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Research Article

Reflective thinking meets artificial intelligence: Synthesizing sustainability transition knowledge in left-behind mountain regions

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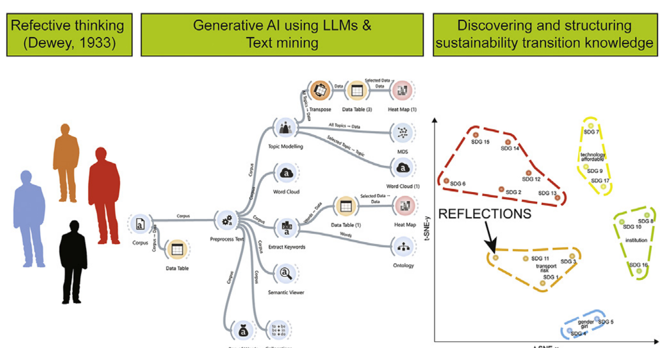
HIGHLIGHTS

- Reflective thinking and AI were merged to structure sustainable transition knowledge.
- Document embedding was used to align expert insights with UN SDGs.
- Infrastructure, education, and resilience are key focus areas for development.
- AI's role in synthesizing data for sustainable policy design was showcased.
- Identified social aspects dominate environmental ones in achieving sustainability goals.

GRAPHICAL ABSTRACT



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ABSTRACT

We demonstrate a multi-method approach towards discovering and structuring sustainability transition knowledge in marginalized mountain regions. By employing reflective thinking, artificial intelligence (AI)-powered text summarization and text mining, we synthesize experts' narratives on sustainable development challenges and solutions in Kardüz Upland, Türkiye. We then analyze their alignment with the UN Sustainable Development Goals (SDGs) using document embedding. Investment in infrastructure, education, and resilient socio-ecological systems emerged as priority sectors to combat poor infrastructure, geographic isolation, climate change, poverty, depopulation, unemployment, low education levels, and inadequate social services. The narratives were closest in substance to SDG 1, 3, and 11. Social dimensions of sustainability were more pronounced than environmental dimensions. The presented approach supports policymakers in organizing loosely structured sustainability transition knowledge and fragmented data corpora, while also advancing AI applications for designing and planning sustainable development policies at the regional level.

1. Introduction

Mountain regions carry significant ecological, economic, social, and cultural value (European Environment Agency, 2010). Sustainable Development Goal (SDG) 15 targeting life on land explicitly mentions mountains among ecosystems to be conserved, restored, and sustainably used (United Nations, 2015). However, in the pursuit of sustainable development, mountainous regions often face unique environmental

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and social challenges (Klein et al., 2019). The rate of warming in mountain ecosystems is projected to be two to three times higher than rates recorded during the 20th century (Nogués-Bravo et al., 2007), highlighting the importance of SDG 13 "Climate action". Natural forest re-growth and abandonment of agricultural land due to depopulation and disadvantaged economic status have altered cultural landscapes and habitats of high ecological value (Gellrich et al., 2007). Key social challenges in mountainous regions are socio-spatial inequalities (SDG 10), centralization, and peripheralization across economic, social, and political dimensions (Tucker et al., 2021). The complexities of promoting sustainable development in mountainous regions requite comprehensive ex ante policy analysis and reform (Cairney, 2023). However, prior to implementing policy reforms, it is essential to synthesize knowledge on environmental and social challenges and the drivers influencing them from economic, social, and political perspectives (Nelson et al., 2023). Understanding the challenges in a multitude of aspects ranging from natural handicaps (e.g., steep slopes, Tian and Lan, 2023) to digital divide (e.g., Liu et al., 2024) is a critical precondition for an effective debate on necessary responses (Lock et al., 2024). Understanding who or what is 'left behind' (Pike et al., 2023) requires a multi-factor and multi-scale perspective offered by development geography (Deng et al., 2023). However, the responses of local residents and state institutions to 'left-behindness', which extend beyond discontent to encompass issues of agency, place attachment, and political strategy, have largely been overlooked (MacKinnon et al., 2024). One reason for this might be that the spatial-temporal cascade of development challenges in mountain areas is often addressed in a top-down manner rather than bottom-up (Sotarauta et al., 2022).

Many challenges in mountain areas can be defined as 'wicked problems', meaning they are highly complex, longstanding, and do not have straightforward solutions (Rittel and Webber, 1973). Alternatively, they can be defined as 'periphery traps', i.e., developmental situations in which regions remain trapped in a state of underdevelopment and marginalization due to strong self-reinforcing controls preventing the flexibility needed for adaptation (c.f. Carpenter and Brock, 2008; Haider et al., 2018; Tidball et al., 2016; Diemer et al., 2022; Yang et al., 2023). Some scholars have emphasized the role of innovation in dealing with highly complex social-ecological challenges (e.g., Melnykovych et al., 2018). Innovation also plays a crucial role in the sustainability transitions of mountain societies (European Commission, 2020; Kastrinos and Weber, 2020; Wyss et al., 2022), ranging from the implementation of technological advancements (Argyroudis et al., 2022) to the development of new and equitable social contracts, i.e., Social Deals (e.g., Hereu-Morales et al., 2024). However, innovation often requires a deliberative process of thinking about the current position in order to be effective (Peters, 2018). Mixed method approaches are particularly suitable for addressing wicked problems because they enable researchers from diverse groups to share a common language for guiding their inquiry, and involve policy actors in the process of problem and solution identification (Gomez, 2014). In this paper we demonstrate a multi-method approach for extracting and organizing knowledge concerning sustainable development challenges and solutions in mountain areas, combining subjective introspective methods with objective and data-driven methods.

A cognitive process that involves considering and reconsidering one's current position, experiences, beliefs, and actions is described as 'reflective thinking' (Dewey, 1933). In policy design, reflective thinking helps navigate the complexities and uncertainties associated with effective and adaptive policies (Spaa et al., 2022), and engages policymakers in a systematic process of reflection at various stages. Reflective thinking encompasses generating i) initial subjective suggestions regarding the problem, ii) analyzing the context, iii) forming a guiding idea, iv) weighing possible courses of action, and v) testing the hypothesis by action (Dewey, 1933). Reflective thinking fosters participatory democratic approaches involving stakeholders and the public (Dewey, 1933; Dewey, 1954), and it aligns with adaptive governance and evidence-based policy principles (Chaffin et al., 2014; Hammersley, 2013). This culture of learning enhances the quality and effectiveness of public policies (Koopman, 2009), particularly in countries with limited institutional capacities.

