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Mapping WUN expert discourse on responsible and ethical AI: a multinational expert network analysis

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The global discourse on artificial intelligence (AI) ethics represents a critical site of scientific and expert communication, where meanings are negotiated, and priorities are set. This study investigates how a transnational network of experts constructs and communicates the concept of "responsible AI." We analyze the deliberative discourse from the World University Network (WUN) initiative on Responsible & Ethical AI (2023) through a multi-method framework combining computational text analysis (TF-IDF) and network analysis (co-occurrence networks) of semantic relationships. By examining expert webinar transcripts, we move beyond isolated principles to map the communicative architecture of this debate, visualizing how core themes like accountability, transparency, and equity are framed and interconnected across academic, policy, and practitioner perspectives. Our findings reveal that expert consensus is built not on a glossary of terms but on a shared conceptual network where technical, governance, and ethical concerns are deeply intertwined. This study contributes to science communication research by: (1) offering a novel methodological pipeline for mapping consensus and divergence in expert discourse, and (2) providing empirical evidence that collaborative academic networks function as vital "communicative infrastructures" for translating theoretical ethical frameworks into actionable policy paradigms.

KEYWORDS

expert communication, responsible artificial intelligence, ethical AI governance, World University Network, network analysis

1 Introduction

Artificial intelligence (AI) has been a significant topic for decades, but it notably emerged as a buzzword in the public and business domain from 2016 to 2017 (Gbadegeshin et al., 2021). This surge in interest was largely driven by advancements in deep learning and the success of AI applications like AlphaGo by DeepMind, self-driving technology, and the increasing use of AI in consumer products.

The launch of Generative Pretrained Transformer (GPT) models and AI-powered assistants further accelerated AI's presence in every sector. By 2022–2025, with the release of tools like ChatGPT and DeepSake, AI became even more prominent across industries (de Murillo Edson Carvalho Souza and Li Weigang, 2025), which, at the same time, accelerated its development.

AI systems have progressed and disseminated quickly, driven by an increasing computational power, open research and commercial incentives—while regulatory, legal and societal mechanisms to oversee its deployment develop far more slowly. AI's new architectures and more powerful models are released every few months (Lu, 2019), while its widespread applications increase everyday. In contrast, many users are still unprepared for the changes involving its implementation (Ridzuan et al., 2024) and few countries have established legislations and frameworks for AI's development and applications (Maslej, 2024).

The diferent speeds in AI regulation and AI advances create a window to harms to the individuals, the institutions, the communities, and the environment. Biases are implicit in out society and culture, and therefore, when trained, AI becomes itself embedded with the same biases (O'Connor and Liu, 2024) with the associated greater risk of perpetrating them when deployed. Other affectations involve the environment, this technology has a carbon footprint that is hard to measure and control. The extensive use of artificial intelligence in daily lives especially in academia and research, has put forward many questions regarding its ethical and responsible use.

There have been many discussions across the globe regarding this issue and it has also become the main theme for funding by the World University Network (WUN) Research Development Fund (RDF). This RDF is an annual competitive grant aimed at fostering innovative, high-quality, and sustainable research collaborations among academic staff from WUN member universities (WUN, n.d.). Eligible projects were required to engage at least three WUN member universities across at least two regions (WUN, n.d.). The member universities under WUN for collaboration are listed in Figure 1.

The objective of the RDF is to stimulate larger collaborative projects that strengthen the WUN network, leading to influential publications and enhancing the competitiveness of collaborating partners for major external grants. By addressing problems of global significance through diverse, international teams, the RDF aims to make substantial progress on sustainable development challenges.

In line with the objective of WUN, 12 universities across the globe came together to discuss the ongoing global issue of "Responsible and Ethical AI." The experts were from different fields of research and presented a very comprehensive discussion on the topics. Table 1 provides the topics that were discussed and the affiliations of the experts.

The discussion contained a lot of areas that are making use of AI technologies. The experts focussed on how the technology is used and what are its use cases in each sector. They also mentioned the areas of concern that need to be taken care of while making use of such emerging AI technologies.

Deep analysis of expert discussions on "Responsible AI and Ethics" is urgently needed because these debates shape the future of technology and society. As AI systems rapidly evolve, their ethical risks such as bias, privacy violations, accountability gaps, and societal harm need to be discussed for structured, evidence-based insights. The experts involved in this work provide nuanced perspectives, but without systematic analysis, their discussions remain fragmented, leaving policymakers and practitioners without clear guidance.

By rigorously examining these conversations, the present work tries to identify consensus, uncover overlooked challenges, and prioritize actionable solutions, ensuring AI development aligns with public trust and ethical imperatives. Therefore, analyzing experts' discussions on Responsible AI and ethics using a multi-method approach (TF-IDF + network analysis) is essential for several reasons. This approach is needed as these topics involve complex, evolving debates where key concerns (e.g., bias, transparency, accountability)

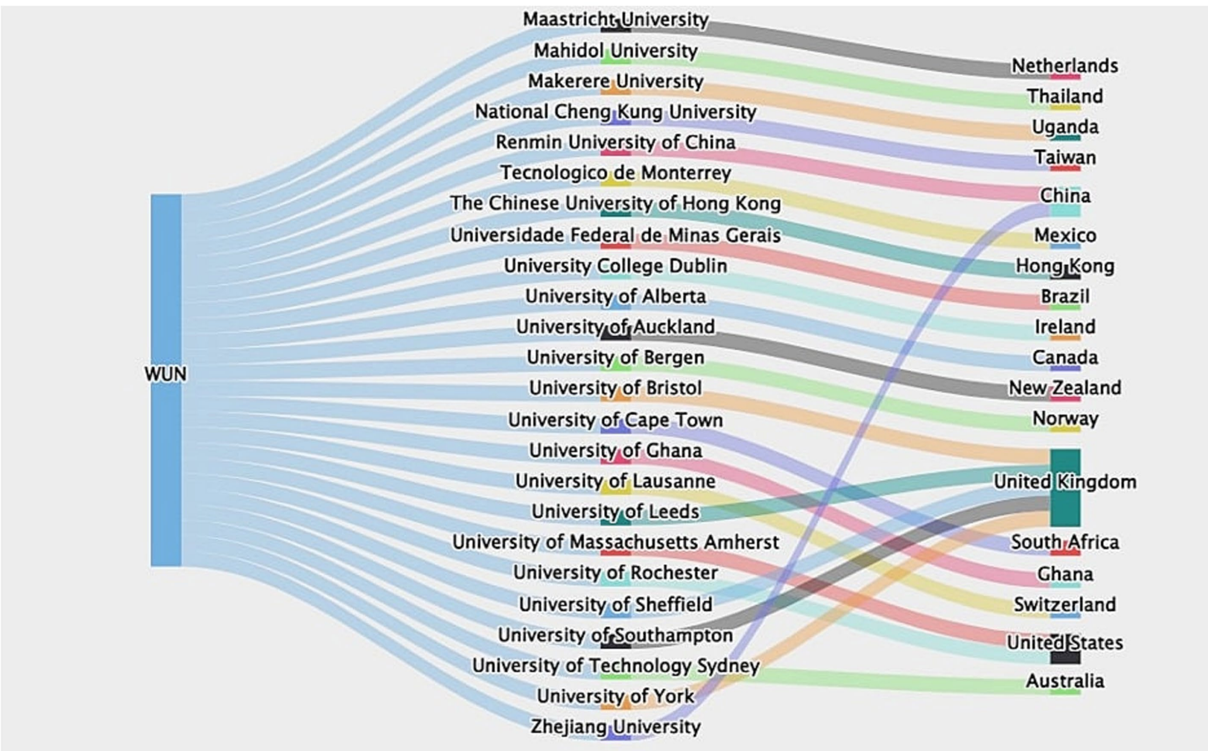

FIGURE 1
Member countries and universities participating in the Worldwide Universities Network (WUN) collaborative research initiative on the ethical and responsible use of artificial intelligence (5–24 April 2024).

TABLE 1 Topics Discussed in WUN's initiative "Responsible and Ethical AI Research" Webinar between 5 and 24 April 2024, and their Associated Participating Universities.

