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A scoping review on climate change education

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Abstract

The growing urgency of the climate crisis necessitates innovative educational approaches to equip people with the knowledge and skills to address climate challenges and be able to influence policy effectively. Education can be a central asset to promoting climate action, yet the importance of climate change education has been underexposed in large and influential assessment reports such as those from the IPCC. This study provides a comprehensive mapping of the literature on climate change education with a particular focus on the time period 2008-2023. By combining human coding and natural language processing (NLP) techniques, we examined a diverse corpus of over 6'000 publications from the peer reviewed literature. The findings highlight the pivotal role of climate education across various disciplines and its alignment with critical climate research themes such as adaptation, mitigation, disaster risk management, and sustainability. Our analysis reveals three predominant topics within the literature which are related to effective learning methodologies, sustainable development education, and the importance of education in adaptation and resilience. Additionally, we identified emerging themes emphasizing the role of youth as change agents, the necessity of transformative educational practices and the importance of energy literacy. Through geoparsing, it was possible to infer country mentions and case studies. These appeared to be largely skewed towards the English speaking countries and in particular the United States and United Kingdom, underpinning the urgency of diversifying research funding and fostering an open data culture. The insights gained from this scoping review underscore the potential of climate education to not only enhance knowledge but also to drive community engagement and policy initiatives, thus contributing to broader climate action efforts. In essence, it suggests fostering innovative educational practices for cultivating an active and informed society capable of addressing the pressing challenges posed by climate change. Importantly, this study calls for the integration of climate change education themes into climate policy-relevant assessment reports.

Introduction

The climate crisis is making headlines every day [1, 2]. The increasing impacts and consequences of the climate risks predicted in the past decades are now a reality almost everywhere

Collection (https://www.webofscience.com/) were screened based on titles, abstracts and key words until July 31st, 2023 using the string searches in square brackets [(((climat* AND chang*) AND education) OR ((global warming) AND education) OR ((climat* AND chang*) AND teach*) OR ((global warming) AND teach))]. To be included, publications had to be indexed in English and be of the type article or book. We excluded records that did not have an abstract or DOI and removed duplicates. For copyright reasons, the full metadata from WoS and Dimension cannot be published. To reproduce the analysis, it would be necessary to apply the search string and download the abstracts from WoS and Dimensions. The list of DOIs and the processed data to reproduce the analysis from the metadata can be accessed here https://zenodo.org/records/13939232.

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[3]. The latest IPCC reports emphasize the time-critical dimension of the climate crisis and that the coming years will be instrumental in securing a climate resilient future for generations to come [4, 5]. The already noticeable and widespread impacts of climate change have led to increasing climate anxiety in young generations across the globe [6].

It is not fully clear however how adults and children alike access and consume information to develop knowledge and understanding to be better equipped to handle these challenges. Social media platforms, blogs, and a growing number of communication channels have made it possible for science to have a more immediate, and broader reach and influence outside of the academic sphere [7–9]. The channels have however also led to the spread of misconceptions and fake news amongst the general public, slowing down positive action [10–12]. Yuan et al. [13] have analyzed more than 7 million tweets about climate change between 2019–2020 and found that aggressive tweets (although a small proportion of total tweets) were more likely to be retweeted and politicised.

To counteract misinformation and bolster action, interventions at the level of communications and education have been deemed essential [14]. Climate change education refers to the process of teaching and learning about the causes, consequences, and potential solutions to climate change [3]. Climate change education aims to enhance public awareness, understanding, and engagement in climate change issues, as well as foster adaptive capacity and support for climate action [15, 16]. Recent developments in university education are moving in the direction of including modules on climate change and the climate crisis as part of compulsory study programmes as a result of activism and public dialogue [17–20]. There are good examples of initiatives and online platforms that provide a broader scope of resources on climate or climate focused environmental education. For example, the EU education and training sector focus on green education https://education.ec.europa.eu/focus-topics/green-education [21] the Office of Climate Education, under the auspices of UNESCO [22]; or initiatives like the GLOBE (Global Learning and Observations to Benefit the Environment) Program, supported by US governmental agencies, which gives students and the public the opportunity to contribute to observations, research and analysis of global environmental data [23]. Existing successful models of climate-focused project-based learning have resulted in increased climate awareness and overall carbon reduction [24]. For example, significant carbon reduction was measured through student-consumer choices after five years of taking a university climate change course, indicating that even a small amount of climate change information and awareness introduced into school curricula has the potential to result in a significant effect [20].

Climate change education is not limited to formal educational systems, such as school and university curricula but is also present in vocational qualifications and informal settings like media and social media platforms [19, 25]. Communication and engagement strategies, such as experiential learning, climate games, and online courses have been described as effective and useful methods for reaching diverse audiences and fostering climate literacy [7, 26]. As a result, research is paying increasingly more attention to the role that education in its different forms plays on its power to catalyse action and empower citizens [27]. Some studies have found that although learning leads to knowledge and skills, the type of information and learning experience can have a profound effect on the outcomes of successful learning and behaviour change and whether there is lasting impact; this is especially true for climate change information where personal relevance to the issue or an engaged learning experience can be critical to solidifying a lasting change, especially for children and young people [17, 19, 20, 28].

On the other side, there is evidence that climate change education often emphasizes individual actions rather than addressing crucial policy actions on climate change as for example in terms of mitigation and adaptation [27]. Key elements such as the 1.5-degree limit envisioned by policy and extensively addressed in IPCC reports and beyond, as well as climate justice, are rarely discussed in educational programs. Along these lines, scholars have reported the considerable challenges when moving from climate change education to effective climate action, therefore arguing that there is still a gap and misconceptions within the teaching and student communities when it comes to climate change [29].

These diverse lines of evidence highlight the contested nature of climate change education and its relevance across various domains. As a result, the body of literature on climate change education is diverse and expansive, encompassing reviews that address the importance of giving children and young people a voice in climate change education [30], the role of health professionals in climate change education [31], and the integration of indigenous knowledge [32], to cite a few.

However, education has, so far, been sidelined in large environmental assessments such as the recent IPCC reports [3, 33]. The Summary for Policy Makers of the Working Group 2 on Impacts, Adaptation and Vulnerability [4] mentions "education" four times, whereas the Summary for Policy Makers of the Working Group 3 on Mitigation [5] mentions it three times. These summaries are the first policy stop for decision makers and therefore play a key role in leading to policy changes, which might apply to education policy leading to climate action. And yet, this angle is rarely explored by climate policy. The marginalisation in influential climate reports indicates a lack of consideration for educational strategies in bringing to the fore front the climate discourse, revealing a gap that demands attention.

In this paper we scope the research on climate change and education using systematic mapping of the peer-reviewed literature. Systematic mapping is an approach that seeks to give an overview of an area of research by identifying, categorizing and assessing the existing literature on a topic [34]. It is different from a systematic review whose scope it is to synthesize evidence, identifying strengths and weaknesses, usually with a very specific formulated goal [35]. A systematic mapping gives a high level overview or map of the research area, which helps to identify gaps and future research directions though visual summaries and mapping of classification categories [36]. The goal of our study is thus to take stock of the literature and explore the main themes, contextual influences, and relationships that emerge on a broad and global level through a systematic mapping. In particular, our scoping review addresses the following research questions: 1) where do we situate the research on climate education in the context of the broader climate change research? 2) what can we infer about the scope of such research 3) what are the main themes, gaps, and identified relationships that merit further attention? and finally 4) can we draw some conclusions on the links amongst education and climate action?

Owing to the exponentially growing number of publications on climate change, the methods for systematic mapping of the literature is situated in the context of big data and big literature [37–39]. This paper is organised as follows. The next section, Methods, describes the methodological approach for data collection and analysis as well as the data set used in our analysis. The Results and Discussion sections summarize and discuss the main findings of the paper, as well as offer some insight on future directions. Finally, we end with Conclusions.

Methods

Systematic reviews and mapping have been valuable assets to synthesize various key topics from the literature on climate change [40–43]. As the amount of literature on climate change has increased exponentially, machine assisted assessments of the literature have started complementing human efforts [37]. Machine learning has been used in assessing progress on human adaptation [38], to map the literature on climate change and health [44], to highlight global adaptation limits [45], for impact attributions [39] and to give insights on the topology of climate change research [37]. This paper adds to the mapping of climate change literature by focusing on climate change education. The notebooks and data used can be found on GitHub [46].

Data collection, search and screening

Publications on the Dimensions API https://www.dimensions.ai/ and the Web of Science, Core Collection https://www.webofscience.com/ were screened based on titles, abstracts and key words until July 31st, 2023 using the string searches in square brackets [(((climat* AND chang*) AND education) OR ((global warming) AND education) OR ((climat* AND chang*) AND teach*) OR ((global warming) AND teach))]. To be included, publications had to be indexed in English and be of the type article or book. We excluded records that did not have an abstract or DOI and removed duplicates. Finally, only papers having both a non null abstract and DOI were selected. After merging the two database datasets and removing duplicates, 18'162 records were retained for further analysis using human coding of abstracts supported by supervised learning. Supervised learning is a type of machine learning algorithm where the model learns to make predictions by being trained on labeled examples [47]. The algorithm is given a set of input-output pairs, where the inputs are the features or attributes of the data and the outputs are the corresponding labels or target values. The goal of the algorithm is to learn a mapping between the inputs and outputs, so that it can make accurate predictions on new, unseen data [48, 49].

In our case, we randomly selected about 10% of the articles in our database of more than 18'000 (i.e. 1776) to create the training and test set. We then proceeded to manually label the papers as either relevant or non-relevant (eight records had to be removed from the train-test sample due to unreadable abstracts). Papers on "school environment" or "school climate" were labelled non-relevant because they had no relation with climate change or global warming. For some papers the relevance was not immediately clear. These papers often mentioned education in the context of broader themes or broad policy recommendation such as strengthening education or improving capacity without education being a main theme of the paper. In these borderline cases, we decided to examine the full text of the paper. This extra step added a layer of confirmation to our decision to exclude or reconsider exclusion for those abstracts and titles that addressed or seemed to address climate change and education in a tangential manner. Papers were labelled and reviewed separately by different authors until agreement was reached on their inclusion or exclusion. The final proportion of papers labelled as relevant corresponded to about 40%. It is important to mention here that in line with the scope of the study being that of big literature mapping, we did not assess the quality/strength of the evidence as it is often done in a traditional systematic review. We did however follow and record each stage of our literature selections using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). The original PRISMA flow diagram has been adapted to reflect the combination of human and machine coding and can be found in Fig 1 and S1 File. The PRISMA checklist is given in S2 File.