However, reflection processes can be time-consuming, and there may be pressures to make policy decisions quickly. More importantly, reflective thinking is inherently subjective and done retrospectively (Jamieson et al., 2023), relying on individual perspectives and interpretations which must not acknowledge participants' own beliefs, biases, and judgement systems (Jamieson et al., 2023). Subjectivity may introduce biases and lead to decisions based on personal experiences rather than evidence-based solutions. The main shortcoming of using narratives in sustainability transitions research is that "it does not offer a good procedure for distinguishing well-founded arguments from unfounded fantasies" (van den Bergh, 2021). Reflective thinking often involves learning from past experiences. While this is valuable, an overemphasis on historical perspectives may hinder innovation or overlook emerging issues that require novel solutions. Sometimes, actors may resist reflective thinking if it seems to challenge established norms or traditional decision-making processes. Lastly, reflective thinking may not always translate into concrete actions or tangible outcomes; policymakers may struggle to bridge the gap between unstructured reflections and policy implementation.

Artificial intelligence (AI) can offer a significant support in knowledge discovery and policy analysis by identifying problems, generating solutions, comparing their likely effects, and making recommendations (Firebanks-Quevedo et al., 2022; Glickman and Zhang, 2024). Discovering knowledge, structuring insights, and presenting them to policymakers as research-informed advice can be performed with vast amounts and different types of data (e.g., Bogers et al., 2022; Tremblay et al., 2021). These methods are particularly beneficial for addressing complex (e.g., Song and Jang, 2023) or unstructured problems. However, to the best of our knowledge they have not yet been applied for such purposes in sustainability transition studies. Automatic text summarization techniques can condense lengthy text into manageable summaries by distilling key ideas (El-Kassas et al., 2021). Machine learning can help extract key concepts, entities, and relationships from unstructured data such as reflections (Minaee et al., 2021). Topic modeling algorithms can uncover hidden thematic structures and identify major topics and keywords in textual data (e.g., Boyd-Graber et al., 2017; Savin et al., 2020; Strazzullo et al., 2023). Visualization tools enable the communication of these reflections without requiring a comprehensive understanding of the algorithms, allowing findings to be translated into compelling policy advice that policymakers can easily adopt. AI-assisted policy analysis can also help overcome the ubiquitous implications of power differences and divergent knowledge systems which undermine the fit between policy issues and real-word problems. It does so by combining extractive and abstractive approaches (Mridha et al., 2021). After flattening the power-related hierarchy of the problem and its solutions, arguments can be compared at the same level to advance deliberations towards a situation where the best argument (rather than the most powerful one) is suggested.

However, AI also has potential limitations when considering accuracy. The accuracy of AI-driven analyses depends heavily on the quality of the training data and algorithms used. If the training data lacks diversity or representativeness, the analysis may overgeneralize or lead to biased results (Mehrabi et al., 2021). In contrast, traditional knowledge co-production and policy recommendation methods, such as workshops, participatory GIS, deliberative mapping (Fagerholm et al., 2021) and multicriteria decision analysis (e.g., Krsnik et al., 2023), though slower, often leverage the contextual knowledge of analysts, provide greater transparency and explainability. Additionally, the 'black-box' problem and trustworthiness of AI models (Barredo Arrieta et al., 2020) may be particularly challenging in complex domains like sustainability science. While AI approaches allow synthesized knowledge to be scaled to the desired level of detail quicker than traditional policy analysis methods, they may suffer from overgeneralization, loss of context and data legitimacy issues. Policy challenges often require sensitivity to historical, cultural or political context. AI may not be able to determine the level of analysis (e.g., national vs. local), which can result in recommendations that are too broad or too specific.

Although the use of AI for summarizing textual inputs is not novel in science, it has not yet been applied in sustainability science suffering from dispersed knowledge and divergent views (Whyte and Lamberton, 2020; Lock et al., 2024). In this paper, we build upon cognitive interdisciplinarity, which states that a common vocabulary is an important condition for knowledge-sharing and collaboration among researchers (Bromme, 2000; Moilanen et al., 2021). We demonstrate a multi-method approach to synthesizing sustainability transition knowledge in marginalized mountain regions, integrating reflective thinking on the current situation, automatic text summarization of these reflections, and machine learning analyses. By embedding the results and SDGs into a common semantic space, we help to clarify the relationship between regional perspectives and SDG goals. The methodology is demonstrated using the case of Kardüz Upland, Türkiye. This paper aims to 1) demonstrate the methodological steps for dissecting the multifaceted challenges and possible solutions within left-behind mountain regions starting with reflective thinking, and 2) uncover the underlying structure of expert reflections and their connections to the SDGs.

2. Materials and methods

2.1. Study area and data collection

Data was collected during a two-day meeting of 67 experts participating in MARGISTAR COST Action workshops in Düzce, Türkiye (the Western Black Sea region), and a field trip to Kardüz Upland in September 2023. MARGISTAR is a European forum for the revitalization of marginalized mountain areas based on collaborative reflection on their natural, environmental, social, and economic inter-relationships (MARGISTAR, 2022). The purpose of these workshops was to synthesize knowledge, identify visions of post-marginalized mountain areas, and define pathways towards post-marginalization by assessing successes and failures in existing policies. Reflective thinking was used as a concept for the study's data collection process (Dewey, 1933; Fig. 1).

The meeting in Düzce began by presenting key organizations' perspectives on the region's current conditions and the challenges of marginalization. Participating institutions included the Association of Foresters, Düzce governorship, Düzce and Gölyaka municipalities, the Düzce Provincial Directorate of Culture and Tourism, the General Directorate of Forests, the Nature Conservation and National Parks Branch Directorate, and the Düzce, Gölyaka, and Sakarya Forest Management Directorates. Participants then discussed the concept of periphery traps, potential solutions, and visions of post-marginalized futures in small groups. Field visits were carried out on the following day in the Efteni wetland, Güzeldere Waterfall Nature Park, and the Kardüz upland (Fig. 2). Efteni Lake (147 m a.s.l.) is a wetland hosting diverse bird species. Güzeldere Waterfall Nature Park (630 m a.s.l.) is an eco-tourism project which faces conflicts arising from trade-offs between the private sector and environmental protection institutions. Ownership is managed by Düzce's Nature Conservation and National Parks Directorate, while business tenders are handled by the Gölyaka municipality. Since 2013, Kardüz Upland (1820 m a.s.l.) has been designated a "Culture and Tourism Protection and Development Zone" and is envisioned as a winter tourism destination. The upland (ca. 180 ha) hosts a small community of subsistence farmers with unregulated housing. Economic decline and limited services endanger rich cultural transmission across generations. Past conflicts between forest villagers and management have resulted in the farmers' exclusion from forest ownership, potentially leading to conflicts over the area's winter tourism plans. Kardüz Upland is an example of a once lively mountain landscape, characterized by pastures, forests, and subsistence farming, now standing at a developmental crossroads: whether to pursue growth as a winter tourism hub to boost economic development in the region, or preserve its unique morphology, climate, rich water resources and flora.

