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People-centric Emission Reduction in Buildings: A Data-driven and Network Topology-based Investigation

EPRG Working Paper 2203

Cambridge Working Paper in Economics CWPE 2202

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Keywords Emission; climate change; building; computational social science; people-centric transition; Twitter.

JEL Classification C63, Q54.

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Publication January, 2022

Financial Support Laudes Foundation, Keynes Fund (JHVH), Bill & Melinda Gates Foundation (OPP1144), UK Space Agency (NSIP), Resnick Sustainability Institute, Caltech.

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December 30, 2021

Abstract

There is a growing consensus among policymakers that we need a human-centric low-carbon transition. There are few studies on how to do it effectively, especially in the context of emissions reduction in the building sector. It is critical to investigate public sentiment and attitudes towards this aspect of climate action, as the building and construction sector accounts for 40% of global carbon emissions. Our methodology involves a multi-method approach, using a data-driven exploration of public sentiment using 256,717 tweets containing #emission and #building between 2009 - 2021. Using graph theory-led metrics, a network topology-based investigation of hashtag co-occurrences was used to extract highly influential hashtags. Our results show that public sentiment is reactive to global climate policy events. Between 2009-2012, #greenbuilding, #emissions were highly influential, shaping the public discourse towards climate action. In 2013-2016, #lowcarbon, #construction and #energyefficiency had high centrality scores, which were replaced by hashtags like #climatetec, #netzero, #climateaction, #circulareconomy, and #masstimber, #climatejustice in 2017-2021. Results suggest that the current building emission reduction context emphasises the social and environmental justice dimensions, which is pivotal to an effective people-centric policymaking.

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*We are grateful for support from the Laudes Foundation to RD, DUS and MHR, the Bill and Melinda Gates Foundation [OPP1144] to RD, Cambridge Judge Business School Small Grant (2020-21) to KM, the Keynes Fund (2021-22) to KM, RB and RD, and the UK Space Agency NSIP Award (2021-22) to RB. RMA's work is supported by Caltech's Resnick Sustainability Institute. We would also like to acknowledge Twitter for providing access to their APIs. All correspondence should be addressed to Ramit Debnath (rd545@cam.ac.uk).

1. Introduction

The Intergovernmental Panel on Climate Change suggests that restricting climate change to 1.5°C requires rapid and extensive changes around energy use, building design and broader planning of cities and infrastructure (1). The buildings and construction sector currently accounts for almost 40% of global energy and process-related carbon emissions (2,3). The International Energy Agency estimates that to achieve a net-zero carbon building stock by 2050, direct building carbon emissions must decrease by 50%, and indirect building sector emissions must cut electricity generation emissions by 60% by 2030 (4). The building sector emissions would need to fall by around 6% per year from 2020 to 2030 to achieve this target (3, p5). At the same time, the built environment must also be resilient to climate extremes. For example, globally, by 2050, over 970 cities could be subjected to extreme heat, more than 500 cities would suffer from water scarcity, and over 570 cities could be impacted by sea-level rise (5).

The United Nations Framework Convention on Climate Change in their *Climate Action Pathway 2020* states that *'action and collaboration are needed immediately from all stakeholders to achieve the paradigm shift to a net-zero and resilient built environment. If action is not taken today, we risk locking emissions and vulnerability into our buildings and infrastructure that will become increasingly costly to mitigate in the future'* (2). A growing body of evidence from the stakeholder community emphasises the need to incorporate public voices in global climate action to enable an equitable and just transition (6–11). It calls for people-centric transition which focuses on how people want to shape climate action and what inspires and motivates them to do the climate action. However, enabling democratic participation of people in the decarbonisation process remains a critical challenge across the local, national and regional scales (12–14). It also remains a fundamental barrier to designing just emission reduction and future-proofing strategies in the built environment (15–17). In order to achieve the aggressive goals in emissions reduction, the mass public needs to understand these priorities and the need for investment in achieving these goals. Additionally, to ensure that the costs and benefits of the necessary investments are born equitably and justly across societies, policymakers and stakeholders much begin to incorporate the perspectives from all sectors of society in the conversation about emission reduction in the built environment.

In this paper, we evaluate three main questions, i) 'What are the characteristics of people-centric transition towards emission reduction in buildings?' ii) 'How has this discourse propagated in social media platforms over time? and iii) What are the leading indicators?'. To answer these questions, we employ a data-driven approach to explore the temporal characteristics this discourse from 2009 to November 2021 on Twitter, one of the largest social media platforms. In doing so, we evaluate how different global climate action events shaped the discussions around emission reduction and low-carbon transition of the built environment using hashtags co-occurrence networks. In the current literature, it is increasingly observed that Twitter hashtags are often used as attention mobilisers, virality tools, and instruments for publicising social issues (18). The choice of using a particular hashtag is influenced by two overlapping processes: attention-seeking behaviour by users, and contagion process driven by the virality of specific hashtags (18,19). Moreover, studies have also found that Twitter hashtags offer a strategic vantage point on social movements as it offers scalability through networked information dissemination (19). These characteristics of hashtags motivated this study to investigate how hashtag networks on emissions and buildings are shaped in the current people-centric climate action discourse.

The novelty of this paper lies in the computational social science-led grounded investigation of people-centric transition efforts towards a low-carbon building sector using Twitter interaction data over 13 years using a multi-method application of natural language processing (NLP) and network theory. To the best of our knowledge, this approach has not been employed before in the building emission reduction and low-carbon future-proofing strategy design context. The findings from this study will be helpful to a wide range of stakeholders who are exploring pathways for people-centric transition and the removal of technological, financial, and/or socio-political barriers to the implementation of future-proofing strategies in the net-zero planning context.

This article is divided into the following sections. Section 2 presents a state-of-the-art overview of people-centric emission reduction in the building sector, suggested strategies and policy efforts. Section 3 provide a detailed account of the multi-method approach of this study along with data collection, network topology extraction and the NLP workflows. The results and discussions are presented in section 4 and section 5, respectively. Finally, the conclusion and policy implications are drawn in section 6.

2. Literature review

2.1 People-centric climate action in the built environment

The emphasis on people-centric climate action in the built environment gained traction in the current call for global net-zero strategies post the United Nations COP-26 in November 2021. For example, a collaboration between the UN High-Level Climate Champions, the COP26 Presidency and the UK's Department for Business, Energy and Industrial Strategy (BEIS) and the #BuildingToCOP26 Coalition announced 26 built environment climate initiatives at the Cities, Regions and Built Environment Day at COP26 (20). It included over USD 1.2 trillion real estate assets under management as a part of net-zero carbon building commitment by the World Green Building Council (21). Also included were 1049 cities and local governments that have joined the Race to Zero through C40 Cities *Clean Construction Action Coalition* of cities and construction sector, representing roughly 722 million people and the commitment to reduce 1.4 gigatons of carbon dioxide equivalent ($GtCO_2e$) by 2030 (22). Climate actions also included building decarbonisation commitments by countries like the UK, Morocco, Mexico, France, Germany, Switzerland, Jordan, Chile, Kenya, Turkey, UAE, and Argentina, while 136 countries have included buildings in their Nationally Determined Contributions (NDCs) (20).

Similarly, the European Union and the White House have emphasised the need to create a democratised space for involving citizens in climate action at various levels of decision-making (8,9,11). This discourse dominates in post-COP-26 decarbonisation discussions across the public and private sector stakeholders (20). Nonetheless, a recent review on Global Climate Action by the United Nations Framework Convention on Climate Change (UNFCCC) found that in most countries, policies that regulate net-zero carbon solutions in the built environment are severely lacking even with NDCs (2). It further suggested the importance of the role of local government in engaging people in climate and planning policies to ensures that any new development provides high social value, embeds resilience and minimises whole-life carbon. At the same time, it prioritises reuse and refurbishment of existing assets (2). The UNFCCC also stated that at a civil society-led action scale, the individuals must be educated and sensitised on the carbon footprint associated with their operational and embodied emissions of buildings and its associated processes (2,23).

From the consumer's point of view, there is a need to understand what behaviours they can change to reduce operational emissions and what the associated financial and well-being co-benefits are if such behaviour changes are adopted at scale (2,24). The International Energy Agency further expanded on this message and emphasised that local governments are uniquely positioned to deliver on the net-zero emissions agenda through big data and digital technologies (25).

However, the strategies to enable people-centric transition in the built environment are anecdotal and not informed by data. Very little academic research is available on this intersectional domain of people and just net-zero transitions in buildings. Researchers have attempted to conceptualise a people-centric transition through the lens of climate justice. For example, the journal *Building & Cities* recently released a special issue on 'Climate justice and the built environment' (15) to explore people-centrism in just transition and how decisions about the built environment in the climate context intersect with human life well-being. It emphasised the need for governance and advocacy to create equitable pathways for providing healthy, low-carbon, climate-resilient outdoor and indoor environments for vulnerable population groups in a changing climate (16).

