Artificial Intelligence in Automation of Community Disaster Resilience Measurement

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*Dedicated to my parents, **Mohsen Katebi** and **Shahin Ebrahimi**, who unfortunately didn't stay in this world long enough to see their son become a doctor.*

ABSTRACT

Over time, numerous frameworks have emerged to gauge a community's resilience, which is the community’s ability to get back to function, in the face of disasters. These frameworks vary in complexity and scope, often encompassing both quantitative and qualitative metrics.

The dichotomy between quantitative and qualitative measurements underscores a critical limitation in current resilience frameworks. While quantitative metrics excel in providing tangible data points and statistical analyses, they often overlook the intricate social dynamics and cultural factors that profoundly influence a community's resilience. In contrast, qualitative assessments offer a more holistic understanding by capturing the lived experiences, perceptions, and narratives of community members. This qualitative data, comprising approximately 80 percent of the information relevant to resilience, provides invaluable insights into the adaptive strategies, cultural norms, and social networks that shape a community's capacity to withstand and recover from disasters.

The pursuit of capturing richer data through qualitative methods, particularly open-ended interviews, stands as a cornerstone of this study. By delving into the nuanced perspectives and experiences of individuals, such methods offer a depth of understanding that quantitative approaches often struggle to achieve. However, despite their potential to yield valuable insights, qualitative methods are not without their limitations.

One significant challenge inherent to open-ended interviews is the potential for inconsistency of capturing community’s resilience. Unlike structured surveys or questionnaires, which provide standardized prompts and response options, open-ended interviews allow participants to express themselves freely. While this flexibility can unearth unexpected insights and perspectives, it can also lead to variability in results, making it difficult to establish clear patterns or draw definitive conclusions. This inconsistency can stem from variations in interviewers' probing techniques causing the interview to follow a different direction.

Another limitation of open-ended interviews is the risk of bias. Human subjectivity inevitably influences every stage of data collection in an interview. In the context of open-ended interviews, bias may manifest in various forms and types, which in this study, gender bias of interviewer is targeted. Interviewers' preconceived notions or personal beliefs can inadvertently shape the direction of the interview, influencing the topics explored and the interpretation of responses.

Another significant aspect is the integration of automation and repeatability into the process of conducting disaster resilience interviews, particularly in mitigating the impact of variables such as inconsistency and gender bias. Automation streamlines data collection and analysis, reducing the potential for human error and enhancing the efficiency of the research endeavor. This standardization is crucial for mitigating inconsistencies in responses, as it promotes uniformity across interviews and facilitates the comparison of findings.

Additionally, automation brings validity by ensuring interviews can be streamlined in an accurate repeatable process.

In tackling the challenges in obtaining holistic data from open-ended interviews, this research adopts a systematic approach comprising five distinct steps. The steps involved identifying a practical measurement approach to effectively quantify inconsistency and gender bias, and then addressing these issues. In the final step, an automation approach is developed to not only assist interviews in maintaining consistency and impartiality but also enable the process to be repeatable.

Building upon these foundational insights, the research proceeds to devise innovative solutions aimed at mitigating the impact of these variables on data collection. Methods of measurement were developed through the utilization of simulated interviews to generate numerical representations. Besides, by leveraging the latest advancements in Artificial Intelligence (AI), novel solutions to address key variables are identified through a structured three-phase design encompassing content analysis, exploratory analysis, and comparative analysis. The AI-driven methods also pave the way for the automation in conducting open-ended interviews.

The variable of inconsistency was quantified using the Interview's Inconsistency Mark (IIM), ranging from 0 to 13, where higher scores denoted increased inconsistency levels. To mitigate this issue, a solution was devised through natural language processing techniques, specifically sentence embedding. This method retrieved consistent information from a knowledge base housing peer-reviewed papers, resulting in significantly reduced inconsistency levels compared to the benchmark interviews, with observed values of 5.13 and 1.35.

Gender bias was assessed using the Practical Measurement of Gender Bias (PMGB) index, represented as a percentage, where higher values indicated greater bias. An approach was developed employing natural language processing methodologies, particularly word embedding, to identify gender-sensitive language. Utilizing a deep learning model named Claude 3 Sonnet helped in replacing gender-sensitive terms with neutral gender equivalents. Consequently, the solution successfully eliminated gender-sensitive values, reflected by a PMGB of zero, in contrast to simulated interviews yielding higher values of 12% and 10%.

Automation was achieved by developing a Decision Support System integrating both inconsistency and gender bias resolution components. Additionally, two complementary components were included: a speech recognition system modeled after SpeechStew for input reception and a follow-up question generator based on Claude 3 Sonnet. This integrated system enables the automation of open-ended interviews, promising high-quality outcomes based on predefined metrics.

Overall, this thesis contributes significantly to the advancement of knowledge in disaster resilience for both existing and future frameworks by offering novel insights and perspectives on data collection. While the study encountered several limitations such as the lack of transparency in existing frameworks utilizing open-ended interviews for data collection, particularly within New Zealand and the challenges in automating aspects of the data collection process, these constraints underscore the indispensable role of human engagement and qualitative insight in certain research contexts. Furthermore, financial barriers associated with testing and utilizing certain AI models were identified. However, with upcoming advancements in AI, this study provides a robust foundation for future enhancements. Integrating the data collection solution into existing and upcoming frameworks, along with longitudinal observations, will enable future studies to gain better insights. By rigorously applying the solution in additional real-world scenarios, its performance can be more comprehensively evaluated, allowing future researchers to fine-tune it to address specific needs and improve its efficacy.

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Milad Katebi

April 2024

Co-authored works

Enhancing Disaster Resilience Studies: Leveraging Linked Data and Natural Language Processing for Consistent Open-ended Interviews

Detection and Addressing Gender Bias in Open-Ended Interviews of Disaster Resilience

Automating Data Collection for Disaster Resilience Open-Ended Interviews using AI and NLP

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1. INTRODUCTION

1.1. Overview

A disaster is a sudden, catastrophic event that causes significant disruption, damage, or destruction to life, property, and the environment, often exceeding the community's ability to cope (UNDRR, 2007). Disasters can result from natural phenomena such as earthquakes, hurricanes, floods, or wildfires, as well as human-made incidents such as industrial accidents, terrorism, or war.

Disasters hold immense importance in New Zealand due to the country's unique geographic location and geological characteristics. New Zealand is situated on the boundary between the Pacific and Australian tectonic plates, making it highly seismically active. This location results in a continuous release of stress along fault lines, leading to frequent earthquakes. While many of these earthquakes are minor and go unnoticed, the region has experienced devastating quakes in the past. One of the most notable was the 2011 Christchurch earthquake, which claimed 185 lives, caused extensive damage to infrastructure, and resulted in a massive rebuilding effort (Ertl, 2016). Moreover, New Zealand has several active volcanoes, including Mount Ruapehu, Mount Tongariro, and Whakaari/White Island. Eruptions from these volcanoes can endanger nearby communities and disrupt air travel, as seen with the eruption of Whakaari/White Island in 2019 (Yong, 2023). Furthermore, variety of storms occur in New Zealand with the most recent one being on the 14th of February 2023, which in Napier, Cyclone Gabrielle caused widespread damage and flooding and resulted in a period of extreme isolation and vulnerability. Napier was without power, communications and access. Over 70,000 residents lacked lifelines, including health services, power, road connectivity, wastewater, drinking water, internet, and cell phone networks (Ng & Radford, 2023). Table 1.1 demonstrates impacts of some major natural disasters in New Zealand.

Table 1.1 - Major natural disasters in New Zealand (EM-DAT, 2023)

Disaster Event	**Year**	**Fatalities**	**People affected**	**Economic damage in USD**
Cyclone Gabrielle	2023	15	15900	4.7 billion
Kaikoura earthquake	2016	2	Not available	3.9 billion
2012/13 drought	2012/13	0	Not available	823 million
Canterbury Earthquake	2011	181	301500	1500 billion
Canterbury Earthquake	2010	0	300002	650 billion
February 2004 storm (flood)	2004	4	5350	394 million
South Island Drought	2001	0	Not available	344 million

1.2. Disaster Resilience

Resilience in simple words has been defined as the ability to get back to function or "bounce back" (Windle, 2011). However, the definition of community disaster resilience consists of more details. Disaster resilience is a multifaceted concept encompassing various phases and strategies aimed at minimizing the impact of disasters on individuals, communities, and societies (Bosher, 2014). These phases are often described as a continuous cycle, emphasizing the importance of proactive measures as well as recovery and adaptation. The four main phases of disaster resilience are depicted in Figure 1.1 which includes mitigation, preparedness, response, and recovery (Bosher et al., 2021).

Figure 1.1 - Phases of Disaster Resilience (Bosher et al., 2021)

1.2.1. Mitigation

Mitigation is the proactive phase of disaster resilience, focused on preventing or reducing the severity of disasters before they occur. It involves identifying vulnerabilities and implementing strategies to minimize the potential impact of disasters. These strategies can include land-use planning, building codes and standards, and environmental conservation efforts (UNDRR, 2007). Mitigation not only helps prevent loss of life and property but also saves significant financial resources in the long run.

1.2.2. Preparedness

Preparedness involves developing plans, systems, and capabilities to respond effectively when a disaster strikes. This phase includes creating emergency response plans, conducting drills and exercises, and establishing communication networks (FEMA, 2023). Preparedness also encompasses the stockpiling of necessary supplies and the education of the public about disaster risks and safety measures.

1.2.3. Response

The response phase is activated when a disaster occurs. It involves the immediate actions taken to address the immediate needs of affected individuals and communities. This can include search and rescue operations, medical assistance, and the distribution of emergency supplies. Effective response efforts rely on well-prepared emergency responders and coordination among various agencies and organizations (UNDRR, 2007).

1.2.4. Recovery

Recovery is the phase that follows the initial response and focuses on restoring and rebuilding affected areas and communities. It encompasses both short-term and long-term efforts to return to a state of normalcy. Recovery may involve rebuilding infrastructure, providing mental health support, and assisting individuals and businesses in regaining their economic stability or even further stepping into “build back better” to reduce the risks in the future (UNDRR, 2007).

Among the mentioned phases, in this research, the focus is on the mitigation step. By adopting a comprehensive and interdisciplinary approach, disaster mitigation not only enhances community resilience but also promotes long-term sustainability and the preservation of ecosystems (Logayah et al., 2022). Mitigation, which involves a series of proactive steps and strategies aimed at reducing the impact of disasters and minimizing their consequences, consists of risk assessments.

1.3. Risk Assessments

Disaster risk assessments include: the identification of hazards; a review of the technical characteristics of hazards such as their location, intensity, frequency, and probability; the analysis of exposure and vulnerability, including the physical, social, health, environmental and economic dimensions; and the evaluation of the effectiveness of prevailing and alternative coping capacities with respect to likely risk scenarios (UNDRR, 2017). There are many frameworks designed to assess resilience levels of a community called disaster resilience measurement frameworks.

1.4. Disaster Resilience Measurement Frameworks

Disaster resilience measurement frameworks are sets of indicators designed as references for cases of communities to measure their resiliency. New frameworks from time-to-time form and bring different sets of metrics called indicators that can be used by authorities, councils, and governments. Chapter two provides a brief summary of the most recent known community disaster resilience measurement framework and also provides a list of common indicators to bring tangibility of disaster resilience frameworks.

The methods of data collection for the indicators of disaster resilience measurement frameworks are either measured by quantitative or qualitative approaches; thus, a framework depends on measurement methods which in the field of disaster resilience methods of qualitative, quantitative, or both are considered for data collection of the indicators (UNDRR, 2017).

Questionnaires, interviews, and focus groups discussions have been common strategies for measuring the indicators of disaster resilience frameworks (Cai et al., 2018). These traditional methods mainly use two types of questions, close-ended and open-ended (Mathers et al., 1998). Close-ended types use pre-set questions, which are asked to all the candidates; on the other extreme, in open-ended types, the questions which are asked are not determined in advance, rather they are spontaneous (Surbhi, 2016). The outcome of these two types of methods results in two types of data, quantitative and qualitative. Quantitative data is data that adheres to a pre-defined data model and is therefore straightforward to analyze (Losee, 2006). on the other hand, qualitative data is data that either does not have a pre-defined model or is not organized in a pre-defined manner (Hurwitz et al., 2019). Qualitative data is typically text-heavy but may contain data such as dates, numbers, and facts as well (Hurwitz et al., 2019). Quantitative sources of data are promising; however, by only considering quantitative data, 80% of the data sources which are an qualitative type of data will be neglected (Assale et al., 2019). Figure 1.2 shows the depth of uncaptured data from quantitative interviews.

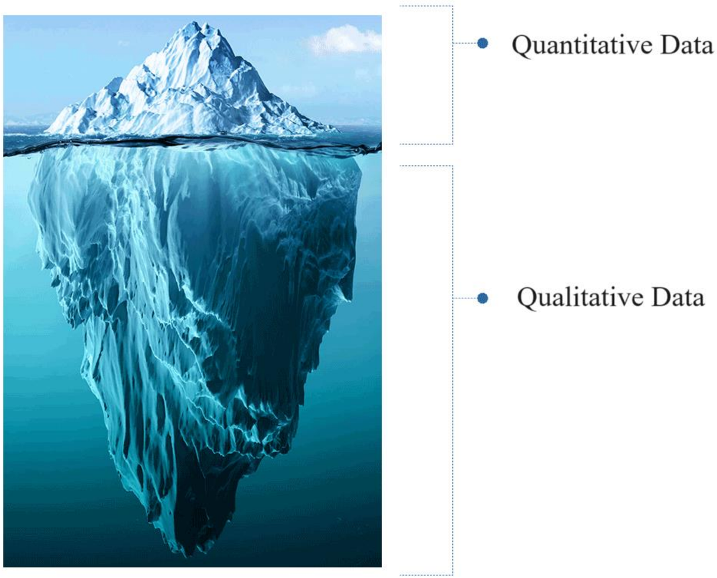


Figure 1.2 – Data depth gained from close-ended vs open-ended interviews (Assale et al., 2019)

1.5. Data Measurement Methods for Disaster Resilience Frameworks

Two approaching methods of interviews are qualitative and quantitative that respectively are correlated with open-ended and close-ended interviews (Taherdoost, 2021). Despite each strategy's shortcomings, there has been interest in both since each of which has its own advantages and challenges. In her comprehensive analysis of the literature, Cai's study demonstrates how close the rivalry is described in Table 1.1 (Cai et al., 2018). Since this research was done in 2018, to be updated about the recent frameworks and methods, in chapter two, a systematic literature review has taken place including the steps that Cai took for her analyzes.

Table 1.2 - Disaster resilience measurement methods (Cai, et al., 2018)

Method	*Number of articles (%)*
Qualitative	69 (39.7%)
Quantitative	68 (39.1%)
Both	22 (12.6%)
Not specified	15 (8.6%)
Total	*174*

1.5.1. Advantages and Challenges

Traditional close-ended interviews have long been a cornerstone in disaster resilience research, serving as a valuable method for gathering structured and quantifiable data. In the context of disaster resilience, these interviews typically follow a predetermined set of questions, allowing for standardized data collection and comparisons across participants. Scholars and practitioners have utilized this approach to explore various facets of disaster preparedness, response, and recovery. For instance, researchers often employ close-ended interviews to assess the effectiveness of community-based initiatives (Prats et al., 2022) or to measure the impact of communication strategies on public awareness and response during disasters (Ferrer et al., 2021). Despite their widespread use, it is essential to acknowledge potential limitations, such as the risk of oversimplification and the potential for respondents to feel constrained in their responses (Forman & Damschroder, 2007). As the field of disaster resilience evolves, researchers may consider complementing close-ended interviews with more flexible qualitative methods to gain a comprehensive understanding of the complexities inherent in resilience processes. Below are a few challenges of open-ended interviews.

1.5.1.1. Challenges of open-ended interviews

- Subjectivity and Bias: Open-ended questions may lead to subjective responses, and interpretations may vary between interviewers. Interviewers' biases can inadvertently influence the direction and interpretation of responses (Hoffmann, 2007).

- Interviewee Comfort: Some interviewees may feel uncomfortable or anxious with open-ended questions, leading to incomplete or guarded responses (Vallano & Compo, 2011).

- Interviewer Skill Variability: Interviewers may vary in their ability to probe effectively or guide the conversation, impacting the quality and depth of responses (Slade & Sergent, 2018).

- Time Constraints: Open-ended interviews can be time-consuming, especially if there is a need for detailed responses. This may limit the number of interviews that can be conducted (Aberbach & Rockman, 2002).

- Difficulty in Analysis: Analyzing open-ended responses can be challenging due to the volume of qualitative data. It may require more time and expertise to derive meaningful insights (Y. Li & Zhang, 2022).
- Leading Questions: Interviewers may unintentionally introduce bias by asking leading questions or influencing responses through their tone or body language (Roberts, 2020).
- Lack of Standardization: Open-ended interviews lack the standardization found in structured interviews, making it difficult to establish consistency in data collection and analysis (Majid et al., 2017).
- Bias: Interviewees may provide desirable responses rather than expressing their true thoughts and feelings (Spokes et al., 2019).
- Limited Generalizability: Findings from open-ended interviews may not always be easily generalizable to a larger population due to the qualitative nature of the data (Ali & Yusof, 2011).

The mentioned challenges can be categorized in two groups, inconsistency, and bias. Inconsistency is composed of the challenges regarding interviewee comfort, interviewer skills, time constraint and difficulty in analysis. The rest of the limitations fall under the umbrella of bias.

1.6. Research Gap

Qualitative and in-depth data play a crucial role in enhancing the depth and breadth of disaster resilience measurement, providing a more comprehensive understanding of the complex dynamics involved. While quantitative data offers valuable metrics for assessing tangible aspects of resilience, such as infrastructure integrity or economic losses, it often falls short in capturing the intricacies of human experiences and community dynamics. As Cutter et al. (2008) argue, the social dimensions of vulnerability and resilience are inherently qualitative and demand a nuanced exploration beyond numerical metrics. Qualitative data, derived from methods such as interviews, focus groups, and ethnographic studies, helps uncover community-specific factors influencing resilience, such as social capital, cultural practices, and local knowledge (Berkes, 2007). These insights are crucial for developing targeted interventions and policies that resonate with the community's unique context. Additionally, in-depth qualitative research enables a deeper understanding of the adaptive capacity, coping mechanisms, and community networks that contribute to resilience (Paton, 2008).

Accordingly, qualitative methods are crucial for capturing a substantial portion of data that can be collected. As section 1.4 discussed, 80 percent of total data can only be obtained by qualitative methods. Qualitative methods recognize the significant value that only qualitative data collection brings to understanding of complex phenomena such as disaster resilience which encompasses various sectors and significant sub-categories. This principle aligns with the idea that certain research questions or insights are best explored, explained, or captured through qualitative approaches.

1.6.1. Stakeholders

Improving data collection in open-ended interviews of disaster resilience necessitates the engagement of a broad spectrum of stakeholders who have vested interests in the effectiveness and accuracy of such data collection processes. These stakeholders encompass various individuals, groups, and organizations with distinct roles and perspectives, each contributing uniquely to the enhancement of data collection practices (Burnside-Lawry & Carvalho, 2016).

One crucial stakeholder group comprises researchers and academics in fields related to disaster resilience, sociology, psychology, and emergency management. Their involvement is pivotal in driving advancements in data collection methodologies, ensuring that interviews are structured to yield rich and meaningful insights while minimizing biases and inaccuracies (Reyers et al., 2015). These stakeholders often contribute by designing and refining interview protocols, validating data collection instruments, and disseminating best practices within their academic communities.

Another key stakeholder group comprises practitioners and professionals working directly in disaster response, recovery, and preparedness. This includes emergency responders, community organizers, policymakers, and non-governmental organizations (NGOs). For these stakeholders, the quality of data collected through open-ended interviews directly influences the effectiveness of their decision-making processes and the implementation of resilience-building initiatives (A. A. Saja et al., 2019). As such, their input is essential in shaping interview protocols that are practical, relevant, and actionable within real-world disaster contexts.

Community members and individuals directly affected by disasters are also vital stakeholders in improving data collection practices. Their perspectives and experiences provide invaluable insights into the intricacies of resilience and the nuanced ways in which communities cope with and recover from disasters. Engaging with these stakeholders ensures that interviews are culturally sensitive, respectful of local knowledge systems, and inclusive of marginalized voices, thereby enhancing the validity and relevance of the data collected (Burnside-Lawry & Carvalho, 2016).

Overall, the collaboration and engagement of these diverse stakeholders are essential for driving continuous improvement in data collection practices for open-ended interviews of disaster resilience. By fostering interdisciplinary partnerships and integrating multiple perspectives, researchers and practitioners can work together to enhance the reliability, validity, and inclusivity of data collection efforts. Ultimately, these collaborative efforts contribute to more effective disaster preparedness, response, and recovery initiatives.

1.6.2. Novelty: Addressing Challenges in Qualitative Data Collection for Disaster Resilience

Recognizing the importance of in-depth data collection for measuring disaster resilience, this research focuses on open-ended interviews, which promise in-depth qualitative data. As discussed, open-ended interviews face certain challenges. Therefore, this research aims to find solutions to address these limitations as mentioned in section 1.5.1.2, the main challenges of open-ended interviews are grouped into two main categories, inconsistency and bias. This study addresses these limitations and considers embedding solutions into recurring interviews. The importance of addressing each of these challenges is detailed below.

1.6.2.1. Inconsistency

The inconsistency in research refers to the absence of consistent and uniform procedures in the design, execution, and analysis of a study (Ioannidis, 2005). This research adopts the same definition. In the context of interviews, inconsistency refers to variations in the way questions are asked, responses are recorded, or data is interpreted, leading to unreliable results (Creswell & Creswell, 2017).

Inconsistency in data collection can significantly impact the reliability, validity, and utility of research findings. Addressing and mitigating inconsistency in data collection is essential for upholding the integrity and credibility of research and ensuring its relevance and impact in informing decision-making and action; otherwise, the outcomes of research can be compromised by the following issues:

- Decreased Reliability: Inconsistent data collection methods or procedures can lead to unreliable data, undermining the trustworthiness of research outcomes (Smith et al., 2017).
- Limited Validity: Inconsistency in data collection may compromise the validity of research findings, as it becomes challenging to accurately measure the phenomena of interest (Jones & Brown, 2019).
- Impaired Comparability: Inconsistent data hampers the comparability of results across different studies, hindering the ability to identify trends or make meaningful comparisons (Garcia & Johnson, 2020).
- Reduced Generalizability: Inconsistency in data collection practices limits the generalizability of findings, making it difficult to apply research outcomes to broader populations or contexts (Chen & Lee, 2018).
- Undermined Stakeholder Confidence: Inconsistent data collection erodes confidence in research findings among stakeholders, potentially leading to skepticism or reluctance to act upon research recommendations (Baker & White, 2021).

Chapter two elucidates the lack of consistency observed in open-ended interviews, particularly concerning disaster resilience, as evidenced by scholarly references. This discussion serves to support the existing gap in literature and emphasizes the critical need for addressing consistency issues within this research domain.

1.6.2.2. Bias

Bias refers to deviations from the true value in the collection, analysis, interpretation, or presentation of data or information (Walther & Moore, 2005). In research, bias occurs when "systematic error is introduced into sampling or testing by selecting or encouraging one outcome or answer over others" (Pannucci & Wilkins, 2010). Here are some of the key impacts of bias in data collection:

- Inaccurate representations: Bias can lead to non-representative samples, causing the collected data to inaccurately reflect the characteristics and diversity of the population under study (Shahbazi et al., 2023).
- Limited generalizability: Biased samples may hinder the external validity of the research, making it challenging to generalize findings to broader populations or contexts (Peters et al., 2022).
- Underestimated or overestimated effects: Bias may result in underestimation or overestimation of the true effects, potentially leading to misguided policy recommendations or interventions (Wittwer et al., 2008).
- Waste of resources: Resources invested in biased data collection may be wasted, as the results may not provide meaningful insights or contribute to a valid understanding of the research questions (Buxton et al., 2021).
- Ethical concerns: Bias in data collection can raise ethical concerns, particularly if it results in unfair or inaccurate representations of certain groups, leading to potential harm or stigmatization (Watts et al., 2020).
- Policy and decision-making consequences: Biased data can influence policy decisions, leading to the implementation of ineffective or inappropriate interventions, especially if decision-makers rely on flawed evidence (Bergram et al., 2018).
- Challenges in replication: Bias in data collection can make it difficult for other researchers to replicate the study, hindering the validation and generalizability of findings (Francis, 2012).

Various types of bias may arise in the process. some of the most common ones are listed below.

- Selection bias: Occurs when the sample chosen for the study is not representative of the larger population (Blackwell & Hodges Jr, 1957).

- Sampling bias: Arises when the method used to select participants or data points favors certain groups over others, leading to an unrepresentative sample (Panzeri et al., 2008).

- Non-response bias: Results from a significant portion of the selected individuals refusing to participate in the study, leading to a biased sample (Berg, 2005).

- Volunteer bias: Occurs when participants self-select to be part of the study, and their characteristics differ from those who choose not to participate (Callahan et al., 2007).

- Observer bias: Introduced when the person collecting or analyzing the data has preconceived notions or expectations that may influence the interpretation of results (Mahtani et al., 2018).

- Confirmation bias: Involves favoring information that confirms one's existing beliefs or hypotheses, leading to a skewed interpretation of data (Peters, 2022).

- Cultural bias: Arises when the cultural context of the study is not taken into account, leading to results that may not be applicable or generalizable across different cultural groups (Friedman, 2017).
- Recall bias: Occurs when participants inaccurately remember past events or experiences, leading to biased data (Sedgwick, 2012).
- Response bias: Happens when participants provide inaccurate or distorted information due to social desirability, fear of judgment, or other factors (Furnham, 1986).
- Publication bias: Arises when only certain types of results are published, leading to an incomplete or distorted representation of the overall research findings (T. D. Stanley, 2005).
- Time-interval bias: Occurs when the timing of data collection influences the results, such as collecting data at a specific time of day or during a particular season (Yadav & Lewis, 2021).
- Measurement bias: Results from errors or inaccuracies in the measurement instruments or methods used during data collection (Jak et al., 2014).
- Geographical bias: Arises when the study is conducted in a specific geographic location that may not be representative of the broader population (Kowal et al., 2022).
- Gender bias: Occurs when the study disproportionately includes one gender over another, leading to results that may not be generalizable to both genders (Upchurch, 2020).

1.6.2.3. Gender bias

Among the various types of bias, gender bias is particularly critical due to its pervasive impact across different research contexts. Gender bias occurs when data collection processes systematically favor or challenges one gender over another, leading to skewed or inaccurate representations of the experiences and perspectives of individuals based on their gender. This bias can manifest in various ways, including in the selection of participants, formulation of survey questions, and interpretation of responses (Risman et al., 2018; Westbrook & Saperstein, 2015). The impact of gender bias extends beyond individual studies, influencing societal perceptions and contributing to gender-based disparities (Ovseiko et al., 2016).

Addressing gender bias in data collection is essential for ensuring the accuracy and inclusivity of research outcomes (Cameron & Stinson, 2019). Researchers must critically examine their methodologies, survey instruments, and sampling procedures to identify and mitigate potential biases (Donaldson & Grant-Vallone, 2002). By adopting inclusive and gender-sensitive approaches, researchers can enhance the accuracy and fairness of their data, contributing to a more comprehensive and representative understanding of the experiences and perspectives of diverse individuals within different gender groups (Hill et al., 2010). Understanding and acknowledging gender bias in data collection is a crucial step toward fostering more equitable and inclusive research practices (Allen & Garg, 2016).

Gender bias in research could be defined as a systematically erroneous gender dependent approach related to social construct, which incorrectly regards women and men as similar/different, thereby compromising the validity of the data (Ruiz-Cantero et al., 2007). In the context of AI and automation, it is crucial to ensure that these systems are designed to recognize and mitigate such biases at various stages of data collection and analysis. This will prevent distorted perceptions of gender-related issues and ensure the collection of unbiased and representative gender data.

Gender bias can manifest in different forms and stages as outlined below:

- Underrepresentation: Occurs when one gender is systematically excluded or underrepresented in a dataset. This can happen if certain groups, particularly women or non-binary individuals, are not adequately included in surveys, studies, or other data sources (Ceci & Williams, 2011).

- Stereotyping: The use of biased language or framing of questions that reinforce gender stereotypes. For example, asking questions that assume certain roles or behaviors based on traditional gender norms (Avitzour et al., 2020).