Immediately following the meeting, all workshop participants were emailed and contacted via WhatsApp with a link to the online form to collect reflections on up to three challenges and their potential solutions (see Supplementary). In sum, 14 experts, all members of the MARGISTAR network, from Albania, Bulgaria, Croatia, Greece, Ireland, Romania, Serbia, Slovenia, Tunisia, Türkiye, and Ukraine responded. Most of these experts were academics (12), while two were active in business and consulting. Their primary fields of expertise were forestry (3), economics (2), soil science (2), agronomy (2), geography (2), politics and business (2), and landscape science (1). The experts serve as panelists, identifying and elaborating on the issues they consider important, rather than acting as representatives of the actors in the study area.

2.2. Text summarization with generative AI

Reflections were transferred into the Generative AI model GPT-3 (OpenAI, 2023) and summarized into a single coherent text in two steps. GPT-3 (hereinafter ChatGPT) uses its deep learning architecture (Minaee et al., 2021) to learn the relationships between different pieces of information and structure the content accordingly. The model utilizes extractive and abstractive methods for summarization, and then generates a response using its natural language generation capabilities to aggregate content by summarizing, rephrasing, or combining the information. While summarization does not eliminate the subjectivity of reflections, it ensures objective analysis by identifying core themes and facts without being influenced by professional or value-based orientations. Text summarization was performed iteratively. In a first step, ChatGPT was tasked with summarizing all reflections reported under the first challenge of the questionnaire in 250 words. The procedure was repeated for the questionnaire's second and third challenges and solutions. In a second step, ChatGPT was instructed to summarize each

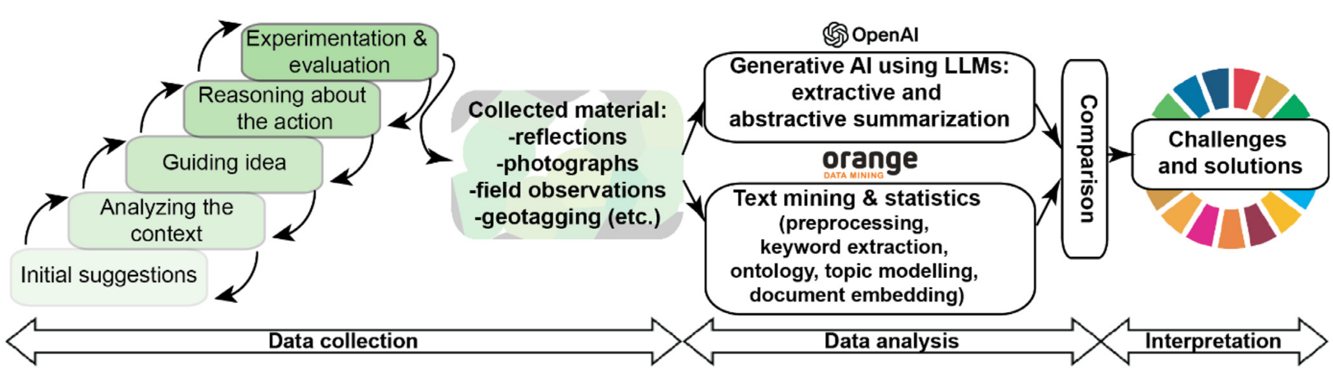

Fig. 1. Research methodology.

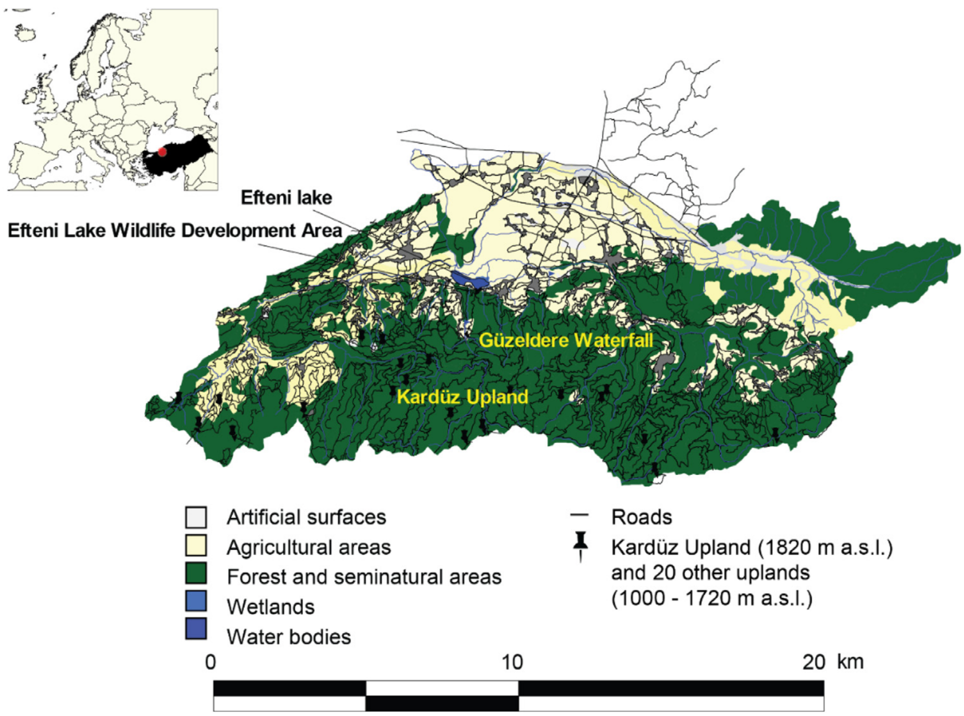

Fig. 2. Study area and field visit locations (Efteni Lake Wildlife Development Area, Güzeldere Waterfall Nature Park, and Kardüz Upland).

250-word abstract into five main clusters of challenges and possible solutions in no more than 50 words.

2.3. Text mining

Gathered reflections were separately analyzed by text mining tools available in the machine learning and data visualization software Orange 3.36.1 (Demsar et al., 2013). Orange allows for more control over analyzes than ChatGPT and combines AI tools with machine learning and conventional statistical methods. It also uses visual programming in specifying the data analysis workflow (Figs. 3 and 4). The user draws the data analysis workflow on the canvas, observes the patterns, and makes necessary adjustments to the workflow.

All reflections were first uploaded as a corpus, read in a data table, and preprocessed. Data preprocessing involved lowercase transformation, removing diacritics/accents and http(s) addresses, tokenization (i.e., splitting the text into words, but keeping punctuation symbols), normalization (i.e., applying stemming and lemmatization to words using Porter stemmer; van Rijsbergen et al., 1980), filtering specific common English stop words ($n = 127$), and creating uni-grams and bi-grams from tokens. N-grams are contiguous sequences of items in a corpus, typically words, within a text corpus, used to analyze and identify patterns, relationships, or features in the text. The most frequent words within the preprocessed text corpus were then visualized by a Word Cloud generator.