No.	Topics	Affiliation
1.	Understanding Generative AI technology to effectively analyze its potential benefits and risks (n.d.)	Tecnologico de Monterrey, Mexico
2.	Global governance of AI and ethical principles (n.d.)	Maastricht University and Research Associate at the United Nations University – MERIT, Netherlands
3.	AI and health (n.d.)	The University of Auckland, New Zealand
4.	Critical dataset studies how to ethically collect data for training sets (n.d.)	The University of Auckland, New Zealand
5.	Implications of Brain-Computer Interface and Artificial Intelligence on the Future Workforce (n.d.)	University of Technology Sydney, Australia
6.	Using AI Ethically in the Education Sector (n.d.)	Makerere University, Uganda
7.	The different normative constraints on Responsible AI: Law, Society, and Ethics (n.d.)	University of York, England
8.	AI Ethics in Healthcare: Challenges, Issues, and Best Practices (n.d.)	Mahidol University, Thailand
9.	Responsible Innovation in AI (n.d.)	The University of Auckland, New Zealand
10.	Fundamentals of Responsible: From the General View of AI/ML Practitioners (n.d.)	Mahidol University, Thailand
11.	Responsible AI: A Legal and Ethical Perspective (n.d.)	The University of Auckland, New Zealand
12.	Thailand's AI Governance Approach (n.d.)	Electronic Transactions Development Agency (ETDA), Ministry of Digital Economy and Society, Thailand

are often discussed in interconnected ways. A single analytical method might miss deeper semantic relationships.

TF-IDF helps identify the most salient terms, while Network Analysis reveals how these concepts cluster and interact (Danyal et al., 2024; Wang et al., 2025). It exposes hidden patterns, conflicts, or consensus in expert opinions. Together, these methods provide a structured, evidence-based understanding of the discourse, helping policymakers, researchers, and practitioners prioritize ethical challenges and align AI development with societal values. Without such analysis, critical insights remain fragmented, hindering actionable solutions. In an era where AI's impact grows daily, this work is not just academic, it is a necessity for responsible innovation.

This research was guided by the research questions:

> *Q1*. What are the most salient terms and concepts that characterize expert discourse on responsible and ethical artificial intelligence?
>
> *Q2*. How do those salient terms organize into coherent thematic clusters within the expert conversations?

The remainder of the paper is divided into different sections. Section 2 provides a concise overview of the current research in responsible and ethical AI, incorporating relevant keywords and themes from the experts' discussion to highlight the diverse perspectives shared across countries. Section 3 highlights the methodology adopted in the present work and Section 4 presents results and discussion. Section 5 concludes the paper.

2 Background knowledge

Artificial intelligence (AI) has reserved a place in every industry in the world. With the growing need for AI, many organizations are coming forward to make sure that it is used ethically and responsibly. This was required as many researchers around the globe have raised questions about its use in academia and research.

Jakesch et al. (2022) surveyed to examine how different groups such as the general public, crowdworkers, and AI practitioners, perceive and prioritize responsible AI values. They found that AI practitioners placed less importance on these values and prioritized different ones compared to the general public. Additionally, women and liberal-leaning participants were more likely to emphasize fairness and responsible AI values. The study underscored the need to involve diverse voices in defining responsible AI.

Trocin et al. (2023) conducted a systematic literature review to analyze the application of responsible AI concepts in digital health. They examined issues related to ethics, transparency, accountability, and fairness, emphasizing the unique moral and ethical challenges in healthcare. Their study provided an evidence-based understanding of the intellectual structure of responsible AI in digital health and proposed a future research agenda.

Alam (2023) developed an interdisciplinary university course titled "Safety, Fairness, Privacy, and Ethics of Artificial Intelligence (SFPE-AI)" to equip students with a comprehensive understanding of the technical and ethical challenges of AI systems. The course included four modules and used interactive lectures, case studies, discussions, and projects to provide practical insights. By completing the course, students are expected to design responsible AI systems and critically evaluate their societal impacts. It also served as a model for other institutions to integrate AI ethics into their curricula.

Díaz-Rodríguez et al. (2023) proposed a comprehensive framework for achieving trustworthy AI, grounded in three pillars: legality, ethics, and robustness. They analyzed seven key requirements including human oversight, transparency, fairness, and accountability from the perspectives of what they are, why they matter, and how they can be implemented. The study emphasized the importance of auditing processes and regulatory sandboxes to ensure responsible AI use. It concluded that effective regulation is essential for aligning diverse views on AI's future and ensuring its societal benefits.

Fosso Wamba and Queiroz (2023) conducted a bibliometric analysis to explore the relationship between AI and digital health, focusing on responsible AI and ethical considerations. They identified four distinct publication periods and highlighted key AI approaches in healthcare. The study offered a comprehensive framework integrating AI applications, discussing associated barriers and benefits. Additionally, five insightful propositions emerged, providing valuable guidance for scholars and practitioners in the digital health domain.

The mentioned works in recent years have highlighted the importance of the ethical and responsible use of artificial intelligence in academia and industry. Various organizations are also working in the same direction to ensure the ethical use of AI, including IEEE (Institute of Electrical and Electronics Engineers), UNESCO (United Nations Educational, Scientific and Cultural Organization), OECD (Organisation for Economic Co-operation and Development), and WEF (World Economic Forum).

The published 10 UNESCO Recommendations on the Ethics of Artificial Intelligence by Morandín-Ahuerma (2023) provided a comprehensive framework for the responsible development and use of AI. These recommendations emphasized principles such as transparency, accountability, fairness, and privacy protection. They aimed to ensure that AI technologies contribute to sustainable development and respect human rights. By addressing issues like bias, discrimination, and environmental impact, the recommendations offered guidance for governments, organizations, and developers in creating ethical AI systems. Ahuerma's analysis highlighted the importance of international cooperation and regulatory frameworks to implement these guidelines effectively.

The report by the OECD on Artificial Intelligence & Responsible Business conduct provided insights into how businesses can align their AI practices with ethical and responsible standards. It emphasized the importance of transparency, accountability, and human rights considerations in AI development and deployment. The report offered practical guidelines for companies to integrate Responsible Business Conduct (RBC) principles into their AI strategies, ensuring that AI systems are fair, safe, and beneficial to society. Additionally, it highlighted the role of stakeholders, including governments and civil society, in fostering responsible AI innovation and mitigating potential risks (OECD, 2019).

The current discussions on the topic and the initiatives taken by various organizations have forced various other stakeholders to come forward and ensure the ethical and responsible use of artificial intelligence in real life. Accordingly, the present study is well-positioned to contribute meaningfully to this evolving discourse.

3 Method

The methodology adopted in the current work consists of observing experts discussions over the topics of "Responsible and Ethical AI" (Responsible and Ethical AI Training Course, n.d.) collecting their speeches and performing multimethod text mining approach. The experts were from different member institutions of the WUN, belonging to different fields in academia and research.

The analytical workflow, illustrated in Figure 2, was implemented using a combination of specialized software tools. All natural language preprocessing and Term Frequency-Inverse Document Frequency (TF-IDF) analysis were conducted in Python, utilizing the pandas and scikit-learn libraries. Subsequently, the network construction and analysis were performed using Gephi (version 0.10.1), where algorithms for metrics such as modularity were applied to generate and interpret the co-occurrence network. This integrated approach allowed for a comprehensive examination of the webinar content through both statistical and structural lenses.

The overall methodology was divided in different sections as follows and it includes AI assisted copy editing. Initially the raw data was pre-processed through Natural Language Processing (transcription, text extraction, cleaning, tokenization, and synonym identification) to delinate the corpus. TF-IDF is a statistical method that gave us the important and distinctive words across discussion of the experts. The selection of TF-IDF over a simple frequency count was deliberate, as TF-IDF addresses a key limitation of raw frequency. While frequent word analysis identifies common terms, it is often dominated by ubiquitous but contextually uninformative words. TF-IDF, in contrast, balances a term's frequency within a specific document (TF) with its rarity across the entire corpus (IDF).

This mechanism effectively discounts common words and systematically surfaces distinctive and discriminative keywords that are central to a specific document's theme. For our analysis, this was critical to identifying the characteristic and salient concepts within different parts of the workshop dialogue, rather than merely listing the most common words used throughout the entire event.

The network analysis helped us to uncover hidden relationships and community structures within the data. We constructed a term co-occurrence network, where words were connected based on their appearance in the same context. In network analysis part using modularity-based clustering, we detected semantic communities which are basically the groups of closely related terms that frequently appeared together, revealing underlying thematic clusters. Additionally, network diameter and other graph metrics helped us assess the cohesion and interconnectedness of these communities, indicating how tightly or loosely the discussions were structured.