Studies also mention the current need for methodically mapping existing strategies for climate risk exposures and vulnerabilities by socio-demographic characteristics at local, national and regional levels (11,26–28). Similarly, an increasing consensus towards people-centric transition is on improving training and capacity-building across academic and professional programs involved in planning, designing and implementing built environment projects (2,15,29–32).

2.2 Methodological approaches in planning people-centric transition

As mentioned in Section 2.1, the literature on people-centric transition is scarce, and most of the current work is in the form of grey literature (like policy reports, white papers, blogs, etc). However, existing evidence shows that researchers are exploring the domain of people-centric transition using multi-method policy analysis approaches. People-centric policies for decarbonisation are evolving around the boundaries of psycho-socio-economic domains. For example, in a computational economic study, Bektas et al. (33) have developed an agent-based modelling approach to explore innovation in preference, emotional attitudes and innovation swaps in non-technological resource shift for decarbonisation of railways in Switzerland (33). Al-Chalabi et al. (34) used a social network approach to investigate intentional and unintentional spillover effects of individualistic behavioural change in decarbonising the UK's transportation system.

In a people-centric decarbonisation context, studies have shown that psycho-social determinant like habits and attitudes are strong determinants of individual behaviour (35). It mentioned habit-breaking mechanism that could help in reducing emission in the mobility sector (35). Kern and Rogge (36) further demonstrated that if political, social and psychological dimensions can support economic and technological innovations, the low-carbon transition can be achieved faster than expected. These studies approach the decarbonisation question of the built environment through the transportation and mobility sector and do not derive direct implications for emission reduction in buildings.

Researchers have recently demonstrated that contemporary approaches in complex systems, when combined with social practices theories can simultaneously capture the socio-techno-economic ontologies for people-centric decarbonisation (37). Combined complex system and social practice perspectives were found to offer critical insights on the internal coupling of processes in large service infrastructures that are increasingly disrupted by climate change (38). In a similar methodological approach, a garnering route of enquiry for public opinion on climate policy is through social media-led big data analysis using data from Twitter, Facebook, YouTube, Redditt and other social media platforms (39). A recent study explored tweets on the carbon emission trading system for multi-dimensional policy analysis in the European Union (EU) and demonstrated the importance of the public's cognition of climate policies (40). The study found that enabling public engagement (or people-centrism) in climate mitigation measures allows people to express their environmental interests, improves the transparency of policy governance and creates a space for the legitimacy of climate policies (40,41).

Twitter data was used by Kim et al. (42) to examine the public's emotional attitude towards nuclear energy as a low-carbon strategy. Sluban et al. (43) used hashtag networks to explore public emotional tendencies towards 'green energy', 'climate change' and 'carbon emissions' and concluded the need for more public opinion research to enable people-centric just transition. Tweets related to energy-related topics from the EU Sustainability Energy Week were used to map stakeholders' significant energy concerns and emotional tendencies towards these issues by (44). Veltri and Atanasova (45) explored the network topology of climate change tweets and news media articles for automated text classification according to psychological process categories. Recently, Twitter posts that mentioned climate change in the context of three high-magnitude extreme weather events – Hurricane Irene, Hurricane Sandy and Snowstorm Jonas were used by Roxburgh et al. (46) to derive discourses of climate denialism, criticism and polarising political ideologies. An unsolicited public opinion poll on climate change sentiments by Cody et al. (47) used Tweets between 2008 and 2014 to explore the public emotional response to natural disasters, climate bills and oil drillings. Similarly, Debnath et al. (48) have used Facebook posts to explore public perception of climate technology (in this case, electric vehicle) adoption across political, economic, social, technological, legal and environmental policy dimensions.

However, none of the above studies explore the sector dimensions of emission reduction in buildings and its association with climate action. This research gap provides a strong motivation for this study that contribute to the discussions around people-centric emission reduction in the building sector. In doing so, we use Twitter data to explore the network structures and sentiments of climate conversations around emission reduction in buildings which can shape the future-proofing strategies for a net-zero built environment.

3. Materials and methods

3.1 Data source

Digital social media platforms like Twitter have gained extensive public popularity among the users as an effective source of data on public opinion about environmental issues and climate policies as it enables a diverse range of user-generated contents (UGCs) (like texts, images, pictures, audio, video and live conversation) (39). Tweets offer certain advantages over traditional methods (including online and face-to-face surveys) for exploring public perception and attitudes (49). For example, Twitter users can independently publish and deliver UGCs of their choice. It adds depth to their opinions. Besides, the brief amount of information in a tweet allows users to navigate public interest towards a topic easily, determine their attitudes, and understand the broad narrative (50). Moreover, users can interact through conversational replies, retweets, and likes, showing the relationships and reflecting the social nature of information transmission (50). As a data platform, Twitter can gather real-time data on an extraordinary scale and dimension (i.e., time, location, user attributes) and echo public awareness and response to social and environmental policies, facilitating discussions and information propagation (51). Finally, Twitter slows academic researchers to collect and analyse data from their platform.

In this study, we use the Twitter Academic Research Product Track v2 Application Programming Interface (API) endpoints to collect historical tweets for a 13-years period. The v2 API endpoints offer an advantage over the standard v1.1 API endpoints by providing access to the entire archive of (as-yet-undeleted) tweets published on Twitter, a monthly cap of 10 million tweets and the ability to access data with more precise filters and query functions permitted by the v2 API (52,53). We used the R-programming language to build the query parameters for data collection using the academictwitteR v0.3.0 package (53). The tweets are downloaded as separate JSON files for a tweet- and user-level information separately on each query, as per the requirements of the package (53). These data packets are then bound into an R data.frame object or tribble for further analysis in the R environment.

As a search query, we used two specific hashtags (#) '#emission' and '#building' with the logical operator 'AND' to capture any available tweet in public Twitter domain during this 13-year timeframe, collecting only in English-language posts without any geographical restrictions. This produced a dataset of 256,717 tweets and retweets containing the above hashtags. We kept the search query as broad as possible to capture the largest bandwidth of public interactions with hashtags on emissions and building in the current climate change discourse. We specifically use hashtags as they are a critical communication device on Twitter and have become an essential part of Twitter-led data analysis (54). Users deploy hashtags to annotate the content they produce, allowing other users to discover their tweets and enable interaction on the platform (55–58). Also, adding a hashtag to a tweet corresponds to joining a network or community of users (Tweeters) discussing the same topic. Finally, hashtags are also used by Twitter to calculate trending topics, which encourages the users to post and engage in these communities (56). By tweeting a hashtag, users explicitly annotate their tweets for a specific network of Tweeters or communities (55,57).

We acknowledge that our Twitter dataset potentially embeds certain unintentional biases, for example, the Twitter user-demographics are typically not representative of many real-world demographic (59). For example, Twitter's user base consists of primarily young users; 38.5% of 211 million active users are in the age range of 25 – 34 as of April 2021 (60,61). In addition, we limit our search query to English language tweets which also adds a socio-demographic boundary. Similarly, another unintentional bias with the data collection is the embedded influence of malicious users artificially causing a topic or a hashtag to trend, or they can misrepresent already trending items (62). Bots are regularly deployed to make the specific account more prominent and create artificial trending topics (63). It also includes activities like crowdturfing and shills that generate fake news and misinformation (54). We follow the best practice guidelines in mitigating such biases as per the recommendations of (54,64,65). Therefore, basing the generalisability of our study with due acknowledgement to such biases.

In addition, the ethics clearance for this research was obtained through the Ethical Review Board at the Cambridge Judge Business School, University of Cambridge, UK, while Twitter was informed about this research during the v2 API request. We also followed the ethics protocols as per the guidelines of the Menlo Report on handling Twitter datasets (66).

3.2 Natural language processing of the Twitter data

The R data.frame constructed in section 3.1 was processed using a natural language processing (NLP) workflow using the tidyverse v1.3.1 (67), and tidytext v0.3.2 (68) packages in R. The workflow consisted of text pre-processing, feature extraction for n-grams and sentiment analysis. The pre-processing stage consisted of tokenisation, stemming and lemmatisation. In NLP, tokenisation refers to the process of breaking down the given text into smaller units in a sentence called token (69,70). Stemming in NLP is a morphological technique that breaks words into their root form (70,71). Lemmatisation is another normalisation technique used to reduce inflectional forms of words to a common base form (70). It is different from stemming as it uses lexical knowledge bases to get the correct base forms of words (70). At this NLP pre-processing stage, we removed the stopwords in the data.frame using the tm v0.7-8 package in R (72). Stopwords are the most common words in any language (like articles, prepositions, pronouns, conjunctions, etc) and do not add much information to the text. For example, common stopwords in English are "the", "a", "an", "so", "what" (70). This workflow extracted the cleaned base form of words from the 256,717 tweets and generated the document-term-matrix (dtm) needed for sentiment analysis.

