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What does my technology facilitate? A toolbox to help researchers understand the societal impact of emerging technologies in the context of disasters

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Abstract Disaster risk is increasing globally. Emerging technologies – Artificial Intelligence, Internet of Things, and remote sensing – are becoming more important in supporting disaster risk reduction and enhancing safety culture. Despite their presumed benefits, most research focuses on their technological potential, whereas societal issues are rarely reflected. Taking a societal perspective is vital to ensure that these technologies are developed and operated in ways that benefit societies' resilience, comply with ethical standards, are inclusive, and address potential risks and challenges. Therefore, we were particularly interested in understanding how societal impacts can be considered and leveraged throughout the development process. Based on an explorative literature review, we developed a toolbox for professionals working on emerging technologies in disaster risk reduction. By applying a Delphi study with experts on AI in seismology, we iteratively adapted and tested the toolbox. The results show that there is a need for guided reflection in order to foster discussion on the societal impacts. They further indicate a gap in the common understanding of how a technology is defined and what role it should play in disaster risk reduction. That is crucial for developing inclusive technologies or defining regulations. Our toolbox was found to be useful for professionals in reflecting on their developments and making technologies societally relevant, thereby enhancing societies' resilience.To extend the implementation of the toolbox, it is essential to facilitate additional promotion through avenues such as workshops and conferences. This process should align with the established framework of project management and the policy cycle.

Non-technical summary The frequency and severity of disasters, from both natural hazards such as flash floods and human hazards such as terrorist attacks, are increasing. Newly developed technologies are one way to improve the prevention of and response to these disasters. Recent research has mainly focused on the technological issues of those technologies, with a view to analysing their efficiency. Little research has been conducted to assess whether the technologies help societies in dealing with disasters. This study tries to fill this gap by proposing a toolbox for professionals who work on and with those technologies to help and guide them through a reflection process on what the impact of the technology is on societies. The toolbox was iteratively developed based on a literature review. We tested the toolbox with experts on AI in seismology by using an expert elicitation method (Delphi study). The results show that the toolbox is a helpful starting point for reflection and that the beginning of the discussion needs to be a common understanding on what these technologies are. Only then can the discussion lead to a fruitful further development of the technology to help people deal with disasters.

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1 Introduction

Disaster risk is increasing globally, through both natural and anthropogenic hazards such as earthquakes, wildfires, and terror attacks or chemical accidents (UNDRR, 2022). As the climate crisis evolves, natural hazard events will become more intense and more people will be exposed and negatively affected in the coming decades (IPCC, 2023). Disaster Risk Reduction (DRR) measures are indispensable to mitigate those impacts. The United Nations Office for Disaster Risk Reduction (UNDRR) has formulated the *Sendai Framework for Disaster Risk Reduction* for the period 2015 to 2030 as a response to the need for proper and collaborative actions to address the increasing complexity of disasters (Aitsi-Selmi et al., 2015).

In recent decades, emerging technologies have considerably influenced societies' safety cultures and, consequently, DRR efforts (ITU, 2019). Emerging technologies such as Artificial Intelligence (AI), Internet of Things (IoT), and remote sensing are applied for multiple hazards and for various steps in the disaster management cycle (ITU, 2019), i.e. prevention, planning,

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and response. Besides enhancing the efficiency and reducing the costs of DRR efforts, emerging technologies can also increase the digital divide, meaning that these technologies are not available for everyone and, thus, could make DRR efforts unjust and only accessible to certain parts of societies (Shaw, 2020).

To date, little research has been conducted on the societal impacts of these technologies for DRR. Lucivero et al. (2011) propose a combination of ethical tools to assess the expectations on these technologies. Gevaert et al. (2021) state that there is a need to explore the societal impacts in order for AI to be fair and just. Gevaert et al. (2021) and Izumi et al. (2019), for example, call for more co-production among researchers and developers when assessing innovation for DRR. This again should not happen during the last mile, but in the first mile of the technology development (Shaw, 2020). Professionals' perspectives and user needs should thus be included from the beginning to enhance DRR efforts.

With our study, we address this research gap by developing a toolbox based on an explorative literature review. The toolbox aims to support professionals (researchers and developers) to reflect on their technologies with regard to their potential societal impacts, answering the question: "What is the potential role of my emerging technology in enhancing safety culture and DRR efforts from a societal perspective?" The toolbox is a set of guiding questions covering the functionality, usability, and societal issues of a technology and can help to identify potential gaps or further need for reflection. We also performed a proof of concept on the example of *AI in seismology* by conducting two rounds of a Delphi study with experts in the field to evaluate the accuracy and usability of the toolbox and answer the following two research questions:

1) Can we iteratively derive a toolbox from literature to support professionals in reflecting on the societal impacts of a technology in order to enhance safety culture within DRR?

2) Does this toolbox support professionals in reflecting on the societal impact of a technology for safety culture within DRR, i) in general and ii) for the example of AI in seismology?

2 State of the Art

2.1 Safety culture and DRR

Disaster risk reduction describes efforts of preventing new and reducing as well as managing already existing risks to enforce resilience (U.N.D.R.R., 2024). Safety culture as part of DRR considers contextual factors and describes "the behaviors and actions of individuals inclusive of decision-makers both public and private, and civil society that reflect a commitment to and are concerned with minimizing risk, injury and losses to human life and the environment" (Marshall, 2020, p5). Safety culture thus describes societal dynamics that are manifested and reproduced in individuals' actions when it comes to safety and encompasses how people deal with disaster and disaster risk and whether they apply safety measures. Consequently, a system, community, or society, which is exposed to any risks and hazards reacts differently depending on its existing safety culture. Therefore, it is crucial to understand local safety culture to enhance DRR and to successfully implement a technology for DRR. If local safety culture is neglected, the implementation of DRR measures may not be successful.

2.2 The role of emerging technologies for DRR and safety culture

In order for technologies to be successfully used, inclusive, and societally relevant, it is crucial to understand safety culture and the influence the technology has on disaster risk reduction. One approach to enhancing DRR and safety culture lies in innovations (Izumi et al., 2019), of which emerging technologies are a part, alongside social innovations such as participation. Emerging technologies for DRR are understood as technologies that are broadly used and have the potential to essentially influence the way societies deal with disasters (Shaw, 2020) and to enhance their resilience (Sakurai and Shaw, 2021). The focus in this study is on AI, IoT, and remote sensing, because these three technologies can be understood as umbrella terms for a broad range of technologies, and, combined, can increase the impact for DRR (e.g. IoT can be combined with AI for predicting hazardous events, Furquim et al., 2018). **AI** refers to Artificial Intelligence and its broad spectrum of applications, e.g. machine learning, deep learning, and natural language processing. **IoT** describes wireless sensor networks that collect data. **Remote sensing** relates to the technology used to study objects from afar, for example with satellites.

2.2.1 The current application of emerging technologies for DRR

In Table 1, we summarize different applications of emerging technologies in DRR, distinguishing between the *technologies* AI, IoT, and remote sensing and the following hazards: terror attacks, flash floods, wildfires, and earthquakes.

Overall, the application and thus the potential of the different technologies for the different hazards do not differ significantly. All of the technologies have the potential to enhance data analysis and processing and, to some extent, forecasting of hazardous events, and are applied before, during, and after disasters. For all three technologies, we found only a few literature studies that assessed the societal impact.

2.2.2 The benefits of emerging technologies

Technological advancements, such as the implementation and development of AI, through for example machine learning or deep learning applications, have created new possibilities for DRR (ITU, 2019). According to ITU (2019), **AI** can improve disaster management by enhancing the recovery and response time. Further, AI is used for different hazards (Surya, 2020; Datta et al., 2022; Khan et al., 2018) and can make disaster management more efficient through faster data analysis, for

	Emerging technologies		
Hazards	Artificial Intelligence	Internet of Things	Remote Sensing
Terror attacks	Detecting potential terror attacks, preventing and predicting mass shootings (Rieland, 2018; Singer, 2022)	Distribution of cheap sensors could help enhance prediction and detection of potential terror attacks, and response to terror attacks in schools or crowds (Gao, 2016; Alsalat et al., 2018).	Counter-terror operations and monitoring applications, e.g. for military operations (Majumdar et al.)
Flash floods	Prediction (Mitra et al., 2016) and forecasting (Costache and Tien Bui, 2019), creating maps for better risk management of flood hazard (Arabameri et al., 2020)	Prediction and monitoring (Furquim et al., 2018; Arshad et al., 2019), management (Goyal et al., 2021)	In combination with machine learning it is used for prediction (Hussein, 2019) and the monitoring and managing of flash floods (Mishra, 2021).
Wildfires	Improvement of early warning and prediction of fire patterns and help with evacuation patterns (Zhao et al., 2020) Prediction of wildfires (Guerrero, 2022).	In combination with remote sensing and machine learning it can improve monitoring (Kaur and Sood, 2019), early detection and warning (Bushnaq et al., 2021; Verma et al., 2021).	Creation of warning maps (Cao et al., 2017) and in combination with machine learning can help to predict fire spread (Huot et al., 2022)
Earthquakes	Improvement of aftershock forecasts and earthquake early warning (Wu et al., 2021)	The use of mobile phones (Zambrano et al., 2017; Wu et al., 2021) can help monitor earthquakes (Taale et al., 2021), and in combination with machine learning improve earthquake early warning.	Analysis of damage after an event (Dong, 2013) and assessment of ground movements (Rathje and Franke, 2016)