In a second step, keyword extraction, the Term Frequency-Inverse Document Frequency (TF-IDF) method was used to quantify the relevance of words, phrases, and lemmas within the corpus. TF-IDF is inversely related to term frequency in the text and consists of two measures (i.e., TF and IDF) multiplied together. Term frequency (TF) gives information on how often a term appears in a document and inverse document frequency (IDF) demonstrates the relative rarity of a term in the corpus (Eq. 1):

$$\mathrm{TF-IDF}_{t,d} = \frac{f_{t,d}}{F_d} \log\left(\frac{D}{d \in D : t \in T}\right) \quad (1)$$

TF-IDF$_{t,d}$ is the term frequency-inverse document frequency of term t in document d, $f_{t,d}$ is the frequency of term t in document d, F_d is the total number of terms in document d, D is the total number of documents, and d is the number of documents containing term t. In calculating the mean relevance of a term across all documents we used the arithmetic mean of TF-IDF$_{t,d}$. The higher the mean TF-IDF score, the more important or relevant the term is. The top 10 terms with the highest TF-IDF score were considered keywords.

Keywords were then used to create an ontology. Ontology in text mining is a structured, hierarchical representation of knowledge that defines concepts and their relationships in a specific domain (Buitelaar and Cimiano, 2008). Ontologies help structure and semantically categorize key messages, making them more understandable. The ontology was created using the genetic algorithm, which resulted in parent-child relationships between keywords to represent broader and more specific concepts nested within the primary ones.

To discover abstract topics in the corpus based on clusters of words found in each reflection and their respective frequency, we performed topic modeling using Latent Dirichlet Allocation (LDA; Blei et al., 2003). LDA assumes that each reflection is a mixture of topics, and each topic is a mixture of words. LDA iteratively assigns words to topics based on their probabilities, allowing the algorithm to discover coherent topics and their distribution across the document corpus. Topics were then projected in a 2D space using Multidimensional Scaling (MDS) to illustrate similarities in their content. To ease the interpretation of the topics and their (dis)similarities, word clouds were laid over the topics and the top 10 keywords in a topic were colored red. Text mining results were then compared to the ChatGPT-derived text summaries.

In a final step, we compared the reflections' substance and contexts to the SDGs using Document Embedding. To that aim, the corpus of reflections was first complemented with the corpus of the 17 SDGs and targets extracted from the 2030 Agenda for Sustainable Development (United Nations, 2015). Then, the text was preprocessed and documents were embedded into a vector space using an open-source pre-trained fastText language model (Grave et al., 2018). Document Embedding parsed the uni-grams and bi-grams of each document in the corpus, obtained embedding for each n-gram using the fastText language model, and collected one vector for each document by averaging n-gram embeddings. The reflections and SDGs were plotted with a t-distributed stochastic neighbor embedding method (t-SNE) to the 2D space by their

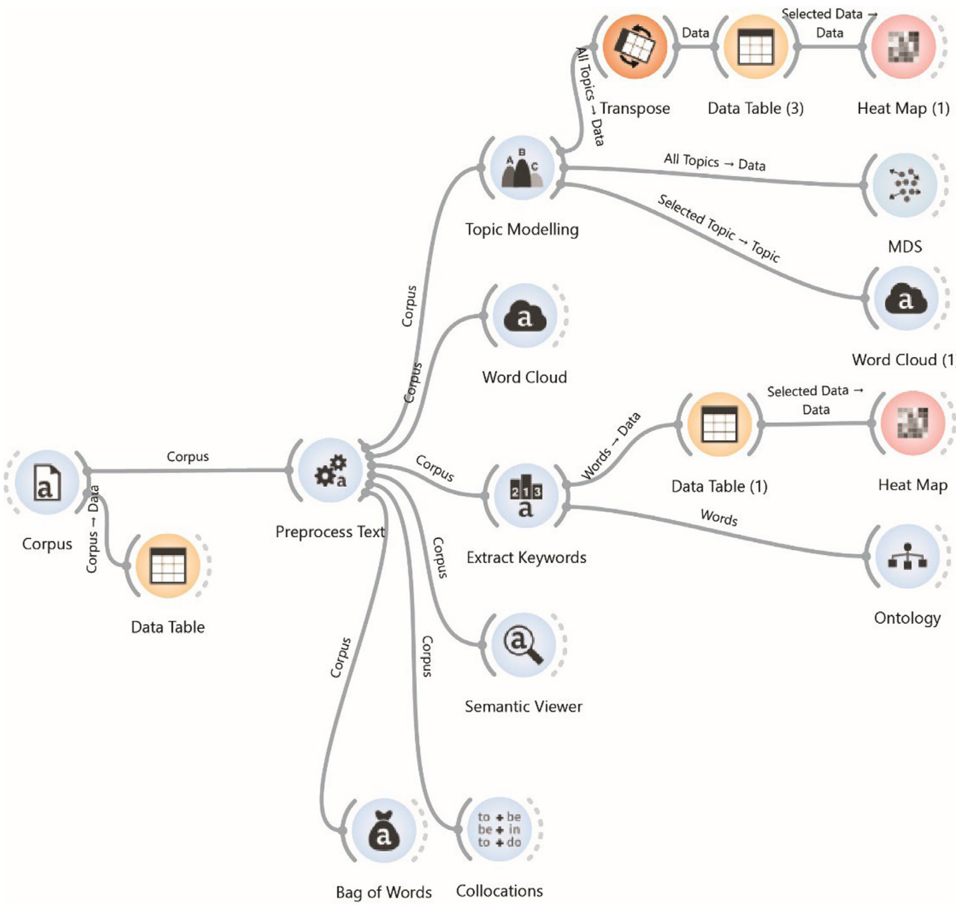

Fig. 3. Workflow of text mining analyses of experts' reflections.

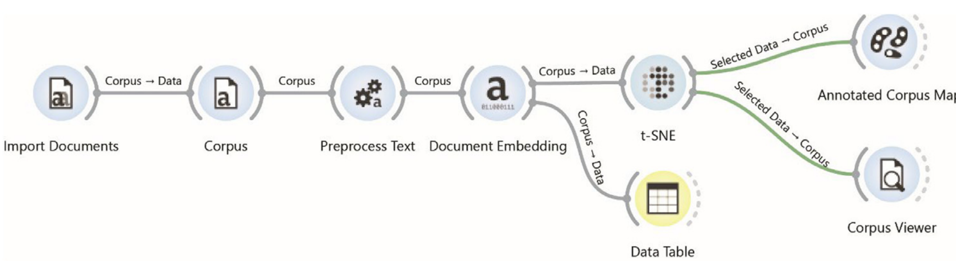

Fig. 4. Workflow of embedding experts' reflections and the SDGs from the 2030 Agenda for Sustainable Development (United Nations, 2015) using the fastText language model, and visualizing and clustering the results in 2D space by their semantic similarity and contextual information using t-SNE and Annotated Corpus Map.

probability distribution and clustered with respect to similarity using Gaussian mixture models. The resulting corpus map was annotated with keywords.