Parallel to this pre-processing, we isolated individual hashtags from the tweet data corpus. The hashtags were extracted from each tweet using a feature extraction like data pipeline using the tidygramr v0.1.0 package (67) to prepare n-gram models. We extracted hashtag unigrams from each tweet (n = 13,743) and stored it as a separate dtm that included feature vectors of #ngram and the number of times it is repeated in an individual tweet (called 'freq'). Both '#ngram' and 'freq' were later used to create the hashtag network graphs (explained in detail in section 3.3). During this hashtag unigram feature selection process, we also ensured to exclude '#emission' and '#building' to reduce overrepresentation biases in the dtm.

We used the NRC Word-Emotion Association Lexicon (73) for the sentiment analysis of the tweets through the syuzhet v1.0.6 package (74). It consists of a list of English words and their connotations with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments (negative and positive); the list of corresponding words/terms to the specific sentiment and emotions can be found here: (73). The derived sentiment scores were then scaled between 0 and 1 (feature scaled) through a min-max normalisation function (see eq. 1) in R to visualise its strengths across the tweet time-series. In addition, the time-series of sentiments were represented through moving average decompositions of 6-months (see eq 2).

$$Normalised.values = \frac{Value - Minimum}{Maximum - Minimum} \qquad (1)$$

$$T_t = \frac{1}{m}\sum_{j=-k}^{k} y_t + j \qquad (2)$$

where, $m = 2k + 1$. the estimate of the trend-cycle at time t is obtained by averaging values of the time series within k periods of t. All of the code necessary to reproduce the pre-processing and analysis are available at (75).

3.3 Network topology and feature analysis

The NLP treatment of tweets extracted 13,743 unique Hashtags ngrams from the data corpus (see Section 3.2). In the following steps, we constructed hashtag co-occurrence networks across four distinct timescales, '2009 – 2012', '2013 – 2016', '2017 – 2020' and '2021', to analyse the use patterns of hashtags associated with the discourse about emissions in buildings. Co-occurrence networks are a graphical representation of how frequently variables appear together (76). In our hashtag co-occurrence network construction, we measure how frequently ('freq') two specific hashtags (#ngram) are presented in a single tweet. A node represents each hashtag in the co-occurrence network, and the co-occurrence between two nodes represents an edge, weighted by its frequency. We constructed undirected networks using the above nodes and edges description in Gephi 0.9.2 (77). The undirected network topologies were evaluated based on the following metrics, commonly used in social network analysis research (78),

Modularity measures the structure of a network or graphs. In network analysis, modularity is often used as a network property that measures the degree to which densely connected nodes within a network can be decoupled into separate communities, groups or clusters that interact more among themselves than other communities (79,80). Higher modularity implies better partitions (81). Modularity as a metric *Q* can be expressed as (see eq. 3) (82),

$$Q = \sum_i (e_{ii} - a_i^2) \tag{3}$$

where, e_{ii} is the fraction of edges in the network that connect vertices in partition *i* to those in partition *j*, and $a_{ij} = \sum_i e_{ij}$ (82).

Eigenvector centrality measures the influence of a node in a network, and also evaluates a node's importance while considering the importance of its neighbours (83). It is based on the principle that links from important nodes are valued more than links from trivial nodes. All nodes start equal; however, nodes with more edges start gaining importance as the computation progresses. Their importance propagates out to the nodes to which they are connected. Through iterative computing, the values stabilize, resulting in the final values for eigenvector centrality (84).

The *Clustering coefficient* is defined in graph theory as a measure of the degree to which nodes in a graph tend to cluster together (85). For an undirected graph, the global clustering coefficient *C* is estimated in terms of the adjacency matrix *A* (see eq. 4),

$$C = \frac{\sum_{i,j,k} A_{ij}A_{jk}A_{ki}}{\sum_i k_i(k_i - 1)} \tag{4}$$

where, $k_i = \sum_j A_{ij}$, is the number of neighbours of a vertex, *i* and *j* are vertices of the graph.

Degree centrality measures the number of edges connected to a node, which is a widely used centrality measure. It is expressed as an integer or count and assigns an importance score based simply on the number of edges held by each node. The nodes with a higher degree are central (84). Mathematically it is represented in eq. 5,

$$D(i) = \sum_j m(i,j) \tag{5}$$

where, *m(i,j)* = 1 if there is a link from node *i* to node *j*.

Graph density measures how many ties between parameters exist compared to how many ties between parameters are possible. The density of an undirected graph is presented in eq. 6,

$$UndirectedNetworkDensity = \frac{TotalEdges}{TotalPossibleEdges} = \frac{Cardinality}{Size} = \frac{m}{n(n-1)/2} \tag{6}$$

where, n is the number of nodes in the network.

The networks were optimised using the ForceAtlas2 (FA2) algorithm based on a force-directed layout that simulates a physical system to spatialise a network (86). Nodes repulse each other like charged particles, while edges attract their nodes, like magnets. These forces create a movement that converges to a balanced state with higher connected nodes placed centrally while nodes with lower connectivity are placed towards the network's periphery (86). This final (optimised) network configuration is expected to help interpret the data. The refinement of the network visualisation was performed by using the *linlog, gravity* and *overlapping prevention* layout settings in Gephi for the FA2 algorithm [A detailed mathematical background for FA2 is provided by Jacomy et al. (86)]. Additionally, further visual refinement of the networks was performed using functions like *Noverlap* and *labeladjust* layouts (77).

4. Results

4.1 Public sentiments on emission reduction in buildings

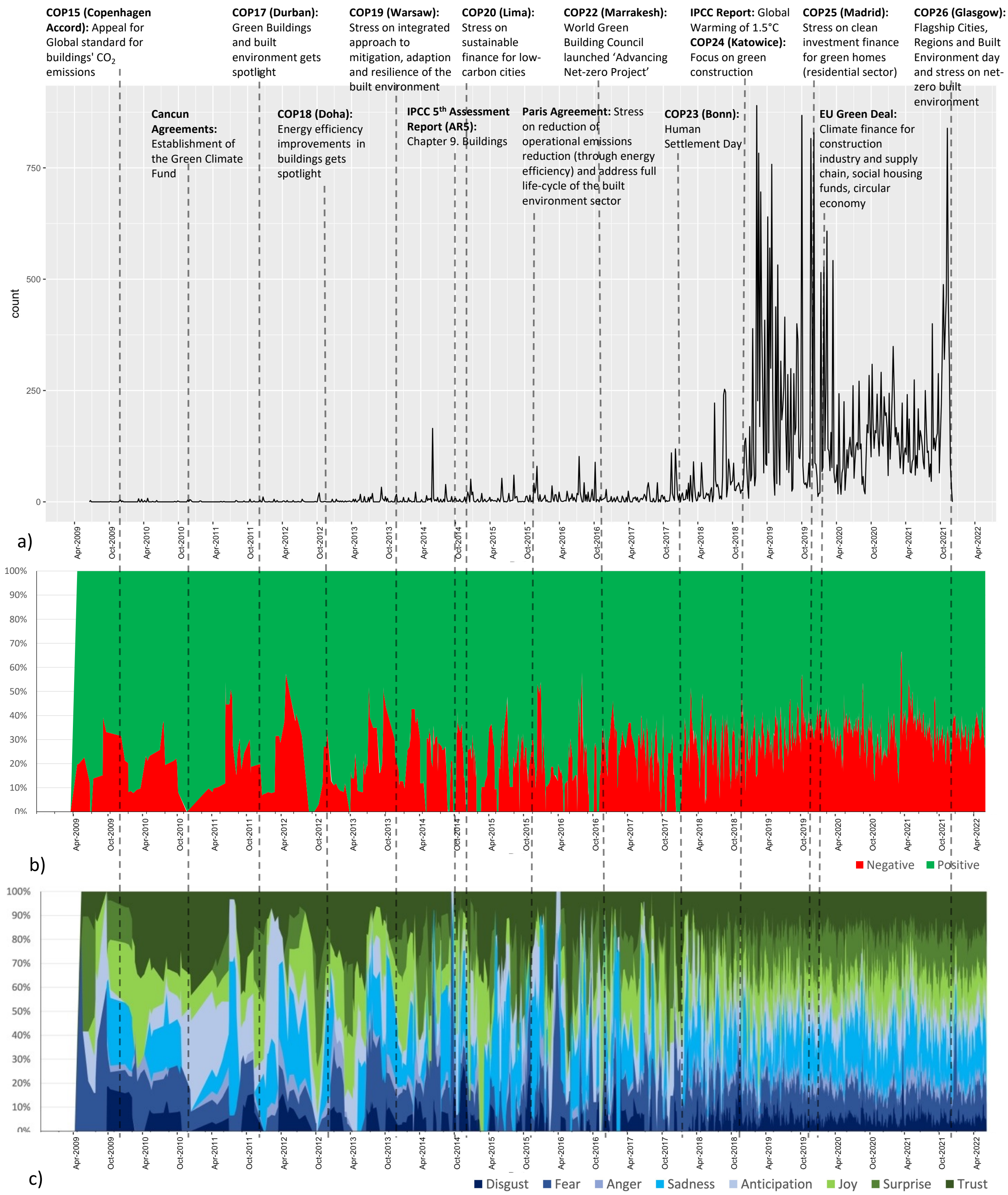


Fig 1. Time-series of twitter reactions with respect to major climate negotiations and policy events (2009 - 2021). (a) Twitter interactions (tweets, retweets, comments) with #emission and #building; (b) 6-month moving average estimates of tweet sentiments; (c) 6-month moving average estimates of tweet emotions from n = 256,717 tweets.