This study employs TF-IDF and semantic co-occurrence network analysis as its core computational methods. This choice was driven by the specific nature of our research question: to map the explicit, shared conceptual architecture of the "responsible AI" discourse within a transnational expert network. While embedding-based models (e.g., BERT, word2vec) excel at capturing deep semantic relationships, contextual meaning, and polysemy, our objective was fundamentally different. We sought to identify the key anchor terms that experts collectively deploy to frame the debate and to visualize the structural relationships between these explicitly articulated concepts.

By integrating methods, we not only identified key terms but also uncovered how these terms were linked, providing a more nuanced understanding of the organizational discourse. This combined approach allowed us to move beyond simple keyword extraction and explore the structural and relational dynamics within the data.

3.1 Data pre-processing

The corpus for this study comprises transcripts of 12 webinars hosted by the World Universities Network (WUN) in April 2024 on

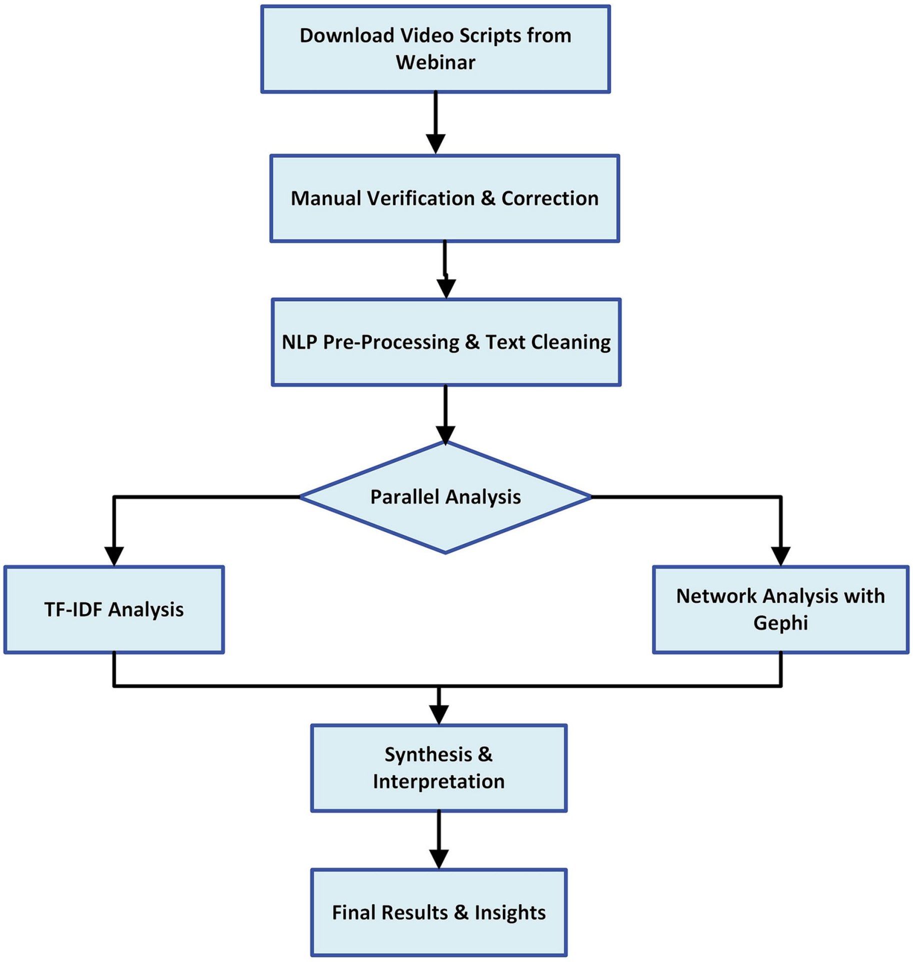

FIGURE 2
Workflow of the analytical methodology. The process begins with the acquisition and manual verification of webinar video scripts. The cleaned data is then processed using Natural Language Processing (NLP) techniques before undergoing parallel analysis using TF-IDF for keyword extraction and network analysis with Gephi for co-occurrence network construction. The final stage involves a synthesized interpretation of both analyses to derive comprehensive insights.

the theme of responsible and ethical artificial intelligence. Raw videos were transcribed using the YouTubeTranscriptAPI and then subjected to a structured cleaning process. The downloaded data contained a lot of noise in the form of raw text, repetitions, stop words (e.g., "the," "is," "and"), and filler words ("umm," "ahh," "like," and "you know"), so it needed extensive cleaning before it could be utilized for the analysis task. The task of filler removal was done based on a regular expression-based approach that can be understood by Equation 1 (Byrne et al., 2004).

$$F(t) = \{x \in T \mid x \notin W_f\} \tag{1}$$

where $F(t)$ = cleaned transcript, T = original transcript text, W_f= set of filler words.

Likewise was done for lowercasing, punctuation, and stop word removal. This process was followed by stemming and lemmatization before synonym detection could work. Synonym detection was performed using contextual similarity based on cosine similarity which is given by Equation 2.

$$\text{Similarity}(W_1, W_2) = \frac{\sum_{i=1}^{n} W_1^i, W_2^i}{\sqrt{\sum_{i=1}^{n}\left(W_1^i\right)^2 \cdot \sum_{i=1}^{n}\left(W_2^i\right)^2}} \tag{2}$$

where W_1^i, W_2^i word embeddings of the words. Based on this, it starts searching for the most suitable synonym in the text and if it does not find the suitable synonym it retains the original word. This was done with all the transcripts for better downstream analysis.

3.2 Term frequency—inverse document frequency (TF-IDF)

The term frequency-inverse document frequency approach is a statistical measure used to evaluate the importance of a term within a collection of documents (Danyal et al., 2024). When analyzing documents for key term identification, including synonyms, TF-IDF was applied once the documents had gone through a few of the predefined steps. These steps include text cleaning, lower casing, lemmatization, stop-word removal, and synonym expansion. Synonym expansion was done using WordNet to ensure term equivalency, which is very important for performing TF-IDF on the documents.

3.2.1 Term frequency (TF)

TF is calculated to know what is the frequency of a particular word when compared to the total number of words in the document. This is calculated using Equation 3.

$$\mathrm{TF}(t,d) = \frac{\text{Number of times t appears in document d}}{\text{Total number of terms in document d}} \tag{3}$$

where t = term, d = document.

3.2.2 Inverse document frequency (IDF)

The importance of a word across all the documents is measured using IDF. A lower IDF score highlights that the term appears in almost all the documents. Equation 4 shows how this score was calculated.

$$\mathrm{IDF}(t,D) = \log\left(\frac{N}{1+\left|\{d \in D; t \in d\}\right|}\right) \tag{4}$$

where N = Total number of documents (in present case, 12), $\left|\{d \in D; t \in d\}\right|$ = Number of documents containing the term t,1 is added to avoid division by zero if the term is not present in any document.

The final TF-IDF score is obtained using the product of the scores of TF and IDF that can be represented as follows:

$$\mathrm{TF-IDF}(t,d,D) = \mathrm{TF}(t,d) * \mathrm{IDF}(t,D)$$

This represented a greater importance of the word in the given document.

3.3 Network construction and analysis

TF-IDF scores were used as a filtering step for network construction: only tokens whose TF–IDF weights exceeded the corpus median were retained as nodes. This approach ensured that the ensuing networks focused on substantive concepts rather than ubiquitous function words or speech artefacts.

Further analysis of the theme was done using the concept called modularity. For this purpose text was converted into a network called co-occurrence network (Wajid et al., 2024), with words as nodes and their relationships (such as co-occurrence) as edges. Modularity analysis helps identify communities within this network. Each community, also called a modularity class, groups together words that were more closely connected to each other than to words outside the group. A higher modularity score indicates that these communities were well-separated and internally cohesive, meaning the words within each cluster were strongly related. The results showed the core community members and the central theme of discussion by the experts. A general framework of community and core member detection is represented in Figure 3.