Table 1 Summary of the different applications of AI, IoT, and remote sensing for terror attacks, flash floods, earthquakes, and wildfires

example (Sun et al., 2020). AI and big data are also applied to prevent or react to mass shootings and terror attacks (e.g. Staniforth and Akhgar, 2015; Rieland, 2018; Singer, 2022; Ionescu et al., 2020) or to model and predict flash floods (e.g. Costache and Tien Bui, 2019; Arabameri et al., 2020). Further, Mousavi and Beroza (2022) have shown that machine learning, deep learning, and AI applications are already broadly used in seismology and have the potential to significantly influence the field: i) using deep learning for earthquake early warning (EEW; Wu et al., 2021); ii) detecting seismic signals and forecasting seismic activities with machine learning (Seydoux et al., 2020); and, to a lesser extent and even controversially, iii) helping to predict earthquakes (e.g. Banna et al., 2020; Marhain et al., 2021). AI applications are also applied for wild fire predictions and modelling, and evacuation procedures (Zhao et al., 2020). In short, there are promising AI applications in all stages of the disaster cycle (before, during, and after an event) and for multiple hazards.

In order to function properly, AI applications need data (Sun et al., 2020). One popular and cheap way to gather data is to use wireless sensor networks, also called **IoT**. As (Adeel et al., 2018) and (Ray et al., 2017) have shown, IoT is a relevant enabler to enhance disaster monitoring and management for multiple hazards such as earthquakes, terror attacks, and flash floods, often in combination with machine learning or AI applications (e.g. Kaur and Sood, 2019; Goyal et al., 2021). The application of IoT seems very promising for DDR as it can be used in real time, e.g. for early warning and rescue operations (Ray et al., 2017). According to ITU (2019), IoT is also suitable for disaster management because sensors can be applied in multiple settings and for different hazards: they can measure and send signals and warnings from a diverse set of locations (e.g. from trees, from the ground, in buildings).

Another type of technology used for DRR is **remote sensing**. Remote sensing is a technology that is used to study objects from afar (Kaku, 2019), e.g. using satellite data to gather data and information about an area. Remote sensing is particularly helpful for DRR because the acquisition of data can happen very fast and cost-effectively, and cover a large area (e.g. Bello and Aina, 2014; Novellino et al., 2018). This leads to a more effective assessment of an area, both before and after a disaster. Remote sensing can also be applied for different hazards (Bello and Aina, 2014). Mishra (2021), for example, has identified the benefits of real-time monitoring of flash floods through remote sensing and the importance of cheap monitoring possibilities, while Dong (2013) has highlighted the use of remote sensing to evaluate the damage after an earthquake.

2.2.3 The barriers to emerging technologies

Despite the numerous benefits described above, literature indicates possible pitfalls for the use of emerging technologies for DRR (e.g. Bello and Aina, 2014; Sun et al., 2020). Generally, there is a lack of accessibility and integration of ethical and social issues (e.g. Boyd and Crawford, 2012; Crawford and Finn, 2014; Sun et al., 2020). Further, as ITU (2019) describes, there is a lack of standardization and systemization to ensure their broad applicability.

The use of emerging technology can also broaden the digital divide (Shaw, 2020). The digital divide, a term firstly used by Katz and Aspden (1997) describes the phenomenon that technological benefits are not accessible to all but only to certain societal groups (Steyaert and Gould, 2009). To make DRR more inclusive, the digital divide needs to be narrowed (Shaw, 2020). Regarding the challenges of **AI** specifically, Sun et al. (2020) state that many barriers arise due to data-related issues: there is too little or no access to data and there are security or ethical issues. However, too much available data can lead to high computational power required to process it, for instance. Additionally, sometimes the results are not reproducible or not trustworthy and, hence, not helpful for DRR. (Ogie et al., 2018) further argue that a lot of factors, such as local cultures and decision responsibilities must be considered, what needs resources. (Gevaert et al., 2021) also describe how AI in DRR still has unintended ethical issues, e.g. biases arising from the disconnect between the developers and the communities.

As regards **IoT**, it still lacks cost effectiveness, standardization, and context awareness, meaning that in order to harness the full potential of IoT, there is a need for contextual knowledge as well as technological improvements (Ray et al., 2017). Additionally, these systems must become more efficient both in data use and resource management in order to actually enhance disaster management (Adeel et al., 2018).

Remote sensing seems to be especially promising for enhancing disaster preparedness efforts. However, according to Bello and Aina (2014), one major barrier is creating a system that can be applied to different natural and anthropogenic hazards. Additionally, the timely provision of data proves to be challenging (Bello and Aina, 2014). Novellino et al. (2018) have shown that remote sensing is already applied broadly, with the main challenge being field verification (i.e. the inclusion of people affected).

2.3 The societal issues of emerging technologies

As mentioned above, societal issues have so far been broadly neglected in the assessment of emerging technologies' potential for DRR. This is also confirmed by a review study on universal design, referring to designs that are usable by everyone with a maximal benefit (Connell et al., 1997). Gjøsæter et al. (2020) conclude that despite the efforts of making ICT emergency technologies more accessible, there is still a gap to design those technologies for everyone, i.e. every possible user. Additionally, they highlight that the needs of diverse stakeholders and a human-centered approach should be included in the design of technologies for emergency management. For instance, Petersen et al. (2023) and Dallo et al. (2022) chose such a path in their research by including relevant stakeholders in the design of hazard and risk communication products. This approach of co-production allows to enhance usability between developers and users to ensure user-centred communication, which is necessary for effective hazard and risk communication as well as the usability of a technology to move from a last-mile to a first-mile approach (Shaw, 2020). Some scholars such as Petersen et al. (2023) argue to include the ethical, legal and social issues in the assessment of those technologies in a nuanced way in order to actually address them. With respect to usability, end users need to have a positive perception of and trust in a technology in order to apply it and accept the decisions derived from the outputs of these technologies (Kankanamge et al., 2021). Additionally, the technologies need to fit into existing structures such as established communication networks, and the local safety culture, and reflect people's capacities and needs. While there are studies about public perception of emerging technologies in general (e.g. on AI: Kelley et al., 2021), there is little literature on the public perception of their use for DRR. The acceptance and support thereof have thus not yet been elicited.

Another societal aspect is inclusiveness, i.e. consideration of the inclusion of vulnerable groups. One way to be more inclusive is to adopt an intersectional approach (Crenshaw, 1991; Vickery, 2017). Applied to DRR, the intersectional approach helps to find the most vulnerable and marginalized groups (people of colour, immigrants, sick, old, disables, queer etc. people) in different disaster contexts by assessing and uncovering intersecting traits or social variables. (Vickery, 2017). The homogenized term "vulnerable" can lead to a neglect of characteristics and traits that have an influence on the outcomes of a disaster response (Vickery, 2017). It is important to acknowledge that every person can be made vulnerable in a disaster, and that this is contextual. Thus, also the International Organization for Standardization (ISO) includes the personal circumstances in the assessment of vulnerability (ISO 22395, 2018). Intersectional awareness helps to understand vulnerability better.

With our study, we aim to close the still existing research gap of including users and considering ethical implications, by providing professionals (researchers and developers of these technologies) with guidance for thinking about the impact of their technology on societies and for the contextual safety culture. To this end, we focused on two specific societal issues: (i) the user-centred perspective in terms of the usability of a technology; and (ii) inclusiveness, i.e. who benefits from a technology and who is excluded.

3 Methods and Material

The methods used for this study are shown in Figure 1. Based on an extensive literature review (section 3.1), we iteratively developed a toolbox addressing the relevant issues when evaluating the potential of emerging technologies for DRR. Afterwards, we conducted a proof of concept by applying a Delphi study with two survey rounds, which allowed us to improve the toolbox based on expert feedback (section 3.2).

