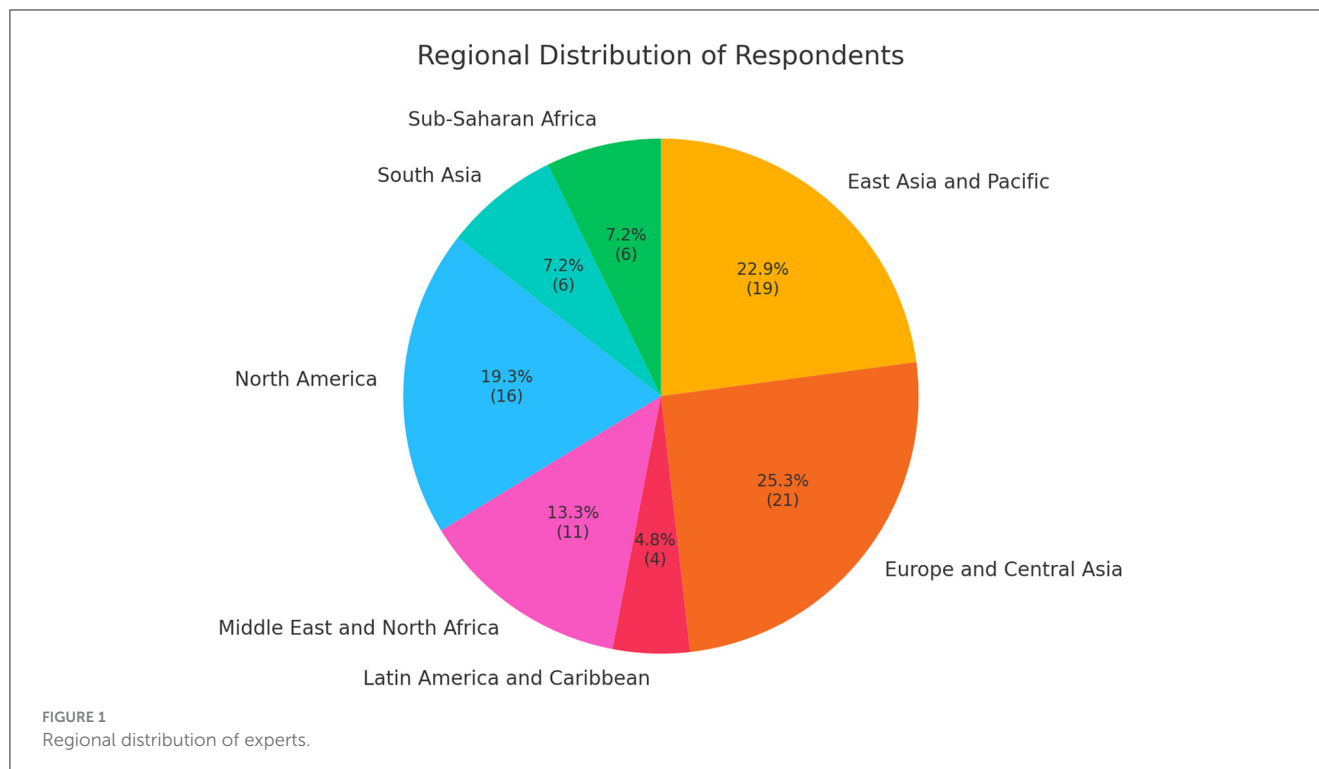
Interpretation and previous studies

In this online international Delphi study, a total of 131 participants from 38 different countries initially gave 539 proposed statements. Through two subsequent rounds of the Delphi study, five statements reached consensus.