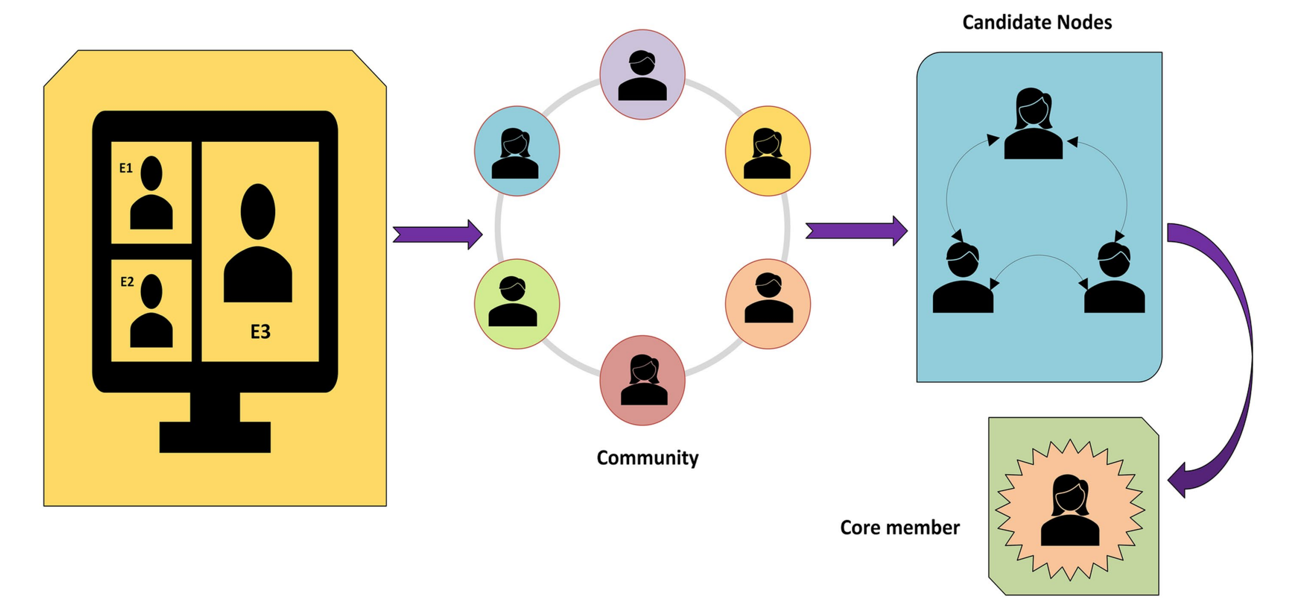

FIGURE 3
Community and core member detection framework applied to expert discussions on responsible AI and ethics. A community is defined as a group of nodes with dense internal connections and sparse links to other groups. Candidate nodes are potential members of a community with moderate connectivity, while core members are highly influential nodes identified using modularity-based clustering and centrality metrics, highlighting key topics and contributors within the discourse.

3.3.1 Community structure

This represents a group of nodes and edges G = (V, E), representing a higher density of edges between them and lower density edges across the groups (Heymann, 2018). This is commonly referred to as community structure. In community structure, the important concept that needs to be taken care of is referred to as modularity represented by Q, which is a proportion of edges. Modularity is a measure to assess the strength of the community structure based on frequency. Modularity is calculated using Equation 5.

$$Q = \frac{1}{2|E|}\sigma(C_u, C_v)\sum_{u,v\epsilon V}\left(e_{uv}, \frac{d_u, d_v}{2|E|}\right) \tag{5}$$

where $|E|$ represents several edges, $ó(C_u, C_v)$ signifies that the function has a value of 1 if nodes u and v are in the same community, else it has a value of 0, d_u is the degree of node u, e_{uv} Represents the direct edge between nodes u and v, Q is modularity, and in real community networks, its value ranges from 0.3 to 0.7. Larger modularity score, stronger community structure.

3.3.2 Community detection

For community detection, the current works use a greedy approach termed as Louvain method that consists of two steps; initialization and modularity calculation. In initialization every node is assigned to its community *N*; where *N* is the number of nodes, and Q (modularity) is used as an objective function for maximization (Heymann, 2018). Following is the Louvain method based community detection algorithm used in present work (Blondel et al., 2008).

3.3.3 Candidate node set

Candidate node sets are the highly dominating nodes in a community. They may be present either within the community or on the boundary (Blondel et al., 2008). Results represent one of the communities (C19) detected from the dataset, on the same community, the proposed approach is used to identify the core nodes of the community.

3.4 External validation through organizational policy term mapping and literature benchmarking

As the aim of the present work is to put forward the most important themes related to the use of AI in daily lives, it is necessary to take into account what other stakeholders and international organizations propose about its responsible use in an ethical way. Therefore, to align the study with the demands of different organizations working towards ensuring the responsible and ethical use of AI, we compiled policy documents, guidelines and frameworks on artificial intelligence ethics produced by the United Nations Educational, Scientific and Cultural Organization (UNESCO), the Organisation for Economic Cooperation and Development (OECD), the World Economic Forum (WEF) and the Institute of Electrical and Electronics Engineers (IEEE).

Each document was manually reviewed to extract normative keywords and phrases that explicitly describe principles, requirements or values (for example, "inclusivity," "data governance," "human oversight," "robustness," "nondiscrimination"). Synonymous terms were consolidated (e.g., "justice" and "fairness") to avoid inflating counts. The resulting terms are mentioned in the result section. This policy term mapping allows us to align the salient concepts derived from TF–IDF and network analysis with the terminologies advocated by major organizations.

To ensure the validity and relevance of current work with the work of the researchers in the area whether in academia or industry, a small data analysis of the Scopus database was also performed. For this reason, published articles in the area from year 2017 to 2025 were searched. The query involved the terms obtained from the discussion of the experts so that both the works can be aligned. For this purpose, the query used was as follows considering both articles published in English and Spanish.

Query: (TITLE-ABS-KEY ("Generative AI" OR "Artificial Intelligence" OR "AI governance" OR "AI ethics" OR "AI in education" OR "Responsible AI" OR "AI and healthcare" OR "Brain-Computer Interface" OR "ethical AI" OR "AI law" OR "AI in workforce" OR "AI and training datasets" OR "AI governance in Thailand") AND TITLE-ABS-KEY (ethics OR responsibility OR governance OR regulation OR "data collection" OR "normative constraints")) AND PUBYEAR > 2017 AND PUBYEAR > 2021 AND PUBYEAR < 2026 AND PUBYEAR > 2023 AND PUBYEAR < 2026 AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "re")) AND (LIMIT-TO (LANGUAGE, "English") OR LIMIT-TO (LANGUAGE, "Spanish")).

The query resulted in 5,363 documents published with general AI topics such as "Generative AI," "Artificial Intelligence," "Responsible AI," "AI governance," and "AI ethics."

4 Results and discussion

4.1 Salient terms from TF–IDF analysis

The analysis of the webinars delivered by 12 experts on responsible and ethical AI revealed key themes through network analysis. Further, based on the methodology adopted in current work the synonyms identification was done and few of the results for same are mentioned in Table 2. The TF-IDF analysis represented in Table 3. The values were calculated by considering the combined input from all 12 experts, capturing the relevance of each term across the entire corpus. Table 3 presents the most representative scores to highlight key terms with the highest discriminative power.

The results reveal that governance emerged as the most prominent term (0.0362), underscoring its critical role in ensuring the effective oversight and regulation of AI systems. This was closely followed by discussions on ethics (0.0307) and responsibility (0.0103), highlighting the emphasis on aligning AI development with moral principles and societal expectations. Concerns around privacy (0.0102) and transparency (0.0098) were also strongly represented, reflecting the growing demand for AI systems to be both understandable and accountable.