Results from the sentiment analysis of the tweets containing #emission and #building between 2009 and 2021 (n = 256,717) are shown in Fig 1. The tweets are traced as per major climate negotiations and policy events by the UNFCCC. For example, it can be seen from Fig 1a that Twitter volume on the above hashtags was significantly higher after the release of the United Nations Intergovernmental Panel on Climate Change (IPCC) Special Report titled 'Global Warming of 1.5 °Celsius' (87). However, the appeal for global standards for reducing building emissions began from the United Nations Conference of Parties (COP) – 15 in 2009. The establishment of the Green Climate Fund at the Cancun Agreement in 2010 further encouraged the green building sector to spotlight on discourse around built environment-centric emission reduction at COP17 in Durban (2011). However, until the COP – 18 in 2012, the focus was skewed towards the energy efficiency and operational emission reduction benefits from green buildings (see Fig 1a, also discussed in detail in the next section).

Similarly, in the 2013 – 2016 period, policy discourse on integrated approaches to climate change mitigation, adaptation and resilience of the built environment took the central stage with the release of the IPCC Fifth Assessment Report on Climate Change (AR5) with a dedicated chapter on forecasting and long-range planning of emissions reductions from the building sector (see (23) and Fig 1a). It led to discussions on the need for sustainable finance for low-carbon cities in COP-20 in 2014 (see Fig 1a). These shaped the Paris Agreement's key messages for the building sector: reducing operational emissions through energy efficiency and addressing the whole life cycle of the built environment sector (also mentioned in (88)). It essentially flagged wide-ranging policy discussions and stakeholder discourses on net-zero buildings and the built environment (see COP-22, Fig 1a).

COP-23 had a specific agenda called 'Human Settlement Day', which generated a relatively higher tweet volume on the selected hashtags (#emission and #building) (see Fig 1b). Furthermore, tweet volume was further exponentially increased with the launch of the IPCC Special Report on Global Warming of 1.5 °Celsius, as mentioned above. It stated the need to enable more profound emission reduction in the urban and infrastructure system through the following scenario:

"… The urban and infrastructure system transition consistent with limiting global warming to 1.5°C with no or limited overshoot would imply, for example, changes in land and urban planning practices, as well as deeper emissions reductions in transport and buildings compared to pathways that limit global warming below 2°C (medium confidence). Technical measures and practices enabling deep emissions reductions include various energy efficiency options. In pathways limiting global warming to 1.5°C with no or limited overshoot, the electricity share of energy demand in buildings would be about 55–75% in 2050 compared to 50–70% in 2050 for 2°C global warming (medium confidence).

… Economic, institutional and socio-cultural barriers may inhibit these urban and infrastructure system transitions, depending on national, regional and local circumstances, capabilities and the availability of capital (high confidence)…" (as stated in C.2.4. (89)).

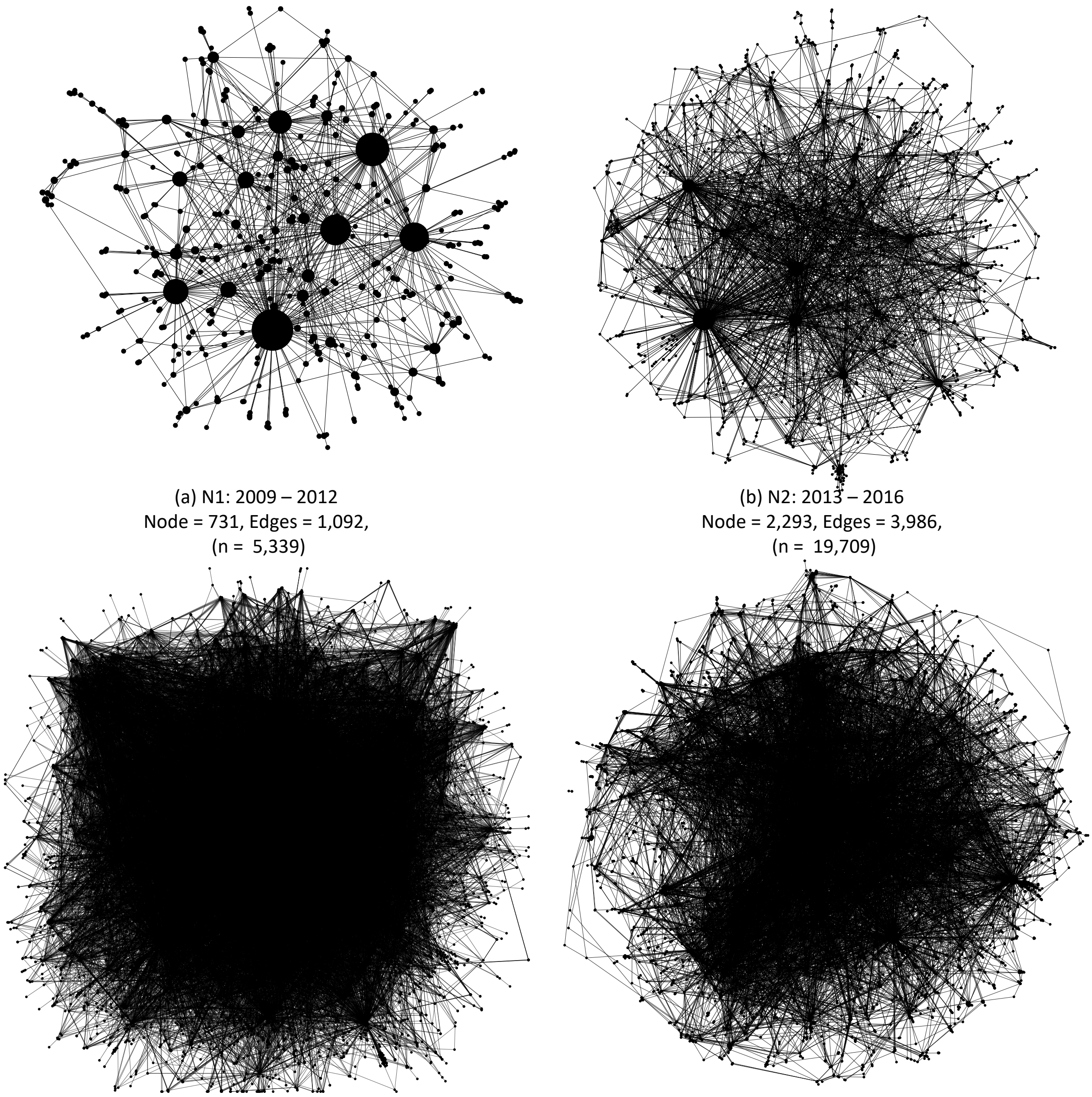
Similarly, the discourse on green/climate finance for residential homes got traction in COP25 in 2019, also reflected in the 'circular economy' and 'social housing fund' discourses of the EU Green Deal (see Fig 1a and (90)). The garnering importance of emission reduction in buildings in the global climate action and policymaking was further illustrated through the flagship 'Cities, Region and Built environment Day' at the recent COP-26 at Glasglow (2021); and its corresponding high Twitter traffic (see Fig 1a).

Fig 1b and Fig 1c provide the characteristics of sentiments and emotions in the tweets through a moving average representation between 2009 – 2021. Sentiment analysis shows that positive sentiment has a more significant share than negative sentiment (the word list can be found in the NRC lexicon (72)) in the tweets, with few peaking events for negative tweets (see Fig 1b). For example, negative sentiment share rose to almost 40% from below 10% post-COP-15. However, this share fell to almost 0% on the announcement of the Green Climate Fund (2010) (see Fig 1b). Similarly, tweets with more than 50% negative sentiment peaked between COP-17 and COP-18 in June 2012 (see Fig 1b). In the same period (i.e., 2009 - 12), sentiment analysis revealed tweets showed a more significant share of emotions like 'trust' and 'anticipation', as shown in Fig 1c.

Sentiment trend for 2013 – 2016 also shows a higher share of positive sentiment (cumulative share ~70%), with negative peaks during the Paris Agreement (~ 50%, see Fig 1b). Between January and April 2013, tweets showed emotions like high 'trust', 'surprise' and 'joy', whose share fell significantly with the rise in negative emotions like 'anger' and 'fear' in August 2013 (see Fig 1c). The share for 'surprise' increased during COP-19. However, critical key emotion shared during with IPCC AR5 release was 'anticipation' (~ 90%) and 'fear' (~ 60%, see Fig 1c). A similar effect was also observed in the tweets during the Paris Agreement, with an additional share in 'trust' (see Fig 1c). Interestingly, the share of sadness increased after the IPCC Global Warming 1.5°C Report to ~30% (2018-2021, see Fig 1c). Peaks in emotions like 'surprise' and 'trust' are seen post-EU Green Deal negotiations. Thus, the sentiment analysis in this section showed that public reactions in the building and emission space are susceptible to high-level policy events. The following section presents how these emotions are shaped through hashtag co-occurrence networks across time scales.