Various supervised machine learning techniques were applied for the supervised task using the Scikit-Learn pipeline [50, 51]. The purpose of a pipeline is to streamline and automate the workflow of preprocessing data to apply machine learning algorithms. It allows to chain multiple steps together into a single, coherent process. A typical Scikit-Learn pipeline includes steps such as data preprocessing (e.g., scaling, dealing with missing values), feature extraction, and finally, the application of a machine learning algorithm. We first employ a selection of pipelines, where each pipeline performs the same set of concatenated steps but each pipeline has a different classifier [47]. In the first step, a count vectorizer transforms each document in a feature vector. Afterwards, term-frequency times inverse document frequency (TF-IDF)

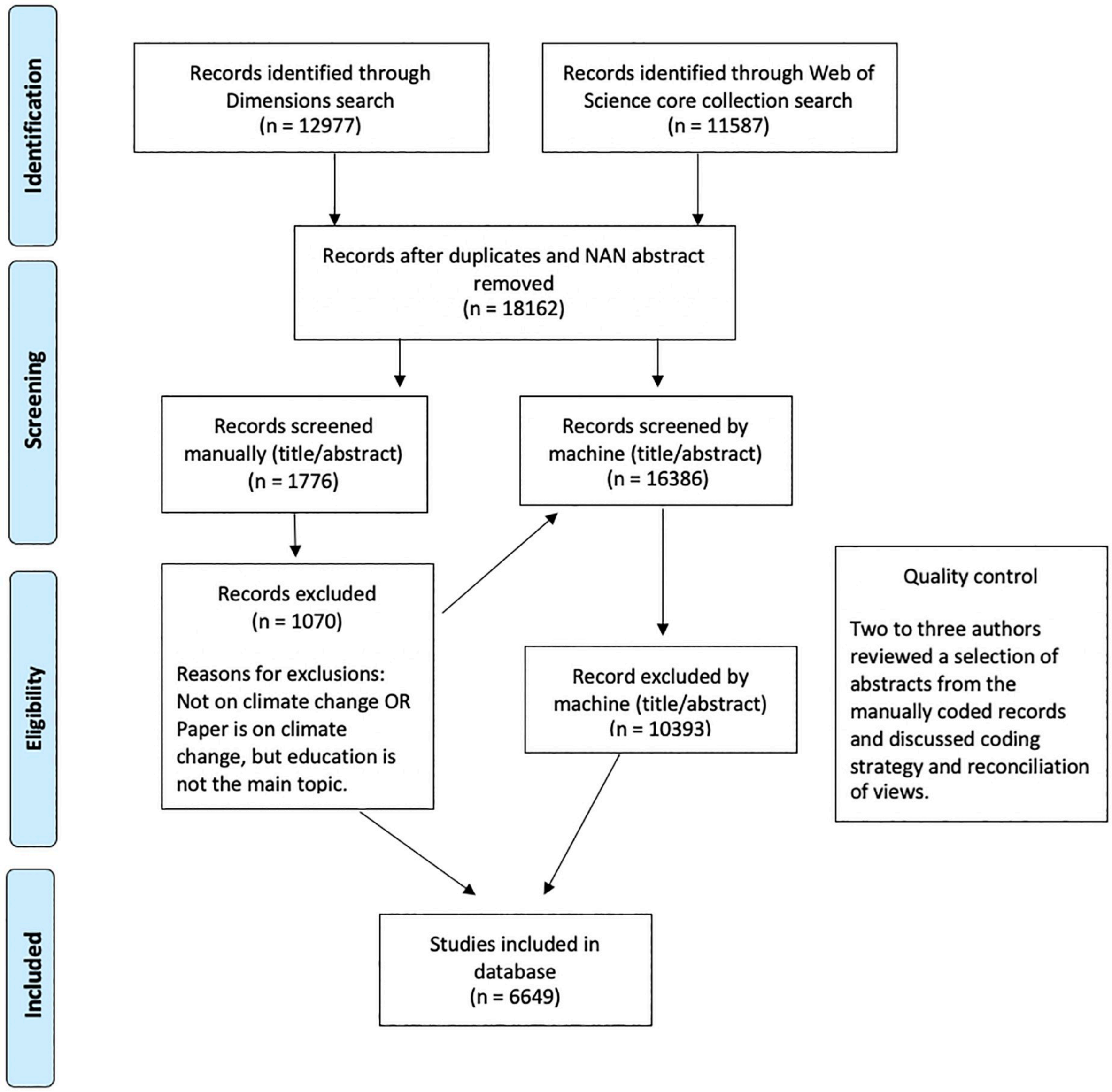

Fig 1. Adapted PRISMA flow diagram. The flow diagram has been adapted to show the combination of human and machine coding.

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transforms the document-feature matrix to scale down the impact of words (or tokens) which occur very frequently in a corpus but are not very informative. TF-IDF is a statistical approach for text mining and information retrieval from a large corpus of documents [52]. Term Frequency (TF) measures how frequently a term (word) appears in a document. It is calculated as the number of times a word appears in a document divided by the total number of words in the document. Inverse Document Frequency (IDF) measures how important or rare a word is across all documents in the corpus. It is calculated as the logarithm of the total number of documents in the corpus divided by the number of documents that contain the word. A classifier is then instantiated, the training data are fed through the pipeline, and finally predictions are made on the test set. Each classifier is trained on about 70% of the data and performance is tested on the remaining 30%.

Table 1. This table gives a summary of the performance of each classifer model expressed as precision, recall, F1-score and accuracy.

	Precision	Recall	F1-Score	Accuracy
Multinomial Naïve-Bayes	0.72	0.66	0.56	0.66
Linear Support Vector Classification	0.81	0.81	0.81	0.81
Random Forest	0.79	0.79	0.79	0.79
Multi-layer Perceptron Classifier	0.80	0.80	0.80	0.80
Nonlinear Support Vector Classification	0.80	0.81	0.80	0.80
Climate-GPT-2	0.80	0.81	0.80	0.85

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Further to this, a Generative Pre-Trained Transformer GPT-2 for climate change related topics (climate-GPT-2 models) is used for the supervised task [53]. The difference between the classifiers and the GPT-2 models lies in their foundational methodologies. Classifiers are based on traditional machine learning algorithms and require explicit feature engineering. In contrast, climate-GPT-2, a decoder transformer, uses the final token of the input sequence to predict the subsequent token. In climate-GPT-2 architecture the last token of the input sequence contains all the necessary information for prediction tasks. We utilized this information to make a prediction in a classification task rather than a generation task. In other words, instead of using the first token embedding to make a prediction as is normally done in encoder transformer models, we used the last token embedding to make a prediction (here in a classification task).

The performance of each model is assessed using a confusion matrix and classification report [54]. In a binary classification problem like the one here, the confusion matrix is a square matrix of the type $\begin{pmatrix} TN & FP \\ FN & TP \end{pmatrix}$ where TN = True Negative, TP = True Positive, FP = False Positive and FN = False Negative. The classification report provides the weighted averages for precision, recall, F1-Score and accuracy, where accuracy is the sum of the true predicted instances divided by the sum of all instances; precision represents the positive predictive value and is given by TP divided by the sum of TP and FP; recall represents the true positive rates and is given by TP divided by the sum of TP and FN. F1-Score is the harmonic mean of precision and recall. For a dataset like ours which is reasonably well balanced between positive and negative instances, accuracy is a good predictor of the model performance. The classification report is given in Table 1. Cross-validation with k-folds is also implemented. In this case, classification is performed on samples of different sets of data for testing and training each time (or for each fold) [50]. The k-fold increases performance of each classifier by a factor between 0.02–0.04. Climate-GPT-2 outperforms all other classifiers in terms of accuracy, whereas the other parameters are similar across all classifiers except Random Forest and Multinomial Naïve-Bayes. Therefore, we select Climate-GPT-2 to make predictions on the whole data corpus.

Data analysis

Our data analysis begins with a bibliographic examination to gain insights into the temporal distribution of publications, the scope of journals, and the citation patterns. In the subsequent stage, we leverage the spaCy library for abstract lemmatization. SpaCy is an open-source natural language processing (NLP) library designed for information extraction from extensive text corpora [55]. The lemmatized abstracts are then fed into the TF-IDF model for various purposes, such as enabling the visualization of words through word clouds. To map the scope of the literature we used topic modeling. Topic modeling is a type of unsupervised learning method for text mining based on Bayesian probability which extracts meaningful topics from short and long texts [56, 57]. It requires domain knowledge to make sense of the topic clustering and it has been successfully deployed for topic mapping of the climate change literature [37, 39, 44]. Topic modelling allows to cluster the distribution of words into representative topics [44]. There are different algorithms to implement topic modelling. Here we follow an approach implemented in [37] and use non-negative matrix factorisation (NMF) [56]. In a nutshell NMF takes the TF-IDF vectorized text matrix and breaks it down in a feature matrix which contains the topics and a weight matrix which contains the weights of those topics. Based on the feature matrix, each abstract is labelled to the topic with the highest weight [58]. To improve the reliability of the topic modelling results, we performed several experiments where we changed the number of topics, the ngram range in the TF-IDF instantiated model and the alpha parameters in the MNF. We used this combination to aim at a convergence between 1) the domain knowledge of the authors refined through an analysis of the abstracts in the human classification task and 2) the coherence score which measures the relative distance of words within a topic [59]. The coherence score algorithm predicted 15 as the best number of topics in our corpus using ngramrange = (1,2). The topic clustering happened to be relatively robust by changing the regularization parameters alpha_H and alpha_W although better results were achieved without regularisation where the parameters were set to 0. We conducted a thorough review of the topics that emerged from our topic modelling, aiming to identify and categorize significant thematic clusters. We validated the final fifteen clusters through meticulous reviews within our research team.