Additionally, terms such as safety (0.0091), discrimination (0.0083), and explainability (0.0068) point to the experts' focus on mitigating AI-related risks and ensuring equitable outcomes. The presence of words like security (0.0066), regulation (0.0065), and accountability (0.0051) further emphasizes the need for robust policies

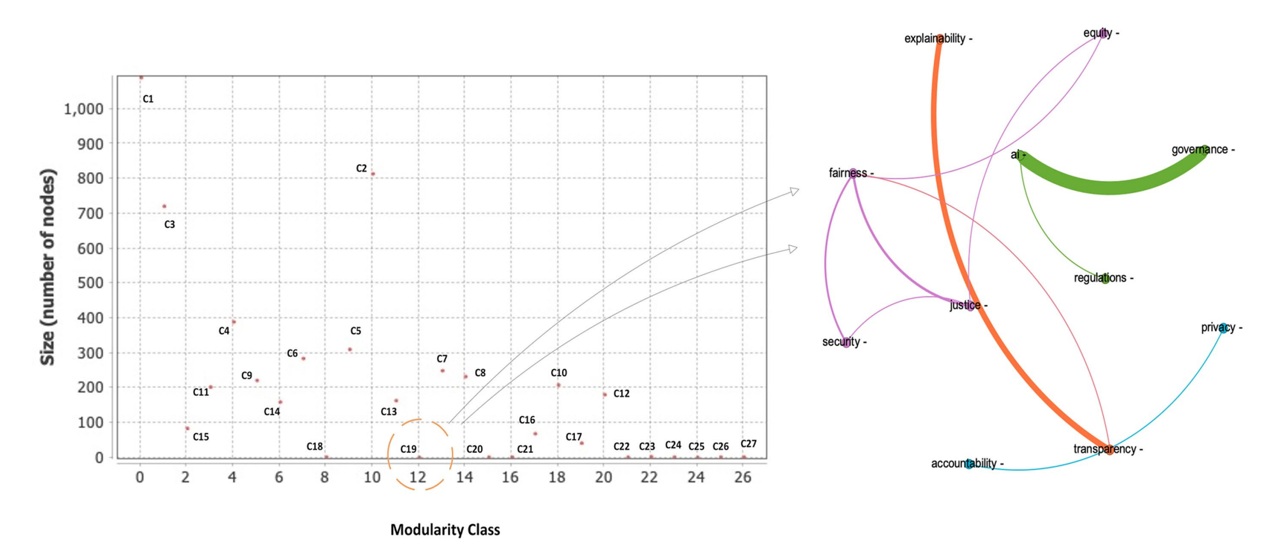

FIGURE 4
Community detection analysis of expert discourse on responsible AI and ethics (as discussed in a WUN member universities webinar). The left panel shows the distribution of detected communities across modularity classes, with the number of nodes (vertical axis) plotted against modularity scores (horizontal axis), illustrating the structural diversity of topic clusters. The right panel visualizes the network topology of Community C19, highlighting labeled nodes representing core discussion topics and their interconnections.

to address the ethical challenges posed by AI technologies. While concepts of fairness (0.0051), justice (0.0045), and bias (0.0040) suggest ongoing concerns regarding algorithmic bias and societal impact, terms like trust (0.0039) and compliance (0.0012) reflect the importance of fostering confidence in AI systems through transparency and adherence to ethical standards.

Notably, equity (0.0009) appeared with a lower frequency, indicating a potential gap in the discourse that could benefit from further exploration. This analysis offers valuable insights into the priorities and challenges experts associate with responsible AI development and implementation.

4.2 Network structure and community metrics

Figures 4, 5 presents a co-occurrence network summarizing the main topics discussed by experts during the webinar on the responsible and ethical use of artificial intelligence. In this co-occurrence network, each node represents a key term or concept. The size of a node corresponds to its importance or centrality within the network; larger nodes are more central and well-connected. Each edge (line) represents a co-occurrence or strong semantic relationship between two terms. The thickness of an edge indicates the strength or frequency of that connection.

It captures key thematic areas and highlights the central ideas around which the discourse was structured, reflecting insights shared by representatives from various WUN member universities.

After preprocessing the text data, the resulting network was analyzed by calculating key structural metrics, including the network diameter and modularity score. This analysis gives us the number of communities, diameter, and average path length which are represented in Table 4 for all the experts.

The number of communities formed from the discussion shows a high variation starting from low as 16 to high as 78. The high number of communities in experts (E2) discussions shows that their discussion triggered many small perhaps fragmented topics of interest (like AI, responsibility, explainability, accountability, transparency, and privacy) that may point to diverse opinions or topics highly specializing and highlighting the aspect related the topic. Smaller diameters and radii (e.g., E2) suggest a more immediate exchange of ideas.

The participants quickly connected around ethical issues (accountability, transparency, and privacy) without needing extensive mediation. Shorter path lengths (e.g., E2: 2.64) imply efficient communication, where ethical concerns and responsibilities were rapidly disseminated and discussed among the different topics. On the other hand, if we take the case of experts E4 and E12 their discussions were centered around common and unified themes such as accountability, transparency and bias.

The high value of modularity count (e.g., E5 at 0.464, E10 at 0.448) shows that the discussion of the experts formed highly separated groups that symbolize that the themes were well compartmentalized in groups like transparency and accountability. This shows that the common themes across different fields when presented together may lead stakeholders to think more properly on the topic and take into consideration all these aspects while formulating the policies related to the use of AI. The Lower Values of modularity (e.g., E2 at 0.184) reflect blurred boundaries between themes, possibly indicating overlapping debates on multiple ethical dimensions.

Networks with larger diameters (E3 and E5: 12) suggest that concepts or arguments took longer to propagate across the discussion, indicating deep, multi-step debates where ideas evolved gradually. Smaller diameters and radii (e.g., E2, E8) suggest a more immediate exchange of ideas, participants may have quickly connected around ethical issues without needing extensive mediation.

TABLE 2 Set of synonyms identified to enhance contextual understanding, ensuring that nuances in language and meaning are accurately captured during the analysis.

Words	Synonyms
AI	AI, AI, artificial intelligence, army intelligence*
Empowerment	Authorization, authorization
Human	Man, human being, homo
Ethics	Value system, morality, ethical code, ethic, moral principle, value orientation, ethical motive, morals, ethics, moral philosophy
Fairness	Paleness, loveliness, fairness, equity, fair-mindedness, beauteousness, blondness, candor, candor, comeliness
Transparency	Transparentness, transparency, foil, transparency
Privacy	Concealment, seclusion, privateness, privacy, secrecy
Accountability	Answerableness, answerability, accountability
Trust	Trust, rely, commit, trustfulness, confidence, cartel, combine, corporate trust, entrust, reliance, hope, faith, desire, confide, swear, believe, bank, trustingness, intrust

*"Army Intelligence" appears as a synonym for AI due to acronym overlap and contextual ambiguity in some text sources. In the context of this study, "AI" exclusively refers to Artificial Intelligence. Such false positives were manually reviewed and excluded where contextually irrelevant.

TABLE 3 Top TF-IDF terms in responsible and ethical AI webinars delivered by experts from WUN universities, extracted through text mining of transcripts.

Top TF-IDF terms related to responsible AI and ethics	
Governance	0.0362
Ethical	0.0307
Responsibility	0.0103
Privacy	0.0102
Transparency	0.0098
Safety	0.0091
Discrimination	0.0083
Explainability	0.0068
Security	0.0066
Regulation	0.0065
Accountability	0.0051
Fairness	0.0051
Justice	0.0045
Bias	0.0040
Trust	0.0039
Compliance	0.0012
Equity	0.0009

Shorter path lengths (e.g., E2: 2.64) imply efficient communication, where ethical concerns and responsibilities were rapidly disseminated and discussed. Longer path lengths (e.g., E5: 3.75) might indicate more layered conversations, where discussions about responsible AI involve more steps, interpretations, or clarifications before reaching a consensus.

Experts such as E5 and E3, showing higher modularity with larger diameters and longer path lengths, likely stimulated deep, well-separated ethical debates, possibly emphasizing complex issues like AI biases, regulation, or human rights. In contrast, E2, characterized by many small communities, low modularity, and short paths, might have fostered quick but diverse discussions, hinting at a broader but less connected exploration of responsible AI aspects.

Once these metrics were obtained, the Louvain method algorithm (Algorithm 1 in methodology section) was applied to detect communities within the network. The purpose of using the Louvain method was to identify potential thematic structures or areas of focus within the text. Following the community detection, the Fruchterman–Reingold algorithm was employed to generate a visual layout of the network. This force-directed layout algorithm helped in better visualizing the relationships between nodes.

As shown in Figure 6, the edges are observed to cluster densely around certain nodes, indicating that these nodes represent central or important topics discussed by the experts within the broader theme of responsible and ethical AI. The dense clustering suggests that these topics are not only frequently mentioned but also strongly interconnected, highlighting their significance in the discourse.

Of the 27 communities identified (Figure 4) through modularity analysis, community 19 (C19) was selected for detailed interpretation as it constitutes the core conceptual structure of the "responsible AI" discourse. The selection is quantitatively justified by the community's high connectivity and the centrality of its constituent nodes. C19 is composed of 11 highly interconnected nodes, representing key themes such as governance, justice, fairness, and transparency. The internal cohesion of this community is evidenced by strong local clustering, with several nodes, including ai (1.0), privacy (1.0), and accountability (1.0), achieving the maximum possible weighted degree within the cluster, indicating they are hubs directly linked to most other concepts in the group.