3. Results

3.1. Text summarization by generative AI

The respondents identified several key challenges in mountainous areas, which can be categorized into eight groups: poor infrastructure, geographic isolation, climate change, poverty, depopulation, unemployment, low education levels, and inadequate social services (Table 1).

To address these challenges, sustainable investment in infrastructure, resilient land-use planning, and smart decision support systems are needed. Initiatives like public cultural community centers (e.g., Chitalishte) and cooperatives can help combat poverty and depopulation, while local knowledge, heritage, and natural resource investments can help tackle unemployment. Education and skill building should be facilitated through government-led programs, and economic diversification can be achieved with responsible agritourism practices. Policymakers should also focus on income enhancement and the promotion of cooperative and sharing models to overcome infrastructure challenges. Coordination and cooperation among stakeholders, IT training, better education accessibility, incentive programs, and increased public investment are essential for revitalizing mountainous areas and addressing the low education levels and social service deficiencies prevalent in these areas.

3.2. Content analysis by text mining tools

The word central to the text corpus was "rural" (Fig. 5a). Other characteristic words were "transport"/"transportation", "people", and "population". In combination with other keywords, the ontology (Fig. 5b) can be simplistically presented as: Transportation problems generate multifaceted handicaps ("lack", "economic", "access") which require investments ("invest") and searches for possible solutions ("path"). The latter task is challenging as it tackles multiple issues and because marginalized mountain areas are trapped in peripheries ("trap"). Education ("educ") and associated investments were identified as important aspects of the suggested solutions in the keyword analysis, the ontology, and in text summarization.

Table 1
Main challenges and possible solutions in mountainous areas identified by the iterative automatic text summarization of expert reflections using ChatGPT 3.5 (OpenAI, 2023).

Challenges and solutions No. 1	Challenges and solutions No. 2	Challenges and solutions No. 3
1. **Infrastructure:** Unsafe roads necessitate sustainable investment from government, institutions, and private sector. 2. **Geographic Isolation:** Vulnerability to disasters calls for resilient infrastructure and land-use planning. 3. **Climate Change:** Mitigated through smart decision support systems. 4. **Poverty and Depopulation:** Addressed by Chitalishte and cooperatives. 5. **Unemployment:** Tackled via local knowledge, heritage, and natural resource investments.	1. **Education and Skill Building**: Essential government-led programs are needed to educate and train local residents. 2. **Economic Diversification**: Responsible agritourism practices can boost economic activity while preserving natural resources. 3. **Income Enhancement**: Policymakers should create job opportunities to address low incomes. 4. **Infrastructure** Improvement: Critical infrastructure, like schools and kindergartens, requires immediate attention. 5. **Infrastructure Solutions**: Cooperatives and sharing models can help overcome infrastructure challenges.	1. **Coordination and Cooperation**: Collaborative efforts among stakeholders, including public institutions, private sector, NGOs, and communities, are vital for mountainous area revitalization with effective monitoring and evaluation. 2. **Low Educational Levels**: Mitigated through IT training, market access, and sustainable tourism promotion. 3. **Education Accessibility**: Ensure easy access through school openings and improved transportation. 4. **Incentive Programs**: Encourage settlement with incentives. 5. **Lack of Social Services**: Overcome with increased public investment and social representation.

Note: The text is a verbatim result of the ChatGPT 3.5 text aggregation in the second step.
Chitalishte is Bulgarian cultural community center selected on the Register of Good Safeguarding Practices by United Nations Educational, Scientific and Cultural Organization (UNESCO, 2023).

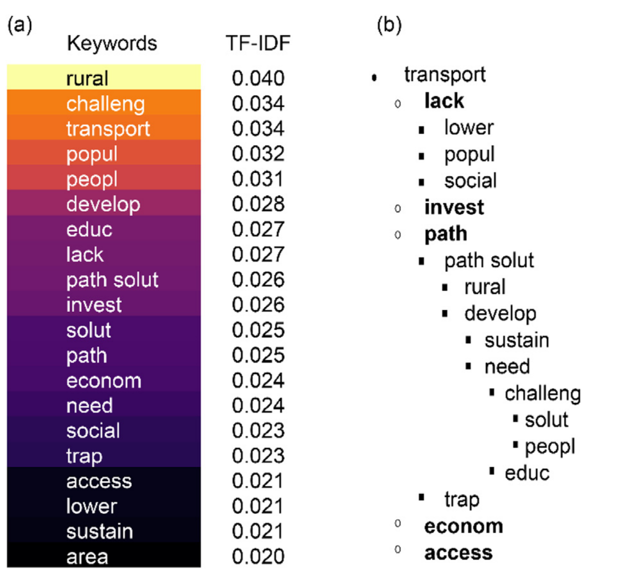

Fig. 5. (a) Heat map of the 20 most characteristic words (keywords) of the expert reflections. The heat map's color intensity represents the relevance of words in the reflections (i.e., TF-IDF value), with lighter colors indicating higher values; (b) The ontology of the reflections, showing how the keywords are interconnected and form concepts or categories.

The topic modeling algorithms identified three main topics, each associated with different keywords (Fig. 6). Topic 1 represents the state of the social-ecological systems in the area. It characterizes mountain areas based on geographical, site, and size features ("mountain", "mountain area", "area", "forest"), as well as economic and social challenges ("econom", "peopl"). Notably, Topic 1 lacks any discussion of potential solutions. This is further indicated by the marginal probabilities of the top 10 keywords in Topic 1 (Fig. 7), where "Area" and "Challeng" are prominently represented.

Topic 2 focuses on solutions to the issues facing these areas, with keywords such as "develop", "transport", "invest", and "educ". Topic 2 has the highest marginal probability among all three topics, suggesting that its content is the most homogeneous compared to the other topics.

Topic 3 includes both reflections on the state of the system and possible solutions. This topic stands out due to its distinct position in the MDS (Fig. 6), where the small dot representing Topic 3 indicates relatively heterogeneous content. The keyword marginal probability analysis for Topic 3 (Fig. 7) supports this, as none of its keywords have particularly high probabilities, making it difficult to clearly characterize the content of Topic 3.

3.3. *Content similarity of reflections and SDGs*

Content-wise, the experts' reflections are closest to SDG 1 ("End poverty in all its forms everywhere"), SDG 3 ("Ensure healthy lives and promote well-being for all at all ages"), and SDG 11 ("Make cities and human settlements inclusive, safe, resilient and sustainable") (Fig. 8). The keywords "sustainable transport" and "risk management" best describe how the experts framed SDGs in marginalized mountain areas. Experts' reflections seem contextually distant from SDG 15, which explicitly mentions mountains among the ecosystems to be conserved, restored, and sustainably used. Rather than natural resources, it emphasizes the importance of social aspects. This is further highlighted after the five clusters (see Section 2.2) are merged in the Annotated Corpus Map (Fig. 8); the orange cluster is first merged with the blue cluster (education and gender, SDG 4 and SDG 5), then with the green cluster (the institutional aspects of sustainable development), and lastly to the combined red and yellow clusters.