- Limited gender categories: Restrictive classification systems that do not account for a diverse range of gender identities. Binary gender categories (male/female) may not capture the full spectrum of gender identities, leading to erasure of non-binary or genderqueer individuals (Dev et al., 2021)

- Unconscious bias: Researchers may unintentionally introduce bias into their study designs based on their own preconceptions or societal norms. This can influence everything from the selection of variables to the interpretation of results (Skov, 2020).

- Non-inclusive language: The use of language in data collection instruments may exclude or marginalize certain genders. For instance, using terms that assume a binary understanding of gender (Sczesny et al., 2015).

The language used in interviews is a primary factor behind several types of gender biases, including stereotyping, limited gender categories, unconscious bias and non-inclusive language. It leaves the underrepresentation, where inclusion is the primary issue. Therefore, this research will focus on reducing gender bias by integrating AI tools that carefully analyse and optimize the language used in data collection instruments. In chapter two, a literature review will demonstrate the topic of gender bias discussed within peer-reviewed publications and explore how AI can help mitigate these biases in the context of community disaster resilience.

1.6.2.4. Automation

Automation reduces the potential for human error, thereby increasing the consistency and reproducibility of measurements (Balfe et al., 2015). By removing manual intervention, automated systems minimize variability in data collection procedures, resulting in more reliable and trustworthy results (Chavaillaz et al., 2016). Moreover, automation streamlines data collection and analysis workflows, allowing researchers to handle larger volumes of data in a shorter amount of time (Reiter et al., 2021). This increased throughput enables researchers to conduct more extensive and comprehensive studies, facilitating a deeper understanding of the phenomenon under investigation (Oesterreich & Teuteberg, 2016).

Automation also plays a crucial role in facilitating repeated measurements. Repeated measurements are vital for several reasons. First, they enhance the reliability and validity of the findings by reducing measurement error and increasing the precision of estimates (Cicchetti, 1994). Additionally, repeated measurements allow researchers to assess the stability and consistency of phenomena over time, which is particularly crucial in longitudinal studies or when investigating dynamic processes (Grimm et al., 2016). Moreover, repeated measurements enable researchers to detect subtle changes or trends that may not be apparent with a single measurement, thus providing a more comprehensive understanding of the phenomenon under investigation (Anderson, 2005). By automating these repeated measurements, researchers can ensure consistency and accuracy across multiple data collection points, significantly improving the quality of the research outcomes.

In the context of measuring disaster resilience, Le De et al. (2020) highlight the need for frequent assessments of disaster resilience indicators, recommending intervals of every 6 months or annually. Regular measurement provides practitioners with timely insights into community resilience and identifies areas for improvement. Given the challenges and time-consuming nature of conducting open-ended interviews, coupled with issues of inconsistency and bias, this research proposes an automated system to integrate these elements.

1.7. Artificial intelligence

In recent years, Artificial Intelligence (AI) has emerged as a transformative method of solution across various fields of study, revolutionizing research methodologies and problem-solving approaches. One significant impact of AI is its ability to streamline processes, analyze vast amounts of data, and derive meaningful insights that were previously unattainable through traditional methods. In the realm of healthcare, for instance, AI-powered algorithms have been employed to analyze medical imaging scans, enabling early detection of diseases such as cancer with higher accuracy rates than human counterparts (Esteva et al., 2017). This not only enhances patient outcomes but also reduces the burden on healthcare systems by optimizing resource allocation and treatment planning.

AI has made significant advancements in finance by development of algorithmic trading systems that utilize machine learning algorithms to analyze market data and execute trades with unprecedented speed and accuracy. These systems can adapt to changing market conditions in real-time, enabling traders to capitalize on opportunities and mitigate risks more effectively (G. Chen et al., 2017). Such advancements have revolutionized trading practices, leading to increased efficiency and liquidity in financial markets while also raising questions about algorithmic transparency and market stability.

Moreover, AI has facilitated breakthroughs in scientific research by accelerating experimentation and hypothesis testing. Through techniques such as machine learning and predictive modeling, researchers can uncover complex patterns within datasets, leading to novel discoveries and advancements in fields such as materials science, chemistry, and genomics. For example, AI-driven drug discovery platforms have expedited the process of identifying potential therapeutic compounds, significantly reducing the time and cost associated with bringing new drugs to market (Stokes et al., 2020). By leveraging AI, researchers can navigate the vast landscape of chemical compounds more efficiently, increasing the likelihood of identifying candidates with the desired pharmacological properties.

1.7.1. AI and Disaster Resilience

With the advancements witnessed by AI in various domains, this research directs its focus towards the critical domain of disaster resilience seeking solutions to enrich and improve open-ended interviews that can help to enhance preparedness in the face of disasters. Informed by the remarkable progress AI has made in fields such as healthcare, finance, and chemistry, this study is in pursuit of leveraging AI technologies to fortify the information gained from communities against the challenges posed by disasters. This research endeavors to not only deepen the understanding of how AI can bolster disaster resilience but also to contribute practical solutions in the midst of adversity.

Even though AI has already played a pivotal role in addressing environmental challenges and promoting sustainability initiatives, for instance, the aid of remote sensing technologies and data analytics, AI systems can monitor environmental changes, track deforestation, assess biodiversity, and predict natural disasters with greater accuracy (Lein, 2009). However, the innovation of this study lies in its application during the data collection phase. By integrating AI technologies into the data gathering process, the study aims to streamline and enhance the efficiency, accuracy, and depth of information acquisition, thereby advancing the field's methodologies and capabilities.

1.8. Research Design

This study follows a structured approach, addressing specific research gaps identified in previous sections. Each step is guided by a research question, objective, and method of investigation. Detailed explanations of each step are provided in the subsequent chapters.

1.8.1. Research step one, inconsistency

The first step addresses the variable of inconsistency in open-ended interviews for disaster resilience data collection. This step is formulated as follows:

- Significance: According to section 1.6.1, the lack of consistency has several impacts if left unattended.
    - Decreased Reliability
    - Limited Validity
    - Impaired Comparability
    - Reduced Generalizability
    - Undermined Stakeholder Confidence
- Gap: Even though open-ended interviews are preferred over close-ended interviews because they can unearth 80 percent of data where their counterparts fail, according to section 1.6.1, they are not without

challenges which one of them is inconsistency. The traces of inconsistency within open-ended interviews will be tracked in chapter two.

- Question: Can open-ended interviews of disaster resilience become consistent?
- Method: A mixed method is considered consisting of a content analysis and experimental design phases. The first method will help in finding a solution from literature; followed by the second method where in two steps, the feasibility, and prerequisites of the found solution will be analyzed and then it will be applied in a comparative approach against ground truth data to measure the improvements gained.
- Objective: The objective of this step is to design a framework for achieving consistency in open-ended interviews focused on disaster resilience that can measurably reflect the improvement; thereby, enhancing the reliability and validity of qualitative data collection in this field.
- Precondition: To be able to compare the results of the found solution against ground truth data, the current state of inconsistency in open-ended interviews of disaster resilience needs to be numerically measured.

1.8.2. Research step two, gender bias

The second step evolves around the existing levels of bias that were introduced earlier in section 1.6.2 or specifically levels of gender bias described under 1.6.2.1.

- Significance: Mentioned under section 1.6.2, bias can have many negative impacts on any interview no matter of its type. Impacts of bias in data collection are as follows.
    - Inaccurate representations
    - Limited generalizability
    - Underestimated or overestimated effects
    - Waste of resources
    - Ethical concerns
    - Policy and decision-making consequences
    - Challenges in replication
- Gap: As it was mentioned under the gap of step one, open-ended interviews have better promises of unearthing data compared to close-ended ones; however, they have challenges. Step two tackles the other challenges impacting the data collection process which is bias.

- Question: Can open-ended interviews of disaster resilience become gender bias free?
- Method: The practice of step one will be applied to this step by replacing the variable of inconsistency with gender bias to find a solution on how to tackle gender bias.
- Objective: The objective of this step is to investigate and develop strategies to mitigate gender bias in open-ended interviews focused on disaster resilience demonstrable by practical measurement, aiming to foster inclusivity and accuracy in qualitative data collection within this domain.
- Precondition: The results of the found solution need to be compared against the numerical measures of current state of gender bias in open-ended interviews of disaster resilience.

1.8.3. Research step three, automation

Having both variables of inconsistency and gender bias tackled, there is a need for a system that could bring these components together and automate the process since repeatability is another significant piece tackled by this research. The formulation of step three is described below.

- Significance: Automation enables studies of disaster resilience to be longitudinal where the measurement of resilience by a consistent and unbiased data collection can give credible and reliable insights. Repeatability of measuring disaster resilience, according to section 1.6.3, has the following significance.
    - Reliability and validity
    - Longitudinal analysis
    - Comprehensive understanding with measurement of subtle changes
- Gap: Section 1.6.3 provided very few papers supporting the need of automation in disaster resilience studies; however, with its significance, the automation need needs further investigation by literature review which will be undertaken in chapter two. The feasibility of integrating the automated system with the components of consistency and unbiasedness will also be dived into.
- Question: How can consistent and bias-free open-ended interviews of disaster resilience become automated?
- Objective: This step aims to explore components of open-ended interview focusing on disaster resilience and develop a methodological framework for conducting consistent and bias-free ones, with the objective of streamlining data collection processes while maintaining methodological rigor and inclusivity.

- Method: To be able to investigate this step, an application of a case study will be applied to the design of a framework based built of Artificial Intelligence (AI) where metrics of evaluations in analysis should supported the evaluation of the design.

1.9. Summary

In this chapter, disaster risk was introduced which it gets assessed by identifiers called indicators bundled together to form disaster resilience measurement frameworks. The measurements use either qualitative, quantitative, or both methods. Each of these methods has their own advantages and challenges; however, this research focuses on in-depth data collection of disaster resilience measurement frameworks which use qualitative measurement methods. Three gaps were defined in this regard including inconsistency, gender bias and automation. With the significance of invalidation of data collection which further invalidates any conclusions, under three steps, methods are provided to address these gaps.

In chapter two, systematic literature reviews are presented to bring clarifications to the terms including disaster resilience measurement frameworks and indicators. Chapter two will also include the summarizations and critiques of existing literature relevant to the research topic. It also identifies the gaps in the literature and establishes the theoretical framework for the study.

Chapter three describes the research design, data collection methods, and analysis techniques employed in your study. Besides, rationale behind the chosen approaches is stated and justifications of their suitability for addressing the research questions of listed steps are discussed.

Chapter four presents the findings of the research in a clear and systematic manner. It utilizes tables, figures, and graphs to illustrate the data and provide supporting evidence. Chapter five is the discussion chapter with the intention of analyzing and interpreting the results in relation to the research questions and objectives. Furthermore, it explores the implications of the results and their significance to the field of disaster resilience with comparisons of findings with existing literature.

Chapter six will summarize the main findings of the research and their implications. Objectives will be restated and demonstrations of how they have been achieved will be listed with recommendations for future research. It will be followed by the references chapter listing all the references.

2.1. Overview

In chapter one, a few foundational claims declared needing comprehensive exploration of relevant literature. Numerous scholars have contributed to our understanding of the subject matter, and their works are instrumental in shaping the assertions made. Notable contributions include the study by (Cai et al., 2018) which established the framework for the comparison of frameworks underpinning the claims. Recent studies also have yielded critical insights into the practical implications of the proposed methods to the hypotheses' questions. The synthesis of these diverse perspectives allows for a nuanced examination of the key concepts, weaving together theoretical underpinnings and practical implications to establish a robust foundation for the subsequent sections of this study. The literature review not only serves to fortify the credibility of the claims but also positions the current work within the broader scholarly discourse, fostering a deeper understanding of the subject matter.

Within this chapter, systematic literature review that was done by Cai will be updated to include the most recent frameworks. Next, a systematic literature review to identify the indicators, which are the underlying measurement tools for frameworks, occurs for clarifications of what happens in disaster resilience frameworks. Finally, the gaps that this research focuses on will be discussed and supported by further literature reviews.

2.2. Literature Review of Existing Disaster Resilience Frameworks

The urgency to update Cai's existing literature review on disaster resilience frameworks (Cai et al., 2018) stems from the dynamic nature of the field, marked by evolving challenges, emerging concepts, and continuous advancements in research. Cai's work, while providing a valuable snapshot of the state of the field at the time of publication, may not encompass recent developments, novel perspectives, or crucial studies that have emerged since then. The landscape of disaster resilience frameworks is ever-changing, influenced by shifting socio-economic dynamics, technological innovations, and a deeper understanding of the complexities involved. Therefore, an updated literature review is imperative to ensure that current research efforts are informed by the latest theoretical frameworks and empirical findings. This update not only serves to enhance the scholarly rigor of the work but also contributes to the practical relevance of the research, aligning it with the most recent and pertinent discourse in the domain of disaster resilience.

2.2.1. Cai's approach

Cai's study on disaster resilience frameworks helped in structuring the literature review of this research by further exploring her approach. However, in order to rely on her work, it is necessary to understand her method and approach in detail. The next sections provide details of her study.

2.2.1.1. *Cai's method of literature review*

She focused on published refereed journal articles on disaster resilience measurement by using the Web of Science as the main search engine. Her search was conducted in January 2017 for the period from 2005 to 2017. She used the following procedure to search articles related to disaster resilience measurement.

She limited the keyword-based search to the title of the articles in order to yield the most relevant literature. Several keywords were used during her search, including 'disaster resilience', 'resilience index', 'resilience indicator', 'resilience indices', 'resilience metrics', 'resilience measurement', 'measuring resilience', 'resilience assessment', 'assessing resilience', 'natural hazards', 'resilience framework', and 'disaster'. Additional search criteria including the time period from 2005 to 2017, document type of article, and the language of English were applied to her search.

The search excluded several irrelevant research areas, for example, astronomy, physics, or sports, by checking the boxes on the screen to avoid retrieving a large number of irrelevant articles. This step resulted in a total number of 256 articles.

Next, she removed the duplicates or irrelevant articles in the assembled articles by manually checking the title and abstract of each article. Then, a total of 20 documents from the research team's personal archive were added. These included the workshop report from the National Institute of Standards and Technology (NIST), technical reports from resilientnola.com, and several highly relevant articles published in 2016 and 2017. Finally, the process resulted in 174 most relevant articles for the review.

To enable systematic content analysis and future ontological framework development, she designed a review table to extract and record major information items from each article. Each article has a unique ID number in her search. The review table included five categories of information: publication information, research context, methodological framework, results and conclusion, and relevance. Table 2.1 lists the information items under each category. The 174 articles were then carefully reviewed, and information was extracted and recorded using Table 2.1 which is her review table.

Table 2.1 - Information items in the review table Cai's work (Cai et al., 2018)

Category	Information Item
Publication information	ID
	Authors
	Publication year
	Paper title
	First author's affiliation
	First author's country
	Journal name
	Keywords
	Number of citations
Research context	Research object

	Disaster type
	Study area
	Country of study area
	Geographic scale
Methodological framework	Concept definition
	Description of other key concepts
	Measurement method
	Specific measurement method
	Method innovation
	Variables used
	Validation
Results and conclusion	Findings
	Conclusion
	Adaptation strategy
Relevance	Reviewer name
	Date reviewed
	Reviewer's comments
	Relevance to index creation
	Relevance to adaptation strategy

2.2.1.2. Cai's method of categorizing methods used in frameworks

Cai has answered the question of "what measurement frameworks were used" with analysis of whether the measurement method was qualitative or quantitative and whether the measurement method has been validated with empirical evidence, either quantitatively or qualitatively. Results in her study show that 69 articles (39.7%) used qualitative methods, about the same number of articles (68) used quantitative methods, and 22 articles (12.6%) used both. (She noted that the measurement methods discussed do not necessarily mean that the articles had created a single or several indices). Of the 73 articles studying general disasters, qualitative method was the top approach used (accounting for 45.2%). When the disaster type was specified as coastal or earthquake, the most commonly used approach was quantitative (accounting for 56.1% and 50% respectively). Figure 2.1 shows the summary of disaster resilience frameworks categorized based on the methods.

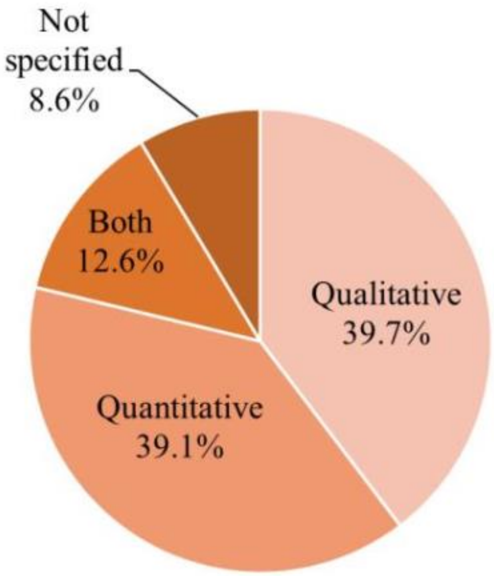


Figure 2.1 - Measurement method summary of Cai's work

She also mentioned that survey questionnaire, in-depth interview, and focus group discussion were the three major qualitative resilience measurement methods used. Other qualitative methods also included self-assessment and comparative analysis. Quantitative studies often involved statistical and data mining methods, with correlation and multivariate regression analyses being most frequently used. The 22 articles that used mixed methods often involved using qualitative methods to derive indicators (e.g., interview, focus group, Delphi study), followed by quantitative methods to calculate the resilience index (e.g., weighted aggregation, principal component analysis, multiple regression).

2.2.1.3. Cai's method of finding indicators

Regarding the third question of "what were the most commonly used indicators to evaluate resilience", the results of her study show that 101 articles have used indicators in their analysis. She recorded from each of the 101 articles the indicators used and categorized them into seven categories, including social, economic, institutional, infrastructure, community, environmental/ecological, and others. She then ordered them based on their occurrences in the literature review.

This study has adapted her strategy, updating the list of disaster resilience measurement frameworks and indicators to include studies published from 2018 so it can include the recent ones combining with her findings. In the next sections the details of this study's approach are presented.

2.2.2. Strategy of Literature Review

The literature review section follows a systematic literature review process as described by (Xiao & Watson, 2019), with step-by-step details presented in Figure 2.1. The literature review commenced by defining a set of keywords, namely (disaster AND resilience AND measurement AND framework) to cover the scope of our research. Besides, the word indicator was added to further narrow down to frameworks only using indicators since the indicators could use structured on unstructured methods of collecting data. Wildcard characters and special terms were employed to identify relevant papers. The keywords were used to search in the abstract, keywords, and titles of peer-reviewed papers. Besides, they were filtered to the papers published since 2018 considering Cai's research for what is published in 2017 and before. The search yielded 38, 10, 16, and 6 papers from Scopus, IEEE, ScienceDirect, and PubMed databases, resulting in a total of 70 papers. By following Figure 2.1, the reasoning and numbers of each step is discussed.

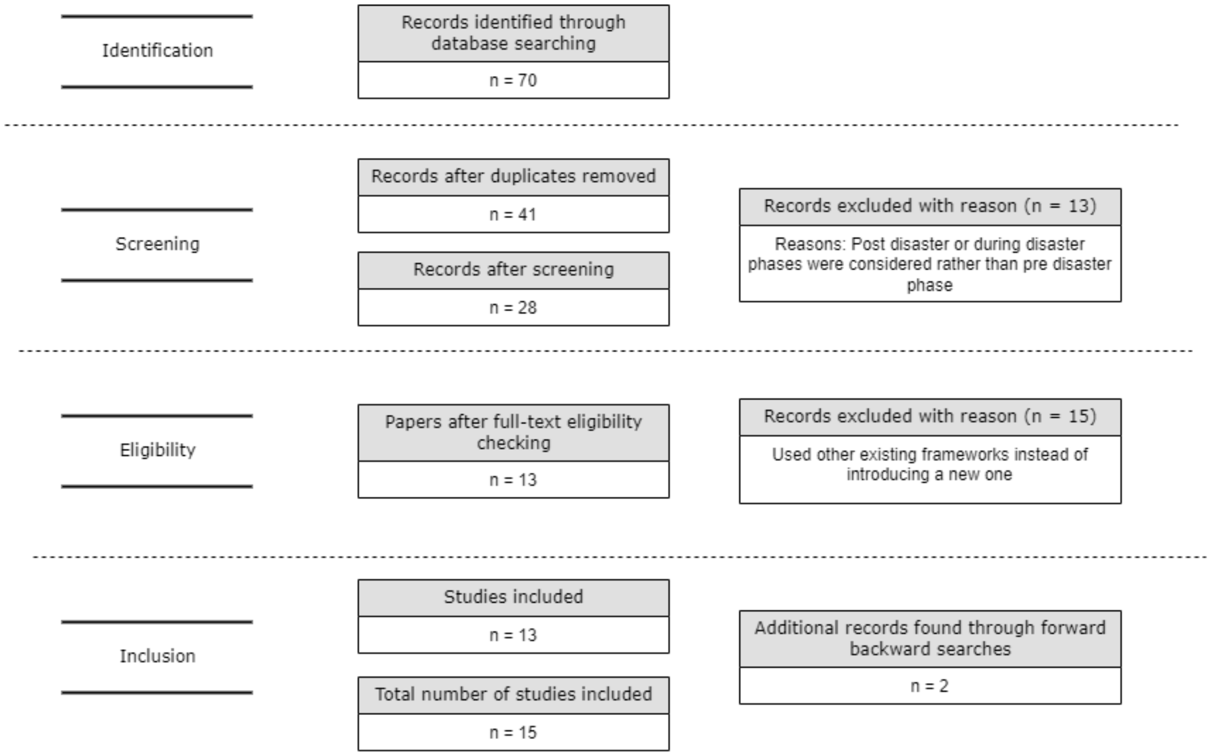


Figure 2.2 - Systematic literature review's strategy of disaster resilience frameworks

In conducting the systematic literature review on disaster resilience measurement frameworks, a meticulous process was employed to ensure the inclusion of relevant and distinct studies. A total of 29 studies were excluded due to duplication, ensuring the elimination of redundant information, and maintaining the integrity of the review. During the screening phase, an additional 13 studies were excluded as they focused on post-disaster including Nozhati and Liu or during disaster resilience measurement including Korukonda and Yesilsirt, deviating from the specific criteria of interest in which pre-disaster interviews should occur (Erol Yesilsirt et al., 2022; Korukonda et al., 2023; Liu et al., 2018; Nozhati, 2021). Further scrutiny during the full-text reading stage revealed that 15 studies did not contribute to new frameworks by either not specifying the methods used or relying on existing ones such as Camacho's work focusing on the BRIC framework from Cutter (Camacho et al., 2023; Cutter et al., 2010). However, through thorough forward and backward searches, two novel frameworks were identified and subsequently added to the review, resulting in a final selection of 15 articles that provided valuable insights into disaster resilience measurement frameworks.

In Cai's study, she identified 36 disaster resilience measurement frameworks with the 15 new frameworks that were found in the process of this study, accumulated to 51 different frameworks. The results with the table of frameworks are discussed in the next section.

2.2.3. Results of literature review

In Table 2.2, an updated list of disaster resilience measurement frameworks is provided. The frameworks are also divided into different categories based on their indicators' reliance on qualitative or quantitative methods.

If some of the indicators used quantitative and some used qualitative, framework is categorized as using both methods.

Table 2.2 - List of community disaster resilience measurement frameworks

Framework	Reference	Qualitative vs Quantitative
Alkire-Forster resilience index (AFRI)	(Hughes & Bushell, 2013)	Quantitative
B16	(Béné et al., 2016)	Both
Baseline Resilience Index for Communities (BRIC)	(Cutter et al., 2010)	Quantitative
Climate Change Agriculture and Food Security (CCAFS15)	(Hills et al., 2015)	Both
Coastal Cities Adaptive Resilience (CCAR)	(Peck & Simonovic, 2013)	Both
Coastal Community Resilience Framework and Assessment (CCR)	(Courtney et al., 2008)	Both
Conjoint Community Resilience Assessment Measure (CCRAM)	(Cohen et al., 2013)	Both
Climate Disaster Resilience Index (CDRI)	(Prashar et al., 2012)	Both
Community Disaster Resilience Index (CDRI2)	(Mayunga, 2007)	Both
Community Resilience Index Korea (CDRI-K)	(Yoon et al., 2016)	Quantitative
Community Disaster Resilience Scorecard and Toolkit (CDRST)	(Arbon et al., 2016)	Qualitative
Community Based Resilience Analysis (CoBRA)	(UNDP, 2014)	Both
COPEWELL	(Links et al., 2018)	Both
Community Resilience to Disasters Saudi Arabia (CRDSA)	(Alshehri et al., 2015)	Both
Community Resilience Index (CRI)	(Ainuddin & Routray, 2012)	Quantitative
Community Resilience Index (CRI2)	(Norris et al., 2008)	Quantitative

Community Resilience Toolkit (CRT)	(Schwind & Localize, 2009)	Qualitative
Climate vulnerability and capacity assessment (CVCA)	(Macchi, 2011)	Qualitative
DRLA/UEH evaluation resilience framework	(Sylvestre et al., 2012)	Both
FAO14	(Alinovi et al., 2010)	Quantitative
JS16	(Jones & Samman, 2016)	Quantitative
L15	(Lockwood et al., 2015)	Qualitative
Localized Disaster Resilience Index (LDRI)	(Orencio & Fujii, 2013)	Both
Livelihood change over time (LCOT)	(Vaitla et al., 2012)	Quantitative
MM07	(Marshall & Marshall, 2007)	Quantitative
NJ13	(Nguyen & James, 2013)	Qualitative
PEOPLES	(Cimellaro et al., 2010)	Both
PRIME	(Smith, 2019)	Both
ResilSim	(Irwin et al., 2016)	Both
ResilUS	(S. B. Miles & Chang, 2011)	Quantitative
Resilience index measurement and analysis (RIMA)	(Fao, 2016)	Quantitative
Self-evaluation and holistic assessment of climate resilience of farmers and pastoralists (SHARP)	(Choptiany et al., 2017)	Quantitative
Tracking adaptation and measuring development (TAMD)	(Brooks et al., 2011)	Both
WB15	(Alfani et al., 2015)	Quantitative
Weather and climate-resilience indexes (WCRIs)	(Kimetrica, 2015)	Quantitative
UNISDR12	(UNISDR, 2012)	Both
LiSeRA	(Pal et al., 2023)	Both
Urban Resilience for Urban Sustainability	(Zeng et al., 2022)	Qualitative
Sustainable and Resilient Urban Transportation System	(Nitwal & Verma, 2022)	Both
distributing disaster resources social equity metrics	(Kim & Sutley, 2021)	Quantitative

spatial disaster resilience profiling (S-DReP)	(Sajjad et al., 2021)	Quantitative
Multi-capital framework	(Wither et al., 2021)	Qualitative
Framework for evaluation and ranking of potential surrogates for social resilience	(A. A. Saja et al., 2020)	Qualitative
PHEP	(Khan et al., 2019)	Qualitative
Urban community resilience framework (UCRF)	(Cui & Li, 2019)	Both
Social capital measurement framework from neighborhood stakeholders	(Kwok et al., 2019)	Both
City resilience framework	(Y. Chen et al., 2019)	Both
Temporal social resilience framework of communities to disasters	(Khalili et al., 2018)	Qualitative
5S	(A. M. A. Saja et al., 2018)	Both
flow-based urban disaster resilience framework	(Z. Li & Yan, 2024)	Quantitative
MSME resilience measurement framework	(Utami et al., 2021)	Quantitative

2.2.4. Analysis of the results of literature review

Even though Cai categorized the published papers to be either using qualitative or quantitative methods, in this study, the aim was categorizing the frameworks instead of the published papers. Figure 2.3 shows the comparison of methods being used by frameworks. It can clearly be noticed that qualitative methods are used 33 times, 10 times as the sole method and 23 times mixed with quantitative methods, which results in more than half or roughly 65% of the times.