The participants judged the use of AI to estimate the size of the affected population at risk as one of the joint highest-ranking statement (mean 6.1/7). Several other recently published studies have also explored this topic. A recent scoping review exploring the application of artificial intelligence technology in urban ecosystem-based disaster risk reduction found 76 publications addressing disasters such as floods, heat related illness, and fires (4). Artificial intelligence guided prediction rules have also been developed for forecasting COVID-19 cases as a model for future pandemics (5). In addition, an AI-based framework explicitly tailored for earthquake emergencies accurately predicted the population requiring relief supplies using historical earthquake data, socioeconomic indicators, and vulnerability indicators (6). Nonetheless, researchers note that there are still many barriers to developing these solutions including data quality, privacy, computational resources, and integration with existing systems (7).

The second joint most important statement, according to the experts, was the use of AI for hazard vulnerability analysis (mean 6.1/7). Ongoing research in this area has been published by several authors. For instance, AI driven models have been developed to assist with risk mitigation for natural hazards, power outages, and earthquakes (8, 9). One recent study used geospatial artificial intelligence for hazard mapping of flood risks on road networks in Portugal (10). Artificial intelligence models coupled to geographic information systems may also hold promise in predicting risks due to climate change (11). However, researchers note that present AI systems may lack human precision and contextual understanding (12).

Joint third in the ranking, with a mean of 6.0/7, was the statement that AI could be useful in disaster response to coordinate the acquisition and distribution of resources. A recent scoping review of 66 studies revealed a wide variety of AI applications across strategic and operational supply chain management phases and highlighted emerging techniques like explainable AI, neurosymbolic systems, and federated learning (13). Currently published AI guided research into healthcare supply chain may hold promise in this area (14). Some research shows that AI systems enable 40% faster recovery times during crises vs. traditional methods, while automated decision support systems



reduce response times to supply chain disruptions by almost 65% (15). Resource allocation in emergency departments appears to be improved with use of machine learning algorithms for certain diagnoses in the emergency department (16). Nonetheless, significant issues may arise in the need to address challenges of implementation and ethical considerations in ensuring equitable healthcare delivery (15).

Participants judged as the joint fourth most important statement—tied with the third most important statement with a mean of 6.0/7—the use of AI in the pre-hospital disaster setting to guide transportation routing. Already much research is taking place on use of AI for ambulance dispatch in the pre-hospital setting (17–19). In contrast to traditional ambulance dispatch systems, AI systems can incorporate large amounts of data into transport decisions such as real-time patient data from the scene, bed occupancy, and the availability of emergency surgeries or procedures (20). In a recent scoping review of 32 studies addressing ambulance dispatch found that AI-enhanced emergency call triage and ambulance allocation reduced response times by up to 10%–20% (21). However, the authors note that “future development should focus on real-time adaptive systems, ethical implementation, improved data integration across the care continuum, and rigorous evaluation of real-time patient outcomes” (21).

Finally, the fifth most important statement, according to participants, with a mean of 5.9/7, was that AI should be used to optimize the distribution of disaster patients within the hospital. Ongoing research in the benefits of AI guided emergency department flow is encouraging (22, 23). A recent scoping review found that machine learning algorithms improved resource allocation, quality of care, and length of stay when applied

to emergency department flow (24). Authors have also cited the potential advantages of information from resource allocation to facilitate converting hospital wards into dedicated units based on the predicted bed demand (25). However, minimal research has investigated use in surge capacity or disaster situations.

Several high-ranking statements that did not reach consensus also bear consideration. This includes AI to be used for: training in disaster medicine. In a recent scoping review of 64 articles addressing artificial intelligence-enhanced remote technologies for disaster medicine training, the authors concluded that the technologies promote learning incentives but that the quality remains uncertain (26). In this study some experts suggested AI be used to support hospital triage capacity during disaster response and to triage mass casualty incident victims. However, published studies investigating use of AI tools, such as for hospital triage, have often reported conflicting levels of practitioner comfort in allowing AI to make high-stakes decisions (27). Many experts supported the use of AI for triage of hazardous materials and chemical /biological/radiological/nuclear/explosion (CBRNE) victims. While much of the ongoing research in this field is still in its infancy, researcher are exploring the use of AI for protection of frontline CBRNE providers, analysis of hypoxia severity at triage, and measurement of signature intelligence (28–30). Some experts also supported the use of AI to aid with distribution of patients to specific treatment areas. When interpreting these statements that had high mean scores but did not reach consensus, it is important to recall that Delphi studies assess consensus to measure agreement of experts with one another. In the case of these statements, not all experts agreed with one another on the level of importance, even though the overall mean was high. Taken from a practical perspective, this shows that not all experts were

TABLE 2 Primary language of experts.