4.2 Hashtag network topologies

The derived hashtag networks are illustrated in Fig 2, labelled as N1 to N4 with their respective dimensions (nodes, edges and data points (n)). These undirected graphs also represent the 13-year time frame of the tweets and the hashtags. E.g., N1 is for 2009 – 2012, N2 for 2013 – 2016, N3 for 2017 – 2020 and N4 for 2021 (see Fig 2). The undirected graph density (estimated using eq. 6) shows N1(0.015), N2(0.005), N3(0.002), and N4(0.002) shows that N1 have the greatest density than the other three networks. It is due to the lower nodes number for N1 as compared to the other graphs (see Fig 2). Table 1 shows network characteristic measures that include average (avg) degree, modularity and avg clustering coefficient. It can be seen in Table 1 that N3 and N4 have higher avg degree scores than N2 and N1, indicating a more significant number of connections to other nodes for N3 and N4, which implicate more spread of interconnected and interdependent hashtags. Modularity scores of N1 and N2 are comparable and higher than that of N3 and N4 (see Table 1), inferring N1 and N2 have a relatively higher dense connection between the nodes within the modules (or clusters) but sparse connections between nodes in different modules, as compared to the N3 and N4 topologies. In terms of hashtags, it implies N1 and N2 represent densely connected hashtags within a specific cluster, acting like information ego centres. For N3 and N4, it implies more hashtags have been diversifying and diffusing across the networks. Nonetheless, relatively higher avg clustering coefficient for N1, N3 and N4 (see Table 1) indicate that nodes here tend to cluster together, therefore, again representing the tendencies of hashtags to form ego-centres within the respective networks.



(a) N1: 2009 – 2012
Node = 731, Edges = 1,092,
(n = 5,339)

(b) N2: 2013 – 2016
Node = 2,293, Edges = 3,986,
(n = 19,709)

(c) N3: 2017 – 2020
Node = 10,489, Edges = 44,660,
(n = 156,065)

(d) N4: 2021
Node = 5,999, Edges = 23,754,
(n = 75,604)

Fig 2. Topologies of hashtag co-occurrence networks (N1 to N4) across the 13-year timeline (2009 - 2021) [Note: The size of the node is respective to its frequency in a particular graph]

Table 1. Macro-level network characteristics

Network	Year	Density	Avg. degree	Modularity	Avg. clustering coefficient
N1	2009 – 2012	0.015	2.988	0.567	0.825
N2	2013 – 2016	0.005	3.447	0.574	0.784
N3	2017 – 2020	0.002	8.516	0.444	0.838
N4	2021	0.002	7.919	0.479	0.846

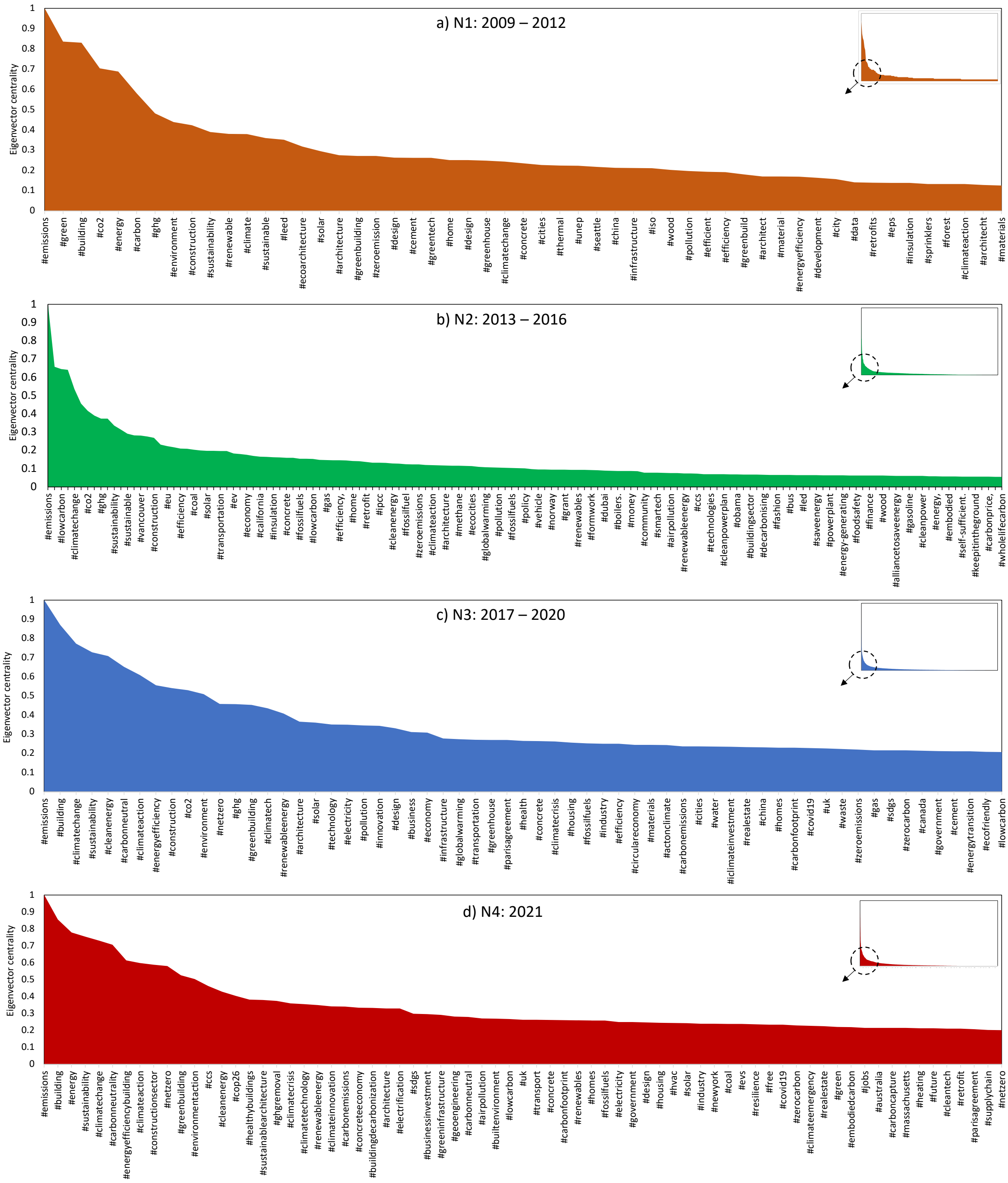


Fig 3. Eigenvector centrality score (> 0.01) distribution with nodes (hashtags) in the N1 - N4 network. [Note: 1 = high influence, 0 = least influence]

The distribution of eigenvector centrality scores (>0.01) of hashtag co-occurrences associated with the N1 to N4 network is illustrated in Fig 3. As mentioned in section 3.2, this metric measures the influence of a node in a network (a score of 1 denotes the highest influence of that node in the graph). Here, Fig 3 denotes the hashtags with the greatest influence in that specific period. For N1, apart from the #emissions, hashtags with higher eigenvector scores (0.90 – 0.60) are #green, #buildings, #co2, #energy and #carbon (see Fig 3a). Between 0.60 – 0.30, the influential hashtags are #ghg, #environment, #construction, #renewable and #sustainability (see Fig 3a). These hashtags represent the most influential or propagating hashtags between 2009 and 2012, as per the N1 network. Contrastingly, in the lower end of the score, the results show hashtags like materials (cement, concrete), architect, climate action, insulation, data, etc (see Fig 3a). The interconnections and clustering between these hashtags are further represented through an n-degree graph. Fig 4 represents a 10-degree graph for N1, showing the hashtags with at least ten connections with other hashtags.