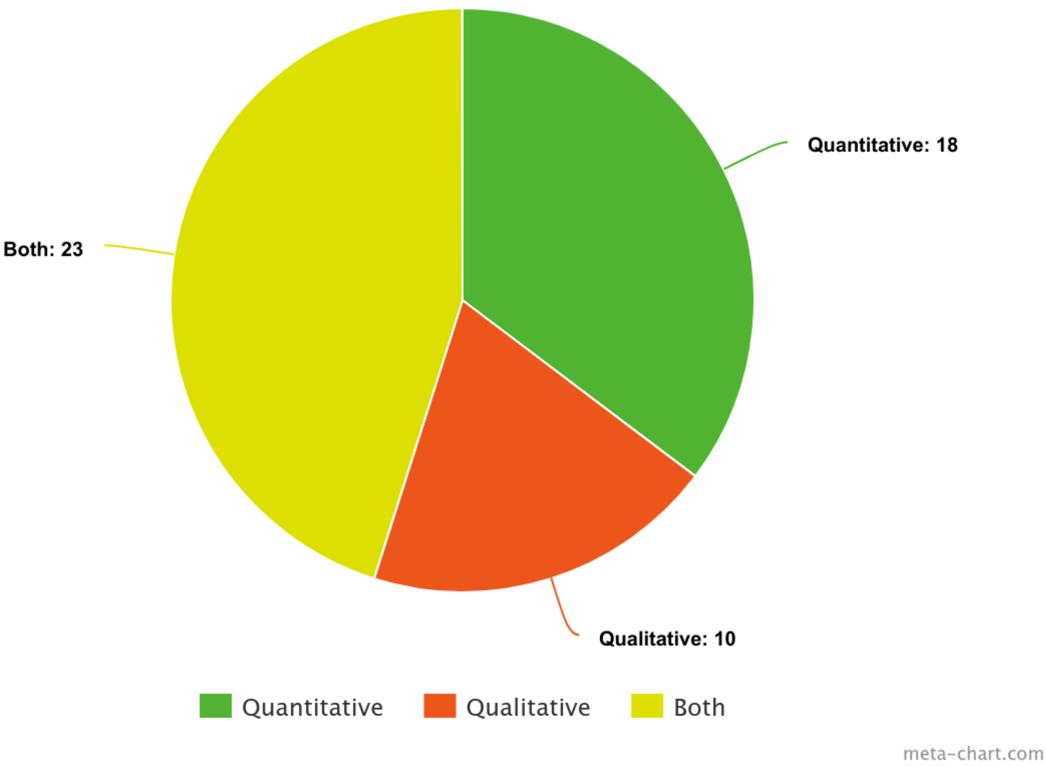


Figure 2.3 - Methods of disaster resilience measurement frameworks

2.3. Literature Review of Disaster Resilience Measurement Indicators

To have a tangible understanding of disaster resilience frameworks provided in the previous section, it should be noted that they are made of indicators. This section just clarifies how the frameworks are defined and built to have a solid ground of understanding of the upcoming gaps in the next sections.

2.3.1. Disaster resilience measurement indicators

A core component of completing a resilience assessment is identifying initial indicators to assess resilience and measure progress over time with frameworks being bundles of them (Mujjuni et al., 2021). An indicator is a quantitative or qualitative measure derived from observed facts that simplify and communicate the reality of a complex situation (Freudenberg, 2003). Indicators reveal the relative position of the phenomena being measured and when evaluated over time, can illustrate the magnitude of change (a little or a lot) as well as direction of change, up or down or increasing or decreasing (Cutter et al., 2010). Each indicator investigates a specific measurable component, and it can only belong to a specific sector, which is a group to categorize indicators. There have been many sectors identified in literature review; however, New Zealand's National Emergency Management Agency, National Disaster Resilience Strategy (NDRS), defined six main sectors to categorize disaster resilience measurement indicators, namely Governance, Built Environment, Natural Environment, Social, Cultural, and Economic, which are depicted in Figure 2.4 (NDRS, 2024).

Figure 2.4 - New Zealand's Disaster Resilience Measurement Sectors (NDRS, 2024)

In the next section, a list of well-known indicators in literature are noted down with the sector they are associated with. This helps in understanding where the qualitative and quantitative methods are rooted.

2.3.2. Strategy of literature review of disaster resilience measurement indicators

Since the frameworks were already listed in the previous section, for the indicators, those frameworks were targeted as the initial point to find indicators. If an indicator was listed in other frameworks, it was only listed once until no new indicators could be found among those frameworks. Besides, other publications from the authors of those frameworks were studied in case of any other indicators to be found. The saturation point was reached when no new indicators were detectable. The process is depicted in Figure 2.2.

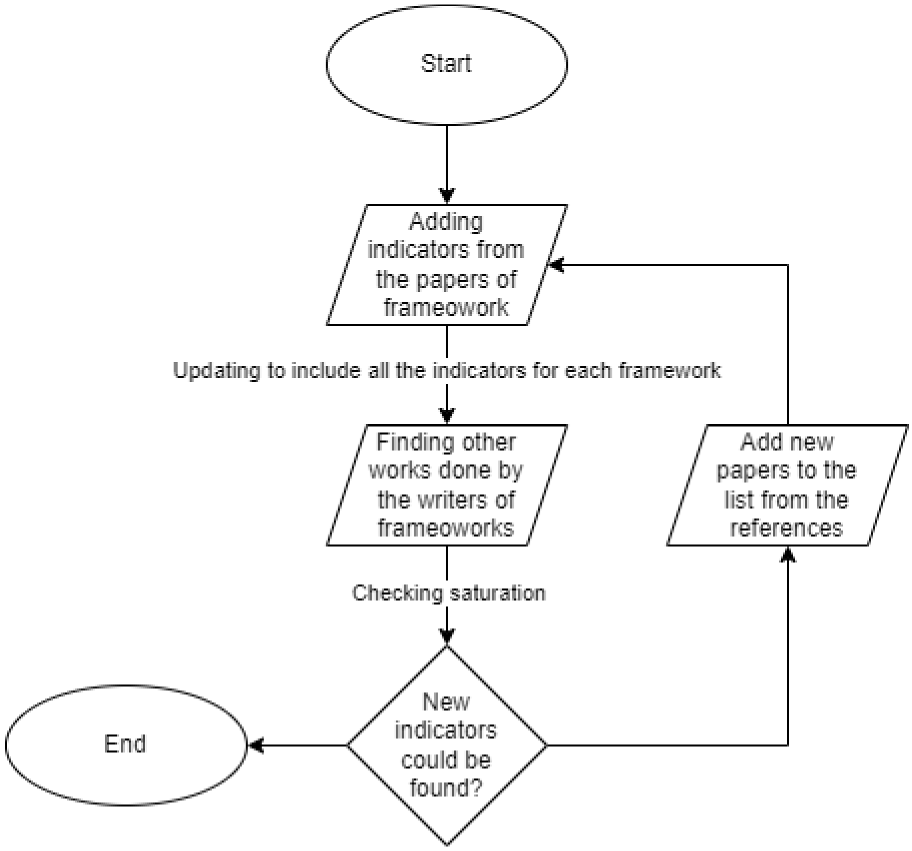


Figure 2.5 - Strategy of finding indicators

The literature started by finding the key contributors with the set of defined keywords. Based on the systematic review presented by Kim, articles older than five years are not considered (H. Kim et al., 2017). Thus, articles from 2019 are included in the review until reaching a saturation point. The saturation point of the strategy was considered to be an inductive thematic saturation. Inductive thematic saturation has been defined as "identification of new codes or themes based on the number of such codes or themes" (Saunders et al., 2018). The analysis of the saturation point was defined as finding new concepts. In other words, the saturation point is the state that no new indicator could be added to the set of indicators. The total number of indicators found was 44 until reaching the level of futility in finding new indicators. The indicators have been ordered based on their appearance in the literature review into insufficient, very low, low, average, high, and very high. Accordingly, insufficient, very low, low, average, high, and very high represent appearances just once, 2-5 times, 6-10 times, 11-20 times, 21-30 times, and more than 31 times. Table 2.3 demonstrates the final set of indicators based on the articles of literature review grouped by sectors.

Table 2.3 - Indicator of disaster resilience measurement

Sector	Indicator	Order of appearance
Social	Education	Very high
	Age	Very high
	Gender	High
	Transportation access	High
	Communication capacity	High
	Language competency	Average

	Race / Ethnicity	Average
	Special needs	Average
	Exposure to hazards	Average
	Health coverage	Average
Economic	Housing capital	High
	Employment	Very high
	Income	Very high
	Single sector employment dependence	Average
	Business size	Average
	Health access	Average
Governance	Mitigation	High
	Social connectivity	High
	Municipal service	High
	Political fragmentation	Low
	Crime	Low
	Early warning	Very low
	Previous disaster experience	Very low
Built Environment	Housing type	Average
	Urbanization	High
	Shelter capacity	High
	Medical capacity	High
	Access/Evacuation potential	Average
	Housing age	Average
	Sheltering needs	Average
	Recovery	Average
Cultural	Place attachment	High
	Political engagement	Average
	Social capital religion	Average
	Civic involvement	High
	Social capital – advocacy	Low
	Innovation	Very low
Natural Environment	Land loss	Average
	Erosion rate	Low
	Biodiversity	Very low
	Flood coverage	Very low
	Coastal defense structure	Average
	Land use	Very low
	Mobility	Very low

Figure 2.6 depicts a better visualization on the appearances of the reviewed indicators using the word-cloud technique. The size of the words corresponds to the order of appearance of the indicator in literature review.

Figure 2.6 - Appearance of indicators in a word-cloud format

Having the list of disaster resilience measurement indicators with the sector they are associated with, it is the time to understand the connection between frameworks, indicators, and measurement methods of disaster resilience, specifically, the qualitative methods.

2.3.3. Indicators and qualitative methods of data collection

Assessing disaster resilience across various sectors necessitates the application of qualitative methods to comprehensively understand the intricacies and context-specific aspects that shape community resilience.

Within social sector indicators and specifically the education indicator, qualitative methods are instrumental in uncovering the impact of disasters on educational institutions. Interviews with school administrators, teachers, and students offer valuable insights into the resilience of the education system and community recovery (Shaw et al., 2011). Besides, qualitative research methodologies can explore community health practices and the effectiveness of emergency response plans for health indicators. Interviews with healthcare providers, community health workers, and residents contribute to a deeper understanding of the adaptive capacity of healthcare systems during and after disasters (Miri et al., 2023). Qualitative research provides a means to explore community cohesion, social networks, and connectivity practices that contribute to resilience by understanding the community's ability to adapt and recover (Cutter et al., 2008).

qualitative interviews with community members can reveal the role of social connections in sharing information, providing emotional support, and facilitating collective actions during disasters for governance sector (Aldrich, 2011). Furthermore, for the indicators such as previous disaster experience, qualitative methods allow researchers to gain insights into the shared history, values, and norms that bind communities together, fostering a sense of collective identity and shared responsibility of communities and government in disaster situations (Cutter et al., 2008).

In the built environment sector, qualitative interviews and focus groups with community members, local authorities, and infrastructure managers can provide valuable insights into the adaptive capacity of physical structures and maintenance practices (Cantelmi et al., 2021). Urbanization is an indicator that is targeted by qualitative methods where continuous qualitative survey of rules' strengths and weaknesses are applied for the adaptation of rules with upstream documents, adaptation of rules with time conditions, and controlling (programs and plans) illegal development (Ghasemzadeh et al., 2021).

In the natural environment sector, qualitative research can involve interviews and focus groups with local environmental experts, conservationists, and community members to explore perceptions of environmental vulnerabilities and adaptive strategies. This qualitative approach can unveil indigenous knowledge about the local ecology, changes in biodiversity, the community's relationship with the natural environment, and land erosion (Berkes & Usher, 2000). Additionally, case studies can provide in-depth insights into specific environmental events or changes, allowing researchers to explore the local context and its implications for disaster resilience. Qualitative data gathered through these methods contribute to a richer understanding of the adaptive capacity of the natural environment and the potential biodiversity vulnerabilities that may affect ecosystem services crucial for community well-being (Adger et al., 2005). Qualitative findings also demonstrated that many participants had a strong connection to the natural environment and land use, experienced considerable grief as a result of its devastation in the fires and drew solace from seeing it regenerate over the following months and years (Block et al., 2019).

Now that a clear idea of the role of qualitative methods within disaster resilience frameworks and the layers underlying which are the indicators are settled, in the next sections, the supports for the claims of the gaps briefly discussed in sub sections of 1.7 where research steps are provided. These sections help in understanding the gaps that this research is based on.

2.4. Literature Review of Gap Identification

Section 2.2.4 showed qualitative methods constituting 65% of the overall frameworks used in disaster resilience studies; further proving the point earlier made by Cai in section 2.2.1.2 that 52.3% of the published papers until 2018 were using qualitative approaches. This implies the significance of qualitative methods of cases when qualitative methods are employed in research endeavors, the research benefits from a profound exploration of the intricacies that quantitative data alone may overlook. This substantial reliance on qualitative methods signifies a deliberate commitment to understanding the depth and disaster resilience studies made by researchers. By embracing qualitative approaches, researchers can capture the rich tapestry of subjective insights, cultural variations, and contextual factors that contribute to a comprehensive understanding of the studied phenomena. The prevalence of qualitative methods in such a significant proportion not only underscores their pivotal role in research but also highlights a recognition of the limitations of quantitative data in fully capturing the complexities inherent in various fields of study, fostering a more holistic and contextually informed approach to knowledge generation.

However, as earlier discussed in section 1.5.1.2, there are a number of challenges followed by qualitative methods that fall under two main roots of inconsistency and bias. In the following sections, the claims to support the existence of inconsistency and bias are traced in literature.

2.4.1. Literature review of inconsistency

In this section, support for the claims of research step one, described under section 1.6.1 is provided. Even though precondition of research step one investigates a ground truth of measurable inconsistency, no support was given that indicates a measurable level of inconsistency. With reference to peer-reviewed papers, existence of inconsistency in open-ended interviews is provided within wider range of studies and then within the field of disaster resilience.

2.4.1.1. Inconsistency in open-ended interviews

Qualitative researchers have expressed concern when confronted with ambiguous narratives (Power, 2004; Sands & Krumer-Nevo, 2006; Watson, 2006). Typically, a search for disconfirming evidence is conducted at the end of analysis and is associated with other systematic processes that are designed to reduce threats to validity (Booth et al., 2013; Denzin & Lincoln, 2011; M. B. Miles & Huberman, 1994; Patton, 1990; Wuetherick, 2010). However, perhaps due in part to debates surrounding validity in qualitative research (Sparkes, 2001), this process has received little attention in spite of the important role it can play in the interpretation of qualitative data. An explicit search for disconfirming evidence into the research design can reveal inconsistencies (Watson, 2006).

Many researchers have noted the problem of inconsistency in qualitative research (Hammersley, 2003; Holstein & Gubrium, 2003; Power, 2004; Watson, 2006). Holstein and Gubrium (1995) suggest that respondents may discuss the same issue quite differently during an interview because the shifting context of an interview causes people to rely on different “stocks of knowledge”. For example, in Watson’s (2006) research on teacher identity and discipline in the classroom, she discusses a case study in which discussions about the use of corporeal punishment revealed two conflicting accounts that corresponded to whether the respondent felt a strong identification with his students or his colleagues at that particular point in the interview.

Inconsistency in open-ended interviews has been a subject of concern in various research studies, with scholars highlighting the potential impact on the reliability and validity of the information gathered. A study conducted by Antin (2015) explored the variability in interviewer judgments during open-ended interviews, revealing that interviewers often exhibit disparities in evaluating candidate responses (Antin et al., 2015). The researchers identified factors such as individual biases, subjective interpretation of responses, and variations in interviewers' expertise as contributors to this inconsistency.

Roulin (2014) delved into the issue of inconsistency in interviewer judgments within the context of employment interviews. The study found that inconsistencies in evaluations were influenced by both individual differences among interviewers and the lack of standardized evaluation criteria. This research emphasized the importance of addressing subjectivity in the interview process to enhance the reliability of collected data (Roulin et al., 2014).

Further insights into the challenges of inconsistency in open-ended interviews are provided by Dana (2013). Their study examined the impact of interviewer gender on the collection of candidates' data, revealing that variations in judgment occurred based on the gender of both the interviewer and the interviewee (Dana et al., 2013). Such findings underscore the complexity of inconsistency in open-ended interviews and highlight the need for standardized approaches to minimize potential impacts of it.

2.4.1.2. Inconsistency in open-ended interviews of disaster resilience

Even though there aren't many references to the lack of consistency in the domain of disaster resilience measurement, the term has already been mentioned a few times. In 2015, Ostadtaghizadeh has mentioned that due to inconsistency in data collection, some of the areas of disaster resilience measurements were excluded from assessment (Ostadtaghizadeh et al., 2015). With the most recent reference in 2022, Laurien described the lack of clear standardization and validation approaches in the measurement methodologies, which lead to inconsistencies and poor data comparability of disaster resilience measurement frameworks (Laurien et al., 2022).

The lack of existing literature supports the novelty of this study; however, this problem has existed ever since that this study provides the levels of its existence. Besides, the problem of inconsistency has been mentioned and addressed in many other domains, especially health with a lot of methods trying to tackle it. In chapter three, further discussion on specific selected methods used for research step one and its precondition is presented.

2.4.2. Literature review of bias

Bias is a pervasive and complex phenomenon that can manifest across various domains, impacting human cognition, decision-making, and communication. Cognitive biases, such as confirmation bias, anchoring bias, and availability bias, exert significant influence on information processing.

Understanding and addressing bias is crucial for fostering fair and informed decision-making. Insights from research on cognitive biases provide valuable tools for recognizing and mitigating the impact of bias. Awareness and critical thinking skills play a pivotal role in navigating the complex landscape of biases, contributing to a more nuanced and inclusive understanding of the world (Gilovich et al., 2002).

Following the discussion happened for inconsistency in section 2.4.1, in this section, similar logic for bias is applied to support the claims of research step two, described under sections 1.6.2 and 1.6.2.1 respectively. With reference to peer-reviewed papers, the existence of bias in open-ended interviews is provided within a wider range of studies and then within the field of disaster resilience.

2.4.2.1. Bias in open-ended interviews

Bias in open-ended interviews is a prevalent concern that can significantly impact the quality and reliability of gathered information. Open-ended interviews, where participants are encouraged to express their thoughts freely, are susceptible to various types of biases, both on the part of the interviewer and the interviewee. One key source of bias is the interviewer's personal beliefs, attitudes, and preconceptions, which can subtly influence the framing of questions, non-verbal cues, and overall interactions with the interviewee (Rubin & Rubin, 2011). This can result in unintentional steering of responses toward the interviewer's expectations or viewpoints. Additionally, cultural differences between the interviewer and interviewee may introduce cultural bias, impacting the interpretation and understanding of responses (Denzin & Lincoln, 2011).

This systematic literature review follows Xiao's process with step-by-step details presented in Figure 2.7 (Xiao & Watson, 2019). The literature review commenced by defining a set of keywords, namely (bias AND open-ended AND interview) to cover the scope of our research. Wildcard characters and special terms were employed to identify relevant papers. The keywords were used to search in the abstract, keywords, and titles of peer-reviewed papers. Besides, they were filtered to the papers published since 2017 to cover the last 7 years. The search yielded 81, 6, 18, and 23 papers from Scopus, IEEE, ScienceDirect, and PubMed databases, resulting in a total of 128 papers. By following Figure 2.7, the reasoning and numbers of each step is discussed.

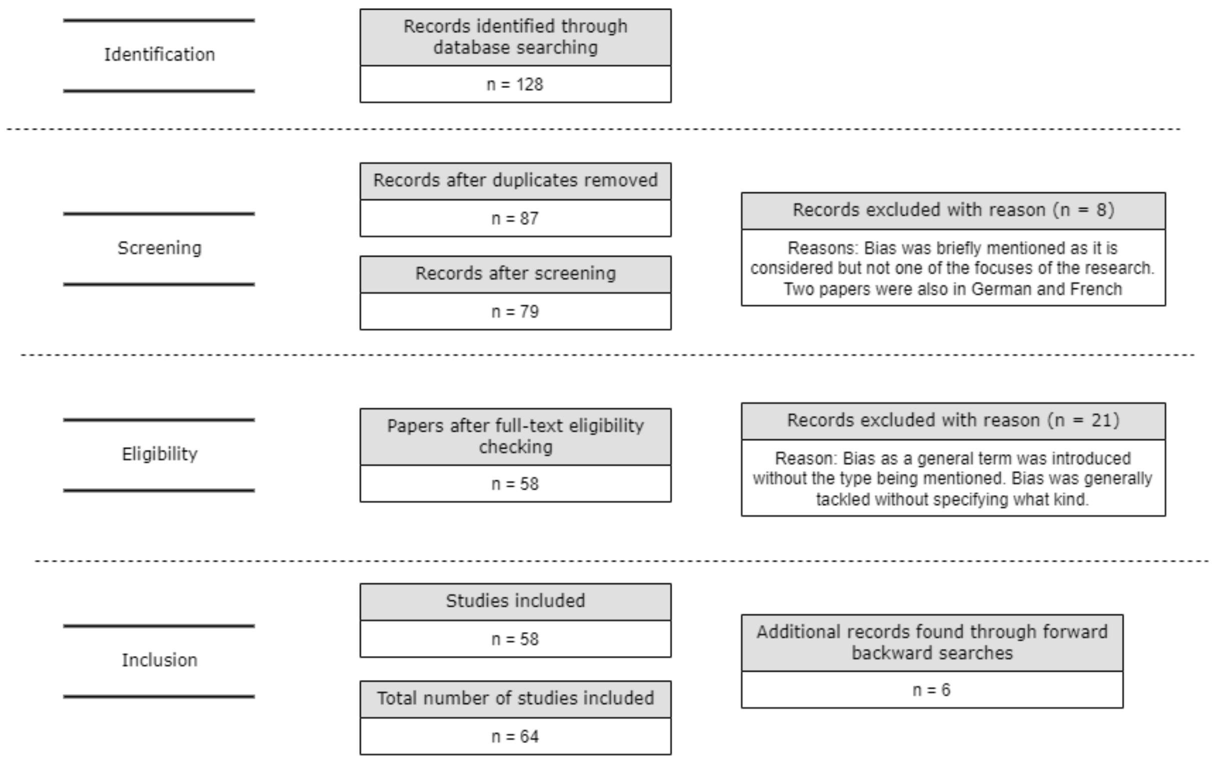


Figure 2.7 - Strategy of systematic literature review of bias in open-ended interviews

In conducting the systematic literature review on bias in open-ended interviews, a meticulous process was employed to ensure the inclusion of relevant and distinct studies. A total of 41 studies were excluded due to duplication, ensuring the elimination of redundant information, and maintaining the integrity of the review. During the screening phase, an additional 6 studies were excluded since bias was not the focus of the research and it was just briefly mentioned such as the Shah's study (Shah et al., 2024). Moreover, there were 2 other papers being in different languages, one in German and one in French (MacKenzie 1 & Dubois, 2019; Zuschlag et al., 2022), which were excluded in screening phase. Further scrutiny during the full-text reading stage revealed that 21 studies did not specify the type of bias. In those studies, bias was mentioned as a general term to be avoided without further delving into the details of the kind of bias including but not limited to Trencher's study (Trencher et al., 2021). However, through thorough forward and backward searches, 6 papers could be found mentioning bias as one of the key points of the research. This resulted in a final selection of 64 articles that provided valuable insights of bias in open-ended interviews listed under Table 2.4.

Two classifications occurred on the papers, one for the domain the study was conducted on, and one for the type of bias. Domain was important to understand the presence of the topic being studied in this research in literature, but also having a comparison in mind regarding the number of studies in the domain of disaster resilience. List of domains to consider were health, education, art, organization, and social. The classification used the following logic.

- Health: Medical related studies including both physical and psychological
- Art: Papers with focuses on theatre, painting, and cinema
- Education: Papers with focus on students, teachers, college, and other educational terms. Papers focused on improving research studies are also involved in this category
- Organization: Papers discussing finance, supply chain for industries, and human resource processes including recruitment interviews
- Social: Related to personalities and studies involving child abuse or sexual or racial focused ones
- Disaster: Papers associated with disasters of any kind

To classify the domain, the field that the paper was conducted on was the main criterion. In cases where the paper could be attributed to more than one domain, such as Gerull (2021) that involved medical students that relates both to health and education, selection of the domain considered to be of domain of the journal in which the paper was published.

The type of bias was also included for the analysis of the types of bias in literature. The type of bias was identified when the paper literally mentioned the type, or it could be inferred from the adjacent words or sentences. The types of bias were scanned through the list provided under section 1.6.2 which are selection bias, sampling bias, non-response bias, volunteer bias, observer bias, confirmation bias, cultural bias, recall bias, publication bias, time-interval bias, measurement bias, geographical bias, and gender bias. If a new bias was described, it was treated as a new type and added to the types of bias for analysis. In the next section, analysis of the literature is provided. Papers with more than one type of bias identified, since there were no other criteria to narrow them down, have all the mentioned biases listed.