Furthermore, the thematic significance of C19 is underscored by the high betweenness centrality of foundational terms like fairness (6.5) and transparency (4.0). These values indicate that these nodes act as critical bridges, not only within C19 but also connecting this core cluster to other parts of the broader network. Therefore, C19 represents a dense, central, and influential thematic module, making it the most suitable for analyzing the principal framework of the expert debate.

The analysis using co-occurrence network represented in Figure 4 gives a meaningful insight into how all 12 experts engaged around the topic "Responsible and Ethical AI". The graph above shows the interconnectedness among the themes discussed by the experts in the discourse around responsible and ethical use of AI. The colored nodes and edges show the community detected using a concept called modularity. It shows various clusters formed and how each cluster influences the concepts and themes in another cluster. The central themes of discussion were also found out by calculating network diameter and modularity score. These were explainability, equity, fairness, governance, regulations, justice, security, privacy, transparency, and accountability.

The modularity-based visualization does not just list ethical AI principles; it exposes how the expert organized their reasoning. Tightly packed clusters imply consensus on certain themes, while cross-cluster edges highlight dependencies. This analysis helps translate abstract discourse into actionable insights. This could pave

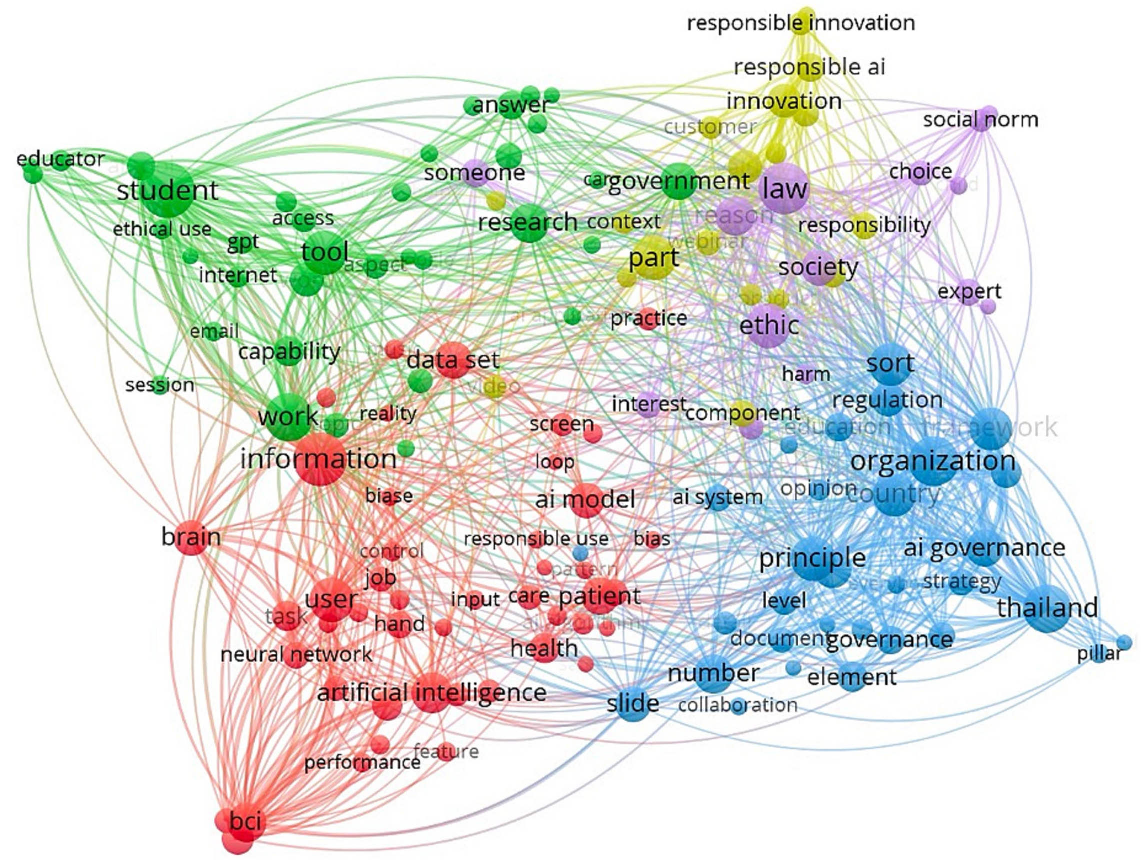

FIGURE 5
Main topics discussed by the experts, focusing on the Responsible and Ethical Use of AI as presented in the webinar by experts from various WUN universities, and the key points around which their general discussion revolved.

TABLE 4 Quantitative network characteristics extracted from expert speech analysis are presented, including community detection outcomes (number of communities, modularity) and structural properties of the discourse network such as diameter, radius, and average path length.

Experts	Number of communities	Modularity	Diameter	Radius	Average path length
E1	19	0.431	9	5	3.49
E2	78	0.184	6	3	2.64
E3	20	0.421	12	7	3.57
E4	16	0.334	9	5	3.14
E5	19	0.464	12	6	3.75
E6	17	0.409	8	5	3.40
E7	22	0.416	8	4	3.40
E8	18	0.306	7	4	2.98
E9	24	0.247	8	4	2.72
E10	17	0.448	10	5	3.54
E11	20	0.414	9	5	3.34
E12	16	0.423	8	4	3.47

the way for prioritizing interdisciplinary collaboration where clusters intersect.

These clusters are represented in different colors. Each color signifies a cluster of closely related terms that frequently co-occur or share strong conceptual ties in the expert's discussion on ethical AI. For example, fairness, equity, and justice are in the same color suggesting that experts treated them as interrelated dimensions of social justice in AI. The cluster of nodes in the graph shows that these

Initialization:
Assign each node to its own community.
Set initial modularity Q.

Phase 1: Modularity Optimization:
Repeat until no modularity improvement:

For each node i in V:

For each neighbor community C of node i:

Compute the modularity gain ΔQ by moving i into C.

Move node i into the community C that yields the highest positive ΔQ.

If no positive ΔQ exists, retain ii in its current community.

Phase 2: Community Aggregation:

Build a new network G′ where:

Each community detected in Phase 1 becomes a single node.

The weight of the edge between two new nodes is the sum of the weights of edges between nodes in their respective communities.

Initialize G=G′ and reassign each node to its own community.

Repeat Phases:

Repeat Phase 1 and Phase 2 iteratively on the new network until modularity no longer increases.

Return:

The final partition of nodes into communities.

ALGORITHM 1
Louvain method based community detection algorithm.

concepts were emphasized more than the others and came out to be the core pillars while making use of AI in daily life. A separate cluster containing governance, regulations, and accountability might reflect a focus on systemic oversight and compliance.

The way clusters are represented in the present co-occurrence network shows that they were frequently discussed in the expert's dialogue. The one important key point that appears in the graph is that it seems less possible to focus on single terms. But to ensure the ethical use of AI, one must take into account the other themes too into consideration. For example, transparency and explainability are crucial for accountability, while governance and regulations ensure fairness and justice.

The absence of some expected terms, like bias mitigation, may indicate a focused discussion, but the overall message seems to be a balanced integration of technical, legal, and societal considerations to foster trust and equity in AI applications. One of the important insights that could be drawn from the analysis is the inter-cluster edges (e.g., a violet line between governance and fairness might signal bridging themes, like how regulatory frameworks (governance) directly influence outcomes (fairness). The co-occurrence network approach using modularity analysis revealed thematic clusters in the expert's discussion on ethical AI.

The present work also uses the TF-IDF (Term Frequency-Inverse Document Frequency) approach of analysis of the documents. This mixed approach is likely to highlight the most distinctive or salient terms in the text. By merging these two approaches, the present work derives a richer understanding of both the structure and emphasis of the experts around the ethical and responsible use of AI in daily lives.

The combined analysis using TF-IDF and network analysis revealed that there is a strong interaction between technical, ethical and govermental dimensions with AI and Governance (TF-IDF score: 0.0362) sharing a thick edge in the network, indicating their central and highly interconnected roles. This visual prominence aligns with the TF-IDF results, where governance emerges as the most significant term, reinforcing its critical function in structuring ethical AI frameworks.

The intermediate edges connecting terms like Transparency (0.0098), Accountability (0.0051), and Fairness (0.0051) illustrate how ethical principles are operationalized in AI systems. These connections align with mid-range TF-IDF scores, indicating that while these concepts may not dominate term frequency, they serve as crucial mediators between high-level governance and technical implementation. This alignment between network structure (edges and colors) and TF-IDF term weights confirms that responsible AI is not just about isolated principles but about their interconnectedness. The findings advocate for holistic frameworks that balance governance, technical safeguards, and ethical imperatives, ensuring AI systems are both accountable and equitable.