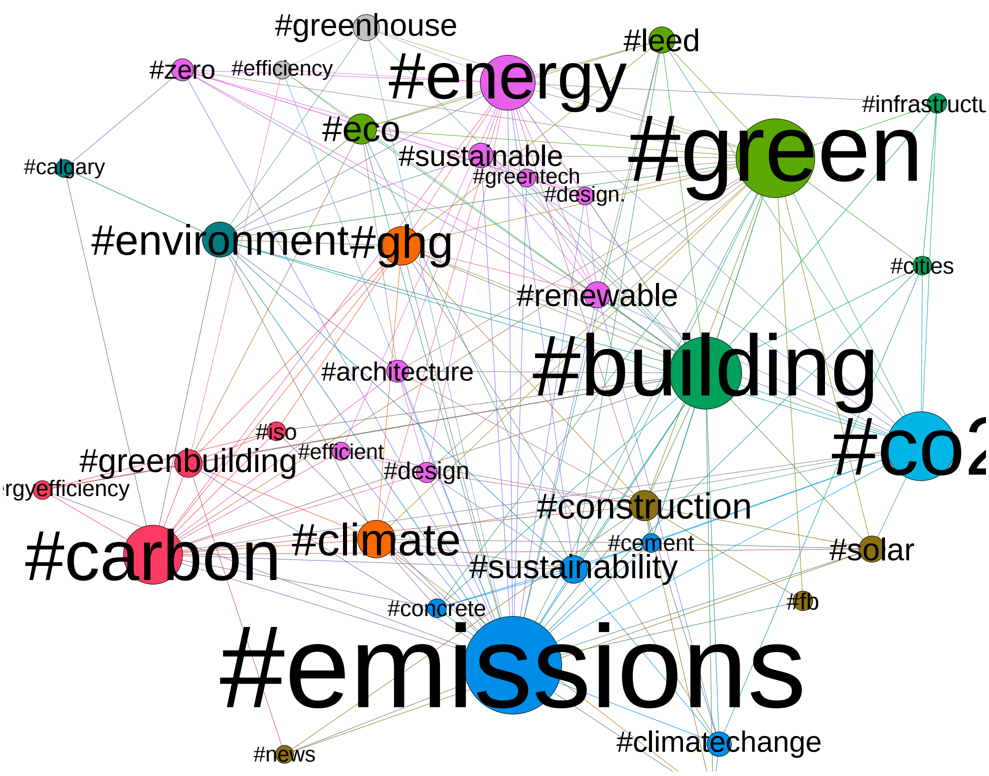
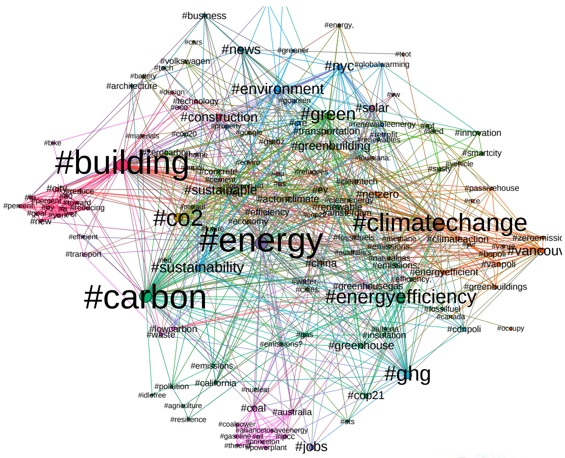
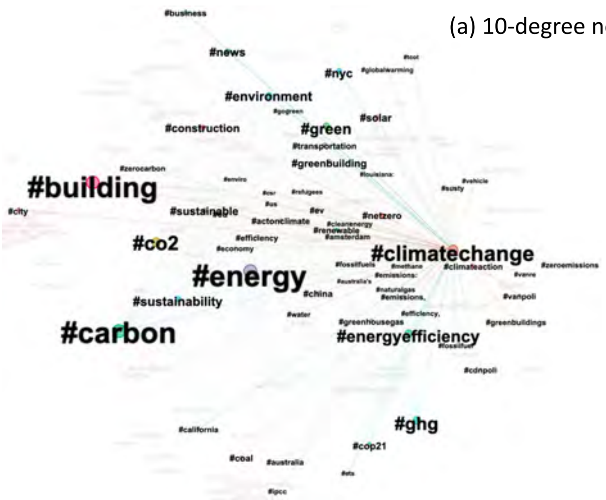


Fig 4. A 10-degree graph for N1 [Note: Size of the nodes is proportional to its eigenvector scores and the colours denotes classification of nodes in the same cluster]

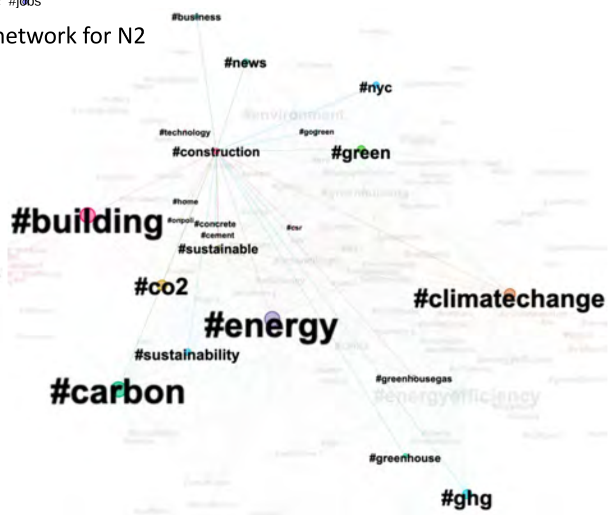
N2 is a significantly bigger network than N1 (see Fig 2). The influential hashtags in N2 can be seen in Fig 3b, showing #lowcarbon, #climatechange and #ghg with the highest eigenvector centrality scores (0.90 – 0.60) distinct from Fig 3a. In the next range of centrality scores (0.60 – 0.30) leading hashtags were #sustainable, #construction and #eu. Compared to N1, these gained higher scores and showed the addition of new hashtags in the 0.30 - 0.10 score range like #coal, #solar, #transportation and #ev (see Fig 3b). Such shifts in eigenvector scores indicate empirical shifts in the climate policy discourse during the 2013 – 2016 period (as shown in Fig 1). Fig 5 further visualises the interconnections amongst the hashtags using a 10-degree graph (Fig 5a) and the influence of specific hashtags (#climatechange and #construction) with high eigenvector centrality (see Fig 5b and Fig 5c).



(a) 10-degree network for N2



(b) Interconnections of #climatechange



(c) Interconnections of #construction

Fig 5. A degree-10 network for N2 with sub-plots for hashtags with high eigenvector centrality scores.

Fig 5b shows the more significant association of #climatechange with #energy, #carbon and #building (as these hashtags have comparable node sizes) in N2. Furthermore, the association of #transportation and #ev in the same nodal linkages can also be seen, demonstrating the garnering discourse on the importance of electric vehicles and decarbonisation of the built environment through the transportation sector (see Fig 5b). Similarly, in the same hashtag network, #solar, #renewable, #efficiency, #actonclimate and #greenbuildingsis are featured, emphasising the increasing focus on climate action through renewables and solar photovoltaic (PV) integration in the built environment emission reduction context. Additionally, #green, #jobs and #economy in the same network (see Fig 5b) implies the possible policy effect of high-level discussions on green jobs, green and transitioning economy in the COPs (see Fig 1a). Finally, parallel inferences can be drawn for #construction in Fig 5c, which demonstrates the shifting narrative of the public for the construction sector towards emission reduction actions through #green #buildings, focus on #cement and #concrete industries and #greenhouse gas removal.

N3 has the highest average degree score (8.516, see Table 1) that infers higher interconnectivity in the nodes, which can be visually assessed through Fig 2c. The eigenvector centrality scores for N3 shows the addition of new influential hashtags like #carbonneutral, #climateaction, #energyefficiency, #netzero, #renewableenergy, #climatetech and so on in the higher score range (0.90 – 0.60) (see Fig 3c and Fig 6), as compared to N1 and N2. Similarly, in the mid-score range (0.30-0.30) new additions include #technology, #innovation, #design, #parisagreement, #health, #climatecrisis, #concrete, etcetera (see Fig 3c and Fig 6). It shows the change in public narratives towards the need for innovation in technology and design for addressing the climate crises, especially action for reducing concrete emissions in the construction industry. The addition of #health further emphasised the growing concerns on the built environment and climate change effects on health. These narrative/discourse shifts can be attributed to the aftermaths of the Paris Agreement and the launch of IPCC AR5 and Global Warming 1.5°C reports (Fig 1a). Attitudinal shifts are also evident from the tweets' changes in sentiment and emotion shares, as illustrated in Fig 1b and Fig 1c.

Furthermore, in the lower end of the score (0.10-0.30), additions like #carboncapture and #masstimber were new and provide a critical clue towards the changing focus on the whole life cycle of emissions and sequestration through carbon capture and storage (CCS), natural materials, nature-based solution and mass timber housing (see Fig 6). N3 has a complex network topology due to the high density of nodes and edges (see Fig 2c). Therefore, we labelled the broad themes according to their clusters that approximately represented the zones of influential hashtags, see Fig 6.