Table 2.4 - Literature review of bias in open-ended interviews

Title	(Author, Year)	Domain	Bias type
Is Coming Out in the Community College Classroom an "Occupational Hazard?"	(Sundblad & Dansereau, 2024)	Education	Response and gender

Enhancing supply chain information sharing with third party logistics service providers	(Valashiya & Luke, 2023)	Organization	Observer
Predictive algorithms and racial bias: a qualitative descriptive study on the perceptions of algorithm accuracy in higher education	(von Winckelmann, 2023)	Education	Cultural
Remote evaluation of STH program coverage: Experiences from the DeWorm3 study, India	(Aruldas et al., 2023)	Health	Volunteer, gender and response
Racial biases in healthcare: Examining the contributions of Point of Care tools and unintended practitioner bias to patient treatment and diagnosis	(Singh, 2023)	Health	Cultural
Exploring the Value of Improvisational Theater in Medical Education for Advancing the Doctor-Patient Relationship and Health Equity	(Rusiecki et al., 2023)	Health	Cultural
Co-Writing Screenplays and Theatre Scripts with Language Models: Evaluation by Industry Professionals	(Mirowski et al., 2023)	Art	Response, confirmation and gender
Allies as organizational change agents to promote equity and inclusion: a case study	(Y. L. Li et al., 2023)	Organization	Observer, gender and cultural
Sure you are ready? Gendered arguments in recruitment for high-status positions in male-dominated fields	(Dutz et al., 2023)	Organization	Gender
Some key questions: Pregnancy intention screening by community health workers	(St Clair et al., 2023)	Health	Gender
Small things—'It felt like love'—The experience of being deeply moved in therapy: Clients' stories of the small things that matter in therapy	(Alessandrini, 2023)	Health	Measurement

Analysis of Peer and Self-Assessments Using the Many-facet Rasch Measurement Model and Student Opinions	(DEMİR, 2023)	Education	Observer
Marking parties for marking written assessments: A spontaneous community of practice	(Vaccari et al., 2023)	Education	Observer
Adjusting Parenting Roles and Work Expectations Among Women With Children During COVID-19	(Childress et al., 2023)	Social	Gender
"He told me my pain was in my head": mitigating testimonial injustice through peer support	(Vigouroux et al., 2023)	Health	Gender
Identification of Domestically Sex Trafficked Persons in Social Service Settings in Canada: A Qualitative Study	(Elliott et al., 2023)	Social	Gender
Heuristic-driven biases as mental shortcuts in investment management activities: a qualitative study	(Ahmad & Wu, 2023)	Organization	Confirmation
Patient Experiences With Thyroid Nodules: A Qualitative Interview Survey	(Naunheim et al., 2023)	Health	Observer and measurement
Associations between emotions and psychophysiological states and confirmation bias in question formulation in ongoing simulated investigative interviews of child sexual abuse	(Segal et al., 2023)	Social	Confirmation
How Do Developers' Profiles and Experiences Influence their Logging Practices? An Empirical Study of Industrial Practitioners	(Rong et al., 2023)	Organization	Observer
Perceptions of retirement savings: Through the lens of Black amaXhosa women in South Africa	(Willows & October, 2023)	Health	Gender and cultural

Protocol to develop a core outcome set in incisional hernia surgery: The HarMoNY Project	(Harji et al., 2022)	Health	Publishing
Vertical Versus Horizontal Assessment Methods for Scoring Physiotherapy Entrance Interviews	(Smith-Turchyn et al., 2022)	Health	Measurement
A qualitative study of the acceptability of remote electronic bednet use monitoring in Uganda	(Alexander et al., 2022)	Health	Response
Explainable Personality Prediction Using Answers to Open-Ended Interview Questions	(Dai et al., 2022)	Organization	Response
Spousal support and work performance during the COVID-19 pandemic among elected women representatives in rural Bihar, India: A cross-sectional, mixed-methods study	(Priyadarshini et al., 2022)	Social	Response
Spontaneously reported persistent symptoms related to coronavirus disease 2019 one year after hospital discharge: A retrospective cohort single-center study	(Zuschlag et al., 2022)	Health	Observer and measurement
Sunk-Cost Bias and Knowing When to Terminate a Research Project	(Perignat & Fleming, 2022)	Health	Sunk-cost
Women Physicians in Transition Learning to Navigate the Pipeline from Early to Mid-Career: Protocol for a Qualitative Study	(Leung et al., 2022)	Health	Gender
"It Makes Me a Better Person and Doctor": A Qualitative Study of Residents' Perceptions of a Curriculum Addressing Racism	(Jindal et al., 2022)	Health	Gender
Comparing Traumatic Brain Injury Symptoms Reported via Questionnaires Versus a Novel Structured Interview	(Emmert et al., 2022)	Health	Response

Next steps toward an inclusive country? Inviting and amplifying youth voice in public anti-hate messaging	(Pollock et al., 2022)	Education	Cultural
Peer involvement in service provision: how US human service nonprofit organizations include sex workers as organizational staff	(Anasti, 2022)	Social	Gender
Why Do College Counselors Perceive Anxiety as Increasing? A Semi-structured Examination of Five Causes	(Martin, 2022)	Education	Selection
EFL teachers' critical literacy instructional perspectives and practices: The case of the Egyptian university context	(Latif, 2022)	Education	Confirmation
The patient perspective, experience and satisfaction of day case unicompartmental knee arthroplasty: A short-term mixed-methods study	(Patel et al., 2021)	Health	Recall
Does Medical Students' Sense of Belonging Affect Their Interest in Orthopaedic Surgery Careers? A Qualitative Investigation	(Gerull et al., 2021)	Health	Non-response
Progress in climate change adaptation research	(Sietsma et al., 2021)	Disaster	Geographical
Approaches to patient satisfaction measurement of the healthcare food services: A systematic review	(Lai & Gemming, 2021)	Health	Confirmation and response
Women Leaders in Academic Urology: The Views of Department Chairs	(Huen et al., 2021)	Health	Gender
Understanding thoracic surgeons' perceptions of administrative database analyses and guidelines in clinical decision-making	(Shemanski et al., 2021)	Health	Selection

Exploring Cancer Treatment Experiences for Patients with Preexisting Mobility Disability	(Agaronnik et al., 2021)	Health	Sampling
Potential development of digital environmental surveillance system in dengue control: A qualitative study	(Purnama et al., 2021)	Health	Time-interval
Strategies for Detecting Insincere Respondents in Online Polling	(C. Kennedy et al., 2021)	Education	Volunteer and confirmation
Patient engagement in the design of an intervention to prevent muscle loss in individuals with knee osteoarthritis and a body mass index (BMI) ≥ 35	(Godziuk et al., 2022)	Health	Observer and gender
Reflections of healthcare experiences of african americans with sickle cell disease or cancer: A qualitative study	(Dyal et al., 2021)	Health	Gender
Topological Data Analysis to Engineer Features from Audio Signals for Depression Detection	(Tlachac et al., 2020)	Health	Measurement
Assessing public behavioral health services data: a mixed method analysis	(Vaughn et al., 2020)	Health	Non-response and geographical
Using a person-generated mental health outcome measure in large clinical trials in Kenya and Pakistan: Self-perceived problem responses in diverse communities	(Harper Shehadeh et al., 2020)	Health	Response and measurement
Shared decision-making around anal cancer screening among black bisexual and gay men in the USA	(Acree et al., 2020)	Health	Cultural
A Mixed-method Analysis of Community-Engaged Theatre Illuminates Black Women's Experiences of Racism and Addresses Healthcare Inequities by Targeting Provider Bias	(Wasmuth et al., 2020)	Art	Gender

Predicting Personality Using Answers to Open-Ended Interview Questions	(Jayaratne & Jayatilleke, 2020)	Organization	Confirmation
An initial exploration of the perspectives and experiences of diverse learners' acceptance of online educational engineering games as learning tools in the classroom	(Cook-Chennault & Villanueva, 2019)	Education	Sampling
Quality-adjusted life year weights and treatment bias: Theory and evidence from cognitive interviews	(Patenaude & Bärnighausen, 2019)	Health	Treatment
Older Adults' Coping Strategies With Changes in Sexual Functioning: Results From Qualitative Research	(Ayalon et al., 2019)	Health	Selection
Original Research: Journalists' Experiences with Using Nurses as Sources in Health News Stories	(Mason et al., 2018)	Health	Gender
Reporting on selective voices of 'resistance': Secularism, class and 'Islamist' rap	(Moreno-Almeida, 2018)	Art	Cultural
An Examination of the Shared Beliefs of Ecotherapists	(King & McIntyre, 2018)	Health	Observer
What works in promoting and maintaining diversity in nursing programs	(Gates, 2018)	Education	Selection, volunteer and cultural
Institutional racism in public health contracting: Findings of a nationwide survey from New Zealand	(Came et al., 2018)	Health	Cultural
Community college minority female administrators as mentors of minority female students	(Fonts, 2018)	Education	Gender and measurement
Methods matter: Contrasting undergraduate research experience outcomes based on surveys and interview methods	(Bielefeldt et al., 2017)	Education	Response and confirmation

Critical review of willingness to pay for clinical oral health interventions	(Tan et al., 2017)	Health	Response, confirmation and measurement
Inclusive assessment for linguistically diverse learners in higher education	(Kaur et al., 2017)	Education	Measurement

Among the predefined list of types of bias from section 1.6.2, two new types of bias could be found within literature that were not identified before. These two types of bias were treatment bias and sunk-cost bias, each of them recognized separately. In the next section, the analysis of Table 2.4 with figures depicting key points is presented.

2.4.2.2. Analysis of bias in open-ended interviews

Figure 2.8 demonstrates the number of published papers in each domain. It can be readily understood that health related studies, with more than half of all the reviewed papers, sits in the first place followed by education and organization. This means that researchers in these domains, especially the health domain, care a lot about bias involved in their publications. Each field is followed by a few publications, referring to Figure 2.8, there are not many attentions to the existence of bias in open-ended interviews related to disaster resilience with only one publication focused on climate change studied by Sietsma (Sietsma et al., 2021). Without a doubt, bias exists in open-ended interviews, and it is being addressed in other domains; however, it is being less considered within researchers of disaster studies. Thus, by targeting this gap, this research aims to bring the attention to disaster related studies and also giving solutions to this existing gap from the experience of researchers in other domains.

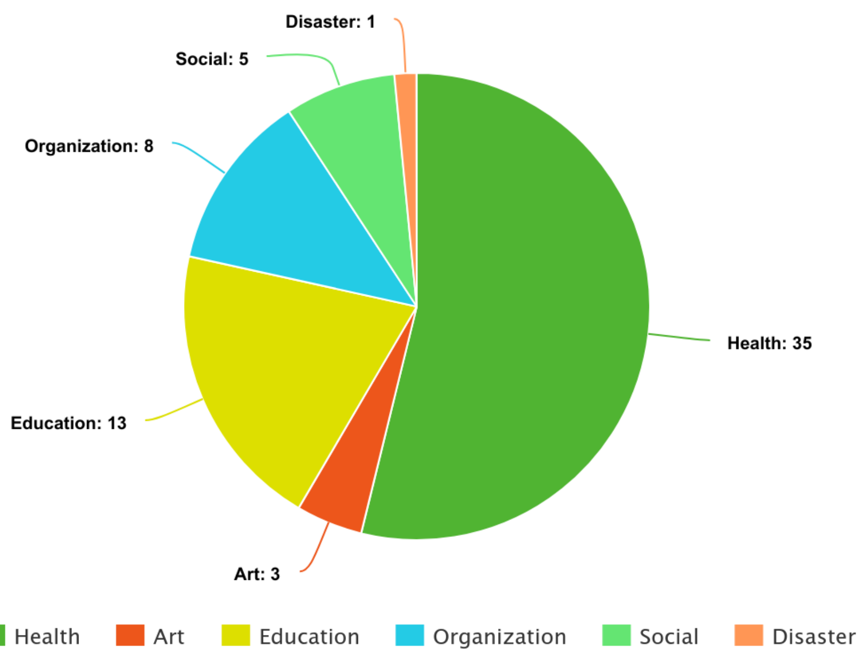


Figure 2.8 - Domains of publications with focus on bias in open-ended interviews

To analyze bias within the listed literature, in the same manner the domains were analyzed, the number of each type of bias is considered within all domains. This helps in understanding what type of bias has got more attention which gives clues on the focus of this research study. Figure 2.9 depicts the summary for better visualizations.

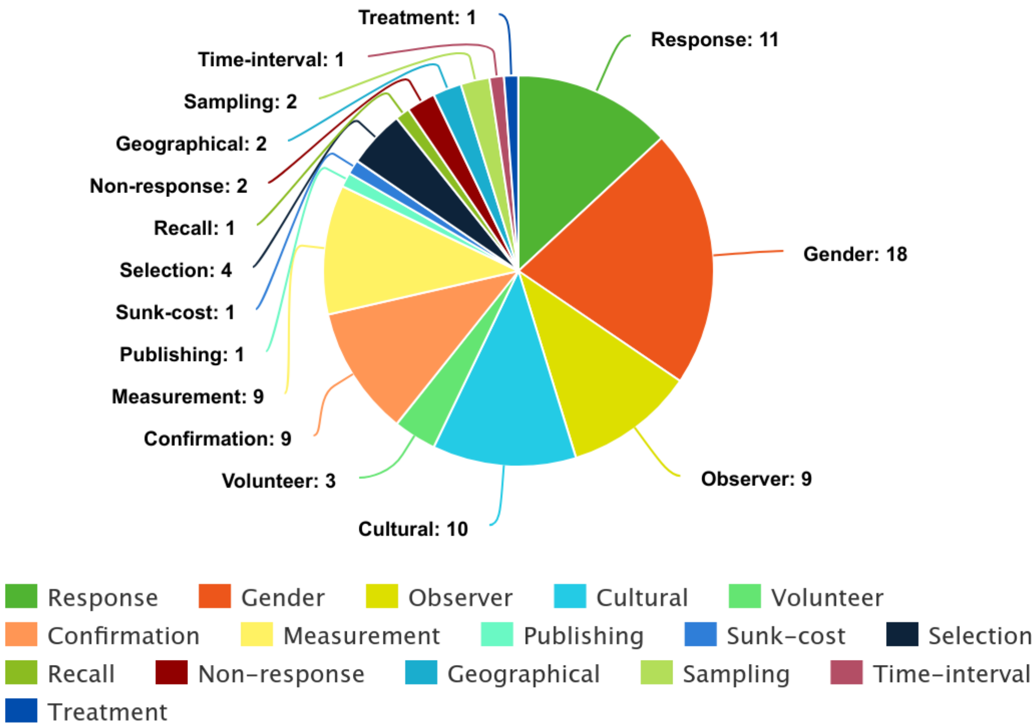


Figure 2.9 - Types of bias in systematic literature review

From Figure 2.9, it can be clearly seen that Gender bias is the most noticeable type of bias. This literature further supports the reasoning behind the focus of this research on gender bias rather than other types of bias. Even though within the reviewed literature no paper could be found targeting gender bias of open-ended interviews in disaster related studies, the number of papers targeting gender bias clearly approves its existence in any open-ended interviews.

To mitigate biases in open-ended interviews, it is essential for interviewers to be self-aware, employ standardized protocols, and use techniques such as bracketing, which involves acknowledging and setting aside personal biases during the research process (Creswell & Creswell, 2017). Incorporating diverse perspectives and ensuring cultural competence in the interviewing process are also crucial steps toward minimizing bias and enhancing the validity of the data collected. The details of how to tackle bias in open-ended interviews are described in chapter three.

2.4.3. Literature review of automation of inconsistency and bias in open-ended interviews

Research step three is focused on the need of automation for real-world applicability of a package with considerations toward tackling inconsistency and bias within open-ended interviews of disaster resilience. The support for the need can be discussed in three different aspects. First, the existence of literature supports the need for automation to help tackle inconsistency. Next, the need for automation in tackling bias supported by literature. Last, the repeatability needs of disaster resilience measurement in support of automation as a tool helping in that regard.

2.4.3.1. Automation and inconsistency

In conducting a literature review on the themes of open-ended, inconsistency, and automation within the scholarly database Scopus, five articles have emerged as significant contributions to the field. While the focus primarily revolves around automation of inconsistency, two articles have delved into areas with automation considered but not for the inconsistency.

One notable article titled "Developing a Program to Assist in Qualitative Data Analysis: How Engineering Students' Discuss Model Types" by Rodgers et al. (2022) investigates the opportunities that utilizing a computer program when working with longitudinal qualitative survey data in helping with inconsistency (Rodgers et al., 2022). In Rodger's paper, a modeling survey was developed to assess student awareness of model types and administered in four first-year engineering courses across the three universities over the span of three years. As a solution, the research team developed a MATLAB program to automatically implement the coding scheme and identify the types of models that students discussed in their open-ended responses. The MATLAB program showed good reliability in case of consistency compared to the students manually applying the coding scheme.

Another pivotal contribution comes from "Automatic detection of inconsistencies between numerical scores and textual feedback in peer-assessment processes with machine learning" by Rico-Juan et al (2019). The authors critically discuss the use of peer assessment for open-ended activities, particularly within scoring and marking in numerical and textual formats (Rico-Juan et al., 2019). The paper identifies possibilities of automatic techniques to detect inconsistencies. Applying machine learning algorithms within four groups of students yielded reliable and consistent results.

Similarly diverging from the automation discourse, "Building interdisciplinary collaboration skills through a digital building project" by Gnaur et al (2012) aims to outline key elements of successful cross-disciplinary collaboration and proposes integrating these aspects into engineering education to better prepare students for interdisciplinary work in the future. Despite growing interest in interdisciplinary education, there remains inconsistencies around the term, particularly regarding its integrative nature. The study explores the implications of interdisciplinarity for engineering education and how enhancing interdisciplinary thinking could impact curriculum planning. It emphasizes the importance of developing cross-disciplinary collaboration skills in real-life settings to foster interdisciplinary competence. The paper draws on data from an annual digital building workshop, "Digital Days," which employs the Building Information Modeling (BIM) method to facilitate interdisciplinary collaboration. BIM encourages automating processes to bring consistent views into information models of buildings, making it a suitable tool for integrating interdisciplinarity into engineering programs. The study highlights further opportunities for interdisciplinary collaboration within engineering education to promote automating tools for consistency.

2.4.3.2. Automation and bias

Conducting a literature review on the themes of open-ended, bias, and automation within the scholarly database Scopus reveals a diverse array of studies, consisting of 29 papers, exploring these interconnected concepts. Open-endedness, characterized by flexibility and lack of predetermined constraints, is examined in various contexts alongside discussions on bias and the role of automation in mitigating or exacerbating biases.

Rico-Juan in his paper of "Statistical semi-supervised system for grading multiple peer-reviewed open-ended works" discusses the benefits of open-ended assignments in education, such as fostering original ideas and facilitating a more engaging learning process for students compared to closed-answer activities (Rico-Juan et al., 2018). However, it acknowledges the significant correction workload for teachers, especially with large groups of students. To address this challenge while preserving the advantages of open-ended assignments, the article proposes a novel methodology. In this approach, students use a rubric (closed Likert scale) to peer-review each other's work, and their assessments are then automatically analyzed for possible biases using statistical tools. If biased scorings are detected, the teacher intervenes to manually correct the assignment. The methodology has been tested on two different assignments with diverse groups of individuals to assess its reliability and robustness. Results show a confidence level of over 95% in the intra-class correlation test between grades computed by the proposed methodology and those resulting from manual correction by the teacher. This indicates that the evaluation obtained using the proposed methodology is statistically similar to manual correction, with a significant reduction in effort.

Another significant contribution comes from "Framing automatic grading techniques for open-ended questionnaires responses. A short survey", which explores the assessment of students' performance, especially regarding open-ended questions such as short-answers or essays, presents challenges for educators due to its time-consuming nature and susceptibility to subjective bias (Casalino et al., 2021). In response, automatic grading techniques have been explored, particularly for short-answer questions. With the rise of Massive Online Open Courses and virtual classrooms due to the Covid-19 pandemic, the use of questionnaires for evaluating learning has increased. This study conducts a systematic literature review spanning 488 articles from 1984 to 2021, focusing on automatic grading of open-ended written assignments. The aim is to analyze research trends and techniques in essay grading automation. The review provides insights and recommendations for future research in the field of Learning Analytics. The same idea is also explored by "Automatic evaluation of open-ended questions for online learning. A systematic mapping", with focus on framing the recent advancement in automatic grading and feedback tools and methods (AGFTM) through a systematic mapping of the research field and a literature review (del Gobbo et al., 2023). The paper mentions that the results indicate that it is a growing research area, with a large set of techniques involved, but still not mature, where practical implementations have yet to come. Align with the works in education comes the paper of "Enhancing Instructors' Capability to Assess Open-Response Using Natural Language Processing and Learning Analytics" which implements an automatic scoring system for open-ended questions and textual responses (Mello et al., 2022). The main novelty of the paper is the replacement of the similarity analysis with a tag recommendation algorithm to automatically assign correct statements and errors already known to the responses, along with an explanation for each tag.

The noticeable paper of "Autonomous Reaction Network Exploration in Homogeneous and Heterogeneous Catalysis" discusses the potential of autonomous computations utilizing automated reaction network elucidation algorithms to elevate computational catalysis to the level of experimental research (Steiner & Reiher, 2022). It highlights several advantages of this approach: (i) automation allows for systematic and open-ended exploration of orders of magnitude more structures than manual inspection, leading to comprehensive understanding of structural varieties and reaction steps. (ii) Fast electronic structure methods with uncertainty quantification ensure efficiency and reliability, enabling predictive capabilities. (iii) High autonomy reduces manual labor, processing errors, and human bias, while still allowing steering towards specific regions of interest and facilitating the addition of new reactant species. This approach fosters high fidelity formalization of catalytic processes and can lead to surprising discoveries. The study reviews the current state of computational catalysis and addresses conceptual issues associated with autonomous computational procedures, using an example catalytic system for illustration.

2.5. Scope of Methods

Recent advancements in AI have pushed many fields forward, offering various methods that can help in addressing identified gaps effectively. This section seeks to leverage these innovations by narrowing the scope of this research to existing AI methods pulled from extensive literature review. With the wealth of methods offered by AI, whether it be machine learning algorithms for predictive modeling, deep learning architectures for complex pattern recognition, or natural language processing techniques for semantic analysis, a mapping solution can be identified within literature.

The search strategy commenced with the combination of keywords "artificial," "intelligence," and "method" to comprehensively identify various methods within the realm of AI. However, to streamline the focus and ensure the inclusion of only highly influential contributions, a threshold was set, considering papers with over 2000 citations as prominent. Since the aim of this literature review is to reach a saturation point where no more prominent AI techniques could be found, the review is only limited to the database of Scopus where enough resources could be found. This search led to the identification of 77 papers. After skimming through the selected papers, various AI methods were identified and compiled into a comprehensive list. Only three papers were omitted from the search as they were generally discussing AI, not mentioning any specific technique. Table 3.1 provides an overview of these methods along with references pointing to the respective papers where each method was mentioned.

Table 2.5 - List of prominent AI techniques

Method	**Reference**
Genetic Algorithms	(Karaboga & Basturk, 2007; K. O. Stanley & Miikkulainen, 2002)

Ant Colony Optimization	(Y. Chen et al., 2014; Dorigo et al., 2006; Fong et al., 2003; Guidotti et al., 2018; Karaboga & Basturk, 2007)
Rule-based Systems	(Arrieta et al., 2020; Guidotti et al., 2018; Hutto & Gilbert, 2014)
Particle Swarm Optimization	(Derrac et al., 2011; Karaboga & Basturk, 2007)
Belief Networks	(Arrieta et al., 2020; Bergstra et al., 2011; Y. Chen et al., 2014; LeCun et al., 2015; Ripley, 2007; Shin et al., 2016; Witten et al., 2005)
Directed Acyclic Graphs	(Ripley, 2007; Scarselli et al., 2008)
Probabilistic Graphical Models	(Arrieta et al., 2020; Fei-Fei et al., 2006; Felzenszwalb et al., 2009; LeCun et al., 2015; Ripley, 2007; Scarselli et al., 2008; Witten et al., 2005)
Variational Inference	(Arrieta et al., 2020; Arulkumaran et al., 2017; Fei-Fei et al., 2006; Witten et al., 2005)
Markov Chain Monte Carlo	(Dietterich, 2000; Fei-Fei et al., 2006; Grady, 2006; Ripley, 2007; Schulman et al., 2015; Witten et al., 2005)
Artificial Bee Colony	(Karaboga & Basturk, 2007)
Backtracking	(Van Beek, 2006)
Swarm Intelligence	(J. Kennedy, 2006)
Recommender Systems	(Lü et al., 2012)
Constraint Propagation	(Bessiere, 2006)
Expert Systems	(Buchanan & Smith, 1988)
Causal Inference	(Pearl, 2010)
Bayesian Networks	(Ben-Gal, 2008)
Symbolic Reasoning	(Landy et al., 2014)
Computer Vision	(Stockman & Shapiro, 2001)
Natural Language Processing	(Chowdhary & Chowdhary, 2020)
Deep Learning	(LeCun et al., 2015)

Artificial Neural Networks	(Zou et al., 2009)
Convolutional Neural Networks	(Z. Li et al., 2021)
Reinforcement Learning	(Kaelbling et al., 1996)
Supervised Learning	(Cunningham et al., 2008)
Unsupervised Learning	(Ghahramani, 2003)
Semi-supervised Learning	(Zhu, 2005)
Transfer Learning	(Weiss et al., 2016)
Ensemble Learning	(Dong et al., 2020)

2.6. Summary

In this chapter, a comprehensive overview of disaster resilience frameworks was provided, emphasizing the systematic exploration of indicators using both qualitative and quantitative methods. The chapter highlighted the significance of qualitative approaches in this context, shedding light on their significance in used frameworks.

Furthermore, the review underscored the presence of literature addressing inconsistency and gender bias in various domains, affirming the relevance of these issues. However, it also noted a scarcity of studies specifically within the domain of disaster resilience, fostering the reason for this research aiming at them.

Moreover, the literature review emphasized the importance of automation in enhancing processes, drawing support from existing literature. It outlined the scope of methods explored in the literature, with a particular focus on solutions derived from artificial intelligence, suggesting the potential for leveraging advanced technologies to address challenges within disaster resilience frameworks.

3. METHOD

3.1. Overview

In chapter one, an introductory explanation delved into the main idea of the research providing details about the topic and its background. Furthermore, the research problem was introduced and questions, gaps, significance, and their scope were defined under three research steps. In chapter two a synthesis and critique of existing literature relevant to the research topic was provided. Moreover, deficiencies within the literature were identified, thereby necessitating refinement. Furthermore, the theoretical framework for the study was established. In this chapter, the research design will be described which will include data collection methods and analysis techniques employed in the study. Moreover, this chapter will discuss the rationale behind the chosen approaches and justify their suitability for addressing the questions under each of the research steps defined in chapter one supported by literature in chapter two.

This chapter's design is as follows. Research steps one and two share similar methodologies, focusing on content analysis to find possible solutions and experimental design of the solution; the process they follow is quite similar. Consequently, research steps one and two are merged under one section. However, preconditions of each need to be separately addressed where the numerical representations of each are formulated; therefore, each of precondition sections are explained separately. Research step three resorts to experimentation and observation within its own dedicated section. Thus, the order will be precondition of research step one, precondition of research step two, method of research step one and two, and finally method of research step three. Figure 3.1 summarizes methods targeting steps of the research.

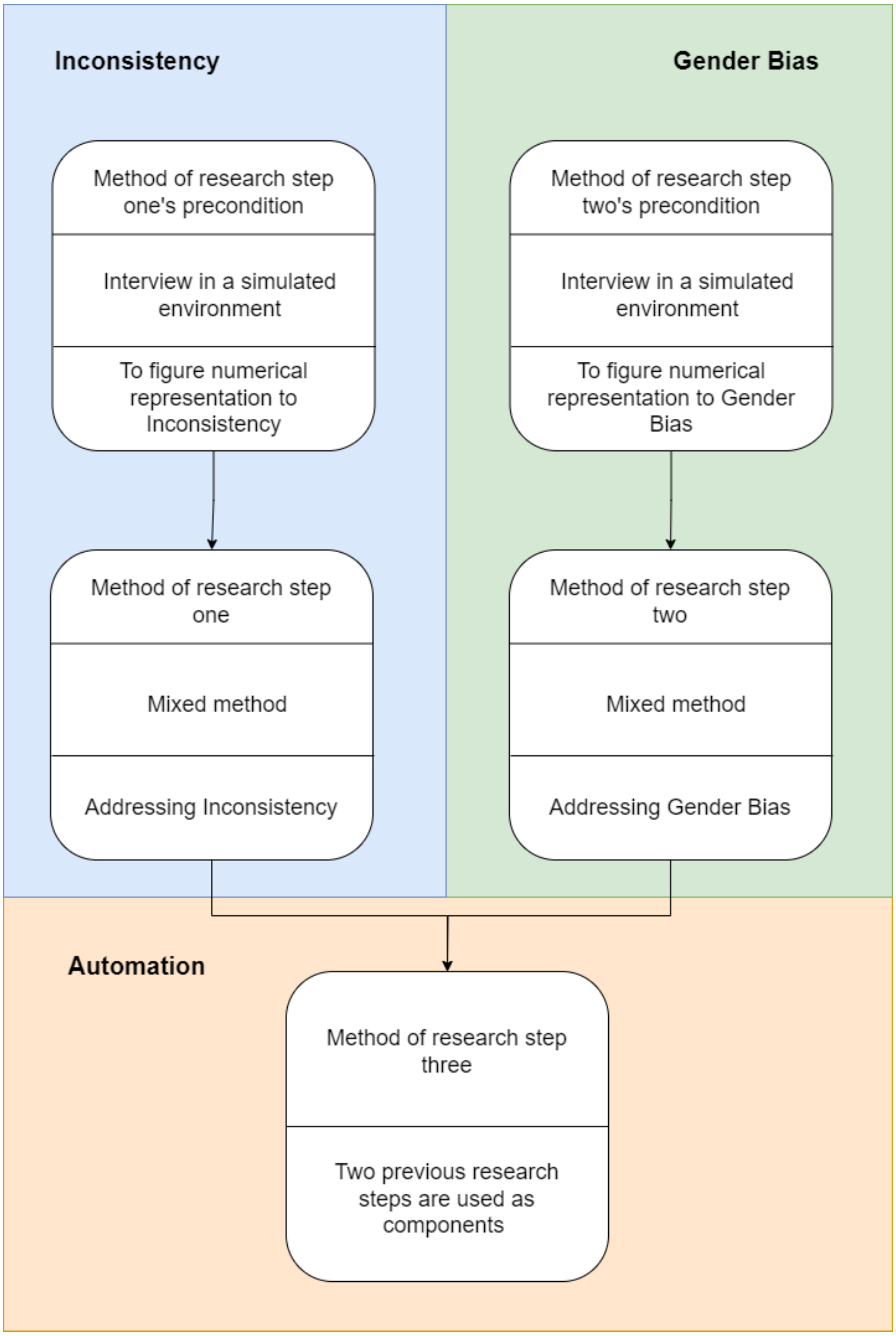


Figure 3.1 - Summary of targeted methods

3.2. Precondition of research step one, forming ground truth to measure the inconsistency of open-ended interviews on disaster resilience

In the context of the first research step, the aim is to explore the practicality of measuring inconsistency within open-ended interviews concerning disaster resilience data collection. A measurable insight into the practical state of inconsistency can relate to the measure of contradiction. It is usual in classical logic to use a binary measure of contradiction: a fact is either consistent or inconsistent (Hunter & Konieczny, 2005). Therefore, by finding a measurable contradiction in open-ended interviews, a tangible perception of inconsistency can be achieved. Diving into a consistent open-ended interview can help in grasping a measurable contradicting point positing that obtaining a measurable understanding of the current inconsistency can be effectively aligned with the measurement of contradiction.

To serve this purpose, the research adheres to the methodological guidelines outlined by Jameel et al. (2018). Their framework includes a set of structured questions designed to prompt interviewees to articulate their thoughts. Additionally, follow-up questions are employed to delve deeper into the interviewees' knowledge. These follow-up questions are tailored to align with the interviewees' thought processes while maintaining the integrity of the interview context. The conceptualization of a consistent open-ended interview as described by Jameel et al. (2018) is depicted in Figure 3.2.