T-distributed Stochastic Neighbor Embedding (t-sne) is then employed as a dimensional reduction technique to visualize the topic scores in a two dimensional space [37, 60, 61]. t-SNE works by mapping high-dimensional data points to a lower-dimensional space in such a way that similar data points are modeled as nearby points, and dissimilar points are modeled as distant from each other. To distill the core ideas of numerous abstracts, making it easier to grasp the central themes and research directions within each topic, we performed text summarisation using gpt-4–1106-preview, an OpenAI Large Language model, integrated in the open source framework LangChain. The approach involves a multi-stage summarisation process following custom prompts. Clarity and iterative development of prompts is essential to achieve good results as outlined also in [62]. This technique allows to process large quantities of texts by initially summarising each small chunk and subsequently merging summaries into one cohesive summary [63]. To assess the accuracy and reliability of these summaries, we triangulate the machine-generated outputs with our domain expertise and insights from the manual classification tasks.

Finally, Geoparsing was used to collect information on where in the world the studies take place and how the topics are geographically distributed. Geoparsing is a technique that can determine the geolocation in unstructured text and has been used previously in the context of climate change impact attribution [39] and for climate health literature mapping [44]. We used the open source software Geotext to extract cities and country mentions from text [64].

We use Jupyter Notebook for our classification tasks and analysis. Our scripts are available on GitHub [46].

Results

After performing the supervised tasks and adding the records screened manually as relevant (706), a final dataset comprising a total of 6649 papers was retained for all remaining analyses. The split between relevant and irrelevant papers can be seen in S1 Fig. The dataset with the relevant papers contains the following bibliometric information: article title, abstract, list of authors, publication year, journal title, DOI and number of citations.

Bibliographic and semantic analysis

The literature on climate change education started to appear more markedly around the last decade of the 20th century and the number of publications has increased by two orders of magnitude in the past two decades (S2 Fig). The number of publications recorded in 2023 has a cutoff date on 31st July. Given the steady increase but relatively low number of publications before 2008, it was decided to focus the rest of the analysis only on papers published between 2008–2023 (Fig 2). This amounts to 6379 papers.

Word cloud visualisations are used to infer the 500 most frequent single words (monograms) (Fig 2, bottom left) and pairs of words (bigrams) (Fig 2, bottom right). Word clouds are graphical representations of word frequencies, with more frequent words appearing larger

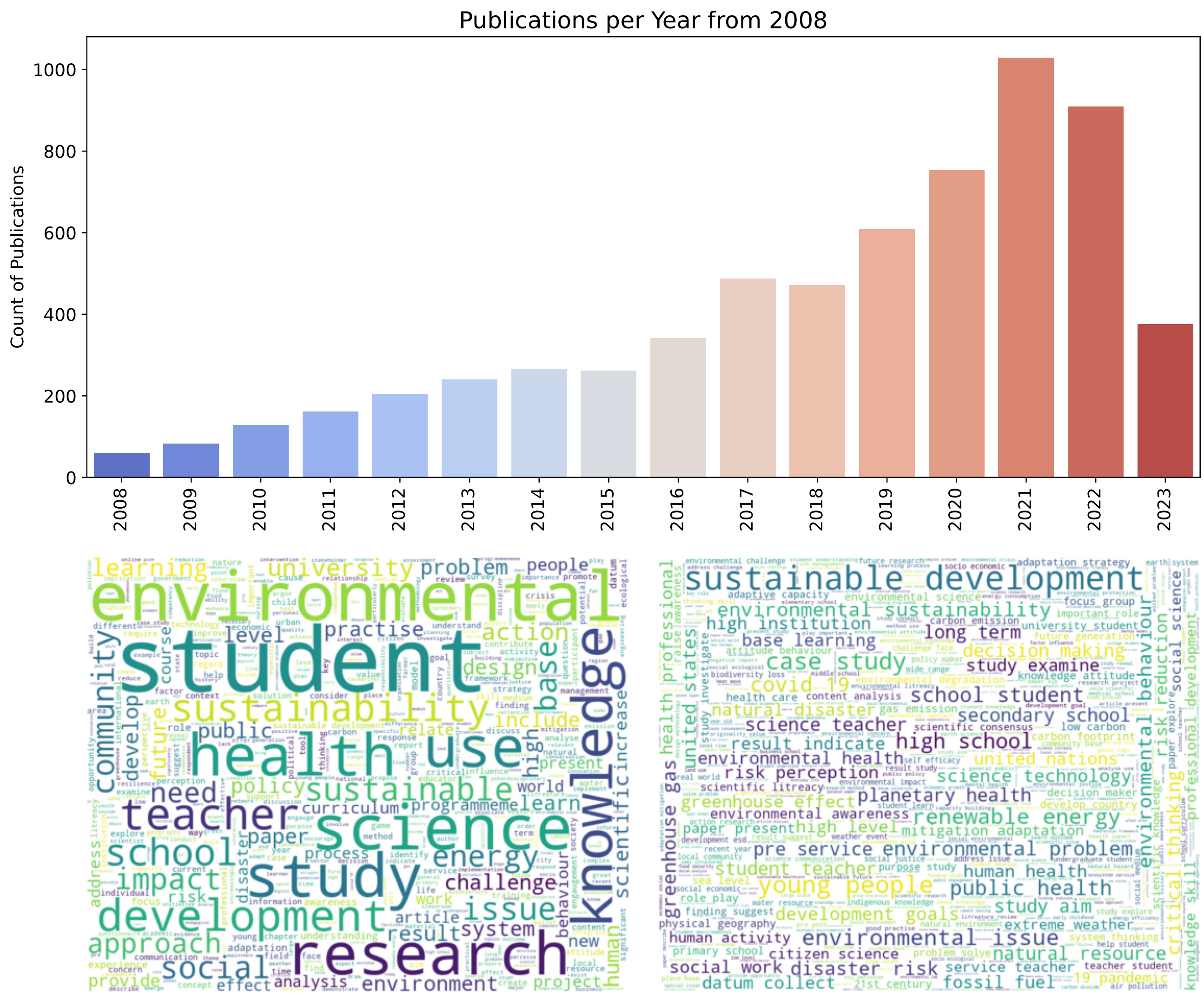

Fig 2. Publication per year and word frequencies. The top plots shows the number of publications per year for the period Jan 2008—July 2023. The bottom plot shows the word cloud of the first 500 most frequent words (left) and word pairs (left). The size of each word/word pairs indicates the relative weight from the whole corpus whose frequency is obtained from the TFIDF abstracts lemmatized using SpaCy.

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in the cloud. From the single words, *student* has the highest occurrence (the largest word shown), followed by *environmental*, *science*, *study* and *research*. Other words with high occurrence are also *health*, *knowledge*, *teacher*, *development*, *school* and *sustainability*. It is worth noting that although *school* has a reasonably high occurrence, *student* and *teacher* are higher (with *student* being by far the highest), *university* is less frequent, as opposed to *research* which scores very high. The word pairs cloud gives insight into key concepts. For example, the prevalence of *sustainable development* can be clearly seen, followed by *young people*, *case study*, *environmental issues*. The concept of COVID-19 frequently emerges in the literature examined within this study. In addition, we have calculated the word frequencies for two time slices, i.e. 1990–2010 and 2011–2023 to explore whether or not any major differences can be inferred. The results are available in the supplementary material (S3 and S4 Figs) and show good similarity across the word frequency for the two periods, albeit some terms in the first period such as *earth*, *scientific* or *model* seem to hinge upon a higher prevalence of papers on physical climate science and education.

In order to infer the influence that specific source titles have on the overall research domain we look at the number of publications per source title as well as the average number of citations (Fig 3). To assess who engages with this type of research, the top twenty journals per number of citations (top panel) and number of papers (bottom panel) are shown. In the climate focused research, high impact journals such as Climatic Change and Nature Climate Change score very high in number of citations, as does the topical journal Environmental Education Research. However, most of these climate focused titles score relatively low in number of publications (while the topical journal Environmental Education Research scores high). It also emerges that both proportion of publications and citations are very scattered with many titles representing less than 0.5% of the total citations.

Topics and clustering

A summary of the topics obtained via topic modeling, their associated 10 most important monograms and bigrams obtained from the lemmatized abstracts per topic is shown in Fig 4. We refer to each topic using word pairs that best capture the keywords. The topics are shown in descending order from top left to bottom right, according to Fig 5, which shows the proportion of papers per topic and topic trends over time. For the topic analysis, we initially defined a total of 15 topics (Topics 0–14), however for three clusters it was not possible to define a clear topic scope from the key words and therefore we classified these topic clusters as undefined (Topics 3, 8, 9; Topic 3 even included several German terms). These topics, in addition to Topic 2 (which had keywords related to physical geography), also had low overall counts of associated documents (with a total number less than 50 over the analysis period 2008–2023, see also Fig 5 for comparison). Given the relatively small size of these topic clusters, as well as Topics 3,8,9 being undefined, we did not consider Topics 2, 3, 8, 9 in subsequent analysis.

The proportion of the 11 different topics across our corpus of abstracts, summed over the analysis period, 2008—2023, is shown in Fig 5, top panel. Overall the most prevalent topics that make up more than 50% of the data corpus are Topics 10, 4, 5 and 0. The bottom panel of Fig 5 shows the evolution of the number of abstracts per topic over the analysis period. It can be seen that several topics experienced an exponential increase from approx. 2016. This is particularly the case for abstracts of the topics *Adaptation_Community* (light green), *Student_Learning* (brown) and *Sustainability_Sustainable* (dark green) (these topics also correspond to the top row in Fig 4).

In addition to identifying the keywords for each topic, we provide a text summary of the main themes in Fig 6.