4.3 Alignment with organizational policy keywords

Table 5 reports the keywords used by international organizations (UNESCO, OECD, WEF, and IEEE) to address the Responsible and Ethical use of AI. It reflects the primary priorities of each organization in guiding the responsible development and application of AI.

The study revealed that fairness and non-discrimination are core ethical challenges in AI, often emphasized by organizations like the IEEE and UNESCO whereas transparency ensures trust in AI systems, as highlighted in frameworks like the IEEE Ethically Aligned Design and OECD AI principles.

Through text mining, it identified that privacy is a critical ethical issue in AI and is universally recognized in standards from IEEE. The organizations have also focused on accountability as it ensures ethical oversight of AI systems and aligns with principles like those in the IEEE's ethical design and the OECD's AI policy observatory. Safety and Security are foundational in guidelines from IEEE and the World Economic Forum. Keywords such as Human Autonomy and Control are much discussed in frameworks like the EU's AI Act and IEEE's emphasis on human dignity and control whereas Societal and Environmental Well-being were much discussed in the UNESCO and WEF guidelines.

4.4 Bibliometric benchmarking

These articles were mainly focused on the application areas such as "AI and healthcare," "AI in education," "Brain-Computer Interface," and "AI in the workforce" as were discussed by the experts in the current WUN project. These articles were specified only in ethical and governance topics such as "ethical AI," "AI law," "normative constraints," "AI and training datasets," and "AI governance in Thailand."

Figure 7 gives the countries with the maximum number of publications in the field, where the United States and China top the list. These two countries are also the main members of the WUN for the current project. Based on the analysis (Figure 4) we can conclude

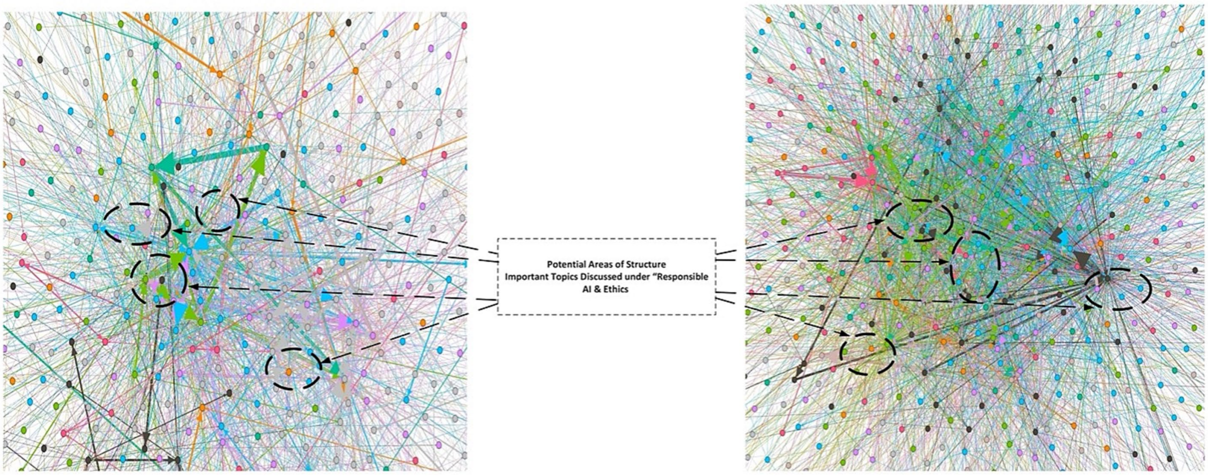

FIGURE 6
Force-directed network graph illustrating aggregated connections around high-degree nodes, revealing dominant discussion themes related to responsible AI and ethics. These insights emerged from expert discourse during a webinar hosted by WUN member universities. Node size represents betweenness centrality, highlighting influential concepts, while edge thickness reflects the frequency of topic co-occurrence.

TABLE 5 Key terminology established by organizations to guide the responsible and ethical application of AI in societal contexts.

Organizations	Key terms
IEEE (n.d.)	Robustness, reliability, harm prevention, risk management, resilience, human oversight, empowerment, autonomy, human-centric AI, and self-determination.
UNESCO (Morandín-Ahuerma, 2023)	Bias, equality, inclusivity, impartiality, justice, non-discrimination, sustainability, social good, public benefit, environmental impact, societal impact.
OECD (2019)	Liability, oversight, governance, ethical responsibility, answerability, confidentiality, data security, consent, anonymity, data governance.
World Economic Forum (2023)	Openness, clarity, interpretability, understandability, accountability, liability, oversight, governance, ethical responsibility, answerability.

These are used to align current study with rules and themes set by the responsible organizations.

that the countries that are working in this domain are also members of the WUN and there is a lot of published research in the field related to the current topic.

The most used keywords by the authors are also mentioned in Figure 8, where artificial intelligence along with ethics and generative model seems to be more influential and the main concern of the researchers. This proves the validity of the current project supported by WUN.

Altogether, the TF–IDF analysis, network metrics, organizational keyword comparison and bibliometric benchmarking converge on a core narrative: responsible AI discourse within the WUN community is dominated by governance, ethical principles and accountability, and these priorities resonate with both international policy frameworks and recent scholarly trends. The network analysis further reveals how these concepts interconnect and cluster—for example, fairness, equity and justice forming a tightly knit group, while governance, regulation and accountability form another. Understanding these relationships helps move beyond simple keyword frequency to a more nuanced view of how responsible AI is conceptualized and debated.

4.5 Semantic gap in responsibility: an equity perspective

Our analysis reveals a telling discursive pattern, the concept of "equity" is significantly underrepresented compared to "fairness" and "justice." This finding is not merely semantic but points to potential structural and geographical biases within the mainstream AI ethics discourse. To understand why, a clear conceptual distinction is necessary. While fairness often refers to impartiality and the absence of improper bias, and justice to the broad moral principle of rightness, equity is distinctively concerned with achieving just outcomes through context-sensitive distribution of resources and opportunities. It explicitly acknowledges that different starting points and systemic barriers require differentiated treatment to level the playing field.

The low TF-IDF weight for "equity" (0.0009) compared to "fairness" (0.0051) suggests that the expert discourse in our corpus, while robust on universal principles, may be overlooking the practical imperative of tailoring interventions to specific group needs. This absence is significant and may reflect a structural bias towards Global North perspectives, where debates often center on fairness within established legal frameworks, rather than on redistributive justice and rectifying deep-seated global inequities. The focus on "fairness" can sideline the needs of historically marginalized communities, both within nations and across the Global South, for whom universal applications of AI can perpetuate existing disadvantages.

This trend is mirrored in international policy and literature. Major organizations (UNESCO, OECD, WEF, IEEE) often advocate for equity-like concepts such as inclusivity and non-discrimination, yet they rarely use the term "equity" overtly (Table 5). Similarly, in the scholarly literature, our analysis of top author keywords from 5,363 documents (2017–2025) shows "fairness" and "justice" predominate, while "equity" is absent (Figure 8). This consistent pattern across expert talks, policies, and publications confirms a semantic gap where