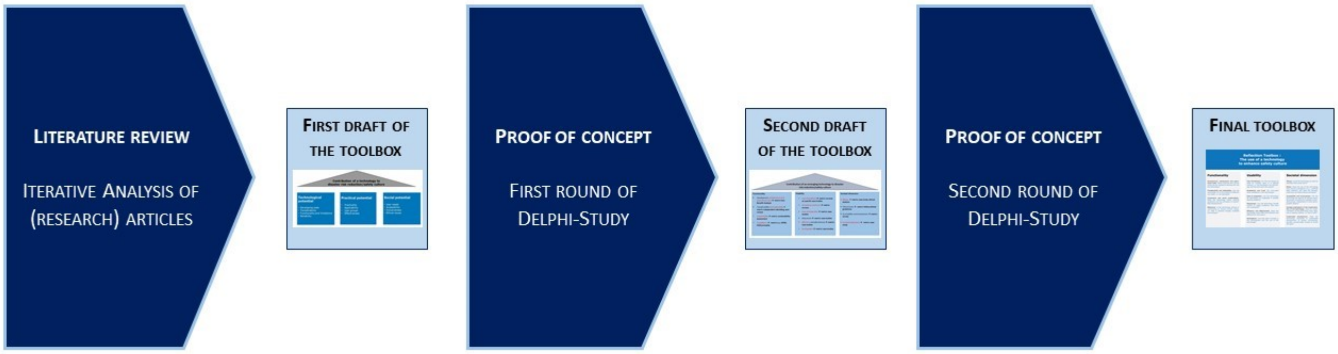

Figure 1 Overview of the methodological procedure: literature review, development and adjustment of the toolbox, and proof of concept with a Delphi study.

	Emerging technologies		
Hazards	**Artificial Intelligence**	**Internet of Things**	**Remote Sensing**
Terror attacks	6	5	2
Flash floods	4	4	2
Wildfires	4	3	2
Earthquakes	4	4	3

Table 2 Number of articles analysed for the four hazards and three technologies [in total 43 articles]

Overarching categories		
Technological potential	**Practical potential**	**Social potential**
Development costs	Practicality	User needs
Transferability	Applicability	Accessibility
Functionality	User groups	Inclusiveness
Reliability	Effectiveness	Ethical issues

Table 3 The three overarching categories and their associated sub-topics

3.1 Literature review for iterative toolbox development

We conducted an explorative literature review based on a search with a number of hazard keywords – earthquake(s), flash flood(s), wildfire(s), terror attack(s), disaster(s) – in combination with disaster risk reduction or disaster management or safety culture or emerging technologies. We searched on the platforms Google Scholar and Web of Science, and applied a "snowballing" method, i.e. looking at the references of the identified literature to access more relevant studies (Greenhalgh and Peacock, 2005). With this literature review, we mapped the current state of the art for the role of emerging technologies in DRR. Based on this, we then iteratively and deductively developed our first toolbox draft. It should be noted that the literature review yielded only a small number of publications overall (see Table 2). In order to gain a broad overview, we first searched for general literature on technologies used for DRR and specifically on the societal impact of those technologies. We found that there was a clear tendency towards the assessment of functionality and sometimes users, but little literature on the societal impact, which is why this became one focus within our toolbox. In order to holistically grasp the potential of an emerging technology to enhance safety culture, we focused not only on the societal issues but also on the practical and technological issues, since these are very interdependent.

Based on the findings and insights from the literature review, we developed a first version of the toolbox. The derived relevant issues for assessing the potential role of emerging technologies to enhance safety culture were organized in three overarching categories –technological, practical, and social potential – each with four associated sub-topics.

In a second round, the chosen studies were analysed to understand what findings, if any, each study provided with respect to these categories. In every article, we examined whether or not each of the categories was assessed.

This iterative procedure combined with discussions with fellow researchers allowed us to complement aspects and to merge certain issues. This led to a first draft of the toolbox ready to be tested in a proof-of-

	Delphi study	
Socio-demographics	Survey – Round 1	Survey – Round 2
# participants	12	7
Average age	37 years	39 years
Gender	n =8: male n =2: female n =2: do not wish to disclose	n =5: male n =2: female
Place of work	n =1: prefer not to say n =1: China n =2: United Kingdom n =2: USA n =2: France n =4: Switzerland	n =1: France n =3: United Kingdom n =3: Switzerland
Years in current position	n =1: 5-10 years n =2: 10-20 years n =3: more than 20 years n =6: 1-5 years	n =2: 10-20 years n =5: 1-5 years
Level of expertise	n =1: no expertise n =1: high expertise n =2: very low expertise n =8: medium expertise	n =1: no expertise n =1: high expertise n =5: medium expertise
Research focus	n =1: earthquake forecasting n =1: earthquake prediction n =2: none n =4: earthquake early warning n =4: rapid impact assessment	n =1: earthquake prediction n =1 rapid impact assessment n =4 earthquake early warning

Table 4 Characteristics of participants in the first and second survey rounds

concept study to determine whether it actually allowed professionals to reflect on the potential of an emerging technology for DRR. For this we chose the Delphi study method.

3.2 Delphi study to test the toolbox

By means of a Delphi study, we conducted a proof of concept of our toolbox and assessed the potential of AI in seismology. Experts on AI in seismology were recruited based on their proven expertise in the field and invited to participate in two survey rounds using the online survey tool *Unipark*(more information about the recruitment and participants can be found in the next section). The tool allows for simple, location-independent, anonymous participation. Anonymity of the participants is one key characteristic and advantage of the Delphi study because it reduces the risks of individuals dominating group discussions, thus pre-empting manipulation and coercion (Dalkey, 1972).

In both rounds, participants had to rate different statements (see Sections 3.2.2 and 3.2.3) on a 5-point Likert scale, from 1=strongly disagree to 5=strongly agree. We also included open-ended questions to let them comment on their ratings. Based on the comments provided in the first round, we adjusted or added new statements to be rated in the second round (Table 3).

3.2.1 Participants

For the expert recruitment, we chose to invite around 90 participants via email. Our selection criterion was that the possible candidates must have written a peer-reviewed article on AI in seismology within the last three years. The target was to reach about 15-30 experts, since this is the number recruited in most Delphi-studies (Hsu and Sandford, 2007). Further, we aimed to reach involve a diverse group of experts. We tried to counterbalance the Eurocentric bias by inviting experts from all over the world, specifically also targeting scientists based on the Asian and African continents, and by inviting experts of all genders. The first attempt to recruit experts via email was not sufficiently successful. We thus contacted experts through our project networks and the expert pool of the Swiss Seismological Service at ETH Zurich. In the end, we had a total of 12 experts who completed the first survey and 7 experts completing the second survey. The socio-demographics of the participants are summarized in Table 4.

3.2.2 First survey round

In the first round, we asked the participants to rank 66 statements about the toolbox and its applicability in assessing the potential of AI in seismology. The statements for the specific case were derived from the literature and discussions with seismologists. The statements tried to encapsulate the state of the art of AI in seismology, which can be summarized as follows:

AI in seismology is used for *fast data processing* (Mousavi and Beroza, 2023). This is especially promising because it seems to be cheaper than previous procedures used for modelling (Essam et al., 2021). AI can help enhance *EEW* (Meier et al., 2020; Iaccarino et al., 2021; Wu et al., 2021; Datta et al., 2022) and improve methods to *forecast earthquakes* (Mousavi and Beroza, 2023; Beroza et al., 2021) using e.g. deep learning (Seydoux et al., 2020). AI is also used for *rapid impact assessments* (Harirchian et al., 2021; Stojadinović et al., 2021). Some scholars even argue that AI can be used to predict earthquakes (e.g., Marhain et al., 2021), but this is heavily disputed since predicting the precise location, time, and magnitude of a future earthquake is not possible at the current state.

Thus, AI in seismology, with its manifold potential in DRR, which is still at an early stage of implementation, offers an ideal case study. Further, the gap in the elicitation of the societal impact is also problematic in this domain.

The rating of the statements was followed by open-ended questions addressing the experts' understanding of AI in seismology and their general opinion on the pillars of the toolbox. We also assessed the experts' age, gender, job, and location of research in order to ensure a diverse set of participants. The survey was pre-tested by a seismologist and several experts in social sciences.

For the data analysis, we followed the procedure of Vogel et al. (2019) and used SPSS. While the sociodemographics were analysed descriptively, the statements were analysed using percentages. We assumed that consensus about a statement was reached when more than 70% of the participants gave answers according to the categories defined as agreement and disagreement (Vogel et al., 2019). We defined these by adding categories 1 and 2 ("Don't agree at all", "Don't agree") to indicate disagreement, and categories 4 and 5 ("Agree" and "Fully agree") to indicate agreement. Category 3 indicated a neutral position. The open-ended questions were analysed qualitatively using Word and an inductive approach. After analysing the first survey, both quantitatively and qualitatively, we found that there was little to no consensus on the statements, which made it difficult to adapt them. Therefore, we chose to adapt the toolbox based on the insights from the qualitative analysis and exclude the statements as a whole from the second survey. This is consistent with the Delphi study procedure, as defined by Pohl (2020), since we followed an iterative process and adapted the survey after each round based on the experts' answers.

3.2.3 Second survey round

In the second round, the experts from the first round were asked to evaluate the adapted toolbox and to comment on a concise definition of AI in seismology. The survey consisted of three parts: (i) a shared definition of AI; (ii) the adapted toolbox; and (iii) demographic information. For the data analysis, we again followed the procedure of Vogel et al. (2019).