	Language	Count	Percent
1	Afrikaans	2	2.6
2	Akan	1	1.3
3	Arabic	9	11.69
4	Bulgarian	1	1.3
5	Cantonese	2	2.6
6	Danish	1	1.3
7	English	39	50.65
8	French	1	1.3
9	German	1	1.3
10	Greek	1	1.3
11	Italian	1	1.3
12	Japanese	2	2.6
13	Nepali	1	1.3
14	Norwegian	2	2.6
15	Polish	1	1.3
16	Portuguese	1	1.3
17	Romanian	1	1.3
18	Slovenian	1	1.3
19	Spanish	5	6.49
20	Swedish	3	3.9
21	Turkish	1	1.3

Experts were not required to answer all demographic questions, so total count may not be equal to the total number of experts.

TABLE 3 Statements reaching consensus.

Statement	<i>n</i>	Mean	SD
AI could be used to estimate the size of the affected population at risk	63	6.1	1.0
AI should be used for hazard vulnerability analysis	63	6.1	1.0
AI could be useful in disaster response to coordinate acquisition and distribution of resources	62	6.0	0.9
The use of AI in the prehospital disaster setting to guide transportation routing should be explored	62	6.0	1.0
AI should be used to optimize the distribution of disaster patients within the hospital	63	5.9	1.0

Consensus was defined as Standard deviation (SD) ≤ 1.0 .

All statements that reached consensus did so in round 3.

equally supportive of these initiatives. However, this study did not investigate why the experts did not agree with one another or under what circumstances they would have achieved consensus.

Several statements ranked very low in importance, ranging from 3.1 to 4.3 out of 7. This includes AI to predict the best extrication methods for trapped victims, AI used to provide personalized medical treatment to specific victims, AI to make disaster management more culturally sensitive, AI for mental

health management during disasters, and AI to help with difficult ethical dilemmas when treating a disaster victim. Interestingly, these lowest-ranking statements appear to all follow a theme, which includes the more human or personalized sides of disaster medicine. This may suggest that disaster practitioners hold a strong sense of responsibility for their decision-making process. Some ongoing research publications suggests that AI technology when used for difficult moral decisions may erode this sense of responsibility (31). However, a recent scoping review on the ethics of AI in healthcare concluded that existing laws and ethical frameworks were not up to date with the current or future application of artificial intelligence in healthcare (32). Of note, while the overall mean rating for these low ranking statements was low, none of the lower ranking statements reached consensus. This indicates that support for these statement varied between practitioners and may warrant further clarification.

Strengths and limitations

The major strength of this project is its international perspective. This was obtained by ensuring that equity, diversity, and inclusion was emphasized from the beginning of the study, including development of the authorship team. The participation of 131 participants from 38 different countries and 15 different disciplines ensured that the study maintained a global perspective.

A second strength of the study lies in the Delphi methodology itself. As this study was completed entirely online, there was mitigation of the tendency for groupthink to limit the creativity of the panel. Furthermore, in the Delphi study, all participants are given equal opportunity to voice their opinions, and all opinions carry equal weight. This contrasts with focus groups or expert panels, where dominant personalities can often overwhelm the opinions of other members of the group. This was particularly important in this topic, ensuring that dominant personalities from high-income countries did not overpower the voice of low- and middle-income countries.

A third strength of this study involved the direct participation of clinical practitioners. Throughout this study, the emphasis was on clinical practitioners' needs. The study purposefully did not focus on AI experts. AI experts tend to think more about what can be done and how it will be done. In contrast, clinicians are more likely to think of what will help their work and what will be useful for practical purposes.