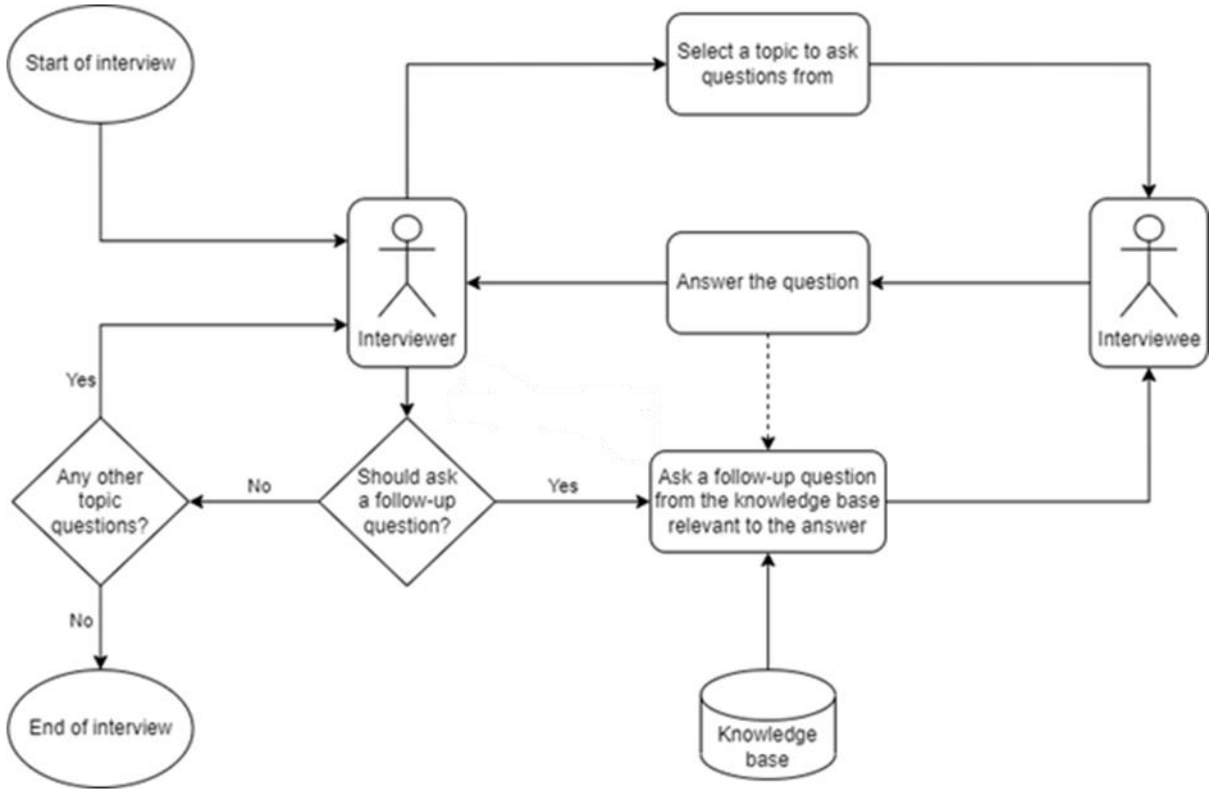


Figure 3.2 - Perception of the process of a consistent open-ended interview

In line with the structured approach outlined by Jameel et al. (2018), the interviewer's role in managing the interview process becomes paramount. While the methodology centers on structured questions to elicit interviewees' thoughts, the interviewer must also navigate the conversation effectively to maintain focus and avoid distractions. This responsibility is crucial for ensuring the integrity of the interview context and guiding it towards the optimal outcome. Analogous to a function with local and global minimums, where the goal is to steer the interview towards the global minimum, the interviewer's guidance plays a pivotal role. A visual representation of a function with local and global minimums is depicted in Figure 3.3.

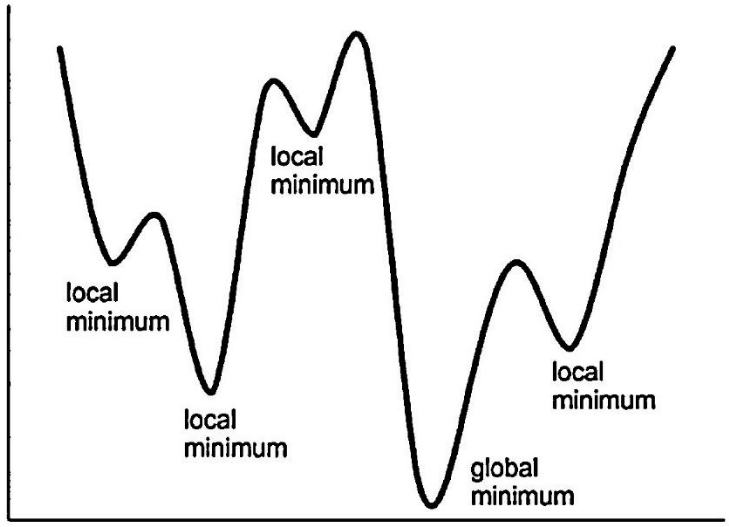


Figure 3.3 - Global minimum vs local minimums (Andreeva & Chaban, 2015)

The intervention of interviewers through the use of follow-up questions can significantly influence the dynamics of interviews. However, in the context of maintaining consistency, if interviewers interject their own cognitive perceptions into the interview process, it can inadvertently steer the conversation towards their mindset rather than aligning with the interviewees' perspectives. This intervention underscores the critical importance of how the interviewer frames and manages their involvement, as it can significantly impact the integrity and validity of the interview. As shown in Figure 3.4, the interviewer's intervention serves as a pivotal focal point, highlighting its potential contradiction and the necessity for careful handling to ensure adherence to the interviewees' mindset.

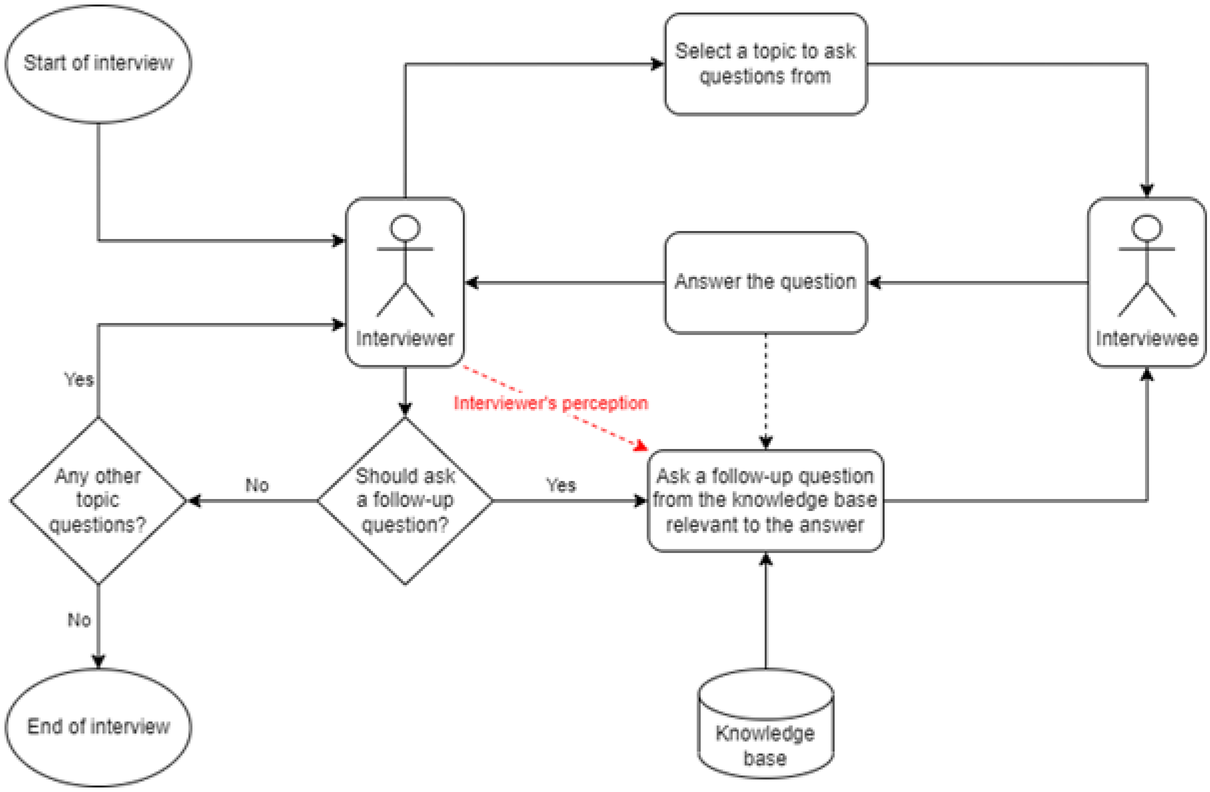


Figure 3.4 - Impact of interviewer on the process of an open-ended interview

3.2.1. Method of research step one’s precondition

Building upon this foundational knowledge, to facilitate a comprehensive understanding of how to measure the contradiction and assess the inconsistency within open-ended interviews of disaster resilience, a simulated interview scenario was crafted. Within this design, an environment suitable for conducting open-ended interviews was established allowing for the assessment of interviewers' decision-making processes regarding follow-up questions. A sample interview was needed for the simulation to be based on it to make it as real as possible. Therefore, drawing inspiration from a dialogue excerpt obtained from a webinar hosted by United Nations Office for Disaster Risk Reduction (UNDRR, 2020), keywords from the webinar dialogue were selected to conduct a search within the Scopus database. This iterative process aimed to identify pertinent peer-reviewed papers containing additional questions related to the specified topic, which could effectively serve as follow-up inquiries. Subsequently, the key topics covered in the top twelve relevant articles were compiled to form the options for use during the interview session. These preparatory steps were undertaken prior to the commencement of the interviews, ensuring a structured and methodical approach aligned with the research objectives.

At the outset, the participants, who are defined in the next section, were presented with a pair of questions and answers. Subsequently, they transitioned into the role of interviewer for the remainder of the interview, tasked with posing follow-up questions. The follow-up questions had to be chosen from the twelve options found on Scopus. Participants were then required to select the two most relevant options from the provided twelve options. Furthermore, they were prompted to elaborate on the reasoning behind their decision-making process for selecting the options. Contradictions arose when interviewers made discrepant decisions regarding follow-up questions, thereby altering the trajectory of the interview. In this way, non-controlled variability in the questions and answers are avoided, with interviewers' perceptions emerging as the most significant influencing factor of the interview flow. Thus, by observing the frequency of selection for different options, irrespective of their relevance, a measurable criterion of inconsistency could be established. Details regarding data collection including insights from participants' and their choices are provided next.

3.2.2. Data collection

The designed interview aimed to simulate open-ended interviews to comprehend the practical state of inconsistency. The participants should have had a brief knowledge to enable them to conduct the interview, while it should not have been at an expert level, allowing them to draw from their own knowledge. Therefore, final year students who studied disaster resilience related courses were used as the potential targeted population due to two attributes they possess; first, they have recently acquired up-to-date knowledge and skills relevant to disaster resilience; and secondly, they often have open minds and are receptive to new ideas which they could learn from this process and apply consistent open-ended interviews in their interviews.

The number of papers published about a topic in a year gives an indication of the level of attention given to that topic in that particular year. The population’s sample size was determined based on the number of papers published in 2022 with the keyword set of “open AND ended AND disaster* AND resilience*” in Scopus, which yielded thirteen papers. The Cochran’s formula for small population sizes was applied with a confidence level of 95% resulting in a sample size of 13 (Nanjundeswaraswamy & Divakar, 2021). The sample interview is attached under appendix b. The next section provides the details on how the analysis of the interviews is designed to be carried out.

3.2.3. Data Analysis

Statistical analysis was applied for the data analysis step with a few considerations. As explained, the number of topics was restricted to a manageable dozen for each question. Each topic aimed to encompass various viewpoints expressed by the interviewees. However, it's worth noting that in practice, a larger number of topics would have been required to capture a broader range of knowledge and fully reflect the perspectives of the interviewees. While limiting topics to twelve options may have meant that every possible perspective in the simulated open-ended interview was not covered, this decision was necessary to prevent overwhelming participants with too many options, thereby reducing the likelihood of confusion and oversight.

To calculate probability of options selections, the complement rule was utilized, a fundamental concept in probability. Specifically, focus was on calculating the likelihood of a topic not being selected, which is the complement of the desired outcome. If the number of topics is denoted as n, the probability of not selecting a topic in one attempt is represented as $(n-1) \times n$. Extending this to two attempts, the probability becomes $(n-1)/n \times (n-2)/(n-1)$. By applying the complement rule, the probability of selecting at least one topic in two attempts can be derived (Lefebvre, 2009). This approach provides a robust framework for understanding the likelihood of achieving the desired outcome.

$$Probability\ of\ a\ Topic\ Selection\ (PTS)\ in\ two\ attempts = (1-(n-1)/n \times (n-2)/(n-1)) \times 100$$

Simplifying further:

$$PTS = \left(\frac{n}{n} - \frac{n-2}{n}\right) \times 100 = \frac{200}{n} \tag{3.1}$$

Given the interview scenario with only twelve topics, the rounded value of Probability of Topic Selection (PTS) is approximately 16.67%. As the number of topics (denoted by 'n') increases, the probability of each choice being selected decreases. Conversely, with only two topics, each of them will have a probability of 100% to be selected. This prompts us to delve into the selection process, considering the number of options provided to interviewers for generating follow-up questions.

In the ideal scenario, it is assumed that every participant selects only a pair of topics and no other topics for the follow-up questions. However, in reality, which likely differs from the ideal scenario, the top two selected choices can be considered as the probable answers. The number of times they were selected was designed as the Probable Answer (PA), and the number of times other choices were made as the Secondary Choice (SC). Thus, the calculation of the discrepancy ratio could be simplified using the following formula:

$$Discrepancy\ Ratio\ (DR) = SC/(PA + SC) \times 100 \tag{3.2}$$

A lower DR indicates a closer approximation to an ideal interview, which should ideally approach a DR score of zero with minimal errors. The maximum value of DR can only be achieved if each topic for follow-up question option is selected exactly once or twice. Out of the 26 selections that can be made by the participants (13 total participants each of them making two selections), 24 options will be selected twice, and two options will be selected three times; therefore, the Probable Answers (PA) will be equal to 6 since (3 for the most selected plus 3 for the second most selected choice). The Secondary Choices (SCs) will be equal to total number of selections which can be 26 (13 students and each of which could select 2 topics) minus the selection of the PA = 6, which is 20. By applying the formula 3.2, the result will be 77%. A seventy seven percent error is significant and can impact data collection; thus, measuring DR in a real-case scenario, is crucial to understand its implications. It should be noted that the value of DR can fluctuate between 0% to 77% with the median of 39%.

To provide a comprehensive evaluation of an interview's thoroughness, consistency, and the presence of discrepancies in the selection of follow-up question options, a novel metric is introduced. This straightforward metric involves the multiplication of PTS and DR, with lower values indicating a more valid and reliable interview. Termed 'Interview's Inconsistency Mark' this metric is calculated as follows:

$$Interview's\ Inconsisteny\ Mark\ (IIM) = (PTS\ \times DR)/100 \qquad (3.3)$$

The reason that the values are multiplied is to underscore the significance of achieving a DR of zero. When DR is zero, it implies that even if the two most obvious topics are selected, the individual probabilities of each topic become inconsequential. In the context of the designed interview, the Interview's Inconsistency Mark (IIM) can vary between zero and 12.84 (approximately 13). An IIM value of 13 indicates the interview is highly unreliable in data gathering, primarily due to inconsistencies arising from the interviewer's follow-up questioning.

3.2.4. Validation

The process of conducting the interview and its subsequent analysis is meticulously detailed step by step to ensure repeatability, which is crucial for establishing credibility, validation, and verification. To further ensure reliability, a second set of questions and answers. Along with another twelve options are provided to the participants for a repeat of the interview process attached under appendix b. The results obtained from this second round are then compared with those of the initial interview. Consistency between the results from both rounds serves to validate the robustness of the process. Therefore, all the steps in conducting the interview for the second time, including the application of formulas to measure inconsistencies, are replicable. This internal validation step ensures the reliability of the process and allows for external verification through repeatability.

3.3. Precondition of research step two, forming ground truth to measure gender bias of open-ended interviews on disaster resilience

In contrast to precondition of research step one focusing on inconsistency, precondition of research step two is anchored to bias in open-ended interviews of disaster resilience. To identify the practical state of measurable bias, further elaboration on measurement methods of bias is required. Measuring bias in open-ended interviews involves assessing the extent to which interviewer influence or preconceptions may affect the responses provided by interview participants. One common indicator to measurable bias in open-ended interviews is through reflexivity, which involves the interviewer's awareness and acknowledgment of their own biases and perspectives throughout the research process (Finlay, 2002). From reflexivity, interviewers can actively monitor and critically reflect on their assumptions, interpretations, and interactions with participants, thereby reflect the potential bias in the interview data (Silverman, 2009). Additionally, employing techniques such as member checking, where participants review and verify the accuracy of their responses, can help indicating existence of bias within the data collected of open-ended interviews (Creswell & Miller, 2000). Furthermore, conducting peer debriefing sessions, where interviewers discuss their experiences and interpretations with colleagues, can provide valuable insights and perspectives to find and enhance the rigor and credibility of the interview process (Guba & Lincoln, 2001). Overall, measuring bias in open-ended interviews requires a combination of reflexivity, member checking, and peer debriefing to mitigate the potential influence of interviewer bias on the research findings.

As it was mentioned under section 1.6.2.1, the scope of bias is narrowed down to gender bias in this research, reflecting to build a ground truth for the base comparison of solution to be found for research step two. Understanding the extent of measurable gender bias in open-ended interviews is crucial to understand how gender-related factors may influence the research process and the data collected studies of disaster resilience. Gender bias can manifest in various ways, including the framing of questions, the interpretation of responses, and the treatment of participants based on their gender identity. Specifically for gender bias, one approach to understand its extents is through the analysis of interviewer behavior and language during the interview process. Researchers can examine whether interviewers display differential treatment or implicit biases towards participants based on their gender, such as interrupting or dominating the conversation more frequently with participants of a particular gender (West & Zimmerman, 1987).

Since the conversation between the both sides of interview is the key indicator of existence of gender bias, content analysis of interview transcripts can reveal gender bias's extent in the types of questions asked, the topics discussed, or the language used by interviewers when interacting with participants of different genders (Morgan, 1993). For example, researchers can examine whether interviewers employ gender-stereotypical language or assumptions when addressing participants or discussing gender-related topics.

3.3.1. Method of research step two's precondition

Researchers have long been studying bias; thus, it is expected to find applicable solutions of gender bias's measurable extent within literature. Text analysis has emerged as a prominent method for identifying gender bias across diverse contexts. By scrutinizing linguistic patterns in texts, researchers can uncover subtle manifestations of bias that might otherwise go unnoticed. For instance, studies have utilized text analysis to examine job descriptions for gendered language that may implicitly favor one gender over another in recruitment processes (Gaucher et al., 2011). Similarly, analyses of media representations have revealed pervasive stereotypes and tropes that perpetuate gender biases (Formanowicz & Hansen, 2022). Moreover, text analysis has been instrumental in uncovering gender disparities in educational materials, revealing biases in textbooks and curricula that reinforce traditional gender roles and stereotypes (Mwakabenga & Komba, 2021). By employing coded words analysis, researchers have been able analyze texts, providing comprehensive insights into the prevalence and nature of gender bias (Gaucher et al., 2011; Gerull et al., 2021; Kotek et al., 2021). Overall, text analysis and word coding stand out as a versatile and widely used method for uncovering gender bias, offering valuable insights for efforts aimed at promoting gender equity and inclusivity.

In this research, Gaucher's work is further investigated as it has already applied a set of gender codes to some posted job advertisements providing evidence of gender bias existence within job advertisements (Gaucher et al., 2011). The method of Gaucher's research, as a possible indicating tool to measure gender bias is described below.

3.3.1.1. Gaucher's gender bias assessment

Gaucher has discussed the nature of subtle wording making gender differences in job advertisements supported by literature. For the list of wording, lists of masculine and feminine words were created with published lists of agentic and communal words; e.g., individualistic, competitive, committed, supportive (Bartz & Lydon, 2004; Rudman & Kilianski, 2000) and masculine and feminine trait words; e.g., ambitious, assertive, compassionate, understanding (Bem, 1974; Hoffman & Hurst, 1990; Schullo & Alperson, 1984). Complete list of the words that were coded are listed in Table 3.1 which is consistent with previous research that has examined gender differences in language by coding for specific words (Newman et al., 2008).

Coded words were used in two studies to measure the percentage of gender related wording existing across randomly selected job advertisements. This analysis confirmed the most straightforward prediction: Job advertisements within male-dominated areas contained greater masculine wording than advertisements from female dominated areas. Moreover, at the individual level, masculine wording affected women's appraisals of the job, suggesting that the wording differences found at an institutional level in both studies have the ability to affect individuals in a way that maintains gender inequality in numerous fields. Additionally, three more studies were conducted depicting that job advertisements with masculine wording were seen as less gender diverse, and women found those jobs less appealing, compared with jobs advertised with feminine wording implying the existence of gender bias. The last study demonstrated that gendered wording did not affect people's appraisals of their personal ability to carry out a job further implicating that both men and women have full capability of carrying the job.

Gaucher demonstrated an indicator of gender bias in job advertisements supported by several studies. Following Gaucher's peer-reviewed design, her design can be followed and re-applied on samples of open-ended interviews within the domain of disaster resilience. The design of applying her method includes using codes provided in Table 3.1, applying them on a set of data from open-ended interview of disaster resilience and statistically analyzing of coding occurrences using a content analyzing software. The steps of providing data for the process and the analyzing tool are mentioned in the next sections.

Table 3.1 - Gender coded words extracted from Gaucher's study (Gaucher et al., 2011)

Masculine coded words	Feminine coded words
active-	agree-
adventurous-	affectionate-
aggress-	child-

ambitio-	cheer-
analy-	collab-
assert-	commit-
athlet-	communal-
autonom-	compassion-
battle-	connect-
boast-	considerate-
challeng-	cooperat-
champion-	co-operat-
compet-	depend-
confident-	emotiona-
courag-	empath-
decid-	feel-
decision-	flatterable-
decisive-	gentle-
defend-	honest-
determin-	interpersonal-
domina-	interdependen-
dominant-	interpersona-
driven-	inter-personal-
fearless-	inter-dependen-
fight-	inter-persona-
force-	kind-
greedy-	kinship-
head-strong-	loyal-
headstrong-	modesty-
hierarch-	nag-
hostil-	nurtur-
impulsive-	pleasant-
independen-	polite-
individual-	quiet-
intellect-	respon-

lead-	sensitiv-
logic-	submissive-
objective-	support-
opinion-	sympath-
outspoken-	tender-
persist-	together-
principle-	trust-
reckless-	understand-
self-confiden-	warm-
self-relian-	whin-
self-sufficien-	enthusias-
selfconfiden-	inclusive-
selfrelian-	yield-
selfsufficien-	share-
stubborn-	sharin-
superior-	agree-
unreasonab-	

3.3.2. Data collection

The data of this precondition is collected in the same interview held in section 3.2, where the data collection of research step one's precondition was described, with an extra stage. As an extra stage, the participants are requested to ask a follow-up question with the options they have selected. The questions generated by the participants are gathered as the sources of bias analysis data. The data is then used to find occurrence of gender bias using coded words of Table 3.1.

The population's sample size follows the same logic described under section 3.2, which is determined based on the number of papers published in 2022 with the keyword set of "open-ended AND disaster AND resilient" in Scopus using wildcard, which yielded thirteen papers. The Cochran's formula for small population sizes was applied with a confidence level of 95% resulting in a sample size of 13 (Nanjundeswaraswamy & Divakar, 2021).

3.3.3. Data Analysis

Measuring gender bias through the analysis of feminine and masculine coded words within the text of questions generated by participants offers a quantitative method to assess the presence of gender stereotypes and biases in research inquiries. This approach involves systematically identifying and quantifying the occurrence of words that are culturally associated with femininity or masculinity within the language used by participants where questions are formulated. Feminine-coded words typically connote qualities such as nurturing, emotionality, and domesticity, while masculine-coded words often evoke attributes such as assertiveness, strength, and leadership (Swim et al., 1995).

To conduct this analysis, based on the Gaucher's work, NVivo as a computer assisting text analysis tool is utilized to identify and count the frequency of feminine and masculine coded words within the text of participants' questions (Gaucher et al., 2011). NVivo is a helpful tool for sorting, organizing, and analyzing qualitative data that can assist the researcher by offering tools and features to organize and structure the data collected (Dhakal, 2022).

By quantifying the prevalence of the gender-coded words from Table 3.1, the extent to which gender biases are reflected in the language used by participants can be assessed. Any occurrences of coded words within any given sentence, no matter the gender inclining to feminine or masculine, marks the word as a non-neutral gender word. Measuring the ratio of the number of times each coded word appeared in a follow-up question against the total number of words in that question can now be defined as Gendered Word Ratio (GWR). The extent of measuring gender bias is then defined by summing the GWR for each question, zero for the questions not containing gender biased coded words denoted as Non-Gender Biased Questions (NGBQ) and one for the others denoted as Gender Biased Questions (GBQ) and diving them by the Total Number of follow-up Questions (TNQ). The Practical Measurement of Gender Bias (PMGB) can be simplified into formula 3.4 as follows.

$$PMGB = \frac{GWR \times ((\mathrm{NGBQ} \times 0) + (\mathrm{GBQ} \times 1))}{TNQ} = \frac{GWR \times \mathrm{GBQ}}{TNQ} \tag{3.4}$$

3.3.4. Validation

The details of conducting the interview and how to analyze it are described step by step ensuring it is repeatable for credibility, validation, and verification. To be further assured of process repeatability, with the second set question, answer, and twelve options, the participants are requested to generate questions with the new selected options. The gender bias occurrences are compared with the occurrences of the first interview and observations of results to be similar, within a reasonable margin of error, can certify the validity of the process.

3.4. Addressing research step one and two

Research step one centers on resolving inconsistencies encountered within open ended interviews and research step two on resolving gender bias encountered within open ended interviews. Both of these research steps seek an answer to the question of how to resolve the effects of two different variables, inconsistency and gender bias. The method of both will be approached through a mixed method strategy involving content analysis of peer-reviewed publications to explore existing solutions for addressing variables of inconsistency and gender bias. Moreover, experimental methods to assess the feasibility of these solutions within the domain of disaster resilience will be explored.

3.4.1. Method

To address inconsistency and gender bias observed in open-ended interviews, in the context of disaster resilience as a pioneer, employing a mixed methodological approach can provide a nuanced and multifaceted perspective. The prevalence of inconsistency and gender bias in open-ended interviews is evident in numerous publications, as discussed in sections 2.4.1.1 and 2.4.2.1. Thus, utilizing a content analysis approach will be instrumental in identifying existing strategies to tackle inconsistency and gender within the literature. Content analysis is a highly flexible research method that is applied across qualitative, quantitative, and mixed research frameworks. It encompasses a wide range of analytical techniques to extract meaningful insights and contextualize findings (White & Marsh, 2006). Through this method, proven solutions will be collated, categorized, and prioritized to enhance open-ended interviews in disaster resilience research. Considering the scenario, content analysis can serve as a foundational tool to identify patterns, themes, and ideas of existing solutions that could be applied to disaster resilience. By systematically coding and analyzing the solutions given in other publications, valuable insights into the underlying factors contributing to inconsistency and gender bias can be determined.

Despite the potential of content analysis to identify solutions, as outlined in section 2.4.1.2 and 2.4.2.2, the suitability of these solutions within the domain of disaster resilience warrants scrutiny. Once key themes and patterns have been identified through content analysis, experimental design of the selected solutions can further investigate the suitability and feasibility of the solution within the domain of disaster resilience. Therefore, a complementary experimental approach is adopted as a second method. Through the first phase of experimental design which is exploratory analysis, the feasibility of identified solution in the context of disaster resilience will be evaluated and prerequisites of the solution will be found. It will assess the applicability of solution, resource requirements for implementation, and potential inconsistencies and biases arising from their application. In the second phase of experimental design, the identified solution will be applied to the corresponding designed interview for inconsistency and bias defined under the methods of research step one and two in sections 3.2 and 3.3, respectively. The results will be compared to what could be obtained from the interviews showing how much improvement could be gained from the identified solutions. The process of applying all the methods in order to achieve the results is depicted in Figure 3.5 with the details of each described in the upcoming sections.