4 Results

In sections 4.1 to 4.3, we describe the results of the explorative literature review and iterative toolbox development (section 4.1) and the first (section 4.2) and second (section 4.3) rounds of the Delphi study survey. The in-depth literature review can be found in the supplement in the tables lr1, lr2, and lr 3. The results of the Delphi study follow the structure of the surveys, starting with the findings for the toolbox in general and then the specific case *AI in seismology* (Supplement, Delphi Survey (DS) – Round 1). These results show the in-depth answer to the research questions (section 1) concerning whether the developed toolbox is applicable and suitable for professionals to reflect upon the potential role of an emerging technology to enhance safety culture.

4.1 Results of the explorative literature review and iterative toolbox development

With our literature review, we iteratively and inductively developed the first solid draft of our toolbox to test in a Delphi study (Figure 2). The first draft consisted of three distinct pillars with four categories in each, all of which can be assessed individually, as shown in Figure 2. The goal was to holistically cover the role of an emerging technology in enhancing safety culture. In addition to the technological and practical issues, we aimed to elicit the societal impact of a technology, because very little literature was found on this.

4.1.1 Definition of AI

In the first part of the survey, we asked the experts to define AI in general and to explain what they thought was the potential of AI for DRR. We identified three common thoughts: i) AI is a term used to describe computational processes that involve learning; ii) AI mimics human intelligence; and iii) AI is able to process information fast. Nine out of 12 experts also agreed that AI could help enhance DRR, but that this potential should be assessed when AI has developed further. Based on these findings, we derived a definition for AI in seismology, which we then presented in the second survey round for the experts to comment on.

4.1.2 Feedback on toolbox

In the second part of the survey, we presented the first draft of the toolbox (see Figure 2). Concerning the toolbox as a whole, 6 out of 12 experts found it difficult to understand in which context and for what purpose the toolbox would be used and what the concrete implementation would look like. However, 7 out of 12 experts stated that it was a good starting point with room for improvement when it came to context, objectives, and specific items within the pillars. Additionally, a general feedback was that the metrics for all the categories within each pillar should be added, as the following statement shows: *"I like these categories and I believe they are well described. But it will be hard to quantify how transferable or how limited a technology is* (ID10)."

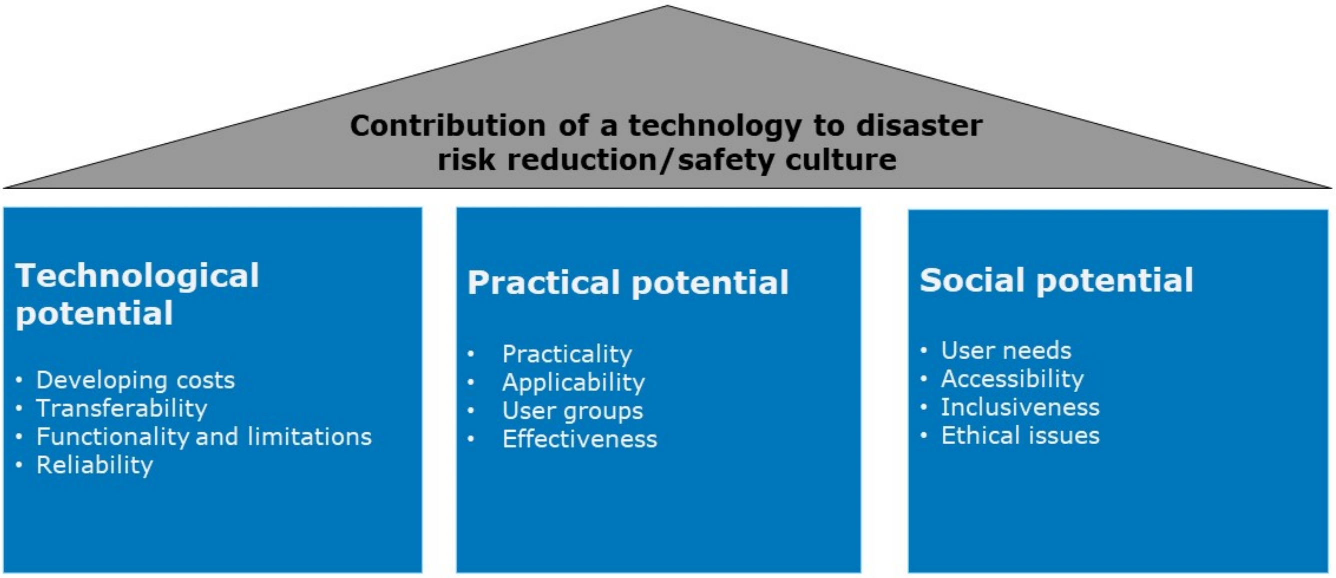

Figure 2 First draft of the toolbox after the literature review for the first survey round of the Delphi study. The toolbox was derived from the literature review. It consists of three pillars – technological potential, practical potential, and social potential. Within these pillars, there are categories that can be assessed independently in order to understand the respective pillar.

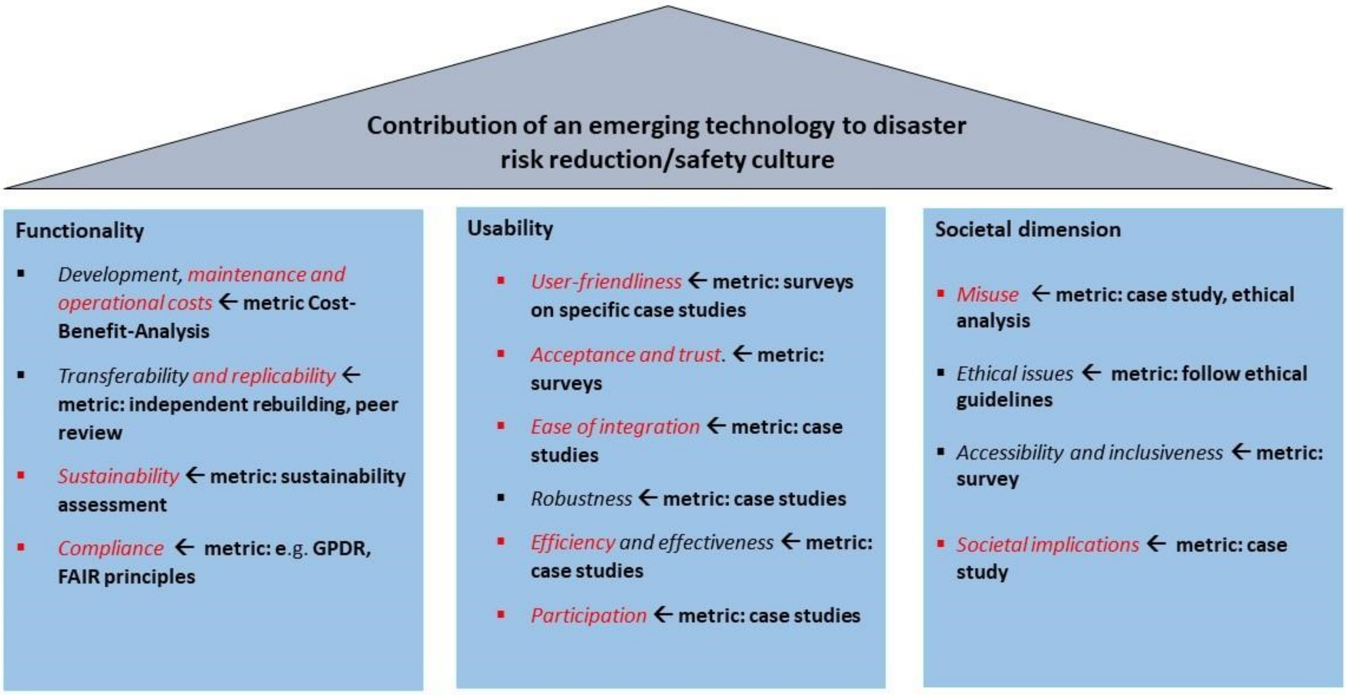

Figure 3 Adapted toolbox based on first round of the Delphi study. Changes are highlighted in red. The adapted toolbox was presented in this form in the second Delphi study survey round.

We then asked the experts to comment on each pillar separately. For each pillar, the experts provided general feedback and were able to suggest additional issues that in their opinion were missing.

For the *technological potential* pillar, in addition to better clarifying the purpose and providing metrics, there was a consensus that the "Developing costs" category should be expanded to include maintenance and operational costs as well as benefits, as the following statement underlines: *"[...]. For example cost has no sense if benefit is not added* (ID2)*."* Besides these costs, the participants mentioned other factors to be added to the pillar, such as sustainability (see Figure 3).

For the *practical potential* pillar, the feedback was similar. Participants said they would like to have more context in order to better understand the application of the toolbox. They also suggested extending the focus on end users, which was considered in the second draft (Figure 3). The feedback on this pillar also included the question of what role users should play within the development of AI in seismology.