4. Discussion

4.1. *AI-assisted text summarization versus text mining*

Results show that the AI-assisted summarization and the text mining tools present the same main challenges and solutions in mountainous areas. Both methods highlight the importance of education, infrastructure, and economic diversification as key factors for improving the living conditions and opportunities of rural populations. However, text summarization provides a more concise and structured overview of these challenges and solutions, while text mining reveals more nuances and connections among the keywords. The text summarization method also uses more natural and coherent language, while the text mining methods rely on technical terms and visual representations (Westergaard et al., 2018). However, researchers can also use multimodal summarization, employing models that can process both textual and visual information

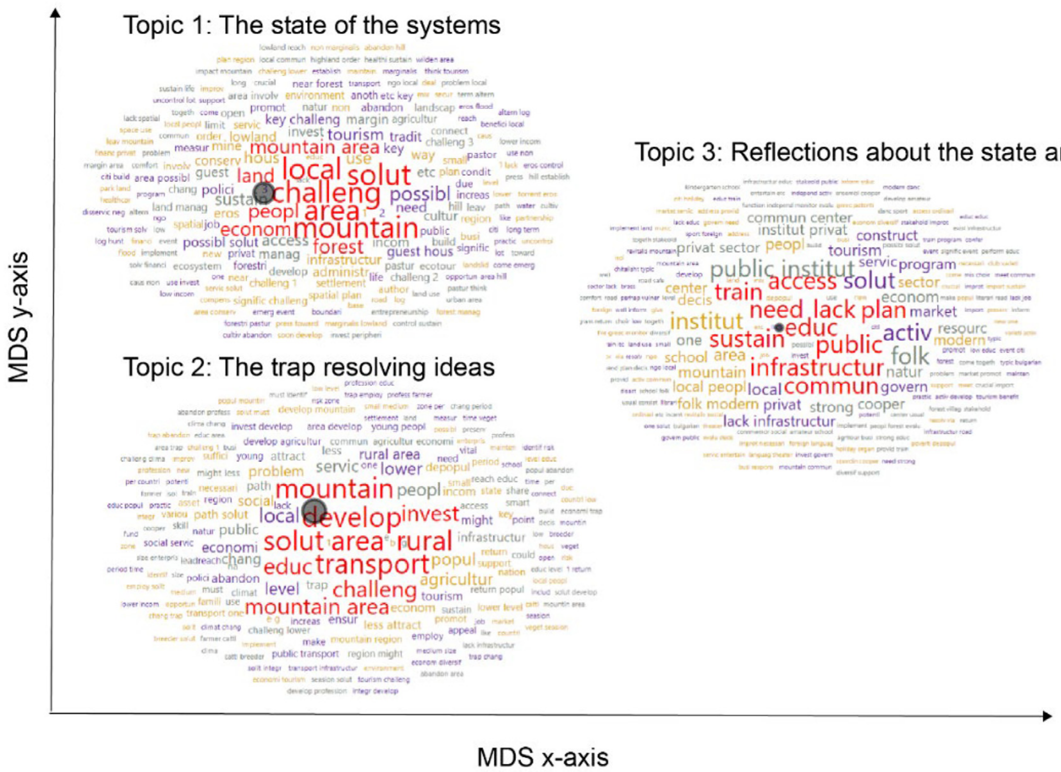

Fig. 6. Multidimensional scaling (MDS) of the three sustainability topics, identified by topic modeling. The size of the grey point corresponds to homogeneity of the topic. Red colored tokens in word clouds represent the top 10 topic keywords. Note that axes in the MDS merely preserve the dissimilarity between the topics and have no special meaning.

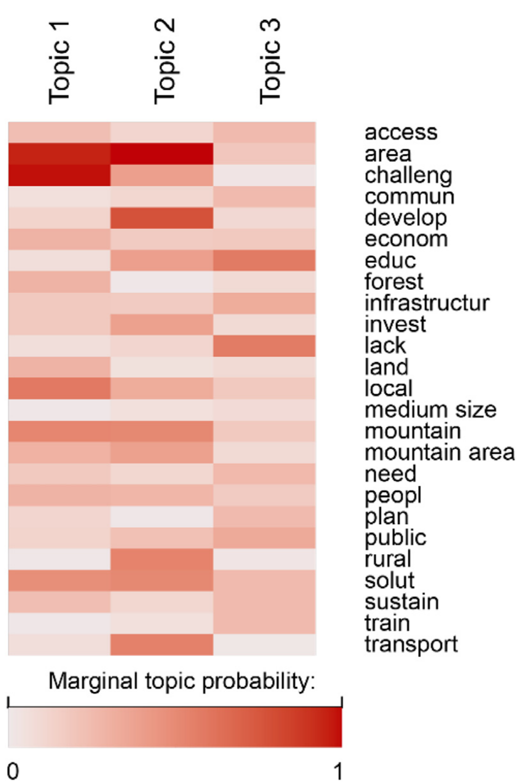

Fig. 7. Homogeneity of the content of the three topics characterized by the marginal probabilities of the top 10 topic keywords. The darkest keyword is the most characteristic of the topic, the darker the column, the more homogenous the topic.

and generate a summary that integrates insights from both modalities (Glickman and Zhang, 2024). This is particularly useful when dealing with unstructured data that contain both text and images or when the primary intention of collecting reflections is concealed to prevent socially desirable responses or dominating powerful actors. On the other hand, text mining methods enabled nuanced quantitative analyses and further use of the developed ontology models. Both methods complemented each other in providing a comprehensive and in-depth analysis of reflections.

The heat map and the ontology structured the main themes and topics that emerged from the expert reflections. While the heat map helped us identify the most important and relevant words, the ontology illustrated the connections and meanings of these words. We see that the word “rural” is central to these reflections. Other words suggest that experts also focused on the difficulties that rural populations face in mountainous areas, including poor transportation, depopulation, and a lack of social services. The ontology shows that the experts proposed some possible solutions to address the challenges of marginalized mountain areas, such as investing in infrastructure, education, and economic development, finding alternative paths or solutions, and overcoming the traps or barriers that hinder the progress of rural areas.