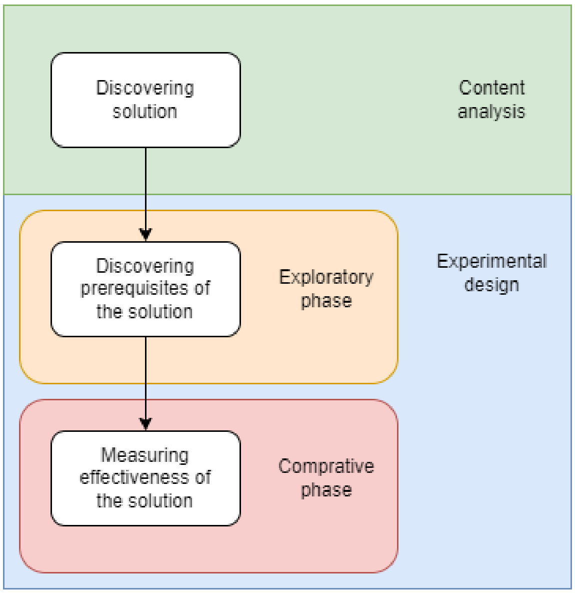


Figure 3.5 - process of methods to research step one and two

3.4.2. First method, content analysis

In a mixed-methods approach aimed at addressing inconsistency and gender bias of open-ended interviews and assessing the suitability of experimental interventions, content analysis plays the initial role of solution identification. The data collection and analysis of this method is described below which can be applied to both of the variables of inconsistency or gender bias in a similar way.

3.4.2.1. Data collection

The data that content analysis will be applied to consists of the titles, keywords, and abstracts of publications containing the keywords of 'open-ended' and the variable's name, inconsistency or gender bias. The search was just narrowed to Scopus since each of the databases can provide sufficient data to find a suitable solution.

Content analysis requires coding which in this case, codes are the possible solutions to resolve either inconsistency or gender bias. Further narrowing down the solutions, the scope is limited to any Artificial Intelligence (AI) based solutions discussed in section 1.7 where the advancements of AI as a method of addressing challenges in various research domains was shown to be promising. Therefore, the codes are the list of any possible AI based solution for the content analysis method. The codes are generated from literature by finding any possible AI based methods which are listed under Table 2.5.

3.4.2.2. Data analysis

With the completed list of codes, processed both manually and automatically with NVivo, quantitative analysis of the codes' frequency can help in identification of the solution. The code associated with the highest frequency was designated as the primary solution. The feasibility of the solution and prerequisite requirements to find the solution's suitability to the domain of disaster resilience is then processed in the next method which is an experimental design.

3.4.3. Second method, experimental design

Experimental design includes an experiment to test the applicability extent of the solution derived from the content analysis method to the domain of disaster resilience and the comparison of results by applying the solution. Therefore, experimental design comprises of two sequential stages of exploratory and comparative analysis with the former answering the needs to re-apply the solution to disaster resilience and the latter checking the results of applying this solution versus the cases of solution not being applied.

3.4.3.1. Data collection

Since there are two different steps in this method, two different approaches need to be applied to support them both. The data of exploratory comes from the cases where the selected solution of content analysis step was applied. After selection of the solution, cases where the solution was applied need to be found within literature. This step can be achieved by literature review of the solution's keyword plus the variables names which are the keywords of inconsistency or gender bias. Within the retrieved literature, the prerequisites of each case need to be listed to be used for the exploratory analysis.

In the comparative phase, the data will be the ground truth built in preconditions of research step one and two. The selected solution from the content analysis refined by the exploratory phase to cover its prerequisites will need to be applied to the same sample used in the interviews. The reason is that the results of the ground truth gained from interviews conducted need to be compared against the results of the found solution to compare how effective the solution is.

3.4.3.2. Data analysis

The experimental part, comprising two sequential stages of exploratory and comparative analysis, constituted the second step. The exploratory phase focuses on identifying key variables essential for implementing the solution derived from the content analysis, particularly concerning the requirements for applying the solution within the domain of disaster resilience. To achieve this, keywords consisting of the variables of either inconsistency or gender bias mixed with the found solution's name need to be reviewed within literature. The scope of the search will be limited to Scopus since sufficient practical approaches with recommended prerequisites can be found. Expected to find a list of prerequisites, each paper needs to be scanned through to find the list of requirements to execute the given solution. This process continues until saturation point of no more new requirements or prerequisites can be found. Each of the prerequisites will need an extra literature review in Scopus to find how they were generated within the domain of disaster resilience. If the prerequisite is already addressed, the idea will be replicated; otherwise, based on the found solutions within other domains, an approach on how to replicate it within disaster resilience will be given. The process continues until all the prerequisites are addressed. Figure 3.4 describes the case.

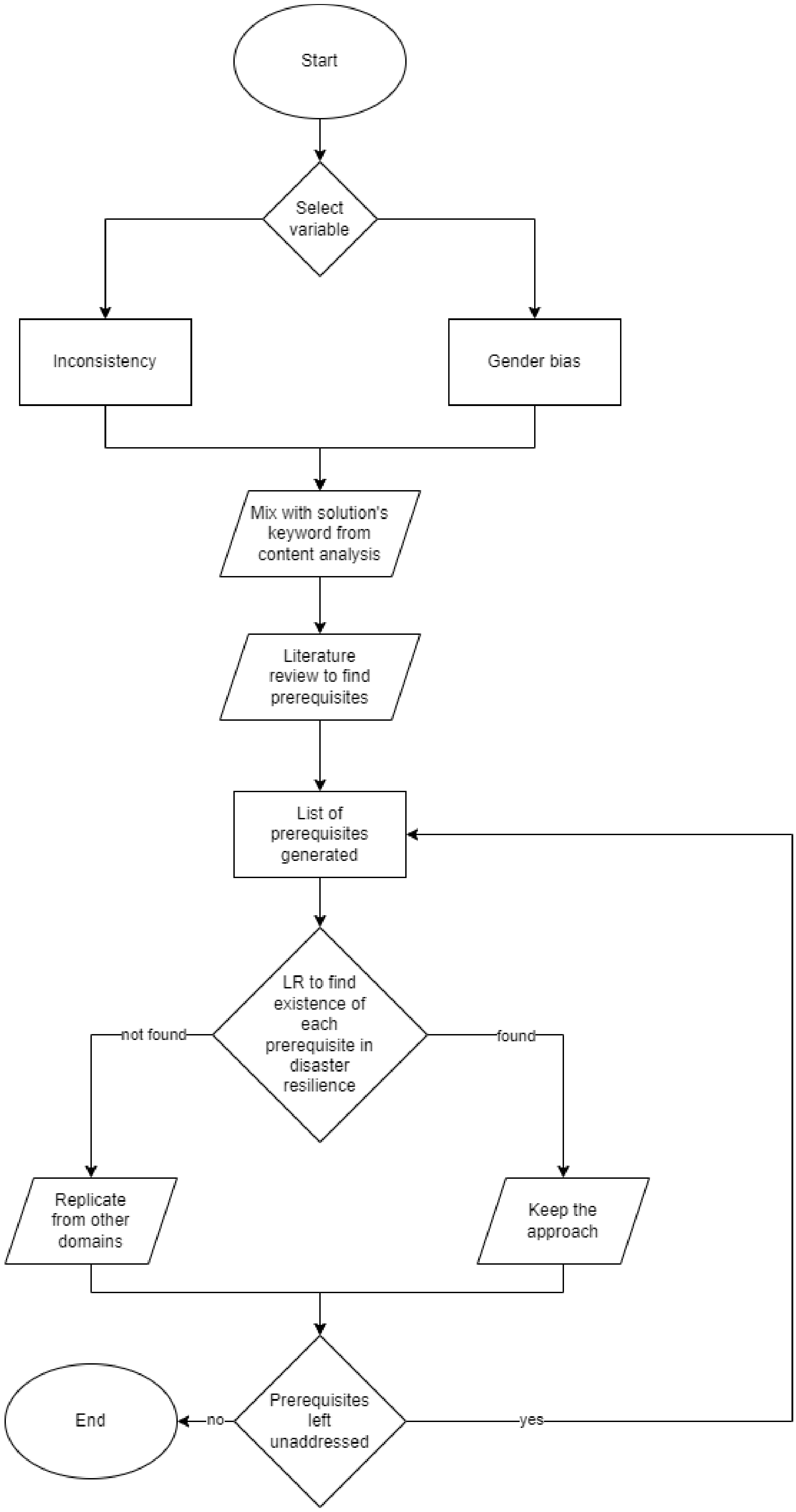


Figure 3.5 - approach of exploratory phase

In the comparative case stage, the efficacy of the proposed solution will be compared against the outcomes generated by the results of preconditions one and two, where the ground truth of measurable inconsistency and gender bias are reflected. Since the same interview sample collected for interviews of preconditions one and two will be used, the same methodological approach needs to be applied to align with those of research step one and two, ensuring a consistent scenario for comparison purposes. This further means that formulas 3.3 for the case of inconsistency and 3.4 for the case of bias will be applied with the given solution found from the content analysis and refined by exploratory phase. These formulas work as the metrics to measure the effectiveness of the found solution and the results of the solution will be discussed against the results of the conducted interviews.

3.4.4. Validation

The validation method consists of applying the solution to the second sample of interview same as the scenario defined for preconditions of research step one and two. With the second application, more reliable results can be achieved with the statistical analysis of formulas defined for both variables of inconsistency and gender bias. This will involve employing statistical distribution analysis to evaluate the confidence levels of the proposed method in comparison to existing levels, as applied to the interviews conducted for research step one. Additionally, in the next chapters, discussions will be provided regarding the method’s generalizability across different datasets or conditions. This comprehensive approach to validation aims to provide a thorough assessment of the method's validity and applicability within the research context.

3.5. Research step three

Research step three revolved around the idea of a fully-fledged framework of automating open-ended interviews of disaster resilience which are gender bias-free and consistent. This research step sums up a comprehensive framework addressing gender bias and inconsistency; besides, it also looks into the components of automation added to the framework for repetition of use in research and industrial use-cases.

3.5.1. Method of research step three

The method of research step three is a case study. A case study approach involves in-depth investigation and analysis of a specific phenomenon (Baskarada, 2014), which in this case is the scenario of designing a framework to automate the process of open-ended disaster resilience interview. This can help in examining the practical challenges faced, outcomes achieved, and lessons learned from adopting the design to the case (Yin, 2009). Case studies provide rich, contextual insights (Baxter et al., 2008), which its application can inform best practices for implementing automation of open-ended interviews of disaster resilience. A designed based on Decision Support Systems serves as the cornerstone of the framework, enabling the formulation of research step three.

Decision support systems (DSS) are vital components of modern decision-making processes, offering analytical tools and information processing capabilities to assist in making well-informed choices (Bonczek et al., 2014). By integrating various data sources and analytical models, DSS enables users to evaluate alternative courses of action, assess risks, and anticipate outcomes with greater accuracy and efficiency (Mir & Quadri, 2009). These systems leverage advanced technologies such as artificial intelligence, machine learning, and big data analytics to provide real-time insights and scenario analysis, empowering decision-makers to navigate complex, dynamic environments (Turban, 2011). In the domain of disaster resilience, DSS has been increasingly challenged and opportunities, the strategic deployment of DSS has emerged as an effective decision-making, driving sustainable growth and competitive advantage in today's digital era (Sarker et al., 2020).

Once a DSS based framework is developed, the system can be tested using the case study method. The effectiveness of the DSS can then be evaluated based on various metrics with the list given in the upcoming section of data analysis. Through testing and refinement, the DSS can evolve to better address research step three and similar challenges in decision-making of open-ended interviews for disaster resilience domain.

3.5.2. Data collection

For purposive data sampling, it is imperative to gather recent case study data from a proficient researcher professionally and actively engaged in the field of disaster resilience who is experienced enough in running open-ended interviews. With the given attributes, the data of case study is taken from a sample open-ended interview provided by Balaei et al (2018) for data collection of framework designed for water supply resilience in New Zealand. With the provided sample, attached in appendix c, the designed DSS to will be challenged and analysis of the metrics will be observed.

3.5.3. Data analysis

Analysis approach will be qualitative description of the framework. The description consists of the details on how the framework handles automation of inconsistency and gender bias cases. Designed DSS should fit into the process of open-ended interviews and improve the process where the perceptions of interviewers cause inconsistency or the wording causing of them causing gender bias. Considering the designed DSS as a black box, Figure 3.6 depicts the process of the improved open-ended interviews needing to be applied in disaster resilience interviews.

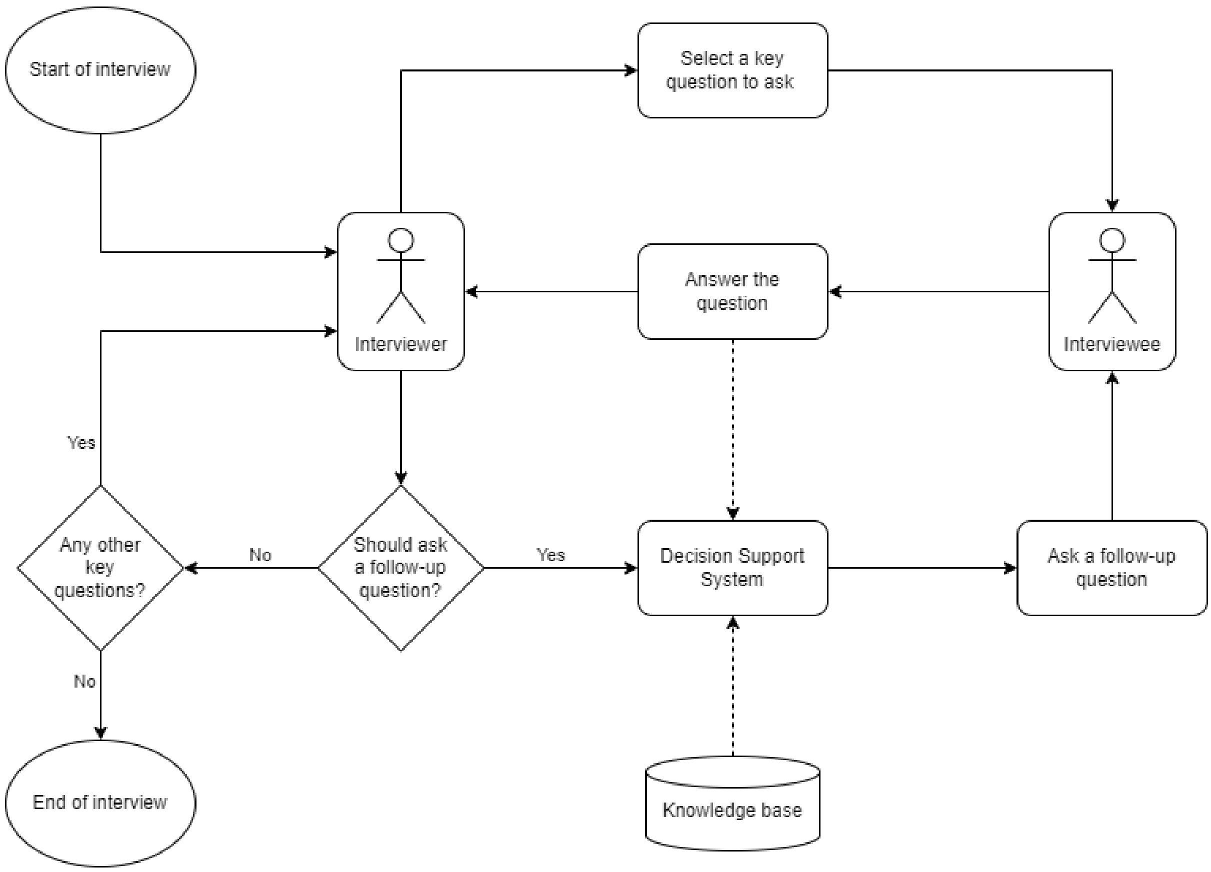


Figure 3.6 - process of an improved open-ended interview with a DSS

With the framework serving as a DSS designed specifically for processing open-ended interviews, it naturally invites consideration of how the quality of these interview questions can be assessed. Therefore, the metrics of measuring the quality of open-ended interviews can be applied to assess the designed framework. The list of metrics for evaluating the effectiveness of open-ended interviews questions includes:

- Richness of Content: Assesses the richness and diversity of content covered in the interview, which is the breadth of perspectives explored (Gubrium & Holstein, 2002).
    - The measurement approach will be determined by the extent to which participants offer novel insights or perspectives during the interview. A higher number of novel insights indicates a richer content. This value can be gained from the total number of topics that can be discussed with the interviewee where they should come from the knowledge base. It should be noted that the topics are limited to the objective of the interview.

$$Richness\ of\ Content\ (RC) = Number\ of\ topics\ in\ the\ knowledge\ base \tag{3.5}$$

- Relevance to Objectives: Evaluates the extent to which interview process aligns with the objectives and research questions of the study (Fu, 2011).
    - The measurement approach will be the percentage of references to the objectives of the interview. The number of times questions including keywords of objectives divided by the total number of questions can indicate relevance to objectives.

$$Relevance\ to\ Objectives\ (RO) = \frac{Number\ of\ questions\ containing\ keywords\ of\ objectives}{Total\ number\ of\ questions\ asked} \tag{3.6}$$

- Exploratory Nature: Analyzes the effectiveness of follow-up questions in eliciting additional information and clarifying responses. It also determines whether interviewers probe deeper into topics of interest and encourages elaboration from interviewees (Patton, 2014).
    - The measurement approach will be the open-endedness of the follow-up questions. The percentage of questions asking open-ended questions instead of yes/no questions is the metric of Exploratory Nature.

$$Exploratory\ Nature\ (EN) = \frac{Number\ of\ non\ yes\ or\ no\ follow\ up\ questions}{Total\ number\ of\ follow\ up\ questions} \tag{3.7}$$

- Ethical Considerations: Considers ethical considerations such as confidentiality, respect for participants' autonomy, and sensitivity to cultural norms. Ensures that the interview process respects participants' rights and safeguards their well-being (Lewis, 2015).

- The measurement approach will be the number of times any Personal Identifiable Information (PII) can be detected within the interview. The lower the value, the higher this measurement will be.

$$Ethical\ Considerations\ (EC) = Frequency\ of\ PIIs\ in\ the\ interview\ question \tag{3.8}$$

- Interview's Inconsistency Mark: Tackling inconsistency as a gap identified under section 1.6.1 represents another significant metric to consider in evaluating the effectiveness of the framework.
    - The measurement approach will be applying the formula 3.3 defined under section 3.3.3. The lower the value of Interview's Inconsistency Mark (IIM), the more consistent the interview.
- Absence of gender bias: Consideration of gender bias, which was mentioned in section 1.6.2, stands as another critical metric to be considered within the evaluation framework.
    - The measurement approach will be applying the formula 3.4 defined under section 3.4.3. The lower the value of Practical Measurement of Gender Bias (PMGB), the more gender neutral the interview.
- Efficiency of Automation: Within the framework, another metric deserving evaluation is the efficiency of automation. This aspect gauges the effectiveness of automated processes in execution of an open-ended interview process.
    - The measurement approach will be determined by calculation of the percentage of tasks in the interview process that are automated compared to those that are manually performed. The lower the value, the more automated the process is.

$$Efficiency\ of\ Automation\ (EA) = Number\ of\ automated\ tasks\ /\ Total\ number\ of\ tasks \tag{3.9}$$

By employing these metrics, the quality of open-ended interview questions can be assessed and informed judgments about the reliability, validity, and effectiveness of the collected data can be made; thus, facilitating evidence-based analysis of the designed process.

3.5.4. Validation

The validity of the designed framework, while initially will be demonstrated through a case study, extends its applicability to various other scenarios. Despite its limited initial application, the transparent nature of the framework ensures its validity and transferability to different cases. By openly detailing the design methodology, parameters, and decision-making processes, the framework invites scrutiny and replication, thereby fostering trust and confidence in its outcomes. The robustness of the framework lies in its adaptability and scalability, allowing it to be readily applied to diverse contexts and datasets. Through systematic replication and testing across multiple cases, the framework's effectiveness can be verified and refined, bolstering its reliability as a tool for decision support. This emphasis on transparency and replicability not only enhances the credibility of the framework but also encourages continuous improvement through iterative iterations and feedback loops. In essence, the validity of the designed framework transcends the constraints of any single case study, paving the way for broader and more impactful applications across various domains and scenarios.

For the repeatability test to bolster the validation, the necessity arose for generating questions from an alternative source to ensure the comprehensive assessment of the framework. Therefore, applying a second case study where questions generated by Claude 3 Sonner are utilized further strengthens the framework's versatility and generalizability, affirming its effectiveness beyond the initial demonstration. The second case is attached under appendix d.

3.6. Ethical Considerations

The application of interview process has been ethically considered and approved by Auckland University of Technology's Ethical Committee (AUTEC). All the approved documents including interview sample, participant consent template, and AUTEC forms can be found under the appendices.

3.7. Summary

In this chapter, research steps one, two, and three were thoroughly explored, analyzed, and validated, with a detailed description of their data collection methodologies. Both research step one and two employed a mixed method approach incorporating content analysis and experimental design. The content analysis phase involved identifying a viable solution from another domain and assessing its relevance and applicability to the domain of disaster resilience. This was followed by an experimental design phase, which included prerequisite analysis to determine how the identified solution could be implemented and any additional requirements it may need. In the comparative analysis, the results of the proposed solutions were compared to ground truth data, which served as benchmarks. The ground truth for research step one focused on addressing inconsistency, while for research step two, it centered on addressing gender bias. These served as preconditions for evaluating the effectiveness of the proposed methods.

Furthermore, the method chapter discussed the components of the task that could be automated in research step three, aiming to streamline and improve the interview process. Additionally, metrics for evaluating the final solution were outlined, providing a comprehensive framework for assessing its effectiveness.

4. RESULTS

4.1. Overview

The genesis of this study lies in the formulation of three research steps in the first chapter, providing background literature support to the research steps in chapter two and the methodology employed to tackle the gaps in chapter three. In this chapter, the outcomes are presented for each research step, including their preconditions.

4.2. Outcomes of research step one's precondition

In the designed interview process of section 3.2, the value of Probable Answer (PA) of the first interview was found to be 18 and the Second Choices (SC) was 8. Therefore, using formula 3.2, the value of Discrepancy Ratio (DR) equals 30.77. The value of Probability of a Topic Selection (PTS) from formula 3.1 was pre-calculated equaling to 16.67. By having these values in hand, applying formula 3.3 to measure the Interview's Inconsistency Mark (IIM) yields 5.13, indicating a moderate level of inconsistency within the range of 0 to 13. On the other hand, in the second designed interview, values 21 and 5 were found for PA and SC respectively. Upon applying the formulas, an IIM of 1.35 was derived representing a favorable level of data reliability and reduced inconsistency within the range of 0 to 13. These results indicate values falling within the lower half of the normal distribution (between 0 and 13) concerning real-world open-ended disaster resilience measurement interviews. However, this does not negate the possibility of encountering discrepancies near values such as 5.13, which align with the median value of 6.5.

4.2.1. Discussion of outcomes

The measured values of inconsistency in open-ended interviews may appear schematic at first glance, yet they offer a valuable practical insight into the nuanced nature of inconsistency within such interview formats. Based on their quantitative nature, these measurements serve as tangible indicators, shedding light on the variability and unpredictability inherent in human communication. By quantifying the degree of inconsistency, a deeper understanding of the dynamics during interviews can be gained, allowing for more informed analysis and interpretation of qualitative nature of inconsistency. Thus, while seemingly abstract, these measured values provide a concrete means to gauge and assess the reliability and validity of open-ended interview data.

4.3. Outcomes of research step one

In this section, the selected solution from the content analysis method, where it was applied to other domains, are presented. Besides, the feasibility of the found solution are explored detecting the prerequisites to apply to the solution within the domain of disaster resilience. Ultimately, the results of the solution applied to the same interview designed in research step one's precondition are compared to the results of the interviews.

4.3.1. Solution discovery

In alignment with the methodology detailed in section 3.3, the results of research step one are presented in two steps reflecting the mixed method utilized. In the first step, to find the solution, content analysis of papers within the Scopus database steered the identification of the potential solutions. The search was "inconsistency

AND open-ended", yielded 155 pertinent papers. Figure 4.1 demonstrates the occurrences of AI solutions from Table 2.5 appeared in the papers.

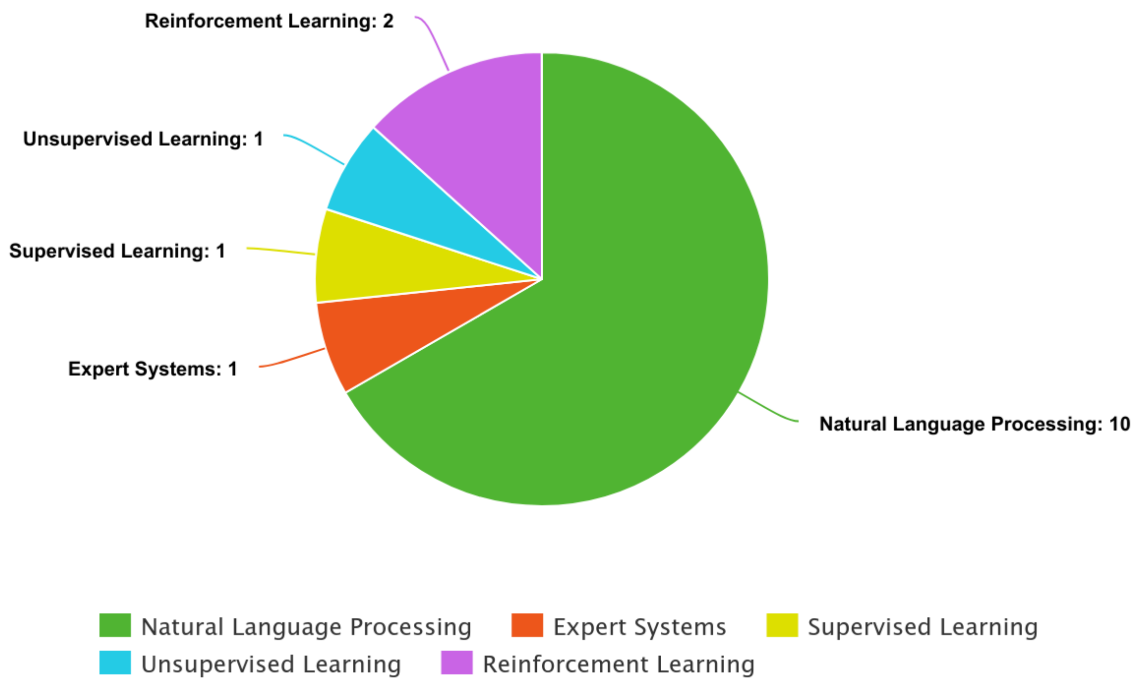


Figure 4.1 – Occurrences of AI solutions to inconsistency of open-ended interviews

Through an examination of highlighted keywords, it becomes evident that Natural Language Processing (NLP) stands out as a predominant theme, appearing in 10 out of 15 instances where AI solutions were employed. NLP has emerged as the go-to solution for addressing the inherent inconsistency challenges associated with open-ended interviews. Leveraging sophisticated algorithms, NLP enables the parsing and comprehension of human language, allowing for valuable interpretation of conversations in interviews. Its widespread adoption underscores its effectiveness in overcoming the inconsistency often encountered in such interviews, providing researchers and organizations with a powerful tool for extracting meaningful information from qualitative data sources.

4.3.2. Solution feasibility in disaster resilience

The first step of applying Natural Language Processing (NLP) to address the inconsistency of open-ended interviews of disaster resilience is exploratory analysis of the solution which needs model or technique selection. NLP consists of several techniques with different purposes including:

- Tokenization: Tokenization involves breaking down a text into smaller units, such as words or phrases which is a fundamental step in many NLP tasks (C. Manning & Schutze, 1999).
- Named Entity Recognition (NER): NER identifies and categorizes named entities within text, such as names of people, organizations, and locations (Nadeau & Sekine, 2007).