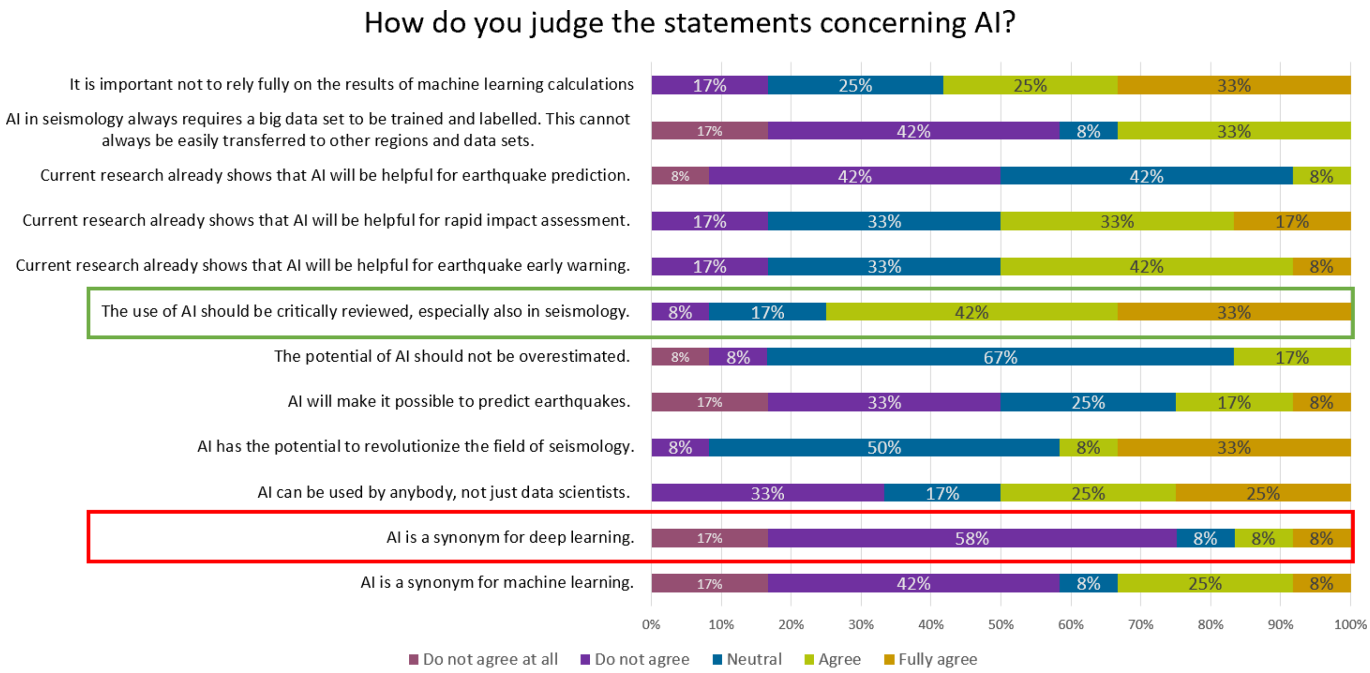

Figure 4 Statements related to AI in general: agreement is highlighted in green and disagreement in red (>70% agree or disagree).

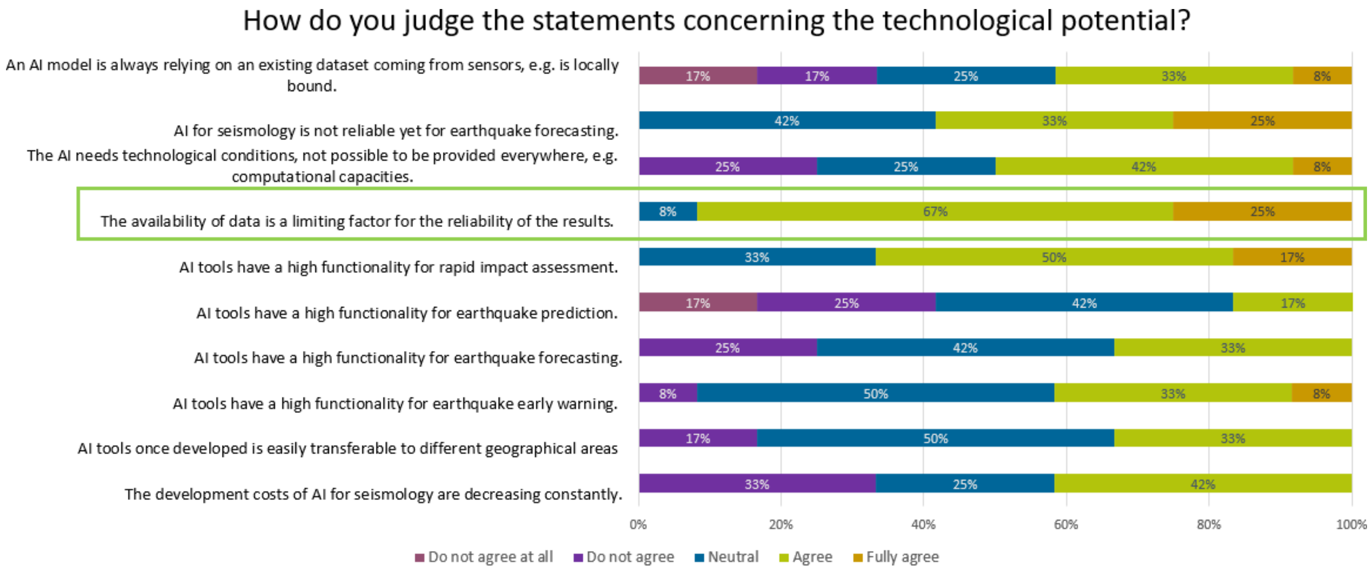

Figure 5 Statements concerning the technological potential: agreement is highlighted in green (>70% agree).

As one participant put it: *"It probably really depends on the intended users/usage scenarios: 'recognize' a disaster from data; 'characterize' the disaster and its potential; support decision making (different stakeholders/users) – I find it impossible to assess practicability 'in general'* (ID9)*."*

4.1.3 Adapted toolbox

Based on the feedback from the experts in the first survey round, we renamed the pillars: technological potential became *functionality*, practical potential became *usability*, and social potential was renamed *societal dimension*. Additionally, we added further relevant categories and metrics to assess them, and a description of the purpose and goals of the toolbox. This helped us strengthen our main goal of providing experts with guiding questions to assess the societal impact of a technology they are developing (see Figure 3).

The comments concerning the *social potential* pillar were very diverse. On the one hand, the need for ethical considerations in the development of these technologies was highlighted. On the other hand, the feedback was that the ethical considerations differ depending on the role of the end users. Some participants also reflected on the responsibility of the different actors, as the following statement shows: *"None of this is related to the tech itself but to the way it is used by the operator. It is unfair to blame the developer of tech for these issues* (ID8)*."* These issues were added to the toolbox, as shown in Figure 3.

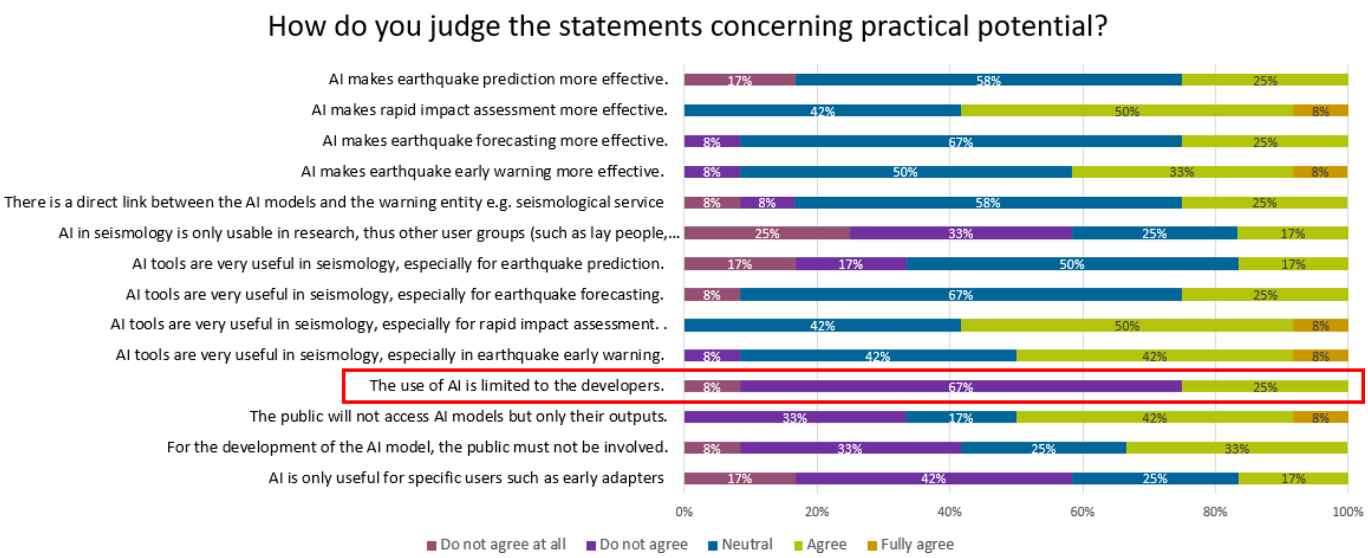

Figure 6 Statements concerning the practical potential: disagreement is highlighted in red (>70% disagree).