Topic modeling then unveiled the key topics. The analysis suggests that experts structured the sustainability transitions discourse into 1) the state of the system, 2) the solutions, and 3) the linkages between 1) and 2). Topic 1 resembles very much Deweyan initial subjective suggestions regarding the problem (i) and the analysis of the context (ii). Topic 2 reflects Deweyan steps iii and iv, i.e., forming a guiding idea, and weighing possible courses of action. Some keywords are shared across topics, such as “challeng”, “solut, “develop”, and “need”. This indicates that these words are relevant for all topics, albeit in different perspectives. Some keywords are specific to one topic, such as “transport”, “educ”, and “forest”, indicating that they appear in a specific context. While “transport”

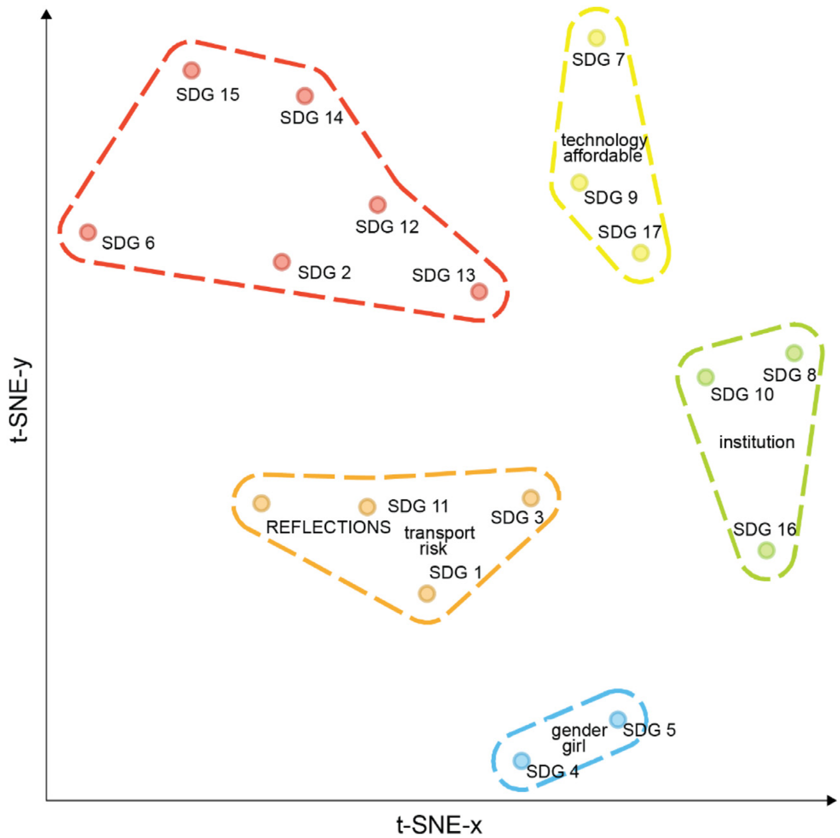

Fig. 8. Annotated Corpus Map showing the semantical closeness of experts' reflections to SDG 1, SDG 3, and SDG 11, and other distinctive semantical clusters of SDGs.

is the key trap-resolving idea in the solutions discourse, "education" is the topical keyword concerning the linkages between the current state (Topic 1) and the solutions (Topic 2). Topic 3 represents the underlying development potential, serving as the basis from which the state of the social-ecological systems and possible pathways are interpreted and derived, as well as the foundation for experimentation and evaluation.

4.2. Relationship between reflections and SDGs and targets

The Annotated Corpus Map (Fig. 8) suggests that infrastructural and social challenges were more pronounced than ecological challenges. Two keywords (i.e. "sustainable transport" and "risk management", Fig. 8) are topical both for the cluster of reflections and SDGs 1, 3, and 11, as well as many other SDGs. In the 2030 Agenda for Sustainable Development, sustainable transport is mainstreamed across several SDGs and targets, especially those related to food security, health, energy, economic growth, infrastructure, and cities and human settlements (United Nations, 2015). It is intriguing, however, that none of the SDGs focusing on institutional challenges clustered with the reflections. For instance, SDG 10 ("Reduced inequalities"), did not emerge as being closely related to experts' reflections despite the evident disparities of mountain areas concerning regional, geographical, and economic inequalities. This absence raises questions about the prioritization of certain SDGs over others in marginalized mountain regions. Perhaps there are underlying complexities or nuances specific to these regions that were not fully captured by SDG 10 alone. Similarly, the lack of emphasis on SDG 16, which pertains to strong institutions, is noteworthy given the extensive criticism of EU policies in rural areas. One might have expected SDG 16 to be highlighted in the reflections, particularly when discussing concepts such as periphery traps. Furthermore, the relatively muted representation of SDG 8, which focuses on decent work and economic growth, is surprising considering the economic challenges faced by mountainous regions. These discrepancies suggest that while institutional factors may play a role in sustainability transitions, they may not be directly addressed in deductive analyses like ours. The reason for that could also stem from methodological limitations. NLP techniques such as Document Embedding and Semantic Network Analysis may fail to identify semantic commonalities between SDGs and local SDG strategies, as SDG progress at the local level is neither contextualized nor measured in the same way as at the national level (Foroudi et al., 2024). Additionally, some SDG targets may not exist at all at the local level (Song and Jang, 2023).

4.3. Challenges and limitations of pre-trained large language models (PTLLMs) for text summarization

Pre-trained LLMs (PTLLMs), such as GPT3+, are transforming how and who can leverage natural language processing (NLP) for knowledge structuring, discovery, and text mining at different scales. Despite their relative novelty, there is already a significant and growing base of literature on the use of GPTs for summarizing complex documents and extracting valuable insights from unstructured data in a range of use cases and contexts (e.g., see Goyal et al., 2022; Yoshimura et al., 2023). ChatGPT 3.5 handled some poorly written reflections with grammatical errors and misspellings quite well (see Supplementary). The use of PTLLMs for text summarization has clear advantages for researchers including greater efficiency, consistency, and customization, all at scale. Literature and scoping reviews, meta-analyses, and unstructured data analysis are just some of the research tasks that might be accelerated and transformed using PTLLMs. Research suggests that LLM-generated summaries, in some scenarios, are not only preferable to humans over human-generated summaries (Goyal et al., 2022; Maynez et al., 2020; Pu et al., 2023), but in many studies PTLLMs outperform human operators with respect to quality (Pu et al., 2023).

Reliance on such models also introduces challenges. Text summarization, as used in this study, requires summaries to be accurate representations of the source document (Maynez et al., 2020). Notwithstanding the growing evidence that suggests PTLLMs outperform humans in text summarization, numerous researchers note that LLMs are prone to 'hallucinations', or generating summaries that misrepresent the original text (Maynez et al., 2020; Pu et al., 2023). This issue is exacerbated by the lack of control researchers have with respect to PTLLMs, particularly when dealing with large document volumes. In our study, solutions identified by the AI-assisted summarization of reflections (Table 1) seem surprisingly state- or authorities-driven. PTLLMs, such as GPT, are updated on an ongoing basis. As such, even if the same data and a prompt is provided by a researcher, results may vary due to changes in the underlying model (Chen et al., 2023). As, by definition, the researcher does not have control over the model, they cannot effectively control the data on which the PTLLM is trained, nor can they have complete knowledge of the training data for the LLM. This may introduce bias and other ethical concerns (Bender et al., 2021; Ray, 2023). While researchers can address some concerns by integrating LLMs into larger analytical pipelines, introducing quality checks, and using smaller corpora (as demonstrated in this study), these approaches also introduce their own set of challenges. For example, a small corpus of documents may limit the LLM's ability to discern and replicate specific contextual nuances, thereby impacting the quality of the summaries.