- Part-of-Speech Tagging (POS): POS tagging assigns a grammatical category (e.g., noun, verb, adjective) to each word in a sentence (Teller, 2000).
- Sentiment Analysis: Sentiment analysis determines the sentiment or opinion expressed in a piece of text, whether it's positive, negative, or neutral (Pang et al., 2008).
- Machine Translation: Machine translation involves automatically translating text from one language to another (Lopez, 2008).
- Topic Modeling: Topic modeling identifies topics present in a collection of documents (Nikolenko et al., 2017).
- Dependency Parsing: Dependency parsing analyzes the grammatical structure of a sentence to determine the relationships between words (C. D. Manning et al., 2014).
- Word Embeddings: Word embeddings represent words as dense vectors in a continuous vector space, capturing semantic relationships between words (Mikolov et al., 2013).
- Sentence Embeddings: Sentence embeddings applies the process of word embedding on scale of sentences to capture semantic relationships within paragraphs and connected sentences (Le & Mikolov, 2014).
- Text Summarization: Text summarization generates concise summaries of longer texts while preserving the main ideas and key information (Widyassari et al., 2022).
- Text Classification: Text classification assigns predefined categories or labels to text documents (Sebastiani, 2002).
- Information Retrieval: Information retrieval involves retrieving relevant documents from a collection in response to a user query (Ceri et al., 2013)

However, not all these techniques are relevant to research step two, which requires understanding interviewee responses and formulating consistent follow-up questions. Given that interviewee responses typically consist of sentences, sentence embedding emerged as a suitable technique for contextual understanding. Once the responses of the interviewees are comprehended, it is essential to pose follow-up questions consistently. Among the NLP techniques, Information Retrieval has been selected as the suitable solution for this task.

Information retrieval involves the process of retrieving relevant information from large collections of text or documents based on a user's query or search criteria (C. D. Manning, 2008). It encompasses various techniques and algorithms aimed at efficiently locating and presenting documents or passages that are most pertinent to the user's information needs (Ceri et al., 2013). This can include tasks such as document retrieval, document ranking, and passage retrieval, among others (Sheetrit et al., 2020). Ultimately, information retrieval aims to facilitate effective searching and accessing relevant information from textual data, which in this case, using information retrieval can help in finding a consistent follow-up question. However, it should be noted that Information Retrieval requires a database called knowledge base to retrieve the knowledge from. This implies the need for a knowledge base which is the prerequisite of applying Information Retrieval. Therefore, complying with the process defined in Figure 3.5, existence of a knowledge base as a prerequisite in the domain of disaster resilience should be reviewed from literature or it should be generated if not supported by literature.

A literature review revealed limited resources on disaster resilience, knowledge bases, and NLP. Only one paper was found that discussed a text-based knowledge base designed to address disaster-related queries. Sermet & Demir (2018) described the idea of a knowledge engine based on several resources including Wikipedia to answer queries with regards to flooding. While leveraging online text resources seemed intriguing, reliance solely on non-peer-reviewed sources such as Wikipedia could mislead interviews. Therefore, utilizing a peer-reviewed database such as Scopus was proposed to enhance reliability. Accordingly, to address the lack of an existing knowledge base to apply the NLP solutions, a knowledge base was designed as follows:

- Before interviews, general keywords would be identified by the interviewee to narrow the scope.
- The keywords were used in Scopus to retrieve relevant peer-reviewed papers.
- The retrieved papers are bundled together to form a knowledge base for information retrieval.

With this approach, the exploratory analysis phase was concluded, fulfilling the prerequisites for an NLP-based solution. The next step involved comparative analysis, wherein the identified solution was applied to the same interview defined for research step one's precondition for comparative evaluation.

4.3.3. Results of solution application

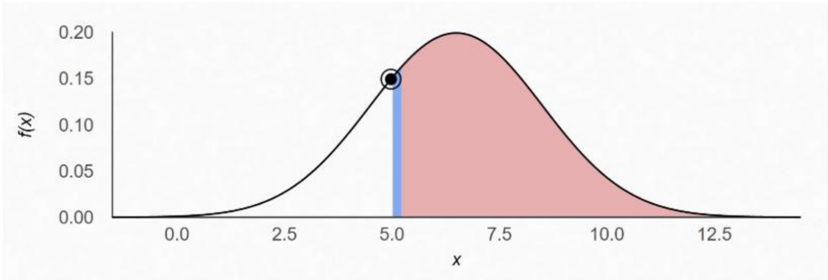
Based on the keywords of the questions of the simulated interviews designed in precondition of research step one, around 1500 peer-reviewed papers were retrieved. The knowledge base was indexed using Anserini's Information Retrieval library for Python, known as Pyserini, renowned for its swift information retrieval *(Yang et al., 2017)*. Since total number of topics equal to 1500, the value of n from formula 3.1 equals to 1500 which results in the value of PTS value from the same formula stands at 0.13, implying an extremely low probability of a topic being selected from a knowledge base of this magnitude, assuming equal weightage for each topic. Conversely, this approach instils a higher confidence level in the designed knowledge base, encompassing a diverse range of topics as options to be chosen from.

To understand interviewee responses and align them with given options, T5 doc2query's sentence embedding technique was employed. This approach can help in speeding up the process with minimal latency, enabling real-time selection of follow-up questions for open-ended interviews (Nogueira, Yang, Lin, & Cho, 2019). The algorithm narrows down the search to the top one percent most relevant papers (15 out of 1500) matching embedded sentences of the interviewee's response.

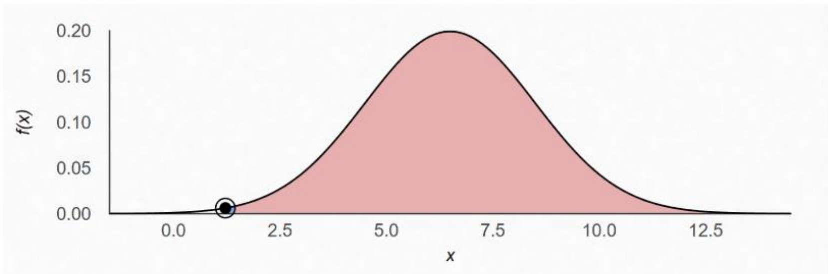
Since the number of options raised from 12 to 15, resulting in a potential variation in the DR value (calculated using formula 3.2) between zero and 86.67, the multiplication of DR and PTS (IIM, from formula 3.3), can vary between zero and 0.11. This range is considerably lower than the possible range of zero to 13 from the precondition of research step one's interview.

4.3.4. Discussion of outcomes

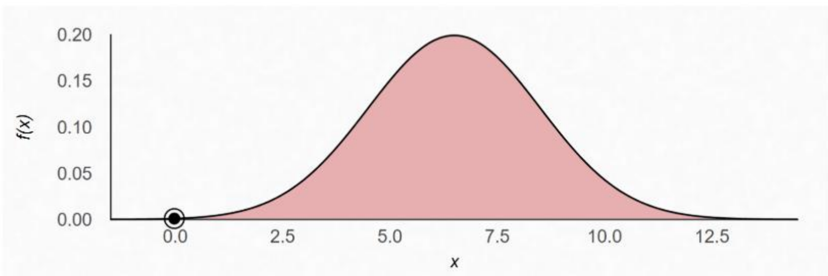
The range value recorded for the Interview's Inconsistency Mark (IIM) in section 4.4.3 remained between 0 and 0.11, which the high value of 0.11 indicates a confidence level of 99%. A confidence level of 99% signifies a dependable level of consistency which with confidence confirms that the discovered solution's values exhibit consistency to a degree of 99%. Figure 4.2 depicts the comparison of this value with those obtained from the interviews in section 4.2.



value = 5.13



value = 1.35



value = 0.11

Figure 4.2 - confidence of values gained for IIM

4.4. Outcomes of research step two's precondition

Among the 13 participants, each selected two topics for follow-up questions, resulting in a Total Number of follow-up Questions (TNQ) of 26. In the first interview, a total of 30 gender biased words were recognized among 520 words yielding a Gendered Word Ratio (GWR) of 0.06. Besides, 23 questions contained gender biased words, using the formula 3.4, leads to an Extent of Measurable Gender Bias (EMGB) of 0.05. In the second interview, the TNQ remained the same at 26, with a GWR of 0.05. Among these questions, 22 were found to contain gender bias, resulting in an EMGB of 0.04.

4.5. Results of research step two

As it was mentioned earlier in section 3.4 research step two follows the same process as research step one with the difference of replacing variable of inconsistency with bias. In this section, the solution of how to address bias in open-ended interviews is found. It's feasibility with prerequisites is described in the domain of disaster resilience and the results of applying it is compared to the results of ground truth from its precondition.

4.5.1. Solution discovery

Similar to the discussions of section 3.3, the outcomes of research step two are delineated in two stages because we were using a mixed method. Initially, as previously outlined, a content analysis of papers found in Scopus informed the selection of a solution. Employing "gender bias AND open-ended" resulted in the identification of 120 papers. Figure 4.3 shows the occurrences of AI solutions from Table 2.5 appeared in the papers.

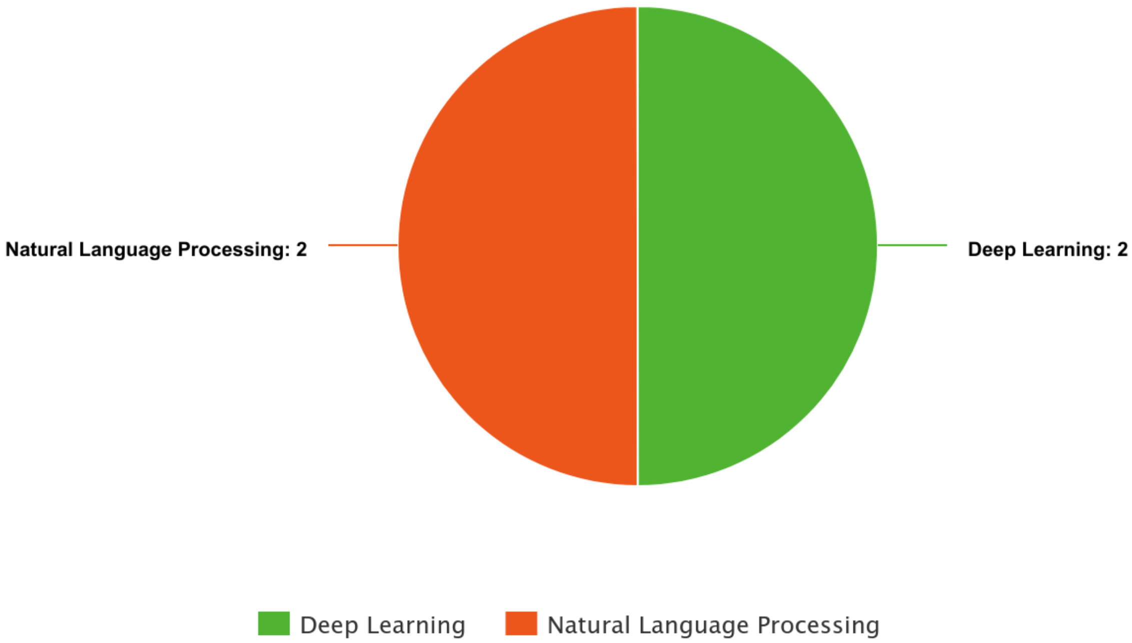


Figure 4.3 - Occurrences of AI solutions to gender bias of open-ended interviews

The examination of highlighted keywords illuminates NLP and Deep Learning as equally prominent candidates, each appearing twice, to address the gender bias inherent in open-ended interviews. These sophisticated AI-based solutions offer promising avenues for mitigating biases and ensuring fairness in the interview process. Natural Language Processing, with its ability to comprehend and analyze human language patterns, presents opportunities for developing algorithms that can detect and mitigate gender biases in interview questions and responses. Similarly, Deep Learning techniques, known for their capacity to extract intricate patterns from large datasets, hold potential for complex tasks including text generation. The parity in occurrences underscores the recognition of both NLP and Deep Learning as vital tools in fostering inclusivity and equity in interview settings, reflecting a concerted effort to leverage technological advancements for promoting fairness and objectivity in research practices.

4.5.2. Solution feasibility in disaster resilience

One area that NLP can help is to ensure that any bias in gender representation is addressed (Zhao et al., 2018). The de-biasing techniques include applying preprocessing techniques using tokenization to mitigate gender bias in data. This may include removing biased or stereotypical language, augmenting underrepresented gender instances, or synthesizing new data points to achieve balance (Zhao et al., 2018). Based on this technique, one part of the solution is data preprocessing of questions containing gender bias. This step helps in removing gender bias from the questions by detecting gendered words and eliminating them from the texts. The prerequisite of this step is finding a list of gender biased words from literature. Even though no such list could be found within the domain of disaster resilience from literature, the generic list presented in Table 3.1 was utilized. However, no solution is given on how to replace the eliminated words which are addressed from the Deep Learning side.

Deep learning techniques refer to a subset of artificial intelligence methods inspired by the structure and function of the human brain's neural networks. These techniques have gained immense popularity and success in various fields, including computer vision, natural language processing, speech recognition, and more. Some of the key deep learning techniques include:

- Recurrent Neural Networks (RNNs): RNNs are a type of neural network architecture commonly used for sequential data processing (Hochreiter & Schmidhuber, 1997).
- Long Short-Term Memory (LSTM): LSTMs are a type of RNN designed to address the vanishing gradient problem by introducing specialized memory cells that can retain information over long sequences (Hochreiter & Schmidhuber, 1997; Graves et al., 2005).
- Gated Recurrent Unit (GRU): GRUs are another type of RNN architecture similar to LSTMs but with a simplified gating mechanism. They are computationally more efficient than LSTMs (Cho et al., 2014).
- Large Language Models (LLM): Large Language Models, such as GPT (Generative Pre-trained Transformer) and BERT (Bidirectional Encoder Representations from Transformers), have revolutionized text generation with their attention mechanisms and self-attention mechanisms (Vaswani et al., 2017; Radford et al., 2018).
- Variational Autoencoders (VAEs): VAEs are a type of generative model that can learn to generate new data samples by sampling from a learned latent space (Kingma & Welling, 2013). While VAEs

are not specifically designed for text generation, they have been applied to text generation tasks by mapping text data into a latent space and then generating new text samples from this space.

- Deep Belief Networks: Composed of multiple layers of stochastic, latent variables, used in unsupervised and semi-supervised learning tasks (Hinton, 2009).

Looking at the sub-techniques of Deep Learning, LLMs can address the problem of replacing the omitted gender-biased words in the interviews by generating texts. GPT has been mostly discussed in text generation which with the launch of OpenAI's GPT-4 in early 2023, the company's advancement in the field has brought a lot of attention to it. GPT-4 is designed to generate responses that are not only more useful but also safer. This latest system is equipped with a broader general knowledge base and enhanced problem-solving abilities, enabling it to tackle even the most challenging problems with greater accuracy. Simultaneously, many other companies started generating their own models. Figure 4.4 reports the recent trained models based on the size they are trained on.

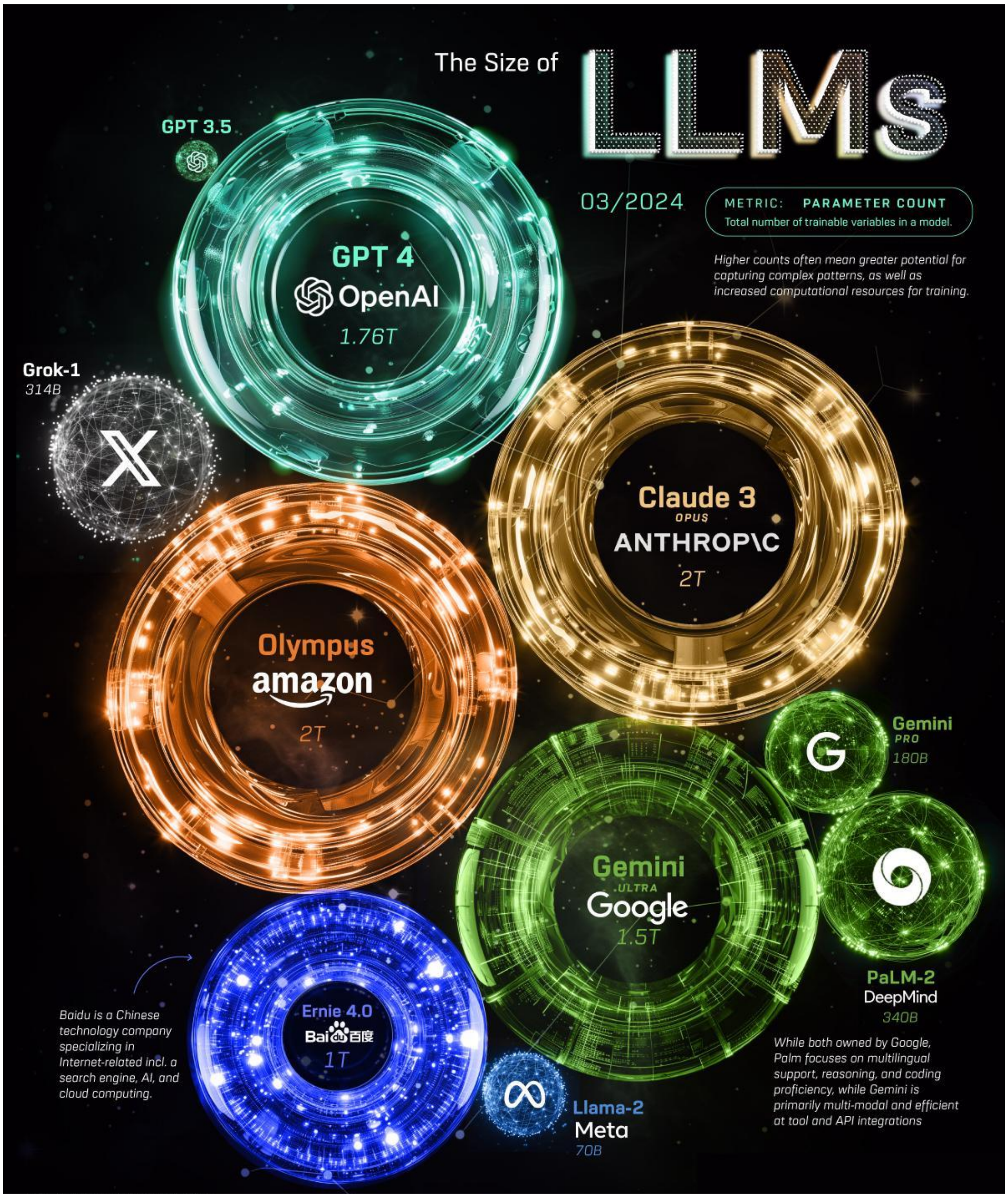


Figure 4.4 - Size of LLMs based on trainable variables (Thompson, 2024)

According to Figure 4.4, the Anthropic's Claude 3 Sonnet model was selected. However, it has the prerequisite of prompt engineering. Therefore, since no design of prompts could be found for disaster resilience, the literature review of prompts for healthcare was reviewed to find the most appropriate one. Four types of prompt engineering could be found listed as automated, manual, discrete, and continuous (Wang et al., 2023). Since this was a one of task that the prompt didn't need to be changed for each entry to replace gender sensitive cases, manual process was preferred. However, a decision between manual prompts of zero-shot to a few-shot prompting should be made which the number of shots corresponds to the number of examples given to the LLM to learn how to react (Reynolds & McDonell, 2021). In the case of open-ended interviews, response time was an important factor, therefore, manual zero-shot prompting was preferred supported from literature (Reynolds & McDonell, 2021). The final prompt considered two variables, list of gender-sensitive words and the follow-up question which were replaced in the prompt as variables. The prompt is as follows:

Prompt: In the follow-up question of {follow-up-question}, replace any gender-sensitive words from this list {gender-sensitive-words} with any other synonyms without changing the meaning of the question.

4.5.3. Results of solution application

Applying computational linguistics, to identify the list of gender- decoded words in interview questions and refining them using Claude 3 Sonnet, the questions were refined resulting in the value of PMGB to be equal to zero from formula 3.4 in both of the interviews. This indicates the effectiveness of the combined approach in mitigating gender bias in question formulation.

4.6. Outcomes of research step three

In this section, the outcomes of the method begin with an overview of the DSS-based framework's design, outlining the structural foundation upon which the subsequent analysis is built. This section provides insights into the architecture, components, and functionalities of the Decision Support System (DSS), elucidating the framework's role in facilitating automation of follow-up question process. Following the design exposition, the narrative transitions seamlessly into the results of the analysis, where empirical findings and data-driven conclusions are presented and discussed in detail.

4.6.1. Outcomes of applying method

The design of the framework to address a fully-fledged solution consists of two core components of previous research steps needing to be integrated together which are inconsistency amending component and gender bias amending component. However, to achieve an automated solution, there are more components that should be involved in an interview including answer transcriber component to feed the given answer to the designed DSS, and a follow-up question generator component to engage with the interview participants. The core components and integrating components are depicted in Figure 4.4.

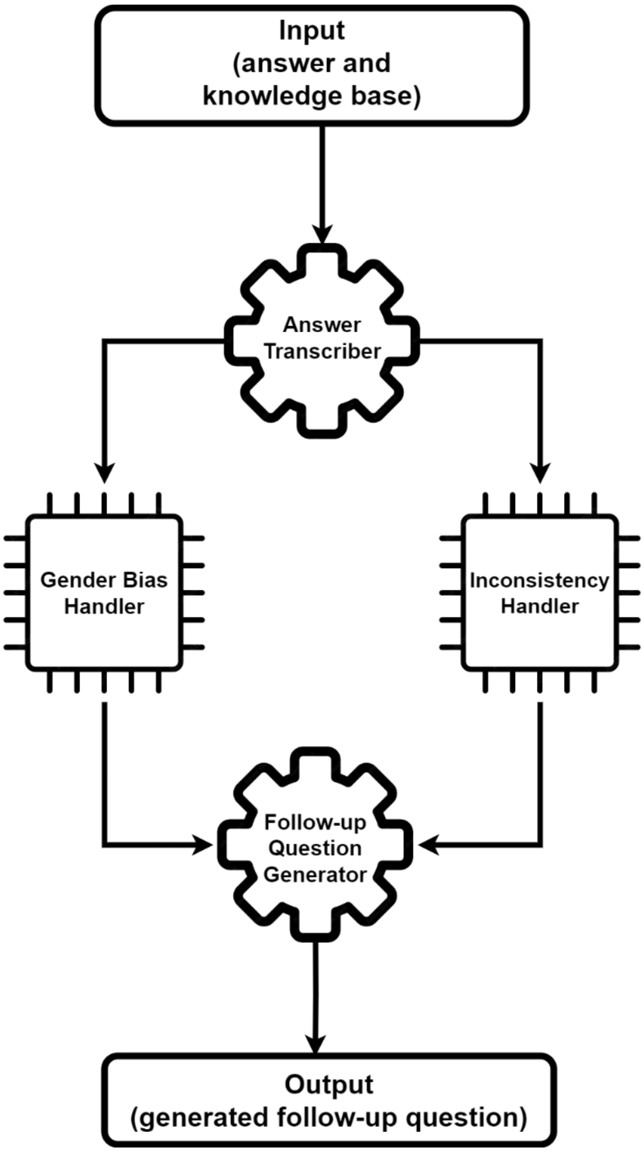


Figure 4.5 - Components of automation design

In Figure 7, there is an input which is the answer coming back from the interviewee and an output which is a refined question to be asked by the interviewer. Added to the two core components handling inconsistency and gender bias, two other components that can affect the flow of interview are answer transcriber to transcribe the given answer by the interviewee into text for machine understanding and the follow-up question generator to refine the questions for the interviewer. The details of these two components are described next.

4.6.1.1. Design of answer transcriber component

Feeding the answer into the system can only be achieved by speech to text tools since the system is designed on the basis of texts. Table 4.1 lists the well-known techniques with the metric of Word Error Rate (WER) for each technique. WER measures the rate of errors in the output text compared to a reference text or a human-generated transcription (Stolcke, 2002). WER provides a quantitative measure of the accuracy of the system's output by considering the overall discrepancies between the generated text and the reference text. Lower WER values indicate higher accuracy, while higher WER values indicate more errors in the output.

Table 4.1 - well-known techniques of speech to text

Technique	**Reference**	**WER**
DeepSpeech	(Hannun et al., 2014)	7.3
Conformer	(Gulati et al., 2020)	1.9
HuBERT	(Hsu et al., 2021)	1.8
SpeechBrain	(Ravanelli et al., 2021)	2.4
WhisperX	(Bain et al., 2023)	3.1
SpeechStew	(Chan et al., 2021)	1.7
Amazon Transcribe	(Amazon Transcribe, 2023)	5.2
Microsoft Azure	(Microsoft Azure, 2023)	5.0
Google Cloud Speech API	(Google AI, 2023)	6.6
IBM Watson Speech to Text	(IBM Watson, 2023)	11.1

With the given values of WER as the benchmark to compare the techniques, SpeechStew with the lowest value has been selected as the technique to be embedded into the answer transcriber component of the designed DSS to transcribe the given answers.

4.6.1.2. Design of follow-up question generator

After the given answer of the interviewee transformed into text for the DSS to digest, the core component of inconsistency handler is to find consistent topics from its knowledge base related to the answer. With the help of the second core component, a follow-up question devoid of gender bias is generated. The generator's purpose is to convert the results back to the interviewer to keep the flow of the interview. For this reason, the state-of-the-art text generator of Anthropic's Claude 3 Sonnet is used again with the prompt of generating a question with the found topic of inconsistency handler where all gender biased words are replaced with neutral gender words.

While the question generator is adept at creating questions, the designed DSS remains flexible to accommodate additional inputs from interviewers, allowing for adjustments to align more closely with their specific preferences and intentions. Therefore, in the prompt given to the Claude 3 Sonnet model, the input of the interviewer is also asked for and if it is provided, the generated question reflects the keywords provided by the interviewers. This capability acknowledges the nuanced perspectives and unique requirements that interviewers may bring to the table, enhancing the relevance and applicability of the generated questions. It's crucial to recognize that the results provided by the system serve as suggestions, offering valuable guidance to interviewers during their sessions, rather than imposing rigid solutions. This collaborative approach empowers interviewers to tailor the questioning process to best suit their needs and the dynamics of the interview, fostering a more productive and insightful exchange.

4.6.1.3. Discussion of the outcome of applying method

The design of the decision support system (DSS) strikes a delicate balance between automation and human interaction, recognizing the importance of genuine engagement in the interview process. While the system could have been fully automated to streamline tasks and increase efficiency, the presence of a human interviewer is deemed essential to foster meaningful connections with interviewees. The human touch brings a level of empathy, intuition, and adaptability that automated systems cannot replicate, particularly in interpreting nonverbal cues such as eye contact and hand gestures. As a result, the DSS serves as an interview assistant tool, leveraging automation to augment the capabilities of human interviewers rather than replacing them entirely.

4.6.2. Outcomes of applying analysis

Integrating the sample questions described in section 3.6.2 into the designed Decision Support System (DSS) serves as a compelling case study, shedding light on the system's efficacy and performance through metric observation. The inclusion of sample offer a real-world scenario, enriching the DSS with practical context and relevance. As users engage with the system, metrics such as accuracy, relevance, and efficiency come into focus, allowing for a comprehensive evaluation of its effectiveness in aiding decision-making processes. Through meticulous analysis of metrics mentioned in section 3.5.8, patterns emerge, showcasing the DSS's ability to interpret and address the queries effectively. Moreover, the case study unveils insights into potential areas of improvement, guiding iterative enhancements to bolster the system's capabilities further. Ultimately, this case study underscores the symbiotic relationship between user input, system design, and metric evaluation in refining Decision Support Systems for optimal utility and impact in the disaster resilience domain. Followings are the metrics' evaluations applied to the case study.

- Richness of Content (RC): The questions in the provided sample yielded 8695, 10967, 8925, 2851, 13861, 8939, 2243, 1282 papers from Scopus. The measurement of RC corresponds to the returned values which is the size of the knowledge base or in other terms, the different topics that could be discussed. For the generated sample the questions yielded 1278, 2395, 1232, 3575, 1227, 2772,1748, 3520.
    - Discussion: In reality, even with the great mind of chess players, they can only think of 15 to 20 different options as the next move. In a real-world open-ended interview, having more than 20 different topics to be selected from is already more than enough which in the shown case study, the values have reached above 1000!
- Relevance to Objectives (RO): In each of the given eight questions of sample or generate one, the keywords of objectives were repeated at least once. Besides, each of the follow-up questions were

generated using the objective keywords and sample questions' keywords. Therefore, no questions were asked without having keywords of objective which resulted in the value of RO to be equal to 100%.

  - Discussion: Sticking to the objectives is an automated piece where the keywords are always considered within the interview. The design of the system to return 100% for RO is an inseparable piece no matter what the case study is.

- Exploratory Nature (EN): No follow-up questions were generated having a yes/no design, giving the value of EN to be equal to 100%.

  - Discussion: The nature of the system not generating yes/no questions comes from the prompt given to the questions generator. In the real-world scenarios, the interviewers may ask yes/no questions to confirm an idea which can disrupt the process of interview to be open-ended. The interviewer can intervene and ask any questions during the interview, whether it was generated by the designed system or not; however, asking yes/no questions is not what the system is designed for.