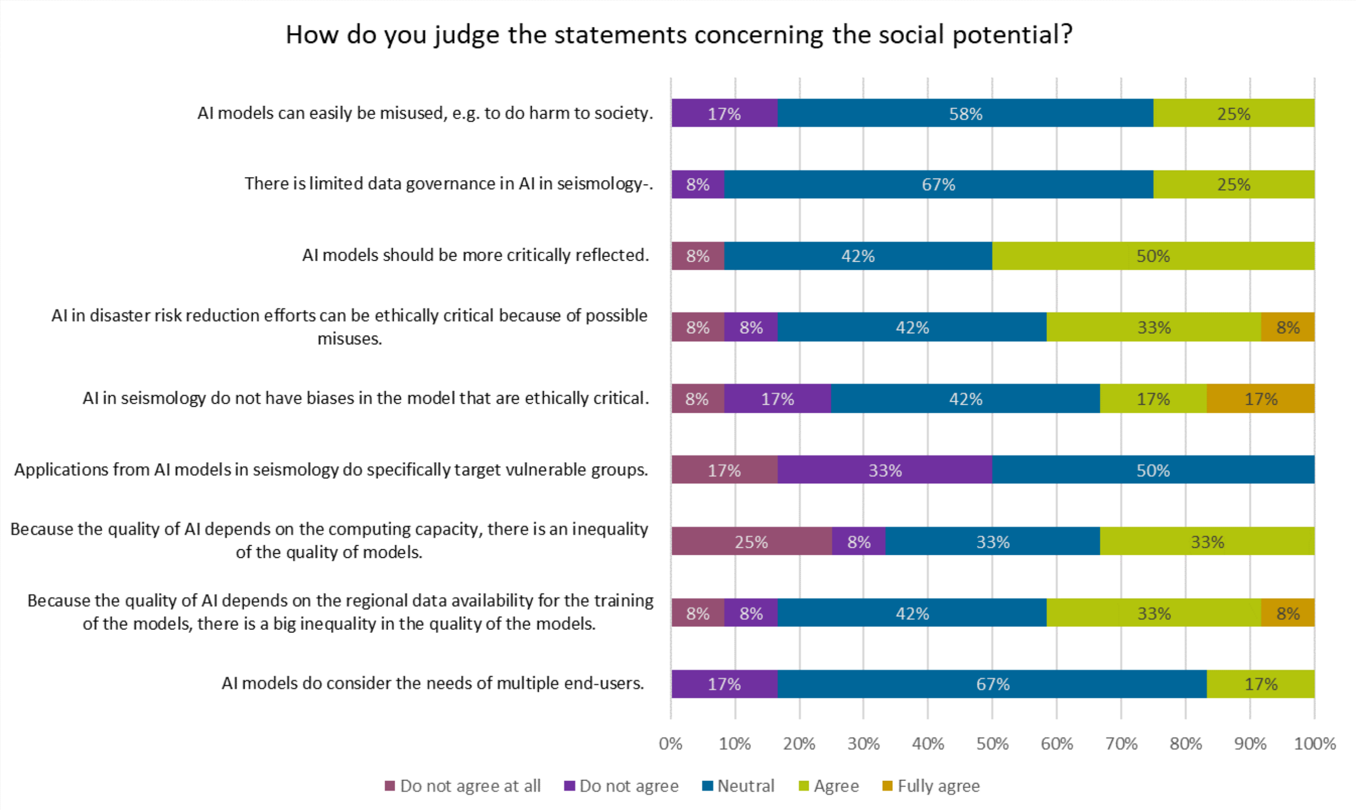

Figure 7 Statements concerning the social potential

4.1.4 The case study

In the third part of the survey, we asked specific questions concerning AI in seismology and wanted to test whether our toolbox actually helped the experts to reflect upon the societal potential of AI in seismology. The question *In which fields of seismology does AI play an important role?* elicited very diverse answers, ranging from communication and earthquake early warning to prediction. However, there was a consensus that the use of AI is still in its beginnings in seismology and that the acceleration of data processing will lead to more achievements. On the question of the greatest potential, the answers ranged from data processing and predicting damage to earthquake prediction.

We also presented statements on the potential of AI in seismology to ascertain whether the experts found the toolbox applicable.

The first batch of statements focused on the general potential of AI in seismology. It is notable that there were only two instances of clear consensus (see Figure 4). The experts agreed on the statement that the use of AI should be critically reviewed, especially in seismology. Further, there was consensus that AI is not a synonym for deep learning. The statement that AI is a synonym for machine learning came close to achieving

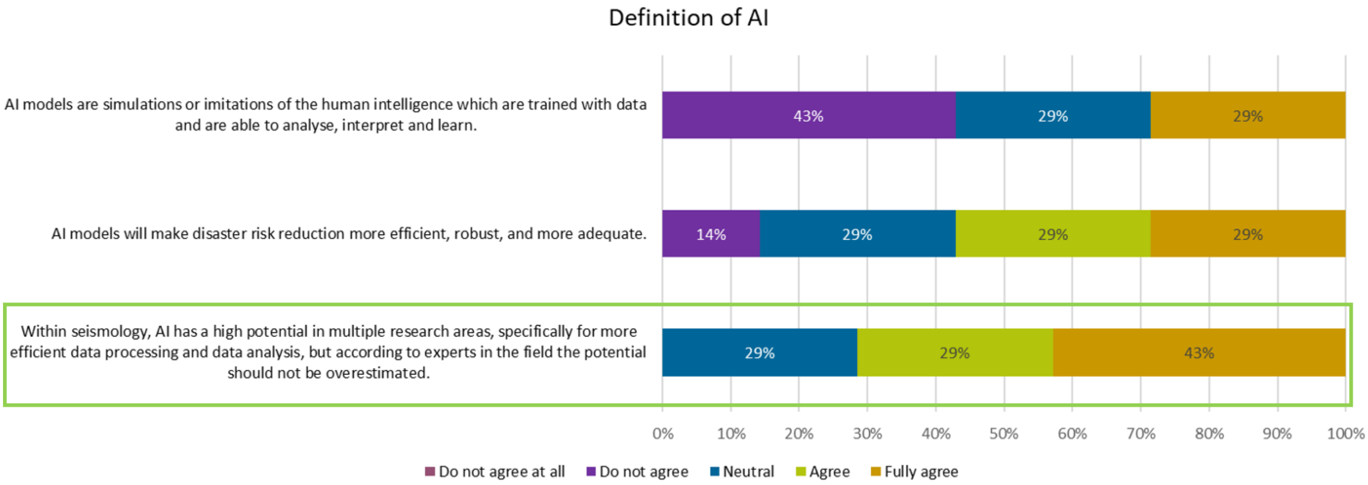

Figure 8 Definition of AI in seismology: consensus is highlighted in green (>70% agree).

a consensus (59%). For the other statements, there were few indications of a consensus, which suggests that the experts do not agree on the potential of AI in seismology and also that the applications of AI in seismology are very broad.

Because there was only very little consensus and a lot of dissent, we chose not to include these statements in the second round. However, the results of this first batch were used to formulate the proposed definition of AI for the second round of the Delphi study.

The statements concerning the three different pillars showed only little consensus.

Concerning the technological potential, there was only one instance of agreement, namely that the availability of data is a limiting factor for the reliability of the results (see Figure 5). The statement "AI has a high functionality for rapid impact assessment" almost reached consensus (67%). Some of the answers show a high degree of neutrality (over 40%).

For the practical potential, the experts agreed that the use of AI is not limited to the developers (Figure 6). No other statement achieved a consensus. The closest to consensus was for the statement "AI is only useful for specific users such as early adapters" (57%). For this user-focused category, there were even more neutral answers than for the technological potential.

For the statements concerning social potential, no consensus was reached. The statements that came closest to a consensus were "AI models should be more critically reflected" and "Applications from AI models in seismology do specifically target vulnerable groups" (50%). All statements attracted over 30% neutral answers (Figure 7).

4.2 Results of the Delphi study – Second round

In the second round, 7 of the initial 12 participants filled out the survey (Table 4). The second survey (Supplement, Delphi Survey – Round 2) was shorter because we chose to focus on the possible common definition of AI in seismology and the adapted toolbox as a whole (Figure 3). Consequently, the experts were no longer asked to rate statements on the specific case of AI in seismology. The new toolbox was again broadly commented on and the changes were viewed positively. One participant called it *"a good start for reflection* (ID7)*"*, which was exactly our goal. Still, several experts suggested some reformulations, renaming, and adjustments, which led to the final toolbox as shown in Figure 9.

4.2.1 Definition of AI

The definition of AI compiled from the answers of the first survey round consisted of three parts, which the experts were able to judge separately (Figure 8):

1) AI models are simulations or imitations of the human intelligence which are trained with data and are able to analyse, interpret and learn;

2) AI models will make disaster risk reduction more efficient, robust and more adequate;

3) Within seismology, AI has a high potential in multiple research areas, specifically for more efficient data processing and data analysis, but according to experts in the field the potential should not be overestimated.