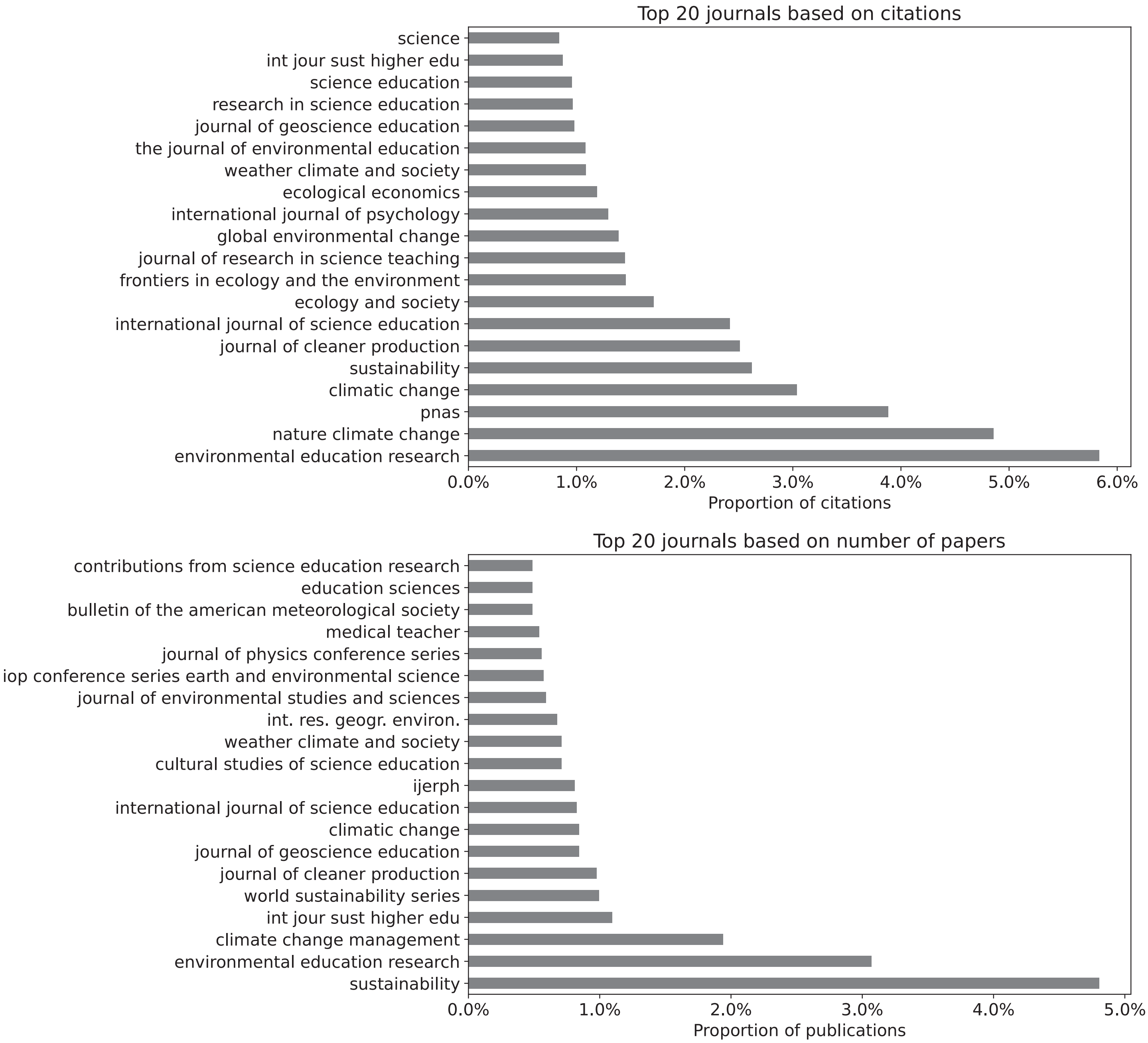

Fig 3. Proportion of publications and citations. Top 20 journals based on the number of citations per title (top) and number of papers per title (bottom). For the sake of clarity only the top 20 journals are shown.

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To understand the relationship between the topics, we visually render the topic clustering using t-SNE. This allowed us to explore the structure of our literature and to identify patterns in our complex dataset of abstracts. Fig 7 illustrates the topic clustering, with each colour representing a distinct topic and each dot representing an abstract. For instance, the cluster labeled *Science_Research* (blue) contains points that are grouped closely (also some grouped together as sub-clusters), with the proximity of the dots indicating more similarity in abstract

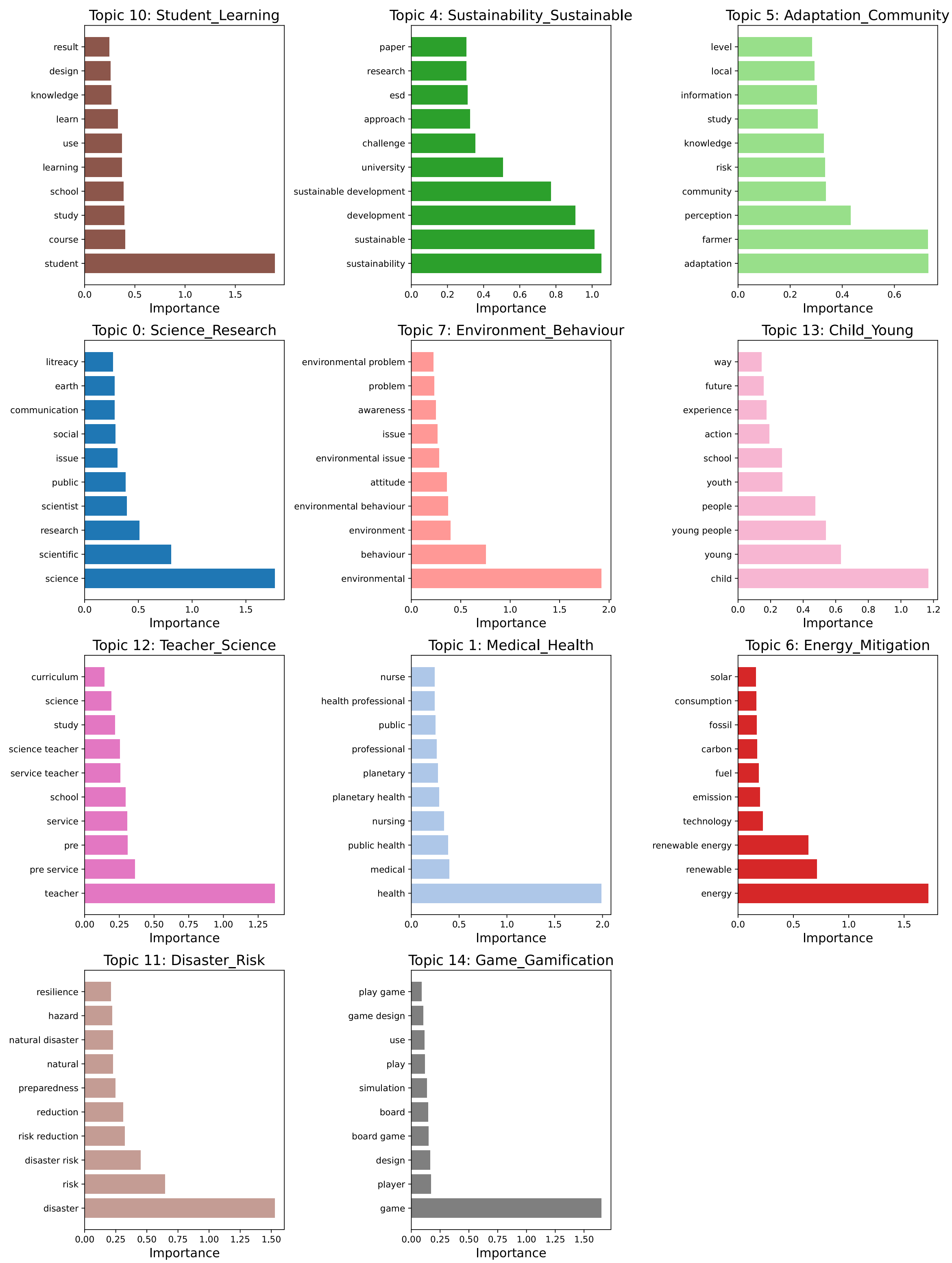

Fig 4. Proportion of words per topic. This figure shows the first 10 words associated with each topic based on their prevalence. The topics are shown in descending order from top left to bottom right, according to Fig 5, top.