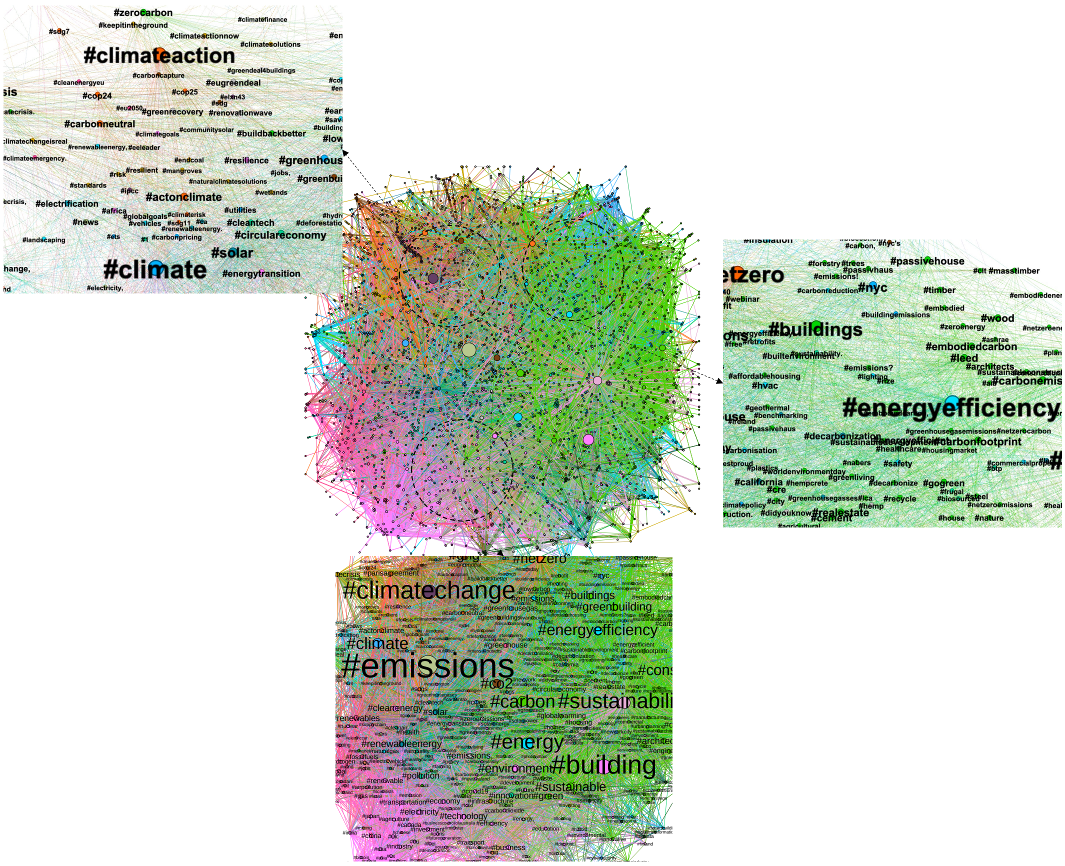


Fig 6. N3 network with cluster maps of influential hashtags

While there are significant overlaps between N3 and N4 in terms of hashtags with high eigenvector centrality values as they are part of recent climate policy events (see Fig 1a), new hashtags in N4 can be tracked from Fig 3d. It includes #ccs and #climatetechnology in the higher score range (0.6 – 0.3), a shift from N3. This shift can be attributed to its association with #cop26, which increased its network influence. Additions also include #businessinnovation, #geoengineering, #concreteeconomy in the same range. Moreover, it can be seen from Fig 3d that greater emphasis on #homes, #retrofit, #supplychain in the lower score range (0.1 - 0.3) indicates a shift in the residential sector and its emission reduction efforts, with added pressure from #covid19 (see Fig 3d). Like N3, N4 is a complex network with many edges and is visualised in Fig 7 as clusters of such influential hashtags.

Fig 7 also shows the associated hashtags with #cop26 in the N4 network. Some of the associated hashtags are #buildingtocop26, #woodforgood, #healthyclimate, #housingcrisis, #scaleupnow, #climatejusticenow and so on. It indicates a paradigm shift in the emission and building policy narratives towards broader social and environmental justice contexts. For example, N3 and N4 #masstimber and #woodforgood featured with high eigenvector centrality values showing that people-centric transition is thinking of alternate low-carbon materials to concrete construction. Similarly, the housing crisis, healthy climate, scale-up, and climate justice are all related to the social justice movement associated with global affordable and healthy social housing narratives.

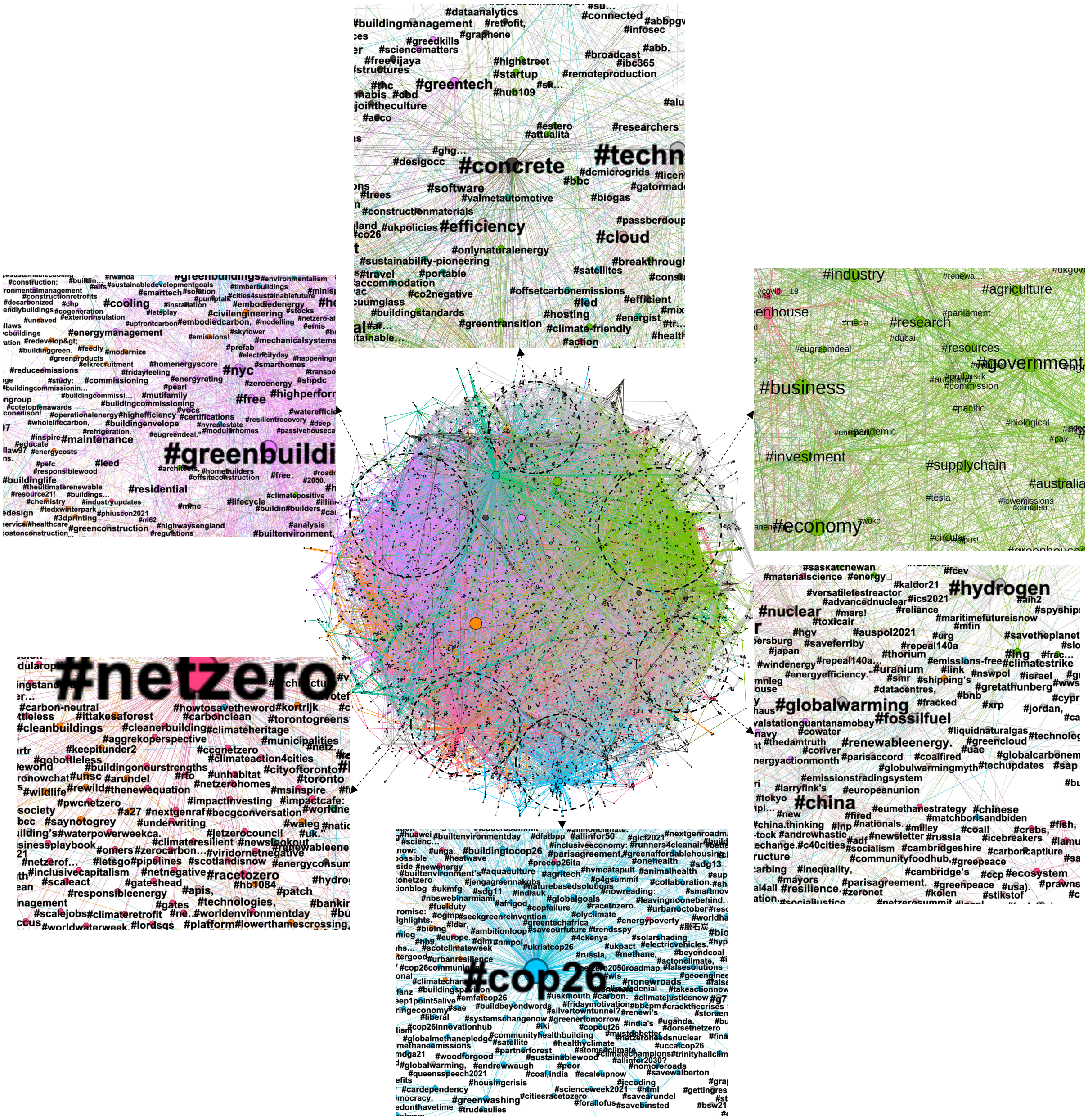


Fig 7. N4 network with the influential hashtags

5. Discussion

This study investigated the hashtag progressions in Twitter using network analysis concerning emission reduction in the buildings in the current policy discourse of people-centric low-carbon transition. Four hashtag co-occurrence networks are constructed through a big data approach analysis approach of n = 256,717 tweets between 2009 – 2021 (N1 – N4, see Fig 2). The tweets' public attitudes and sentiments were attributed to high-level climate negotiations and policy events like the UN COPs and IPCC Assessment Report release (see Fig 1a). The general trend in the sentiment analysis over the 13 years demonstrate a more significant share of positive sentiments. However, 6-month moving average estimations further showed that post-2014, there has been a steady rise in the share of negative sentiments (~ 30-40 %, see Fig 1b). It can be attributed to greater sensitivity and increasing public awareness and opinions to climate change, and the addition of Twitter users in the period.

Moreover, there have been critical policy events like the IPCC AR5 release with a dedicated chapter on buildings in 2014, the Paris Agreement in 2015, several COPs, the release of the IPCC 1.5°C Global Warming Report (2018), EU Green Deal (2019) and the latest COP-26 with a flagship-built environment and cities day (see Fig 1a). While evaluating the exact policy effect of such events on the public was beyond the scope of this study, our results showed how Twitter users reacted to such events with the #emission and #building. We used it as a proxy for studying people-centric transition. For example, Fig 1c further disintegrates the two sentiments into eight emotions. Between 2009 – 2012, the share of trust and anticipations was relatively high, especially during significant policy events like the COP-15 and Cancun Agreement. This trend followed until the first half of 2013, with a sharp increase in negative emotions like anger and fear (see Fig 2c).