- Ethical Considerations (EC): With the redaction of any questions containing Personal Informative Information (PII), it was granted that the value of EC to be equal to 100%.

  - Discussion: With elaborations on the prompt of the questions generator to redact any PIIs, the system is designed to always return the value of 100% for EC.

- Interview's Inconsistency Mark (IIM): With regards to section 3.3.3, the value of IIM obtained was 0.01.

  - Discussion: From section 4.4.3, it was expected that the value of IIM would be within the range of 0 and 0.11 where to the confidence level of 99%, the interview is consistent.

- Absence of gender bias: With regards to section 3.4.3, the value of EMGB obtained from applying formulas was 0.

  - Discussion: From section 4.4.4, it was expected that the value of PMGB would be within the 0 where all gender biased terms were transformed into neutral words.

- Efficiency of Automation (EA): Out of all the tasks, only the task of initializing the knowledge base with the keywords of questions was not tackled. The other 4 tasks were automated giving the value of EA to be equal to 80%.

  - Discussion: Even though automation of this task was attempted, finding keywords only within a sentence was not accurately achievable with the current methods of artificial intelligence.

Interviewer intervention in this task is an important piece to keep the knowledge base within the interview objectives.

4.7. Summary

This chapter discussed the results of applying methods to each of the research steps. In research step one, a sentence embedding technique was identified that consistently provided relevant follow-up questions based on feedback from interviewees. This method had the prerequisite need of a knowledge base which was defined to contain peer-reviewed papers relevant to interview questions. Comparative analysis demonstrated its high consistency and confidence compared to simulated samples.

Moving to the research step two, a mixed method involving word embedding and a generative model called Claude 3 Sonnet was discovered. This approach aimed to produce follow-up questions devoid of gender bias. To achieve this, prompt engineering was an essential prerequisite, and manual few-shot prompting was utilized, providing concrete examples of bias-free questions for the model to generate more accurate results. The comparative analysis included consideration of all gender-sensitive cases encountered in simulated interviews.

Finally, in research step three, a decision support system was developed, automating 80 percent of the tasked components. The system not only considered metrics of well-designed open-ended interview, but also included the detection and correction of inconsistency and gender bias.

5. CONCLUSION

5.1. Overview

The primary of this study was to enhance the data collection process for disaster resilience studies. The study emphasized the critical role of open-ended methods, which have been found to capture approximately 80 percent of data than closed-ended methods fail to capture. Consequently, the research focused on refining open-ended interviews to improve data accuracy.

Despite their effectiveness, open-ended interviews present certain challenges notably, bias (particularly gender bias) and inconsistency in data collection. To address these issues, the study utilized a systematic approach, beginning with the quantification of bias and inconsistency. This foundation enabled a comparative analysis of various solutions targeting these specific issues. By examining each issue in detail, the study aimed to develop practical mitigation strategies.

Inconsistency and gender bias in open-ended interviews of disaster resilience significantly undermines the validity, reliability, and ethical integrity of collected data. Inconsistent interview protocols can lead to fragmented understandings of resilience, hindering the development of comprehensive strategies. Gender bias can perpetuate inequalities, marginalizes diverse perspectives, and distorts the representation of gender dynamics, thereby limiting the efficacy of resilience interventions. These issues can erode trust between researchers and participants, potentially hindering future engagement and collaborative knowledge creation, which are essential for effective resilience-building efforts.

In response to these challenges, the research formulated a comprehensive framework that not only addresses gender bias and inconsistency but also streamlines the collaboration between various components by leveraging automation in data collection. By integrating these advancements, the research endeavored to elevate the quality and reliability of disaster resilience studies, thereby contributing to more robust understanding of disaster preparedness conditions to mitigate the impact of disasters.

5.2. Summary

In this section, the study provides summaries of the defined steps, which served as the main guide for the research. These steps are linked with the methods outlined in chapter three, elucidating the systematic approach undertaken to address the research objectives. By delineating the steps and corresponding methodologies, this section establishes a clear understanding for investigation, ensuring rigor and coherence in the research process.

5.2.1. Summary of step one, inconsistency

Step one addressed the variable of inconsistency in open-ended interviews used for data collection on disaster resilience. The significance, gap, question, method, precondition, results, and objective achievement of this step are detailed below:

- **Significance**:

  According to section 1.6.1, the lack of consistency in open-ended interviews has the following significant impacts if it is left unattended.

  - Decreased Reliability
  - Limited Validity
  - Impaired Comparability
  - Reduced Generalizability
  - Undermined Stakeholder Confidence

- **Gap**:

  While open-ended interviews can unearth approximately 80 percent of data, surpassing close-ended interviews (section 1.6.1), they are not without challenges, one of which is inconsistency. Section 2.4.1 highlighted concerns about inconsistency in open-ended interviews, providing references that indicated increased attention to this issue in recent years.

- **Research Question**:

  Can open-ended interviews of disaster resilience become consistent?

- **Method:**

  As section 3.5 explained, a mixed method was approach was employed. A content analysis method was used to identify potential solutions from the literature. This was followed by an experimental design in two phases: first, assessing the feasibility and prerequisites of the identified solution; second, applying the solution in a comparative approach to precondition phase results to measure improvements.

- **Precondition:**

  As section 3.3 described, the selected method involved conducting a simulated open-ended interview with participants. By observing their decisions, and selection of different options for follow-up questions, a measurable ground truth for inconsistency comparison was established.

- **Results:**

  The identified solution was based on sentence embedding, utilizing a knowledge base of peer-reviewed papers. This resulted in an Interview's Inconsistency Mark (IIM) fluctuating between 0 and 0.11, compared to simulated interviews where IIM of 5.13 and 1.35 were obtained. Therefore, with a confidence level of 99%, the solution significantly improved the consistency of open-ended interviews in the context of disaster resilience.

- **Achievement of the Objective:**

  The primary objective was to develop a methodological framework using sentence embedding informed by a knowledge base comprising of peer-reviewed papers. This approach successfully reduced the IIM values to between 0 and 0.11, ensuring consistency in open-ended interviews within the field of disaster resilience. This enhancement significantly improved the reliability and validity of qualitative data collection in this critical field.

5.2.2. Summary of step two, gender bias

Step two addressed the variable of gender bias in data collection from open-ended interviews within the domain of disaster resilience. The step is detailed below.

- **Significance:**

  As discussed in section 1.6.2, bias can significantly impact data collection. It was explained that bias can result in:

  - Inaccurate representations
  - Limited generalizability
  - Underestimated or overestimated effects
  - Waste of resources
  - Ethical concerns
  - Policy and decision-making consequences
  - Challenges in replication

- **Gap:**

  Open-ended interviews while promising in unearthing rich data compared to close-ended ones; however, have inherent Challenges. One major challenge is bias which can affect the credibility of data collection. Section 2.4.2.1 highlighted the existence of gender bias within open-ended interviews, and section 2.4.2.2 identified gender bias as the most frequently noted type by researchers.

- **Research Question:**

  Can open-ended interviews of disaster resilience become gender bias free?

- **Method:**

  Step two followed the same method defined for step one, with gender bias as the variable. The detailed process is described in section 5.2.3.

- **Precondition:**

  As outlined in section 3.4, the same interviews were used to analyze gender bias. Follow-up questions provided by participants enabled the practical measurement of gender bias.

- **Results:**

  Using a mixed method approach, consisting of a word embedding to find gender-sensitive cases and deep learning model of Claude 3 Sonnet helping in replacement with gender neutral cases, gender biased terms within open-ended interviews were addressed.

- **Achievement of the Objective:**

  The designed and developed strategy helped in targeting gender-sensitive cases which removed the occurrences of these cases within open-ended interviews of disaster resilience. This ameliorates challenges in data collection imposed by gender-bias including generalizability. With the given approach, reliability of having bias-free data is ensured for making future conclusions.

5.2.3. Summary of step three, automation

With the issues of inconsistency and gender bias addressed, the next critical step is to develop a system that could integrate these components and automate the process, particularly emphasizing repeatability. he details of this step are detailed below.

- **Significance:**

  Automation enables longitudinal studies of disaster resilience by ensuring consistent and unbiased data collection, thereby providing credible and reliable insights. The repeatability of measuring disaster resilience, as discussed in section 1.6.3, has several key benefits:

  - Reliability and validity: Ensures that measurements are accurate and dependable over time.
  - Longitudinal analysis: Facilitates the study of changes and trends over extended periods.
  - Comprehensive understanding: Captures subtle changes and provides a deeper insight into the phenomena being studied.

- **Gap:**

  Section 1.6.3 highlighted a lack of literature supporting the need of automation in disaster resilience studies; However, the significance of automation was further explored in section 2.4.3 that frequent measurement gives a snapshot on ‘how well’ the community is over time. Besides, the focus on integrating automation with consistency and unbiasedness was elaborated in the sections of 2.4.3.1 and 2.4.3.2.

- **Research question:**

  How can consistent and bias-free open-ended interviews of disaster resilience be automated?

- **Method:**

  As detailed in section 3.6, a case study approach was employed to design a Decision Support System framework was designed utilizing Artificial Intelligence for automation. This framework included metrics of evaluations to support the assessment of the design.

- **Results:**

  The DSS-based design facilitated the automation of open-ended interviews while addressing gender bias and inconsistency. The system was validated by the following metrics:

  - Richness of Content: The knowledge base contained at least 1,000 entries, surpassing the capabilities of a human interviewer.
  - Relevance to Objectives: Inclusion of keywords ensured that interviews remained focused on the research objectives.
  - Exploratory Nature: The system generated elaborative follow-up questions, avoiding yes/no responses to maintain the exploratory nature of open-ended interviews.
  - Ethical Considerations: Personal Informative Information (PII) was automatically redacted to ensure ethical standards were met.
  - Interview's Inconsistency Mark (IIM): The design kept for inconsistency levels within the range of 0 and 0.11, ensuring a 99% confidence level in consistency.
  - Absence of gender bias: The system did not generate gender biased terms, resulting in a PMGB value of zero.
  - Efficiency of Automation: 80% of the tasks were automated, with interviewers handling the remaining parts.

- **Achievement of the Objective:**

  This study successfully developed an automated open-ended interview process using a DSS design that addressed concerns of gender bias and inconsistency in the context of disaster resilience. The system was validated through metrics such as Richness of Content, Relevance to Objectives, Exploratory Nature, Ethical Considerations, Interview's Inconsistency Mark (IIM), Absence of gender bias, and Efficiency of Automation. It ensured the streamlining of data collection processes while maintaining methodological rigor and inclusivity.

5.3. Limitations

While this study has contributed valuable insights to the field of disaster resilience research, it is important to acknowledge its limitations. These limitations should be addressed in future research to enhance the robustness and applicability of the findings:

- **Lack of transparency in existing frameworks for open-ended interviews in New Zealand:** There is a significant lack of clarity and documentation regarding the data collected from open-ended interviews, particularly within New Zealand context. This opacity hinders the ability to evaluate the quality of the collected data comprehensively. Addressing this limitation would involve developing and implementing standardized protocols and documentation practices to ensure transparency and improve data quality evaluations.

- **Infeasibility of full automation due to the need for physical interaction with interviewers:** The nature of open-ended interviews inherently requires direct interaction between interviewers and participants to capture nuanced conversations and spontaneous responses. These qualitative aspects cannot be fully replicated through automation alone. Therefore, while automation can enhance certain aspects of data collection, the necessity for human interaction poses a challenge to achieving complete automation. Future research should explore hybrid approaches that combine automation with human oversight to balance efficiency and depth of data collection.

- **Financial barriers associated with testing and utilizing certain AI models:** The implementation and testing of AI models, such as GPT-4 Turbo, involve significant financial resources. Costs related to development, training, licensing fees, computational resources, and technical expertise present practical constraints. These financial barriers limited the scope of AI model exploration within this study. Future research should seek funding opportunities or cost-effective strategies to expand the range of AI models tested, thereby enhancing the study's comprehensiveness and applicability.

5.4. Recommendations for Future Works

Building upon the findings and framework established in this study, several recommendations can be made to further advance the field of disaster resilience research and data collection:

- **Continuous Evaluation and Refinement:** It is imperative to continuously evaluate and refine the proposed framework and methodologies. As disaster resilience studies evolve and new challenges emerge, ongoing assessment will ensure that the data collection process remains effective and adaptable.

- **Diversification of Sample Populations:** Addressing gender bias was highlighted as a crucial aspect of improving data collection. Future research should aim to diversify sample populations to ensure inclusivity and representativeness. This may involve targeting LGBTQ communities or culturally minor ones.

- **Integration of Technology:** Leveraging technology, such as AI-driven analytics and automated data collection tools, can streamline processes and enhance the accuracy of data collection. Future studies should explore innovative technological solutions to further optimize the efficiency and effectiveness of data collection efforts based on the upcoming AI technologies.

- **Longitudinal Studies:** To capture the dynamic nature of disaster resilience, future studies should consider adopting longitudinal approaches. Long-term data collection efforts can provide valuable insights into the effectiveness of resilience strategies over time and inform about the limitations or improvements by iterative adaptation of the designed framework.

- **Framework Embedding:** Existing disaster resilience frameworks can adopt the designed system in their data collection. Future studies should prioritize enhancing data collection with the approach of this study to foster ownership and maximize the impact of resilience interventions.

- **Mitigation of other biases:** In addition to addressing gender bias, it's crucial for research endeavors to consider and mitigate other biases that may impact the integrity and validity of data collection processes, particularly within the context of disaster resilience.

- **Application in other domains:** The lessons learned from addressing inconsistency and gender bias in open-ended interviews of disaster resilience can be applied to other domains to enhance data collection practices across various disciplines where there these drawbacks are not yet been adequately addressed.

By incorporating these recommendations into future research endeavors, the field of disaster resilience can continue to evolve and make meaningful contributions to enhancing preparedness efforts in the face of disasters.

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Appendices

Appendix A: Ethics Approval

17 January 2024

Mani Poshdar

Faculty of Design and Creative Technologies

Dear Mani

Re Ethics Application: **23/285 Artificial Intelligence in Automating Community Disaster Resilience Measurement**

Thank you for your responses to AUTEC's conditions.

Your ethics application has been approved for three years until 17 January 2027.

Standard Conditions of Approval

1. The research is to be undertaken in accordance with the Auckland University of Technology Code of Conduct for Research and as approved by AUTEC.
2. All public facing documents must have the AUTEC approval number and be of a high standard of spelling and grammar. Dates on the Information Sheet(s) and Consent Form(s) must be consistent.
3. Any amendments to the project must be approved by AUTEC prior to being implemented.
4. A progress report is due annually on the anniversary of the approval date.
5. A final report is due at the expiration of the approval period, or, upon completion of project.
6. Any serious or adverse events must be reported to AUTEC, this includes unforeseen issues that might affect continued ethical acceptability of the project.
7. AUTEC grants ethical approval only. You are responsible for obtaining management permission for access from any institution or organisation at which your research is being conducted and you need to meet all ethical, legal, public health, and locality obligations or requirements for the jurisdictions in which the research is being undertaken.

The application number and title need to be referenced on all correspondence related to this project.

All forms are available online http://www.aut.ac.nz/research/researchethics

For any enquiries, please contact ethics@aut.ac.nz

(This is a computer-generated letter for which no signature is required)

The AUTEC Secretariat

Auckland University of Technology Ethics Committee

(a) Interview Guide

Dear (name of the potential participant),

My name is Milad Katebi, and I am the Primary Researcher for the research entitled **"Artificial Intelligence in Automating Community Disaster Resilience Measurement"**.

I am writing to invite you to participate in an interview. We want to know to what extent academics make different decisions while asking interview questions in the field of disaster resilience. The interview will be led by the research team members.

What the interview involves
By this interview, we want to understand how different interviewers ask different follow-up questions that can change the collected data of an open-ended interview within the domain of disaster resilience measurement. Therefore, we will be running an interview that is based on case studies of previous disaster resilience interviews and we are seeking your opinion on how you would follow-up the questions in that case study. The process is as follows.

We will be running an online Microsoft Teams session. During this session, a question related to disaster resilience with the answer to it will be given to you. You will also be presented with twelve different options that are relevant to provided question. You will then need to decide the top-two related topics from the twelve options that are closest to the given answer that can be used as a follow-up question. After your selection, we would love to hear your reasoning behind your selected top two choices. Another question with its answer and twelve options will also be given again to repeat the process.

This interview should take no longer than half an hour and it will be recorded for data collection purposes, and you will have the right to turn off your video if you wish. You may also decide to end your participation at any time during the discussion and leave the meeting. If you stop your participation, your contributed ideas will not be used in the study. During the session, recording will take place to produce a discussion transcript for future references. A copy of it will be emailed to you for a review before the beginning of the data analysis process. The recordings and transcripts will be kept for a maximum of 6 years on the AUT secure network protected by password to ensure maximum security and only the research team members will have access to the recorded data.

Your involvement with this process is voluntary. Any information that you share with us will be kept private and confidential. Please be advised that the researchers will take every precaution to maintain confidentiality of the data.

In the next two pages, you will see two different interviews that already happened in the domain of disaster resilience. Each one has a question and an answer. A list of twelve different options is provided for each interview. Please select the top two options that can be used as a follow-up question based on the given answer. Please provide a reason why you selected those two options and how your follow-up question will look like.

We don't need you to have prior knowledge. These options are titles of articles published in relevance to the keywords of the question and they were fetched from Scopus.

First Interview's Question, Answer, and Options:

<table>
<tr>
<td>

Economics of Disaster Risk, Social Vulnerability, and Mental Health Resilience
Unraveling the complexities of disaster management: A framework for critical social infrastructure to promote population health and resilience.
Building Human Resilience. The Role of Public Health Preparedness and Response as an Adaptation to Climate Change
What is health resilience and how can we build it?
Cultural diversity in the integration of disaster mental health and public health: A case study in response to bioterrorism
Measuring psychological resilience to disasters: Are evidence-based indicators an achievable goal?
Resilience thinking in health protection.
Production Capacity Reserve Strategy of Emergency Medical Supplies: Incentive Model for Nonprofit Organizations
Building Community Resilience in Support of Public Health Emergency Preparedness with Big Data and AI
Strategies to enhance resilience post-natural disaster.
Multi-dimensional resilience: A quantitative exploration of disease outcomes and economic, political, and social resilience
Enhancing disaster resilience by reducing stress-associated health impacts

</td>
<td>
Question:
What does social capacity mean in relation to public health?

Answer:
It's about making sure that communities:
a) know what to expect and not to expect from city or central government sources etc.
b) know what they must do for themselves.
c) can do it - they have the right community leadership, engagement, resources etc. Being willing and able to execute social distancing, for example.
</td>
</tr>
</table>

Second Interview's Question, Answer, and Options:

1. Stakeholder participation in building resilience to disasters in a changing climate 2. Stakeholder Value Systems on Disaster Resilience of Residential Buildings 3. Disaster risk reduction and empowering local government 4. Working through Disaster Risk Management to Support Regional Food Resilience 5. School disaster resilience assessment in the affected areas 6. Information Deficits and Community Disaster Resilience 7. Deconstructing the concept of shared responsibility for disaster resilience 8. A stakeholder approach to building community resilience: awareness to implementation 9. A disaster resilient built environment in urban cities: The need to empower local governments. 10. Path towards community resilience: Examining stakeholders' coordination at the intersection of the built, natural, and social systems. 11. Union means strength: Building city resilience through multistakeholder collaboration. 12. Inherent Complexities of a Multi-stakeholder Approach to Building Community Resilience	Question: How do we co-ordinate and bring together so many stakeholders at local level without intervention of higher levels of government? Answer: If there is no higher-level authority then it must be done by persuasion and negotiation - logically, that's the only other option. You will need to think about the proposition for having people collaborate: who gets what and who gives what?

(b) Participant Information Sheet

Date Information Sheet Produced:

18/10/2023

Project title:

Artificial Intelligence in Automating Community Disaster Resilience Measurement

Invitation:

Dear (name of the potential participant),

My name is Milad Katebi, and I am the Primary Researcher for this research. I am writing to invite you to participate in an interview. This step helps me in completing my PhD study. The findings of this research may be used for academic publications and presentations.

What is the purpose of this research?

In this research, we want to know to what extent inconsistency exists in disaster resilience measurement interviews. We believe one of the causes of inconsistency is the decisions made by interviewers during an interview. Therefore, we want to simulate the process and ask you to make a decision during the simulated interview. We will provide you with an existing interview which a question was asked and an answer was given and then you should decide what should be asked as a follow-up question. We provide you with a few options to select from. By understanding existence of different decisions when it comes to running a disaster resilience interview, we aim to design a decision support system based on artificial intelligence and natural language processing that can help in improving the decision-making process.

How was I identified and why am I being invited to participate in this research?

You have received this Information Sheet because you have either heard about this research in-person from me during a presentation in a classroom, or you have noticed the poster and got back touch with me. You have been included in this interview because you are studying in the last year of your bachelor studies, and you have taken courses related to disaster resilience with experience working in the field. You should notice that if you have taken or are currently taking any courses with the research team, you should have been excluded from this interview.

How do I agree to participate in this research?

By writing an email back to me, you agree to participate in this research. Email body message with the following consent to participate statement:

1. I have read and understood the description provided above; I have been provided with an opportunity to ask questions and my questions have been answered satisfactorily. By voluntarily attend the interview on MS Teams, I consent to participate in the study described above, understanding that I may withdraw this consent at any time. I have saved a copy of this consent email for my records.
2. Suggest a few days and time that suit you for attending the interview.

Your participation in this research is voluntary (it is your choice) and whether or not you choose to participate will neither advantage nor disadvantage you. You are able to withdraw from the study at any time. If you choose to withdraw from the study, then you will be offered the choice between having any data that is identifiable as belonging to you removed or allowing it to continue to be used. However, once the findings have been produced, removal of your data may not be possible.

What will happen in this research?

We simulated an interview of disaster resilience and ask you to make a decision during the simulated interview. We will provide you with a question and the answer to it and then you should decide what should be asked as a follow-up question. We provide you with a few options to select from. We will conduct this process with different participants to understand how their decisions are different than yours. This will help us understand the levels of inconsistency made by different decisions.

What are the discomforts and risks?

No level of discomfort or embarrassment is expected. You have the right to withdraw the research at any time.

How will these discomforts and risks be alleviated?

It is unexpected that you experience discomfort because of the participation in this study, however, you will have the opportunity to leave the discussion or decide to avoid participation in conversations related to the questions that make you feel uncomfortable.

What are the benefits?

This study helps me to better understand the process of disaster resilience measurement interviews so I can refine them using Artificial Intelligence based Decision Support Systems. This step helps me in completing my PhD studies. Besides, you will be aware of the existence of this tool to apply it further in your future studies or work by complying to AUT instructions.

What compensation is available for injury or negligence?

In the unlikely event of a physical injury as a result of your participation in this study, rehabilitation and compensation for injury by accident may be available from the Accident Compensation Corporation, providing the incident details satisfy the requirements of the law and the Corporation's regulations.

How will my privacy be protected?

This interview should take no longer than half an hour and it will be recorded for data collection purposes, and you will have the right to turn off your video if you wish. You may also decide to end your participation at any time during the discussion and leave the meeting. If you stop your participation, your contributed ideas will not be used in the study. During the session, recording will take place to produce a discussion transcript for future references. A copy of it will be emailed to you for a review before the beginning of the data analysis process. The recordings and transcripts will be kept for a maximum of 6 years on the AUT secure network protected by password to ensure maximum security and only the research team members will have access to the recorded data.

What are the costs of participating in this research?

There will be no compensation for participating in this interview. However, without your participation this investigation will not be possible. The allocation of your time to this study is highly appreciated.

What opportunity do I have to consider this invitation?

You can consider the invitation for 1 month; however, it is appreciated to consider it as soon as possible.

Will I receive feedback on the results of this research?

You can receive feedback on this study by replying back and I will be providing a page that includes the number of times each topic from the list of provided topics were selected including the topics you selected. Please note that you need to wait until all the interviews have been conducted to receive this information.

What do I do if I have concerns about this research?

Any concerns regarding the nature of this project should be notified in the first instance to the Project Supervisor, Mani Poshdar, mani.poshdar@aut.ac.nz , or on (+649) 9219999 Ext.8956 Concerns regarding the conduct of the research should be notified to the Executive Secretary of AUTEC, ethics@aut.ac.nz , (+649) 921 9999 ext 6038.

Whom do I contact for further information about this research?

Please keep this Information Sheet and a copy of the Consent Form for your future reference. You are also able to contact the research team as follows:

Researcher details:

- Milad Katebi, mkatebi@aut.ac.nz or on (+649) 9219666 ext. 8956

Supervisor contact details:

- Mani Poshdar, mani.poshdar@aut.ac.nz or on (+649) 9219999 Ext.8956

Approved by the Auckland University of Technology Ethics Committee on *type the date final ethics approval was granted*, AUTEC Reference number *type the reference number*.

Many thanks for your time and consideration in reading this invitation to participate and we will be looking forward to hearing from you.

Milad Katebi

(c) Consent Form

Project title: ***Artificial Intelligence in Automating Community Disaster Resilience Measurement***

Project Supervisor: ***Dr Mani Poshdar***

Researcher: ***Milad Katebi***

- ○ I have read and understood the information provided about this research project in the Information Sheet dated dd mmmm yyyy.
- ○ I have had an opportunity to ask questions and to have them answered.
- ○ I understand that notes will be taken during the interviews and that they will also be audio-taped and transcribed.
- ○ I understand that taking part in this study is voluntary (my choice) and that I may withdraw from the study at any time without being disadvantaged in any way.
- ○ I understand that if I withdraw from the study then I will be offered the choice between having any data that is identifiable as belonging to me removed or allowing it to continue to be used. However, once the findings have been produced, removal of my data may not be possible.
- ○ I agree to take part in this research.
- ○ I wish to receive a summary of the research findings (please tick one): Yes○ No○

Participant's signature:

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Participant's name:

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Participant's Contact Details (if appropriate):

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Date:

Approved by the Auckland University of Technology Ethics Committee on type the date on which the final approval was granted AUTEC Reference number type the AUTEC reference number

Appendix C: Case Study

1. I have claimed that technical, organisational, social, and economic factors affect water supply resilience. Do you agree? Please explain why if either you agree or not.
2. I don't believe that environmental factors should be considered for measuring water supply resilience because they are exogenous factors. Do you agree or not? Please share your thoughts.
3. In my papers, I claimed that the technical factors affect the system's functionality immediately after the disaster happens while the other factors mostly affect the recovery of the system. What's your thoughts?
4. I distinguish between factors and indicator. Factors affect the resilience directly while indicators are being used to measure the factors. For example, vulnerability is a factor while pipe age is considered as an indicator. Do you agree?
5. I've gathered 5 main factors to measure technical resilience, namely vulnerability, redundancy, criticality, importance level, and interdependencies. Criticality shows the number of people being served by the pipe and importance level measures the critical services in each area (e.g. hospitals, police station, etc.) being served. Do you think if these factors are accurate? What other indicators should I have considered?
6. I simplified the level of service to see whether the customers receive water or not. Quality, quantity, or pressure have been neglected. Do you think if there was a way to consider them without making the model over-complicated?
7. I considered the impact of social factors on both residents and also the recovery crew. Do you agree? Is there anything missed here?
8. I believe that we need quick access to funds right after the disaster and the quantity is not as important. However, the quantity of fund's importance increases over time. what you recon?

Appendix D: Generated Case Study

1. How do you think cultural factors influence the resilience of a community to disasters? Can you provide examples of how cultural practices have either helped or hindered disaster recovery efforts?

2. In your experience, how does the involvement of local governments versus national governments impact disaster resilience and recovery efforts? Please elaborate on the strengths and weaknesses of both approaches.
3. How important do you believe the role of community education and awareness is in building disaster resilience? Can you provide examples of successful education initiatives?
4. How do economic disparities within a community affect its overall resilience to disasters? What strategies can be implemented to address these disparities in disaster planning and recovery?
5. What is your perspective on the integration of traditional knowledge with modern technology in disaster management? Can you share any case studies where this integration has been successful or unsuccessful?
6. In the context of disaster resilience, how do you think public-private partnerships can be leveraged to enhance preparedness and recovery efforts? Provide examples of effective partnerships you have observed or been a part of.
7. How do you perceive the role of innovation and technology in enhancing disaster resilience? Can you discuss specific technologies or innovations that have significantly improved disaster response and recovery?
8. In what ways do you believe climate change is altering the landscape of disaster resilience? How should communities adapt their resilience strategies to address the increasing frequency and severity of climate-related disasters?