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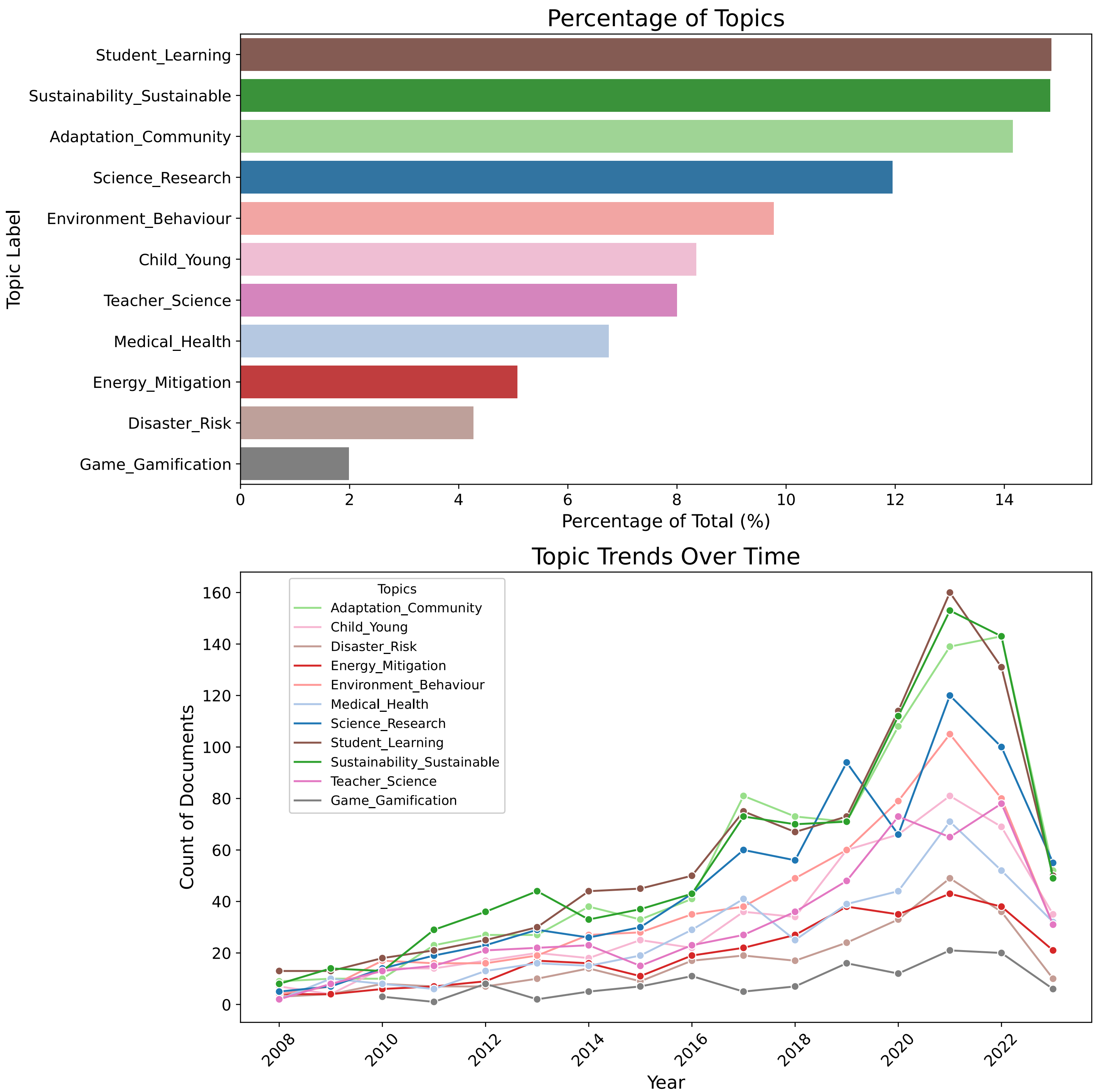

Fig 5. Proportion of papers per topic and topic trends over time. This top figure shows the results of applying "argmax" to determine the most likely topic assignment for a specific paper. The "argmax" operation determines the topic with the maximum probability within a given paper abstract. The bottom figure shows the number of documents over time per each topic between 2008 and mid-2023.

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content. Some clusters slightly overlap (especially for *Science_Research* which overlaps with several other topics in the center), or where clusters are located near each other, indicating that their abstracts share similar topic content. For example, *Adaptation_Community* (light green) and *Disaster_Risk* (light brown) are located near each other, suggesting overlap in themes

Topic Label	Topic Summary
Student_Learning	Key themes identified are the importance of integrating climate change education into curricula, the impact of innovative teaching methods on student understanding and engagement, the role of technology in enhancing learning outcomes, and the significance of fostering critical thinking skills, scientific literacy, and sustainable practices among students. Additionally, the discussions underscore the imperative for educational institutions to prioritize climate change education, sustainability, and social responsibility in preparing students to navigate a rapidly changing world and contribute to positive societal transformation. The findings emphasize the need for interdisciplinary approaches, hands-on learning experiences, and the integration of sustainability concepts into education to empower students to address complex environmental challenges such as climate change.
Sutainability_Sustainable	Key areas of focus include the imperative for transformative action in response to global challenges, particularly climate change, the critical role of education in promoting sustainable development and addressing societal issues, and the significance of interdisciplinary approaches in tackling complex problems. Furthermore, abstracts also include the integration of sustainability principles into various disciplines, the importance of ethical considerations and values in education, and the necessity for community engagement and activism for sustainable development. The abstracts underscore the interconnectedness of environmental, social, and economic dimensions in fostering a more sustainable and resilient future.
Adaptation_Community	Key areas include awareness in addressing climate change, the pivotal role of community participation in adaptation endeavors, the necessity for stakeholder collaboration and the significance of cultural heritage. Other themes are climate change impact on vulnerable populations and the need to integrate indigenous knowledge in fostering climate resilience. The abstracts underscore the challenges inherent in implementing climate change adaptation measures, the criticality of communication strategies in conveying risks and instigating behavioral change, and the integration of scientific knowledge into policy formulation and decision-making processes.
Science_Research	Key areas include the urgency of climate change mitigation, the importance of transformative education and critical thinking in driving collective impact and the role of education in promoting scientific literacy and sustainability. Additionally, the abstracts underscore the value of community-driven science, interdisciplinary research partnerships, and the integration of socio-cultural learning theory in educational interventions. Some abstracts emphasize the impact of societal attitudes, political ideologies, and media communication on climate change discourse, as well as the potential for innovative approaches in science communication and education.
Environment_Behaviour	Key areas include the imperative of promoting pro-environmental behaviors through education, the influence of individual values and attitudes on sustainable actions, the impact of societal factors on environmental consciousness. Additionally, the significance of engaging diverse stakeholders, including youth, educators, and communities, in fostering environmental stewardship and addressing pressing environmental concerns emerges as a central theme. The intersectionality of environmental, social, and economic factors underscores the complexity of environmental challenges and the necessity for holistic and inclusive approaches to environmental education and advocacy. Ultimately, the findings highlight the urgency of cultivating a culture of environmental literacy, ethical responsibility, and proactive engagement to advance sustainability and mitigate environmental degradation.
Child_Young	Key areas explore key themes related to climate change education, youth engagement, community development, and environmental awareness. The overarching themes that emerge include the urgent need to address climate change impacts on vulnerable populations, particularly children, and the importance of education in fostering awareness and action on climate change, and the role of young people as agents of change. Additionally, ethical considerations, critical thinking, and innovative pedagogical approaches are emphasized as essential components in promoting environmental stewardship and sustainability. The summaries underscore the interconnectedness of climate change, education, social activism, and environmental stewardship, advocating for holistic, transformative, and inclusive approaches to addressing the pressing challenges posed by climate change.
Teacher_Science	Key areas include the role of teachers in promoting literacy and the impact of teachers' beliefs on climate change instruction. The critical role of educators in fostering awareness, knowledge, and action on climate change and among students is highlighted alongside the need for ongoing support, training, and resources to effectively address these complex and pressing global issues in educational settings. The importance of integrating climate change into the curriculum and the challenges and opportunities in educating students about climate change are other aspects present in the abstracts. Other themes are the emphasis on critical thinking, evidence-based decision-making, and emotional responses in education, the multifaceted nature of addressing climate change and the various factors that influence teaching and learning in this critical area. The need for further research is also emphasised as a way to enhance teacher knowledge and practices in climate change education.
Medical_Health	Key areas identified include the recognition of climate change as a significant threat to human health, the importance of integrating climate change education into health professions curricula to address planetary health challenges. Additionally, the abstracts emphasize the impact of climate change on vulnerable populations and the need for adaptation and mitigation strategies as well as the importance of advocacy, leadership, and community partnerships in promoting sustainable healthcare practices. Furthermore, the summaries underscore the challenges in integrating climate change education into health professions curricula and the need for faculty development and resources to facilitate this integration. The importance of addressing social determinants of health, equity, and justice in climate change and health education is also highlighted.
Energy_Mitigation	The main themes are the importance of sustainable energy solutions, climate change mitigation, renewable energy technologies, public awareness and behavior towards environmental issues, stakeholder engagement, energy literacy, transition to low carbon energy sources, policy support, technological innovation and societal engagement. Other abstracts underscore the urgent need for promoting renewable energy literacy, fostering citizen participation in sustainable energy initiatives, integrating sustainability principles into education and policy-making efforts, addressing misconceptions about energy, enhancing energy education, and promoting sustainable practices in various sectors. The summaries also emphasize the role of universities in promoting sustainability, challenges and opportunities in energy education, and the need for global cooperation in addressing energy and climate issues.
Disaster_Risk	Themes include the importance of education and training in disaster management, the impact of natural disasters on vulnerable populations, the need for community involvement in disaster preparedness, the role of schools in disaster risk reduction, challenges posed by climate change on resilience efforts, integration of climate change adaptation into disaster risk reduction strategies, value of indigenous knowledge in risk mitigation, significance of early warning systems in disaster response, interdisciplinary approaches. The media's role in raising awareness is also present.
Game_Gamification	Key areas include the use of games and simulations for educational purposes together with the development and evaluation of serious games for sustainability and climate change engagement. Other themes encompass the pedagogical potential of games in promoting climate change awareness and sustainable behaviors, the integration of environmental concepts into education through gamification, the effectiveness of serious games in increasing knowledge and attitudes towards sustainability, the use of gamified decision support systems for urban planning and climate education, the impact of serious games on learning, social learning, and policy changes, the importance of realism, educational potential, and real-world relevance in digital entertainment games, as well as the application of gamification principles to motivate individuals towards engaging in sustainable practices and addressing real-world problems.