Only for the third part of the definition was a consensus reached. The experts agreed that AI has a high potential within seismology but should not be overestimated.

Multiple comments additionally suggested that the focus of AI in seismology does not lie in the imitation of the human brain but rather in computational implementation and data processing. The following comment by a participant illustrates this: *"I have an issue still with linking AI to 'simulating/imitating human intelligence' - I am not an expert in human intelligence, but I believe that, what exactly that is, is still debated... therefore I would rather describe AI as computational implementations of models of learning/reasoning/concluding that are shaped after current understanding of neural (brain) networks (or so...)* (ID7)*."*

4.3 Final toolbox

After analysing the results of the second round, we made two big changes. Firstly, we chose to solely analyse the enhancement of safety culture and not safety culture within DRR and not DRR overall. The rationale

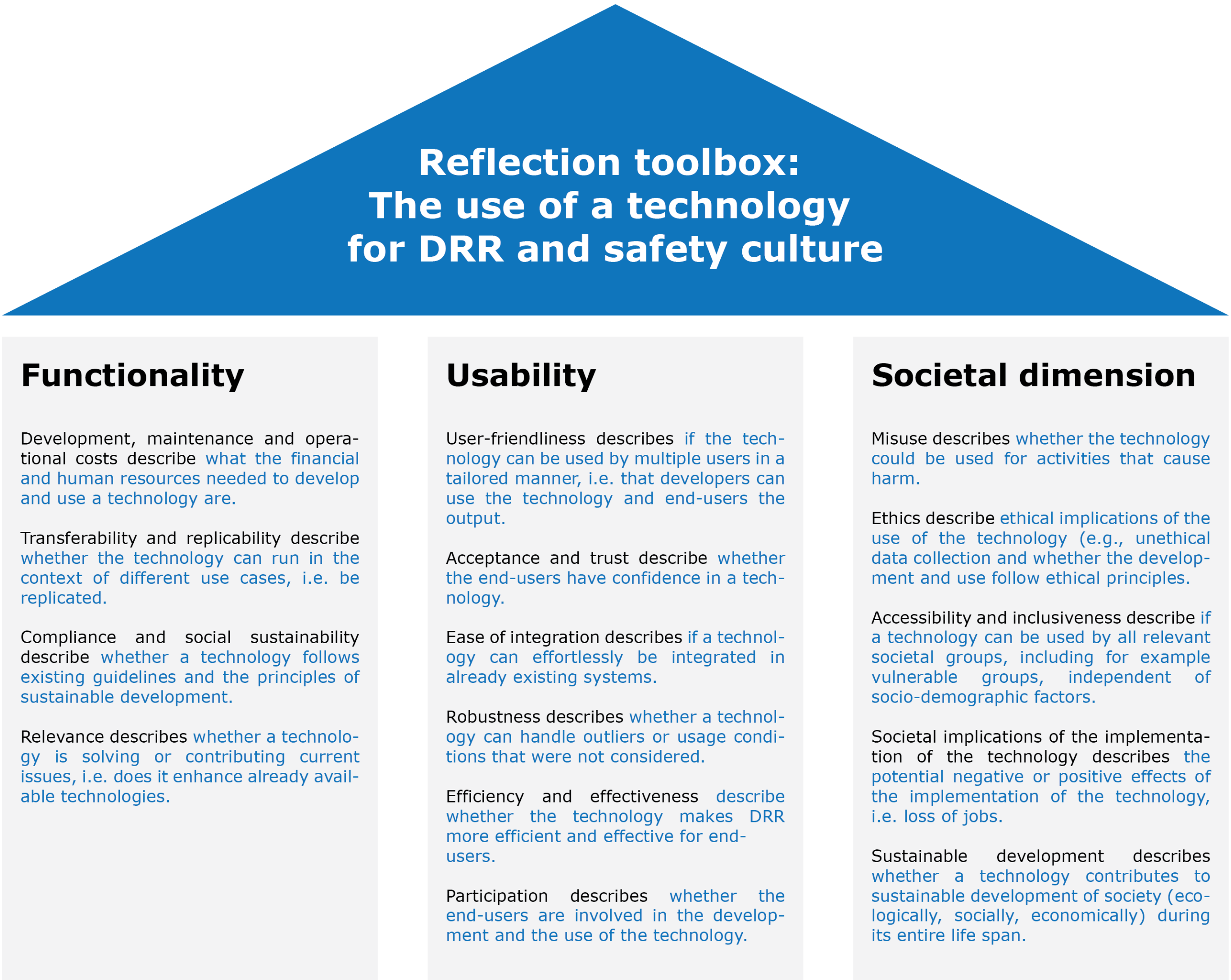

Figure 9 Toolbox to assess the potential of emerging technologies for DRR and safety culture developed in an iterative process consisting of literature review and two Delphi study survey rounds

behind this was that only if the contextual safety culture is improved, DRR effort are/become effective, as realized within the literature review. (see Safety culture and DRR). Secondly, we chose to remove the metrics from the categories. The reasons were that the toolbox should be directly applicable and not require in-depth studies for each category in each pillar. To this end, we formulated questions that can be answered for the analysis (Figure 9). To summarize, we again formulate the main goal of each pillar.

The final toolbox (Figure 9) consists of the following three pillars designed to holistically assess the potential role of an emerging technology in enhancing safety culture:

Functionality: Does it work?
The *functionality* pillar describes whether a technology functions properly during its whole lifespan and contributes to enhancing existing DRR efforts. It can be evaluated by testing the technology in existing applications in laboratory or real-world settings.

Usability: Is it used/usable?
The *usability* pillar describes whether a technology is usable and applicable by different targeted end users (context-independent), and specifically assesses the active use and the intended use of a technology.

Societal dimension: What does it mean for society?
The *societal dimension* pillar analyses the contribution of AI to DRR from a societal and ethical perspective. It addresses possible ethical issues such as misuse of the technology.

5 Discussion

Based on a literature review and a Delphi study, we were able to develop a toolbox to support professionals (developers and researchers) in the systematic reflection on the societal impact of the technology they are developing, implementing, or operating, considering safety culture in order to improve disaster risk reduction.

In the following, we explain how the iterative steps of the Delphi-study has confirmed our findings of the literature review (section 5.1). Further, we discuss how our toolbox could be applied within the project and policy cycle in order to ensure the effective use of the toolbox (section 5.2). Last, we critically reflect on the limitations of our study and discuss future research (section 5.3).

5.1 The comparison of the literature review and Delphi-study

Our toolbox is designed to help professionals to reflect on the technologies' contribution to enhancing societal benefits, encouraging collective actions towards an enhanced safety culture and including marginalized groups within society. The importance of including societal issues emerged from both the literature review and the Delphi study. Past research on the potential of technologies for DRR has mainly focused on the functionality and the usability of those and thereby neglected the societal perspective and their impact on safety culture. The insights from the Delphi study support this finding, with the statements about the technological and practical potential generating most consensus. At the same time, fewer neutral answers were given in these areas (see Figure 6 and Figure 7), indicating a shared scientific understanding.

The International Telecommunication Union (ITU, 2019) conclude in their assessment that disruptive emerging technologies for DRR are improving disaster management but that further research is required to ensure large-scale impacts. With particular regard to increasing societal impacts, they recommend fostering public outreach, i.e. consideration of the purpose and specific target audience, and partnerships between academia and the private sector to improve disaster management overall (ITU, 2019). This is also stressed in the literature review of Gjøsæter et al. (2020) In addition, our study shows that experts are interested in reflecting on their technologies, but emphasize that this is not just their responsibility but the task of all actors involved in the development, implementation, deployment, and use of a technology. This is indicated by the neutral answers for the practical and social potential statements (see Figure 6 and Figure 7). Our toolbox thus consists of questions that are applicable for all actors involved.

The literature review demonstrated that clear definitions of the technologies looked at are lacking: the applications of AI, IoT, and remote sensing are very broad and this is why there is only a tendency towards a common understanding. However, distinct definitions are required in order to be able to discuss the societal impacts of a technology. Consequently, a common understanding needs to be strengthened through further societal and scientific cooperation. This will form the basis for, among other things, drawing up regulations and policies for the development and application of AI (Harasimiuk and Braun, 2021), IoT and remote sensing in order to enhance safety culture.

It is therefore not surprising that AI in seismology is also lacking a common definition, as hinted by the literature review and the Delphi study. Despite the fact that most respondents called themselves experts on AI in seismology, they did not provide the same definition. Given the broad range of possible applications of AI in seismology and the different specializations of the respondents, this seems logical (e.g. Mousavi and Beroza, 2023). Still, the results show that the experts agree on some of the potential and the limitations of AI in seismology. Hence, AI in seismology cannot be reduced to just a single definition but rather should be discussed in the context of each application, with its limitations and pitfalls, and should not be overestimated (Mousavi and Beroza, 2022). In order to understand the potential of AI in seismology to enhance safety culture, the first step should be to understand which specific application of a technology is discussed. Given the variety of definitions, the toolbox and its categories are kept broad, while still serving as a catalyst for critical reflection on the issues under discussion and enabling an assessment of the potential in each specific application.