Unfortunately, this study does have several limitations. Firstly, the Delphi method, while one of the more rigorous methods of obtaining expert opinion, is still based on expert opinion. However, this aligns with the specific objectives which is to create a consensus of opinions. Secondly, although the study made every possible effort to include a balanced view from all world regions, the study team was unsuccessful in recruiting a large number of experts from Latin America, sub-Saharan Africa, and South Asia. To some extent, this might represent where most academic and research efforts in disaster medicine are concentrated, which tends to be in North America, East Asia and Pacific, and Europe and Central Asia. Nonetheless, since experts were recruited directly through personal contacts of the study authors, there is a risk of inclusion

TABLE 4 Statements not reaching consensus after round 3.

Statement	<i>n</i>	Mean	SD
AI should be used to support hospital surge capacity during disaster response	62	5.9	1.2
AI can be useful for training in disaster medicine	63	5.9	1.1
An AI guided triage tool for Hazardous Materials/CBRNE victims should be developed	63	5.8	1.2
AI guided disaster triage tools should be developed	63	5.8	1.3
AI should be used to assist with disaster communication in a multilingual and culturally sensitive manner	63	5.7	1.4
AI can be used for real-time tracking of disaster victims	62	5.7	1.4
AI can assist in appropriate distribution of patients to specific treatment areas	63	5.7	1.2
AI could be used for collection of disaster victim demographics	63	5.7	1.3
AI could be used to provide health education information to the population in the event of a disaster	62	5.6	1.3
AI should be used to manage staff schedules during a disaster	63	5.6	1.2
AI could be used to communicate field records to the local healthcare system in the event of a disaster	63	5.6	1.4
AI could be used to help develop training courses in disaster management	62	5.5	1.2
AI could be used to record the victim's event timeline during a disaster	62	5.5	1.4
AI could be used to obtain clinical information directly from disaster victims in their native language	62	5.5	1.6
AI could be used to facilitate remote consultations with specialists during a disaster (telemedicine)	62	5.5	1.5
AI guided tools should assist in after action review for disasters	63	5.5	1.3
AI could be used to provide just-in-time training for disaster responders	62	5.4	1.3
AI should be used to organize responder staffing assignments during a disaster	63	5.4	1.1
AI should assist with victim identification	63	5.4	1.5
AI-driven technology should be used to deliver targeted public health awareness campaigns	63	5.3	1.4
AI could be used to support context specific (local) disaster plans	63	5.3	1.3
AI should be used for real-time monitoring of disaster victims	62	5.3	1.4
AI should be used to support management of CBRNE victims	62	5.2	1.3
AI should be used to produce a clinical record (chart) for disaster victims	63	5.2	1.4
AI could be used to identify immediate health needs after the disaster	62	5.2	1.1
AI could be used to predict the duration of an ongoing disaster	62	5.0	1.4

(Continued)

TABLE 4 (Continued)

Statement	<i>n</i>	Mean	SD
AI should be used to assist with discharge planning for disaster victims	63	5.0	1.5
AI could be used to aid disaster medicine responders with point-of-care ultrasound	63	5.0	1.3
AI should be used to predict probable injuries for a disaster victim given the mechanism	63	4.9	1.4
AI should be used to dynamically assess the safety of a disaster scene	62	4.9	1.4
AI should be used to manage evacuation decisions during disasters	62	4.9	1.3
AI should be used to improve water/sanitation in disaster zones	62	4.9	1.5
AI should be used to support clinical decision-making for disaster victims	63	4.7	1.3
AI should help with management of victims of climate-related disasters	63	4.6	1.3
AI should be used to predict a disaster victim's clinical course (prognosis)	63	4.6	1.5
AI could be used for management of rare conditions during disaster	63	4.6	1.6
AI could be used to predict the best extrication method for trapped victims	63	4.3	1.6
AI should be used to provide personalized medical treatment to the specific needs of each individual disaster victim	62	4.2	1.6
AI should be used to make disaster management more culturally sensitive	63	4.1	1.7
AI should be used for mental health management during a disaster	63	3.9	1.4
AI should be used to help with difficult ethical dilemmas when treating a disaster victim	63	3.1	1.6