Fig 6. Condensed topic summaries. This figure shows the condensed topic summaries for the abstracts falling within a given topic category.

https://doi.org/10.1371/journal.pclm.0000356.g006

related to the adaptation community and disaster risk management (we can also see this in the overlap with the top 10 words from Fig 4, with the word "risk" high in importance for both topics). Conversely, distinct separation between clusters, such as *Medical_Health* (light blue) and *Game_Gamification* (grey) which are distant to the other clusters (and each other) indicates that these abstracts share little to no overlap in topics (except interestingly, a few other topics (blue, green, brown dots) which overlap at the edges of the *Medical_Health* cluster). The density of points within a cluster can give a rough indication of how extensive or prevalent a topic is within the dataset. Dense clusters like *Teacher_Science* (dark pink) suggest a significant number of documents within this topic have strong overlap, whereas sparser clusters might indicate that topics are more diluted as they overlap with others clusters. Some topics also have sub-clusters that are distant from the main cluster but closer or overlapping with other clusters, for e.g. *Energy_Mitigation* (red), indicating closer similarities across some sub-topics with other clusters. Overall, we can recognise a pattern that places education related abstracts on the left of the diagram and more climate related abstracts on the right of the diagram. There are of course exceptions as for example abstracts that put equal weight on both climate and education have scattered dots in each section of the diagram. The closer to the center of the diagram the less the topic prevalence is and we have abstracts that identify less with distinct

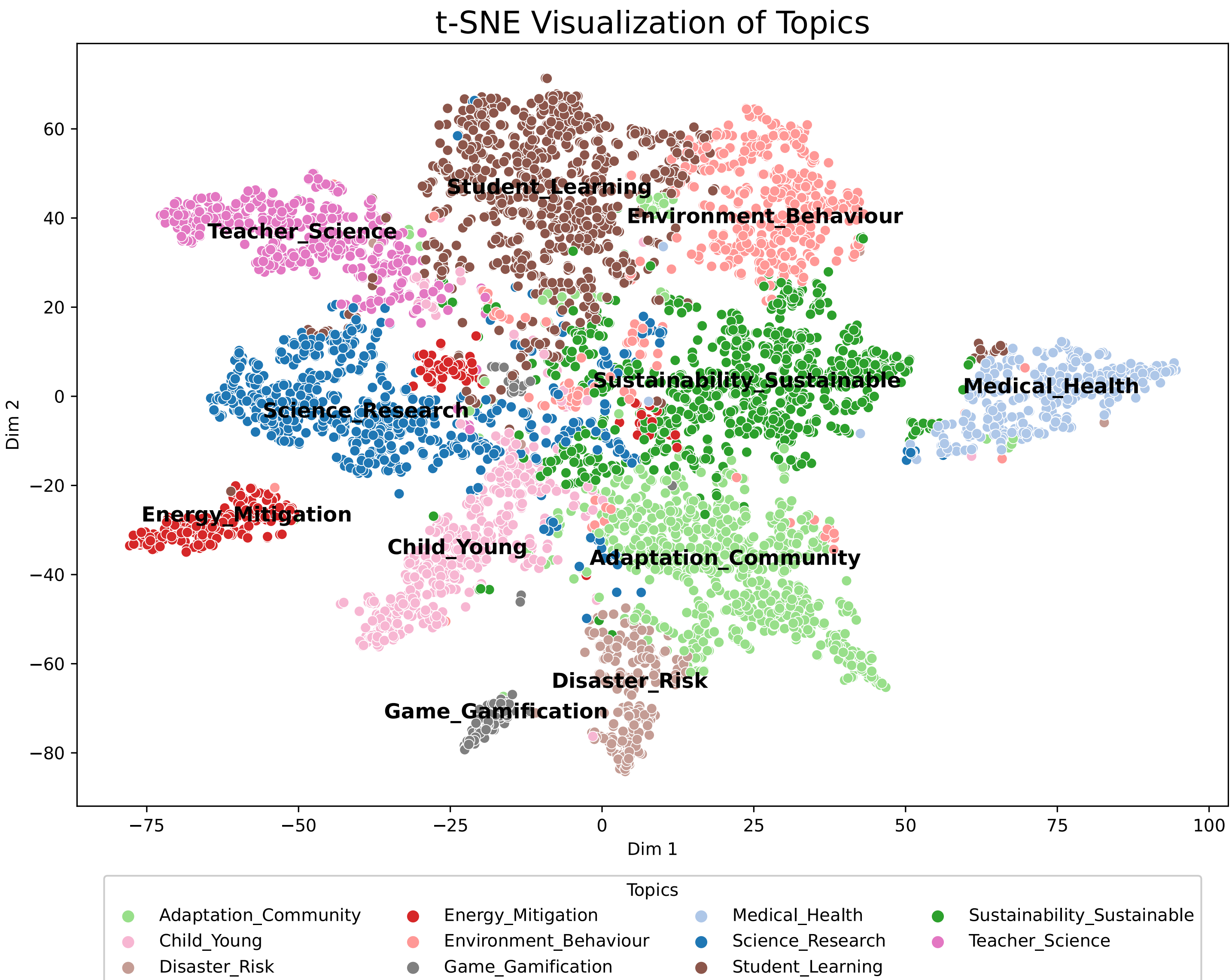

Fig 7. Topic clustering using t-sne. Each dot corresponds to a paper in a two dimensional space. The different colors depict the different topics.

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topics. Topic clusters including *Energy_Mitigation* (red), *Game_Gamification* (grey) and *Medical_Health* (light blue) follow a different pattern altogether being both quite distinct and far apart from the rest.

The heatmap in Fig 8 shows the correlation between two topics based on the NMF coefficients. Higher values (closer to 1) indicate that two topics are strongly positively correlated. For instance, *Student_Learning* and *Teacher_Science* have a stronger positive correlation (0.25), or as we've seen in the previous figures, *Disaster_Risk* and *Adaptation_Community* have a strong positive correlation (0.18) indicating that documents that are associated with adaptation also often address disaster risk concerns. This is also the case for *Child_Young* and *Game_Gamification* (0.14). Conversely, values closer to 0 indicate little to no correlation, while negative values (if applicable) suggest an inverse relationship. There are overall small positive (correlations) as well as small negative values (anti-correlation). For example, there is also

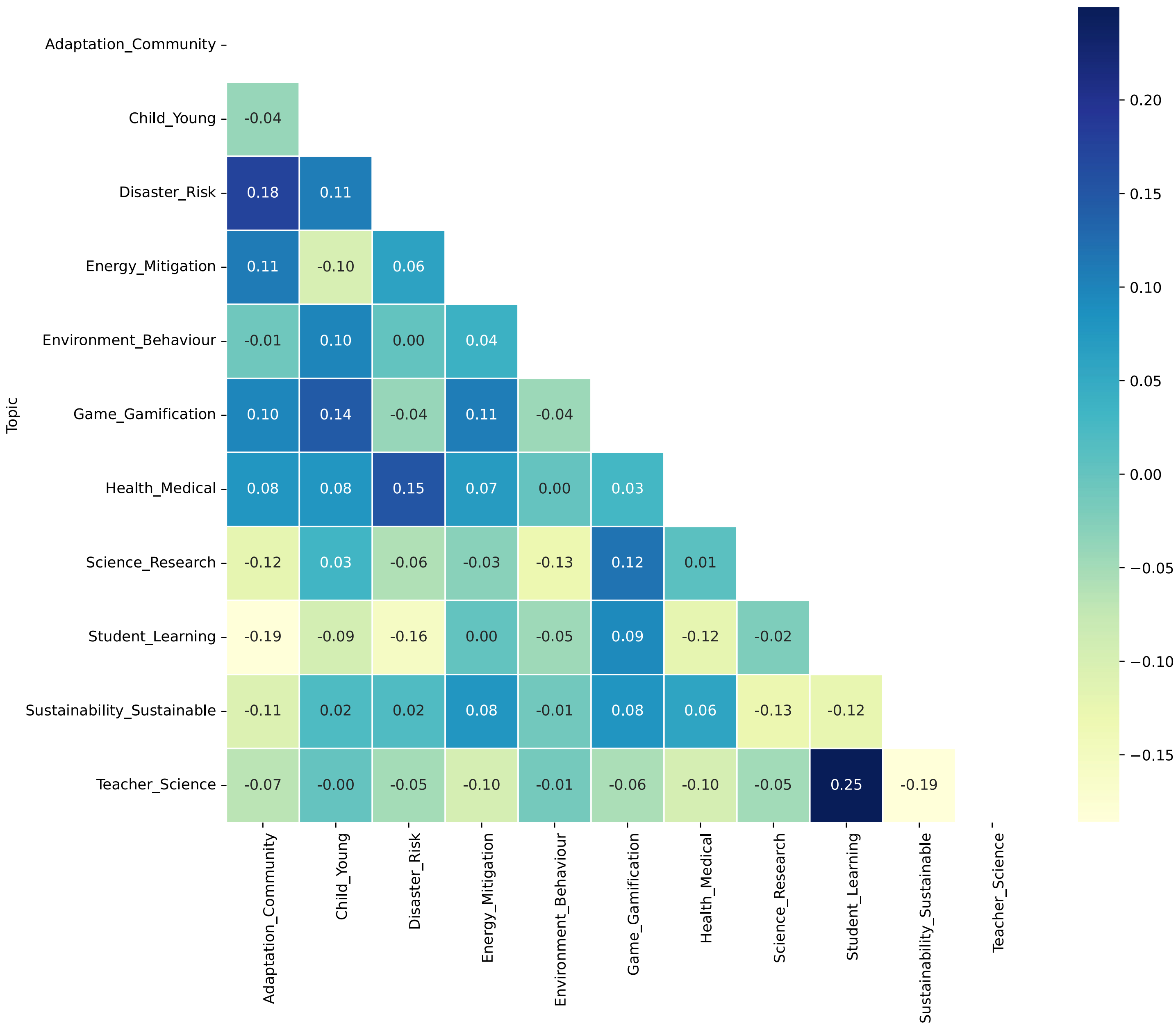

Fig 8. Topic correlation. The heat map shows the Spearman correlation amongst the ten different topics. The heatmap is generated using seaborn and the color and annotated number within each cell indicate the strength of the correlation [65].