Still, the comparison of our literature review and the Delphi study shows that we were able to iteratively derive a toolbox which can support professionals in reflecting the societal impacts for safety culture of the technology they use. The specific case study of AI has shown that the toolbox does support professionals.

5.2 The implementation of the toolbox

To reach the purpose of being further developed, the toolbox should be actively used. This can only be achieved if the toolbox is known. One possibility would be organizing workshops with practitioners, by doing more outreach, possibly with the ITU, in order to ensure further development and, in the end, possibly standardization.

Further, existing research indicates that co-production of knowledge is required to improve DRR measures (Ismail-Zadeh et al., 2016; Izumi et al., 2019), i.e. involving stakeholders from the beginning following the first-mile principle (Shaw, 2020) and strengthening the collaboration between science and society (ITU, 2019). The evaluation of the three pillars – functionality, usability, and societal dimension – of our toolbox within the Delphi-study indicates the same: there is a need for a guided discussion and reflection on the consequences of a technology in the scientific community as well as societies to increase awareness, which the toolbox can facilitate by guiding relevant stakeholders in their reflection from the outset.

Once the toolbox is known, potential areas of influence must be identified. To this end, we linked the elements of the toolbox to the policy cycle adapted from Schubert and Klein (2020), as well as the project cycle adapted from the European Commission (2004); see Figure 10.

Setting the agenda firstly is crucial in the project initiation: in this step the goal to enhance safety culture is manifested, and hence the goal to use the toolbox in the process. With the second step, the formulation of the policy, the different foci of the use of the technology and thus the application of the different pillars of the toolbox is chosen. This then leads to the third step, the decision where the time to reflect is spent. In the two final steps, the implementation and the evaluation of the technology happens, once again with the reflection guidance of the toolbox. All these steps happen cooperatively, co-productively, and iteratively, both first-mile to last-mile.

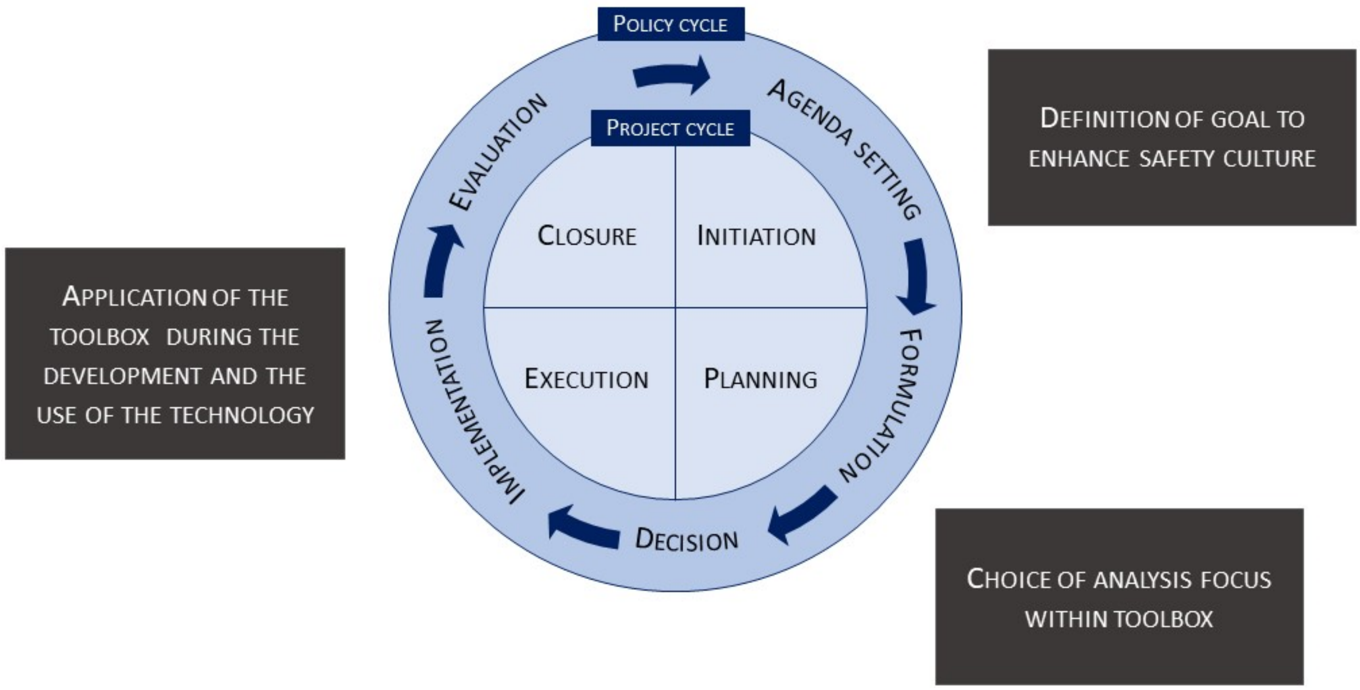

Figure 10 Application of the toolbox (black squares) in the policy cycle (adapted from Schubert and Klein, 2020, blue arrows) and the project management cycle (adapted from European Commission, 2004, blue squares).

5.3 Limitations and next steps

Our study has several limitations that could be addressed in future research.

Our explorative literature review was not conducted fully systematically but rather iteratively, meaning that there was a broad timeframe and limited sample chosen. However, the literature review was solely needed to identify the categories forming the basis of the toolbox and to grasp the state of the art of these technologies in DRR and to then develop the first solid draft of the toolbox. Further, through the expert elicitation (Delphi study), we aimed to overcome these issues by gathering more knowledge and reviewing these results.

The Delphi study is a proven method for eliciting consensus and dissent among experts and identifying potential achievements and developments in the future (Dalkey and Helmer, 1963). A key benefit of the method is that experts around the world can be involved. This was not fully achieved with our sample. We involved experts from different nations, but not from all continents and mainly from the European Union and the United States, so the results may have a Eurocentric bias. One explanation could be that the development of these technologies is still lagging in African and Latin American countries because there are other priorities for DRR. Additionally, we only conducted two rounds, since little consensus was found for the different statements. Our findings indicate the diversity of the topic, as even after two rounds there was still little consensus. However, the experts' answers show some tendencies of opinions and needs. This outcome can be explained by the broadness of the topic but also by the sample size and the participants' characteristics, which are two key limitations within this study. The sample was fairly diverse in terms of the specific research fields of seismology, despite a specific target group being formulated for recruitment. This does not, however, delegitimize the results (Hsu and Sandford, 2007), because the diversity of the group can reveal additional tendencies. It seems that, in order to understand the impacts of these technologies, rather than focusing on a common definition, case studies are helpful to understand the impact of using these technologies for society.

The Delphi study is an appropriate tool to explore policy needs. In the two survey rounds, this was achieved both by showing the differences in the understanding of AI for seismology but also by further developing the toolbox and finding more guiding questions to elicit tendencies as to whether a technology actually enhances DRR and safety culture. These policy needs could be fulfilled by applying a standardized tool for the inclusion of societal matters or targeted funding of research on those matters. Additionally, further research should be conducted with case studies on the other technologies, as well as the different pillars of the toolbox, i.e. the societal dimension and the usability. To this end, it would be beneficial to conduct studies that explore both the acceptance and practical utility of the toolbox, thereby gaining a comprehensive understanding of its usability. Further, to advance the toolbox, it must be actively used and applied by professionals and there must be continuous evaluation of how vulnerability and inclusiveness can be addressed in a technologically fast-evolving world.

6 Conclusion

Emerging technologies such as AI, IoT, and remote sensing are applied in many different fields and can support societies in dealing with disasters. So far, research looking at the practical and societal issues related to emerging technologies for DRR has been limited. This study thus iteratively and inductively developed and tested a toolbox for professionals including developers and researchers, allowing them to critically reflect on and assess the practical and societal impacts of a technology in the context of DRR and safety culture. The toolbox empowers professionals to enhance the accessibility and applicability of their technologies, considering also the needs of vulnerable groups, and encourages a shift in technology assessments from the last to the first mile. Consequently, the societal perspective becomes an integral part of all phases, encompassing the design, development, implementation, and deployment of a technology.

Our case study on AI in seismology has illustrated that the developed toolbox can indeed help and motivate scientists and developers to reflect on the societal issues related to their developments in the context of DRR, but reveals that there is a need for more common understanding and definitions of these technologies, in order for them to be discussed among different professionals.

These technologies have been found to have great potential to enhance DRR and safety culture. We therefore encourage professionals and research groups to use the toolbox for their evaluations of emerging technologies and to further adjust it based on new research findings, since it is a rapidly evolving field and the application always depends on the specific cultural contexts.

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7 Data and code availability

All the data can be found as a supplement under: https://doi.org/10.3929/ethz-b-000636485.

8 Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported on in this paper.

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