Consensus was defined as Standard Deviation (SD) ≤ 1.0 .

bias. Thirdly, only a small number of statements reached consensus. While this may be a true reflection of the lack of homogeneity in disaster practitioner's needs, it is possible that further rounds of the study may have led to additional consensus statements. There was mild attrition of experts through the study rounds. However, the number of experts in all three rounds was well above the minimum standards commonly employed for Delphi studies.

Practice implications

The major value proposition of this project is the prioritized list of AI-guided technologies that are desirable to practitioners. This is designed to provide a clear pathway for vendors to create AI-guided applications that will benefit clinicians. Looking through the most desirable applications for AI, practitioners are most interested in applications that provide logistical support to enable them to better perform their jobs. Conversely, experts appeared to be less interested in AI for difficult decision-making. This appears to contrast with much of the approach that AI vendors are

currently using, which often focuses on making decisions rather than supporting practitioner decisions. In essence, practitioners want AI to assist them in their duties, not to replace them.

Fundamentally, development of AI technologies for disaster medicine may require re-thinking the approach to user research. Currently, most technology developers base their decisions on user experience (U/X) research: a systematic study of how real or potential customers interact with a product or service, with the explicit goal of shaping design and content to drive clicks, sustain engagement, and ultimately convert interest into purchases (33). In contrast, disaster medicine AI development should focus not on “what sells” but rather on what practitioners need to assist them in their clinical duties.

Research implications

While this study provides perspective on disaster medicine practitioners’ overall priorities for AI-guided clinical decision support, further research is required to delineate details. In many cases, these statements can be used as a target for AI development but will need further research. User experience research will be necessary to ensure that tools are usable by practitioners. Furthermore, all AI-guided technology should adhere to rigorous standards for testing and validation for accuracy before any of these tools are used for clinical decision-making. This research should maintain a global perspective and should continue to involve practitioners distributed worldwide.

A survey of current AI research in disaster medicine shows a pre-ponderance of opinion, frameworks, editorials, calls for action, and discussion of the potential of AI (1). What is clearly missing is evidence-based research.

This study demonstrates the utility and feasibility of research through online international Delphi methodology. This methodology can be useful for further research in more specialized areas of disaster medicine clinical decision support or for other topics. For instance, this paper did not pursue detailed preferences for such important topics as training, risk reduction, human resources, simulation, or education.

Conclusions

In this online Delphi study of 131 disaster medicine practitioners, participants clearly stated a preference for AI-guided clinical decision support that would help with the logistical support of their disaster medicine responsibilities. Participants appeared to have much less support for the use of AI in making difficult or critical decisions. Therefore, AI app development for clinical decision support should focus on the needs of the users and be guided by an international perspective.

Data availability statement

The original contributions presented in the study are included in the article/[Supplementary material](#), further inquiries can be directed to the corresponding author.

Ethics statement

The studies involving humans were approved by Human Research Ethics Board of the University of Alberta under Study ID PRO 00135232. The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation was not required from the participants or the participants’ legal guardians/next of kin in accordance with the national legislation and institutional requirements.

Author contributions

JMF: Project administration, Visualization, Data curation, Formal analysis, Conceptualization, Writing – review & editing, Methodology, Software, Investigation, Writing – original draft. MV: Visualization, Data curation, Conceptualization, Formal analysis, Writing – review & editing. JB: Writing – review & editing, Data curation. KH: Data curation, Writing – review & editing. JC: Data curation, Writing – review & editing. LR: Data curation, Writing – review & editing. ES: Writing – review & editing, Data curation. MC: Formal analysis, Data curation, Writing – review & editing.

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Conflict of interest

JMF is the CEO and founder of STAT59. MV has performed contract work for STAT59.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/femer.2025.1698372/full#supplementary-material>

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