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positive correlation between *Disaster_Risk* and *Health_Medical* (0.15). Those showing anticorrelation, albeit a weak one, are papers belonging to the cluster *Adaptation_Community* with those belonging to the clusters *Student_Learning*, *Science_Research* and *Sustainability_Sustainable*. *Sustainability_Sustainable* is also anticorrelated with *Student_Learning* (-0.12) and *Science_Research* papers (-0.13). This can be interpreted as a disconnect amongst the research on sustainability and ESD (education for sustainable development) which in this cluster seems to

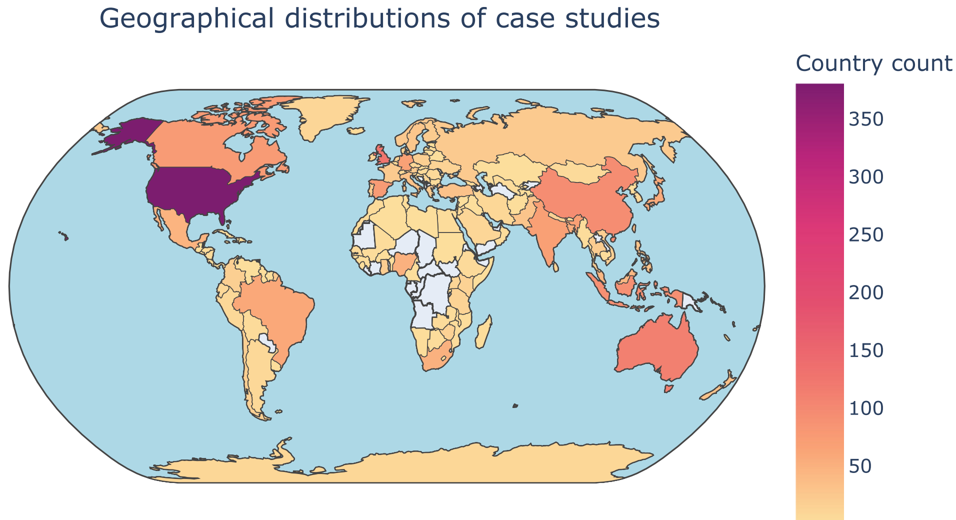

Fig 9. Geographical distribution of studies. The figure shows the geographical distributions of studies based on ISO country codes.

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be mainly applied to the university context and more general keywords of science (including social science) and research on climate change that are associated with *Science_Research*.

Geographic distribution of studies

To gain better insight into which countries were more actively involved in case studies or literature on climate change education (and which are lacking), we tagged country mentions in our analysis. Results are shown in Fig 9 and S5 Fig. Less than 40% of the abstracts however specifically mention countries and/or location. Among those abstracts that have explicit geolocations, the large majority are in the United States, followed by the United Kingdom and Australia (Fig 9 and S5 Fig). It is worth mentioning that the Geotext as setup here does not recognise political unions such as the European Union (or EU). Therefore, if the EU is mentioned with no mention of individual countries, it will not be tagged at the country level and is only identified at the continental level. Most of the countries and world regions are mentioned in at least one study, however there are noticeable gaps for African countries. The continental distribution (not shown, but can be inferred from Fig 9 and summing over the countries in each continent) indicates that Asia has the highest proportion of studies, with North America and Europe sharing a similar proportion, and South America having the least number of studies. It emerges that again Africa as a continent is poorly represented.

We also take a look at the association of countries with the major clusters of topics. For the sake of clarity we only show the countries that appear in more than 20 papers (Fig 10). The United States has the highest score for eight out of the eleven clusters. If we look beyond the United States, we can also see that Australia and United Kingdom are high for several topics including *Sustainability_Sustainable*, and *Child_Young* (also high for Germany), whereas *Energy_Mitigation* is moderately high for China. The *Adaptation_Community* cluster is high for many countries beyond the United States, including Bangladesh, Canada, China, Germany, Indonesia, Nigeria, South Africa, Australia and the UK. The clusters *Science_Research*, *Student_Learning*, *Sustainability_Sustainable* and *Adaptation_Community* are in general higher than average over most countries, and this is also reflected in the overall proportion of papers per topic (Fig 5).

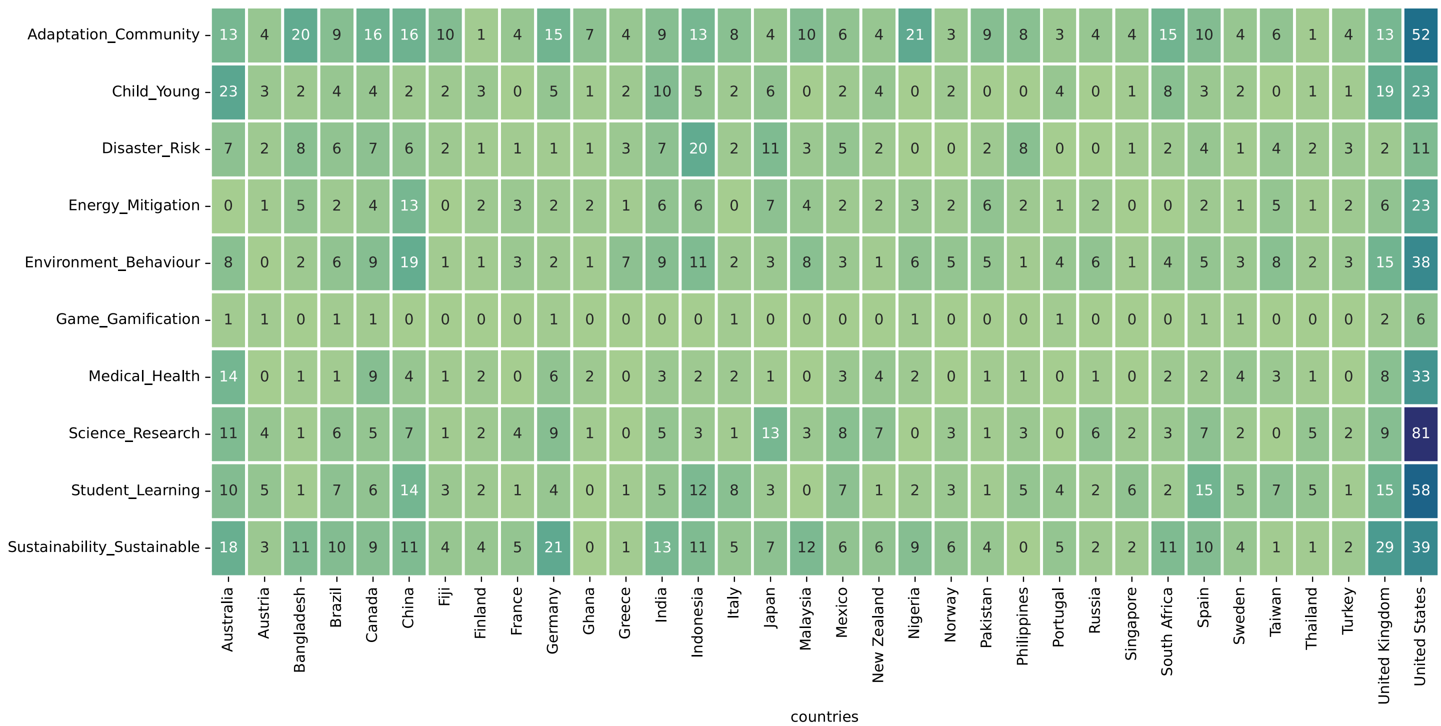

Fig 10. Association of countries and clusters. The figure shows the country counts per each of the more prevalent topics. The darker the color, the higher the number of papers.

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Discussion

Climate change research is rapidly expanding [66]. In response to the increasing output, research syntheses in the form of systematic mapping, reviews and/or meta-analyses have become increasingly popular [37–39, 66]. These studies have benefited from the fast advances in natural language processing (NLP), which make it possible to process and analyse large corpora at reasonable speed and accuracy [37, 67, 68]. Such advances have been essential to inform large assessment reports such as those from the IPCC [4].

Our research is situated within this growing trend of research syntheses that make use of natural language processing (NLP) to make sense of growing literature output [37, 38, 68]. It is driven by evidence indicating that strengthening climate change education and engagement is one of six social tipping dynamics crucial for driving disruptive change toward positive societal transformation [69]. Given the importance of climate change education and an absence of a systematic and broad assessment of the literature to date, we have performed here a mapping of the literature on climate change education. Our mapping exercise has illuminated the main directions (topics and clusters) on the research on climate change education, their prevalence, intersections and geographical distribution.

From our analysis it emerges that climate change education is well represented in main stream climate research ranging from climate change adaptation and mitigation to health science and sustainability. Looking closer at the semantic analyses, climate education is not exclusively associated with natural science terms or education terms, but other important terms including community, sustainable, young people, development and health (Fig 2). This diversity is also confirmed by the topic clustering (Figs 4 and 7). These findings align with Callaghan et al. [37], which analyzed over 400,000 climate change publications from the Web of Science, revealing a great diversity of topics. Similarly, another study examined approximately 130,000 international peer-reviewed climate change articles published between 1990 and 2021, and found a shift from traditional climate science to more interdisciplinary research on impacts and climate solutions [66] somewhat in line with our results in S3 and S4 Figs. From the temporal evolution of the topics in Fig 5 (bottom panel), 2016 represents a pivotal year in our analysis in the number of publications across most topics possibly due to crucial developments in climate policy and international cooperation with the signing of the Paris Agreement and the creation of frameworks such as UN Sendai Framework for Disaster Risk Reduction and Sustainable Development Goals [70].

Topic modelling and visualisations allowed us to draw some conclusions on the extent to which specific themes are unique as well as the presence of common themes shown by the proximity and overlap amongst clusters (Fig 7). These topics are again aligned with the interdisciplinarity reported by extant research [37, 66] and underscore a wide array of themes linked to sustainability, public health, communication, and climate solutions. However, some patterns are discernible in the relations across topics, as for example there are topics closely related to education (i.e. *Teacher_Science*, *Student_Learning* and *Science_Research*) and others where climate change and environmental sustainability are stronger themes (*Environment_Behaviour*, *Sustainability_Sustainable*, *Adaptation_Community*, *Disaster_Risk*). This duality in the research pattern can also be seen in the bibliometric analysis with papers distributed amongst climate and education titles, shown in Fig 3. Notwithstanding, there are several abstracts that span several topics (indicated by the central dots in Fig 7). Meaningful topic proximity is found between *Science_Research* and a sub-cluster of *Student_Learning* given that both have keywords resonating with the scientific, research and tertiary education enterprise. However, there are also some themes that emerge from each cluster which are more distinct.