4.4. Limitations of reflective thinking when combined with AI

The machine analysis of the reflective thinking material can face significant limitations in capturing the depth, context and personal meaning embedded in the material. For example, AI may identify key terms or phrases in the reflections, but it may miss emotional undertones which can only be identified in qualitative analysis. Moreover, AI and text mining prioritize dominant voices, whereas reflective thinking might provide marginalized or less-represented perspectives that would otherwise be obscured in summarization. This means that some challenges and solutions may be overlooked entirely. Additionally, AI-driven analysis tends to favor quantifiable metrics, which might oversimplify complex policy issues. Over-reliance on AI could also lead to a loss of critical thinking skills and judgment among policy makers. If decision-makers defer too often to automated recommendations, they may stop questioning the validity or ethical implications of those decisions. Finally, reflective thinking requires time and patience, but policies often push for quick solutions based on existing data, vested facts or conventionally justified interpretations. This rush toward efficiency may adversely impact the slow, thoughtful processes needed for effective and fair policy decisions.

4.5. From peers' reflections to policy recommendations

The analysis of peers' reflections did not indicate which policies should be adapted or how they should be changed. This is because, at this stage, only the desiderata were formulated, without specific instructions on what to change in a particular policy. However, automatic text summarization can serve as the basis for evaluating gaps in a specific policy. To that aim, we would need to employ another series of models to evaluate existing policies. The models can be AI-based (e.g., Cheng et al., 2018; Firebanks-Quevedo et al., 2022) or use machine learning algorithms to obtain the input data necessary for policy evaluation models (e.g., Huang et al., 2023). In this way, the inductive approach to policy reform meets the deductive analysis. The resulting gap analysis is not only unbiased and comprehensive, but also performs faster than conventional reviewing and classification. In complex challenges (such as developmental challenges), automatic summarization of policy documents is especially preferred over reading and analyzing large corpora that span multiple sectors, ministries, and scales (Firebanks-Quevedo et al., 2022).

Text mining identified "rural" as the most frequently used term in the expert reflections. This implies that rurality (e.g., development, life, (agri)culture, etc.) should be the core concept in policies. Target 2.a in SDG 2 devotes specific attention to rural infrastructure, agricultural research, extension services, and technology development. AI can help greatly in solving wicked problems as the analysis does not need to be policy-specific, but instead focused on the key challenges that need to be addressed (Kulkov et al., 2023). For example, challenges that appeared in text mining (e.g., climate change, transportation, and investments) are pressing, but the analysis suggests that they need to be understood in specific rural contexts. Since policies often operate in sectoral silos, searching for solutions within the sector does not offer a solution to these wicked problems. Reflective thinking can help dismantle the silo mentality within the sector as it stimulates the intersectoral collaboration rather than fast decisions that comes from a siloed mentality. AI then swiftly analyzes and synthesizes enormous amounts and types of material. By engaging in a systematic process of reflection at various phases, the true potential of human capital is used, i.e., to collect material for the post-hoc AI-assisted analyses rather than using AI to harvest "knowledge" from scattered and doubtful information sources.

A final insight of our study is that more attention should be paid to problem definition and the identification of challenges rather than seeking solutions (e.g., Peters, 2018). While policy recommendations in scientific literature often focus on solutions to existing problems, the heat map shows that challenges were more frequently discussed than solutions. This illustrates the importance of situational analysis prior to planning solutions and suggests that the problems of mountain regions are not well structured nor clearly defined. However, it may also reflect that discussing SD challenges was easier than comparing methods of reaching specific targets, even if the initial workshop sessions covered both topics. When it comes to implementation, prioritization is necessary (e.g., Dell'Ovo et al., 2022) as policymakers often encounter manifold wishes or even contradictory proposals from societal actors. For example, climate change is highlighted as the key challenge for mountainous areas (European Environment Agency, 2010; Klein et al., 2019), but was not in the heat map of the keywords (Fig. 5). Therefore, our approach shows promise in identifying key priorities at local levels.

Nonetheless, the relevance of conceptual framing should be verified. One of the key concepts in MARGISTAR is a 'periphery trap'. While scientifically interesting (Carpenter and Brock, 2008; Tidball et al., 2016), its central role in MARGISTAR does not guarantee that the experts embraced this specific theoretical concept in their reflections. The heat map shows that the trap was used in discussions, but not intensively. The reason for this may be that experts felt it more interesting to discuss specific problems and solutions rather than concepts used to analyze them. For example, sustainability itself scored low on the heat map. This may imply that some key concepts in sustainability science may direct discussions, but that their excessive use as framing devices can distract attention from challenges at regional levels.

5. Conclusions

This study demonstrated the potential of Natural Language Processing techniques and machine learning in synthesizing sustainability transition knowledge in marginalized mountain regions. Using a rather small case study, we showed that a combination of reflective thinking and AI-assisted analysis enables discovering, structuring, and synthesizing local knowledge needed for sustainability transition. While generative automatic text summarization offered a structured overview of challenges and solutions, text mining revealed nuanced connections among key terms, enabling deeper quantitative analyses and ontology development. Reflective thinking can process loosely structured knowledge and disorganized large data corpora, integrating them into broader analytical pipelines that offer policymakers prioritized suggestions on which policies to reformed first. While certain SDGs may intuitively seem more relevant in marginalized mountain regions, the actual reflections and discussions reveal different priorities. Social dimensions of sustainability were ubiquitous and recognized by most of the text mining techniques. However, none of the reflections were particularly close to a specific SDG. Furthermore, environmental dimensions of sustainability were almost absent in reflections despite mountain ecosystems being one of the key topics in the 2030 Agenda for Sustainable Development. These discrepancies highlight the need for tailored, context-specific approaches to sustainable development, supported by continuous learning, adaptive policy cycles, and active engagement with experts and local stakeholders. The presented approach aids policymakers in the inductive creation of sustainable development policy and fosters further innovation. Future research could explore integrating reflective thinking with explainable AI (XAI) (Barredo Arrieta et al., 2020), enabling specially trained LLMs to comprehend the subjective and contextual nuances of reflections. By integrating XAI techniques, these models could offer transparent insights into how a specific type of actor in a specific geographical context reflects, while fostering trust and accountability in their analyses.

Declaration of competing interests

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

CRediT authorship contribution statement

Andrej Ficko: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Simo Sarkki:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Yasar Selman Gultekin:** Writing – review & editing, Writing – original draft, Visualization, Project administration, Investigation, Formal analysis, Data curation. **Antonia Egli:** Writing – review & editing, Project administration, Data curation. **Juha Hiedanpää:** Funding acquisition, Project administration, Writing – review & editing.

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Supplementary materials

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