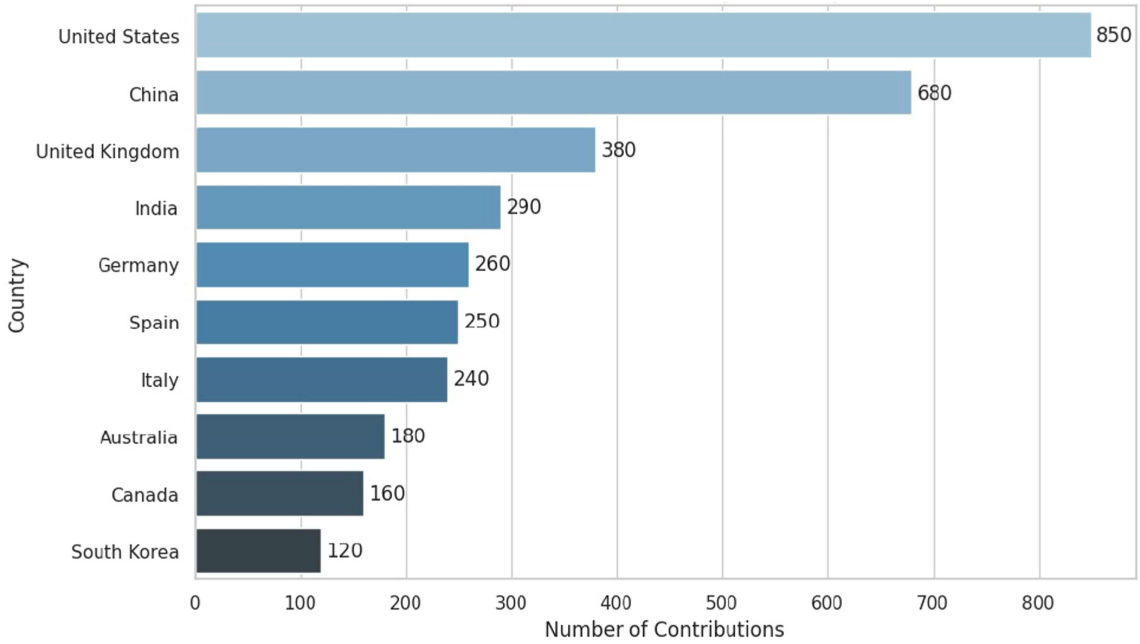

FIGURE 7
Top 10 countries publishing research on AI ethics and governance (in English and Spanish), based on a SCOPUS query detailed in the text. The figure illustrates the geographic distribution of scholarly output, demonstrating alignment between current global publication trends and the Worldwide Universities Network's research priorities, thereby supporting the project's thematic focus.

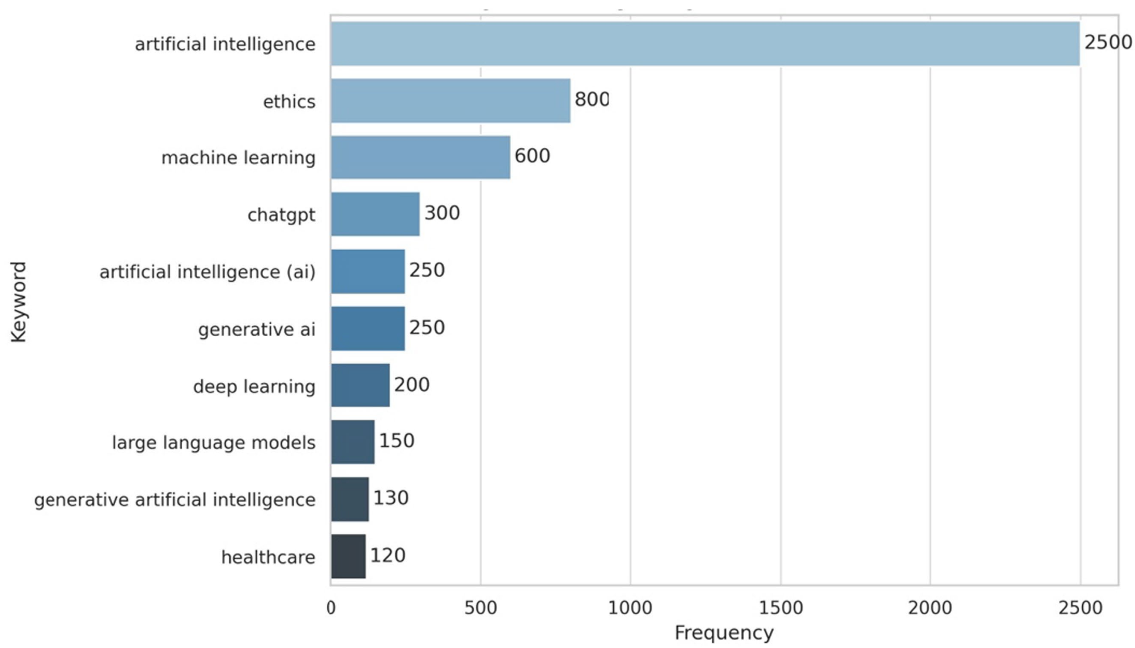

FIGURE 8
Top 10 author keywords from the 5,363 publications analyzed (as retrieved through the SCOPUS query described in the text). The grouping highlights dominant thematic areas within AI ethics and governance research, underscoring their relevance and centrality to the focus of the WUN project.

the core principle of differentiated support remains implicit and under-prioritized.

The relative absence of the token "equity" is, therefore, a call to action. Moving the conversation beyond universal principles to explicitly embrace "equity" is a practical imperative. It necessitates a conscious shift in the academic and policy discourse towards strategies that actively address differential risks and allocate resources to ensure that the benefits of AI do not merely reinforce existing power dynamics but deliver truly just outcomes for all communities, globally.

4.6 Limitations

Despite its methodological rigor, we acknowledge this study as having several constraints. First, the corpus comprises only 12 transcripts of webinars delivered in English by experts affiliated with WUN member institutions. Variability in presentation styles and lengths, and speaker idiosyncrasies may have influenced term frequencies and network structures.

The exclusion of non-English discourse and the absence of cross-cultural ethical framings may restrict the applicability of our findings to broader, multilingual debates on AI ethics. Second, reliance on automated transcription (via the YouTubeTranscriptAPI) and subsequent pre-processing steps, particularly synonym expansion using WordNet, migth have introduced potential artifacts. Although manual review mitigated errors (for example, "Army Intelligence" misidentified as "AI"), residual misrecognitions and parameter choices (e.g., co-occurrence window size, modularity resolution) may have affected community detection outcomes and network metrics.

Community detection was performed using the Louvain algorithm, a widely adopted method in network analysis that provided a robust and interpretable partition of the co-occurrence network for our analytical purposes. It is noted that newer algorithms, such as Leiden (Traag et al., 2019), offer improvements in guaranteeing well-connected communities and represent a promising avenue for future refinement of this analysis.

We acknowledge the limitations of our chosen methods. TF-IDF is a bag-of-words model and, as such, does not capture word order, polysemy (where a word like "bias" could be statistical or sociological), or complex semantic relationships. However, for mapping a high-level, consensus-driven expert discourse, this "limitation" can be a strategic advantage.

While TF-IDF effectively identifies the most salient vocabulary within the discourse, it is crucial to acknowledge its interpretative boundaries. The method operates on the premise that frequent and distinctive terms are conceptually prominent; however, this does not necessarily equate to their normative importance or argumentative depth. TF-IDF may overlook tacit knowledge, deeply held assumptions that are fundamental but rarely stated explicitly.

Furthermore, as a bag-of-words model, it is contextually neutral and cannot discern the sentiment or framing of a term. Therefore, our findings should be interpreted as a map of the explicit, shared conceptual lexicon that structures the expert conversation, rather than a measure of the moral weight or nuanced evaluation assigned to each concept within it.

Finally, the combination of TF–IDF weighting and co-occurrence network analysis, while effective at highlighting salient terms and clusters, does not capture deeper linguistic nuances, such as negation, argument structure, or evolving discourse trajectories, nor does it take advantage of recent advances in contextual embedding or dynamic network modeling.

5 Conclusion

This study underscores the importance of Responsible and Ethical AI by employing a multi-method framework to analyze expert discourse from the WUN initiative, revealing that ethical AI requires interconnected governance, technical safeguards, and societal imperatives rather than isolated solutions. While the methodological pipeline successfully identified key themes, limitations include reliance on curated webinar transcripts, which may not capture the full spectrum of global AI ethics debates. Additionally, the study's findings are constrained by the predominantly academic and institutional perspectives in the dataset, potentially overlooking grassroots or more industry viewpoints. Ultimately, this research lays a foundation for scalable, interdisciplinary frameworks to audit and guide AI ethics, calling for broader stakeholder engagement and iterative methodological refinements to ensure AI aligns with societal values.

For future work, expanding the corpus to include multilingual sources, real-world policy documents, and marginalized voices would enhance representativeness. Integrating advanced NLP (e.g., BERTopic, LLM-assisted annotation) could uncover deeper semantic patterns, while longitudinal analysis could track evolving ethical priorities. In conclusion, our methodological pipeline is novel not in the complexity of its individual components, but in their application to the science of consensus-building. It offers a replicable framework for visualizing the skeletal structure of expert communication, upon which future research using embedding-based models can layer a deeper analysis of semantic nuance.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

MW: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Validation, Visualization, Writing – original draft, Writing – review & editing. CC-Z: Conceptualization, Data curation, Formal analysis, Investigation, Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing.

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Conflict of interest

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

Generative AI statement

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