To have a more conceptual and nuanced understanding of each topic, we have used topic summarisation (Fig 6) which complement the semantic analysis in Figs 4, 5, 7 and 8. From these summaries, it is possible to infer that abstracts in cluster *Science_Research* provide a broader perspective on the role of education in promoting environmental literacy beyond the classroom, involving societal and policy dimensions. In contrast, abstracts of *Student_Leaning* are more centered on the practical aspects of education, focusing on innovative teaching methods, the role of technology in enhancing learning, and hands-on learning experiences. Environmental and behavioural topics have some proximity to both *Sustainability_Sustainable* and *Student_Learning*. This proximity hinges on the centrality of education in shaping both environmental behaviours and education for sustainable development [71, 72]. Two unexpected, separated clusters are *Medical_Health*, including terms climate health and education related terms and that of *Disaster_Risk* in Fig 7. It can be inferred from the key words that *Medical_Health* is mainly about climate change literacy, nursing, medical schools and curricula. However, there is a correlation for certain themes as it can be seen in the heatmap (Fig 8). This could be the reasons why certain papers of *Disaster_Risk* overlap with the main cluster of *Medical_Health* (Fig 7), which is also discernible from the summaries, i.e. *Medical_Health* topics are also concerned with themes of vulnerability and resilient health systems. In general, the evidence of harm to health from climate related disasters remains scattered and often focused on weather related displacement, whereas the large majority of health literature is mostly concentrated on heat health impacts and vector-borne diseases [73]. Moreover, several key themes emerge that are crucial for understanding advancements in research, particularly the role of children as both agents of change and those most affected by climate change. Firstly, the temporal evolution of the topic *Child_Young* in Fig 5 confirms that this body of literature has gained traction since 2018, which most probably coincides with the publication of the IPCC special report on 1.5˚C [33] which was pivotal in inspiring the climate movement [74, 75]. Secondly, summaries for the topic on young people and children reveal the need to make climate change education more relevant and applicable to young people, while also using it as a tool to prepare them for future challenges.

Although a lot has been published on climate change education, and over many different domains, as it can be inferred from Figs 2 and 5, climate change education still remains a niche when it comes to promoting new educational policies which address the climate crisis [76–78]. This is even more compelling given that community participation, youth engagement, and societal attitudes in driving climate action and promoting sustainability are obvious themes in our corpus of abstracts in Fig 6 and hence in the literature [30]. Community-driven initiatives and the influence of political ideologies and media communication are other crucial areas of focus (see Fig 6). To enhance the effectiveness of climate change education, research suggests incorporating policy literacy to educate climate-literate citizens capable of engaging in public-sphere actions [79]. This shift in focus would better align climate change education with current research discourse and potentially lead to more impactful outcomes [20].

An important caveat to this study is that a lot of the primary literature or material on climate change education may be classified as other literature types (governmental reports, white papers, curriculum documents, and the like) rather than as peer reviewed publications or books [80], as we've addressed here. This is naturally due to the nature of climate change education and how this is written about or documented, and dominated by each country's own language (it is obviously more useful for teachers, lecturers and educators to have curriculum documents in their own language). The number of publications is also likely strongly related to the amount of governmental funding for academics in any given country (as well as the number of academics working on these topics), where countries that allocate more spending on these topics will rank higher in number of publications, and will likely also have research focused on case studies or other methods. For example the US, particularly NSF funding which tops the list when we look at the top funding agencies and grant amounts for our publication dataset (S1 Table) and that has a particularly high output of papers associated with the topic *Science_Research* (Fig 10). However, whether this increased research investment, output and country focused evidence have led to increased climate action to mitigate climate change is difficult to infer. There is certainly evidence of individually or locally motivated actions [81, 82], but a detailed look at the Emission Gap report for the US and the UK concluded that they are unlikely to meet many of their nationally determined contributions (NDC) targets [83]. For the rich climate education research exposed here to have a stronger resonance at national and global level, it is essential for influential assessment reports, such as those produced by the IPCC, to assess the critical role of climate education in both adaptation and mitigation action, since these reports feed directly into policy making process by informing on policy relevant science [84]. The inclusion of a dedicated chapter, sub-chapter, or cross-chapter box on climate literacy would be timely and beneficial as work on the 7th assessment cycle commences.

There are some limitations in the approach used here. First, the mapping of the literature did not allow to more deeply explore some themes that emerged in the analysis, for example why certain countries are more prevalent than others or why certain topics are closer to each other. Secondly, the classification algorithm, although it performs very well, still miss-classifies a small percentage of the papers. This is a recurrent limitation when doing reviews in big data fashion, and a topic that has already been highlighted in previous research [37–39]. In the context of extracting semantic information from the body of scientific literature, it is worth mentioning that topic modeling does not generate one-hot encodings. This means that although we assign each paper to its most prominently activated topic, papers could, in reality, be represented as amalgamations of multiple topics. With that being said, topic modeling remains a valuable tool for the purpose of content classification, relying on the inherent semantic structure uncovered within the corpus. By leveraging the probabilistic distribution of topics within documents, it enabled us to discern underlying themes and categorize content according to their predominant topical associations. This method provides a nuanced and data-driven approach to organizing and classifying diverse textual information, enhancing our ability to identify patterns and uncover themes and their potential association from a large corpus.

In order to better assess our progress or impact on climate education on real action or policy outcomes, further studies would need to broaden the data scope used here. This could include other relevant literature, in addition to only research papers (as mentioned above), as well as other relevant datasets to better assess more specific questions related to climate change education outcomes. For example, a recent study [85] highlights global data availability (and gaps) that are needed to properly monitor our progress towards the Sustainable Development Goals (SDGs), including goals on *Climate Action* and *Education*. Using the SDG Monitor tool [86], we see that these goals, in terms of data availability for the period 2010—2023 for 193 UN Member States, reveal *Climate Action* to be ranked 16 (out of 17 goals, i.e., second to last) and *Education* ranked 12 (with *Energy* and *Health* ranked first and second, respectively). A mapping of the country level availability however reveals that developing countries tend to have higher data availability for the *Climate Action* and *Education* goals. This highlights data gaps and availability elsewhere, in addition to the research literature scope used here, which could complement further analysis, allowing more specific research questions and outcomes to be addressed.

In terms of methodology, the integration of machine learning and AI supported screening methods in the analysis of the rapidly expanding body of literature on climate change and education can significantly enhance research efficiency and resource allocation. As noted by van de Schoot et al. [87], these AI methodologies streamline the literature review process, allowing researchers to focus on synthesizing findings rather than spending excessive time on manual screening [88]. This capability is particularly crucial given the increasing volume of publications, where timely access to relevant studies can inform policy and educational practices. Moreover, the development of "living evidence synthesis platforms," as discussed by Sietsma et al. [89] would facilitate the continuous incorporation of newly published research into existing assessments. To this end, our database of abstracts, semantics and topic classification can serve as valuable resources for researchers and practitioners interested in climate education evidence synthesis. However, the use of AI in this context needs to be carefully evaluated since large language models carry the risk of providing outdated and misleading information. To this end, expert knowledge combined with machine capability, as we have proposed in this study, is essential to ensure reliable results [90].

Conclusions

This research provides a global mapping of climate change education literature which combines supervised and unsupervised machine learning methods assisted by human coding of the abstracts. We manually annotated 1776 papers from a corpus of over 18'000 papers obtained from the Dimensions and Web of Science database. Using supervised learning we selected more than 6000 relevant records spanning the past fifteen years, which we then analysed using text mining techniques such as semantic analysis, topic modeling, text summarisation and geoparsing [37–39, 44]. Our study reveals that climate change education is an interdisciplinary field of research embedded in key climate research topics such as climate change adaptation, disaster risks and education, mitigation and sustainability. In summary, we find that the bulk of the literature falls within three main topics that deal with 1) student and learning methods, 2) sustainability and learning/teaching for sustainable development, and 3) the pivotal role of education in adaptation and resilience. Furthermore other themes which are also important include promoting environmental conscious behaviours through education, the importance of transformative education and critical thinking in driving collective impact, youth engagement and the role of children/young people as agents of change. The role of teacher in promoting literacy and awareness is also highlighted. Topics which are also present are relatively smaller are the importance of education and training in disaster management and for climate change mitigation and gamification as vehicles to increase knowledge and awareness. The geographical distributions shows that English speaking countries produce the largest share of the research literature when it comes to case studies or country mentions. This could be an interesting topic to investigate further in order to guide policy, by looking more closely at the share of research funds for climate change education across the globe as well addressing data deficiencies to complement understanding of climate education outcomes.

Based on our results, we call for a key role for climate education as a crucial lever for climate action through its potential to enhancing knowledge, fostering engagement and promoting resilience. We anticipate that the research performed here will not only inspire the broader research community, as evidenced by previous works on big literature [91, 92], but will also lead to recognising the importance of incorporating climate education into synthesis and assessment research relevant to policy making. Last but not least, innovative educational practices across various levels of society should be made essential for cultivating a proactive and informed society capable of addressing the pressing challenges posed by climate change.

Supporting information

S1 File. PRISMA workflow adapted. The file shows the adapted PRISMA workflow that was used for mapping the literature on climate education.
(DOCX)

S2 File. PRISMA ScR checklist. The file shows the PRISMA checklist according to [93].
(DOC)

S1 Fig. Paper split. The barplot shows the split between relevant and irrelevant papers from the total collection of papers.
(EPS)

S2 Fig. Publications per year 1966–2023. Publications per year for the entire period from 1966—2023 (July 2023).
(EPS)

S3 Fig. Word frequency bar plots for two time slices. Left panel shows a bar plot of the frequency of the first most frequent 100 words and word pairs between 1990–2010. Right panel shows a bar plot of the frequency of the first 100 words/word pairs between 2011–2023.
(EPS)

S4 Fig. Word frequency word clouds for two time slices. Left panel shows a word cloud of the frequency of the first most frequent 500 words and word pairs between 1990–2010. Right panel shows a word cloud of the frequency of the first 500 words/word pairs between 2011–2023.
(EPS)

S5 Fig. Proportion of countries tagged in the abstracts. The figure shows the proportion of papers mentioning a given country out of the total of the papers mentioning any country. The

total of the paper mentioning a country or more in its abstract is 2261.
(EPS)

S1 Table. The top funding agencies per country and grant amounts. The table shows the top funding agencies per country with the total number of grants, and aggregated funding amount for our publication dataset obtained with our search from the Dimensions API 2. Only funding amounts over 10 Million are shown (for the top 40 organizations).
(TIFF)

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