There is a general rise in emotions like surprise, anticipation and fear during global policy events (see Fig 1c). For example, with the launch of IPCC AR5, the share of anticipation and fear in the tweets rose by ~90% and ~60%, respectively, in late 2015 and early 2015. A similar effect was observed as reactions to the Paris Agreement, with a further rise in the 'trust' (~ 30%) in October 2015 (see Fig

1c). The share of negative emotions like sadness rose to ~30% post-IPCC Global Warming report. However, peaks in 'surprise' and 'trust' were seen post-EU Green Deal. A greater share of positive sentiments and emotions were also observed in the COP-26 period (see Fig 1c). Such trends provide generalised insights on people-centric transition and reactiveness towards global climate policy events. It shows that such policy actions matter to the public, and with more sensitisation towards decarbonisation and push for low-carbon solutions, emotions are getting more grounded. It is a critical insight for policymakers that people are open to change and care about the climate action towards emission reduction.

In the next step, we explored the influence of hashtags using eigenvector centrality measure on the people-centric transition through four co-occurrence network topologies. The first evidence of greater public engagement was the expansion of networks across the three years (see Fig 2). The centrality score also aided in tracking hashtags that were new additions to that network (see Fig 3). For example, in N1 (2009 - 2012), the most influential hashtags were associated with green buildings and their emission reduction potential in the built environment (#green, #buildings, #co2, #energy and #carbon, see Fig 3a). Finally, the degree measure reported its spatial relationship with other high influence hashtags. For example, Fig 4 showed a 10-degree network of N1 that demonstrated high interconnectivity across #greentech, #efficient, #design and so on, indicating the increasing public interest in the technology and design-led solutions.

N2 (2013 - 2016) was a significantly more extensive network that introduced new high influencing hashtags like #climatechange and #construction along with #lowcarbon, #sustainability, #ghg, #transportation that demonstrated the shifting focus towards sustainable and low-carbon construction, sustainability and decarbonisation of the transportation system (see Fig 3b). Furthermore, Fig 5 quantified the interconnection between such influential hashtags as 10-degree network topology. For example, in Fig 5b, the expanding hashtag network for climate change now includes #business, #energyefficiency, #ipcc, #renewables, #netzero, and so on that emphasised the transcending climate discourse towards net-zero action, energy efficiency in buildings and booming renewable business. A high eigenvector centrality score of #ipcc further demonstrated the public impact of the IPCC AR5 report.

N3 (2017 - 2020) and N4 (2021) networks consisted of recent policy events that created complex network topologies (see Fig 2). Eigenvector centrality scores for N3 revealed garnering public interest in #climateaction (see Fig 6), including #carboncapture, #cleantech and #circular economy. These hashtags appeared with high centrality scores for the first time in N3 that inferred people were interested in circular economy and climate tech-based solutions like Carbon Capture and Storage (CCS). Similarly, a distinct cluster in the network demonstrated influential hashtags on #wood, #masstimber, #embodied emissions, #carbonfootprint, #housingmarket, #affordablehousing, etcetera (see Fig 6) that implied the garnering public interest towards embodied emission reduction through nature-based solutions like timber and wood and reflected its potential application in the affordable housing market. New additions in N3 also included #innovation, #design, #health, #climatecrisis, etcetera (see Fig 3c) that indicated a greater focus on innovation in building design for addressing the climate crisis and health outcomes in the built environment.

As mentioned in section 4.3, #ccs, #carboncapture and #climatetechnology (see Fig 3d) further moved to a higher range of eigenvector centrality, demonstrating the garnering influence of these terms in the N4 network. It can be attributed to more significant discussion and sensitisation of these terms in the COP-26. Moreover, #netzero became significantly influence in N4 as compared to N3 (see Fig 3, Fig 6 and Fig 7) that included hashtags like #municipalties, #netzerohomes, #climateaction4cities, #cleanbuildings and so on, demonstrating the rapidly increasing acceptance of net-zero action in the public domain. It further emphasises that people-centric transition and net-zero action can complement short-term policy discourses.

Similarly, in the N4, #supplychain and its high degree interlinks with #economy, #government, business, #research, #industry (see Fig 7) showed changing narratives on the reiteration of the supply chain, industry and business for net-zero action and emission reduction in buildings. Interestingly, a significant emphasis on #concrete, #software and #digitaltwin was also seen, indicating discourse on newer methods of intelligent decarbonisation in the concrete industry (see Fig 7). Similarly, #greenbuilding in N4 was primarily associated with residential homes and retrofitting that demonstrated garnering interest for decarbonisation of the residential sector, which is generally overlooked in the people-centric transition context. As COP-26 was a significant event in 2021, #cop26 in N4 showed high interconnectivity with new hashtags like #woodforgood, #climatejusticenow, #naturebasedsolutions, etcetera, (see Fig 7) that demonstrated paradigm shifts in building emission reduction efforts by connecting it with global climate justice efforts. It critically emphasises the need to align future-proofing strategies of the built environment with social and environmental justice goals to make it a genuinely people-centric transition.

However, reflecting on current Twitter userbase (~211 million users globally), that we found approximately a quarter million or so tweets on emissions in the building sector during our analysis period indicates that these issues are low salience. So, one important task for policymakers is to raise the salience of these issues immediately, and to develop communications strategies to emphasise the importance of build sector emissions.

6. Conclusion

Enabling justice and equity in low-carbon transition is a global challenge. The buildings and construction sector needs immediate attention from policymakers to reduce its overall carbon footprint. Just transition in this context would mean addressing the emission reduction goals and fulfilling global sustainable development needs. This complexity calls for enabling contextualised climate policy design that embeds collective wisdom of people to improve resilience, adaptation and mitigation strategies to climate change. Thereby allowing the process for people-centric transition.

This study demonstrated the changing perception of climate action for the built environment sector in the people-centric transition context by using a multi-method approach to evaluate Twitter sentiments and hashtag co-occurrences over 13 years. This study showed that people are reactive to high-level climate policies and events that concern emission reduction in buildings. Exploratory sentiment analysis of 256,717 tweets between 2009 – 2021 revealed public attitudes varied as moving averages following the announcement of significant policy actions. For example, the share of emotions like surprise, anticipation and trust peaks at the onset of the Paris Agreement and IPCC report release. However, the emotional share for anger, fear, and sadness in the tweets increased as moving averages in the next few months. It indicated the public reactivity cycle of climate policy events with a critical inference that as sensitisation towards climate change increases, public emotions diversify over time (due to increase in public awareness).

The findings from network topology analysis showed that hashtags influence public attitudes towards climate action and emission reduction efforts in the built environment. For example, between 2009 – 2012, hashtags associated with green buildings were highly influential and dominated the discourse across the construction industry, renewable energy and greenhouse gas removal efforts. However, it was preceded by #energyefficiency, #climatechange, #transportation, #construction and #sustainability in the 2013-2016 period indicating a shifting paradigm from exploration to identification of policy action areas. Furthermore, this transition in focus happened through IPCC AR5 reports, Green Climate Funds and the Paris Agreement. The findings from this study further showed the more significant influence of #climatech, #carboncapture, #masstimber, #wood, #netzero, #climatejustice, etcetera in the 2017-2021 timeline, which infers shifting public narratives towards climate solutionism through net-zero actions, CCS technologies and stress on the inclusion of natural materials (like timber and wood) in the built environment.

Key conclusions that can be drawn for future-proofing the built environment and people-centric transition perspective are that emission reduction in buildings is no longer a top-down policy objective but a social and environmental justice phenomenon. The evidence showed that COP-26 hashtags associated with emission reduction in buildings had been firmly attributed to the intersection of public health, affordable housing, and decarbonisation of the built environment. This study also concluded that for enabling people-centric transition, there is a need to understand the dynamics of public sentiment and attitudes following high-level policy actions. These sentiments drive the conversation on social media platforms like Twitter, providing the required collective intelligence for just and holistic climate policy design. Another important conclusion that this study provides is that people-centric emission reduction policies must not overlook the importance of social dimensions of low-carbon transitions as it determines their effectiveness over the long run.

While this study assumes that the Twitter dataset reflects the current public discourse, it must be noted that the generalisability may be limited by the socio-demographics associated with Twitter users. Moreover, the scope for sentiment analysis was limited to the subjective judgement of the NRC lexicon database and did not represent the causation of policy events. Similarly, the interpretation of hashtag networks was limited to the authors' knowledge that could have introduced interpretivist biases. However, these limitations can be addressed through field-based surveys and participatory workshops for capturing rich narratives of just transition from the public, which remains future work. Nonetheless, this study paves pathways towards advanced discourses on the people-centric theory of change and behavioural transitions of global climate policies.

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