



## Review

## Beyond separate silos: identifying convergent themes in digital social innovation and air quality management

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## ABSTRACT

Air pollution remains a critical global challenge, necessitating a shift from traditional, top-down management toward dynamic, inclusive governance. While Air Quality and Pollution Management (AQPM) has historically focused on technical optimization and regulatory compliance, the complexity of modern pollution dynamics requires integrating technological advancements with active social participation. Digital Social Innovation (DSI) offers tools to bridge this gap, yet the intersection of these fields remains underexplored. This study maps the thematic connections between DSI and AQPM through a bibliometric analysis and topic modelling of 442 documents from the Web of Science (1975–2025). Results indicate that DSI and AQPM operate as structurally independent domains with minimal cross-field integration. AQPM has matured into a consolidated discipline centered on measurement, modelling, and health accountability, whereas DSI appears as a fragmented, emerging theme focused on participatory platforms. However, the analysis identifies five key areas of convergence: digital infrastructures for smart urban systems, participatory data governance, co-creative policy design, addressing inequality, and regional adaptation. The findings highlight a ‘strategic gap’ where technical capacity for real-time monitoring exceeds the institutional mechanisms required to translate data into equitable action. The study concludes that while digital tools offer the ‘socio-technical glue’ to democratize air quality governance, realizing this potential requires overcoming the digital divide and designing interoperable, inclusive frameworks. Future research must prioritize longitudinal impact assessments and ‘equity by design’ strategies to transform citizen-generated data into legitimate, policy-relevant environmental intelligence.

### 1. Introduction

Air pollution remains a critical global challenge, particularly in urban areas where industrial activities and vehicular emissions significantly impact environmental sustainability and public health (Giri and Nagendra, 2024). Historically, the foundational literature conceptualized air quality management as a constrained planning problem, where emissions control, industrial siting, and policy feasibility were solved jointly through optimization models (Cooper et al., 1997; Guldmann and Shefer, 1977). However, the complexity of modern pollution dynamics has forced a progressive redefinition of managerial competence; it is no longer sufficient to merely optimize industrial locations. Instead, effective management now requires the ability to make decisions when uncertainty is intrinsic, multi-dimensional, and policy-relevant (Liu et al., 2003). Addressing these evolving issues requires a synergy of

technological advancements, legislative regulation, and active community participation to ensure effective and equitable solutions (Mehmood and Imran, 2021). For instance, the directive 2024/2881 embeds social participation directly into air quality governance: it mandates that citizens be informed in a timely, transparent, and comparable manner, and guarantees their right to justice. This legislative shift enables civil society to act not merely as recipients of air-quality information, but as active stakeholders in monitoring and enforcing air quality norms (European Union, 2024). In this context, Digital Social Innovation (DSI) and Air Quality and Pollution Management (AQPM) represent two complementary approaches to tackling air pollution. While AQPM focuses on the technical aspects of monitoring and mitigating pollution, DSI offers digital and social tools to enhance public engagement, collaboration, and the co-creation of solutions.

Effective AQPM is essential for safeguarding public health and

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environmental sustainability; however, rapid urbanization and industrialization have exacerbated pollution levels, creating significant challenges for monitoring and mitigation efforts (Galvao et al., 2020). Traditional air quality monitoring systems, while foundational, are often geographically sparse and cost-prohibitive, limiting their ability to capture localized pollution dynamics in high-risk areas such as traffic corridors and industrial zones (Alshbatat, 2023; Kakarla et al., 2019). These systems typically produce averaged data, which fails to account for rapid fluctuations in air quality caused by localized anthropogenic activities (Minh et al., 2009). Financial and technical constraints further hinder AQPM efforts, particularly in resource-limited settings where municipalities often lack the funding and expertise to deploy comprehensive monitoring networks (Chae and Park, 2011). Additionally, reliance on emissions inventories introduces uncertainties when localized data are unavailable, while translating satellite-derived pollutant concentrations to ground-level exposures remains a technical challenge due to meteorological complexities (Milford and Knight, 2017; Pisoni et al., 2019, 2024). Consequently, the field has witnessed a “strategic gap” in governance, where cultural and behavioural dimensions often decouple technical plans from effective action (Cannibal and Lemon, 2000).

In response to these limitations, the viewpoint of AQPM has shifted from simple regulatory compliance toward health-anchored accountability and distributive justice. This outcome-oriented turn embeds AQPM within broader social risk governance, explicitly framing environmental equity as central to management strategies (Marteniés et al., 2015; O’Neill et al., 2008). To support this shift, the contemporary digital state of the art has evolved beyond single decision support systems toward ecosystem-level integration of Internet of Things (IoT), Artificial Intelligence and Machine Learning (AI/ML), and cloud architectures (Kaginalkar et al., 2021). Emerging technologies, such as remote sensing, low-cost sensor networks, and Unmanned Aerial Vehicles (UAVs), offer promising solutions for real-time, hyper-local monitoring (Bai et al., 2024; Bakirci, 2024; Bousiotis et al., 2023). Furthermore, the operational frontier is advancing toward dynamic management, where forecasting and control-theoretic approaches enable real-time decision cycles rather than just long-term planning (Sangiorgi and Carnevale, 2023). However, integrating these advanced abilities into cohesive systems requires overcoming significant interoperability and calibration challenges (Anastasi et al., 2021; Bai et al., 2024).

Beyond technical barriers, AQPM also faces social challenges rooted in environmental inequalities, where unequal exposure to pollutants disproportionately affects marginalized communities. The most vulnerable populations; including low-income communities and those living near industrial areas; are often the most exposed to harmful air pollutants while having the least access to monitoring resources (Rautela and Goyal, 2024). These disparities are compounded by limited public awareness of pollution-related health risks and inadequate communication of localized air quality data, which undermines proactive mitigation efforts and perpetuates cycles of environmental inequalities (Giri and Nagendra, 2024). Even in regions with advanced monitoring systems, gaps between technological initiatives and community needs persist, highlighting the importance of aligning policy with public engagement (Kaginalkar et al., 2022). This necessitates a move from model-centric decision support toward data-centric governance, where the core challenge becomes aligning heterogeneous data streams with policy workflows while maintaining trust and interpretability.

To address these complexities, DSI utilizes digital platforms to address complex societal needs, improve service efficiency, and cultivate new forms of stakeholder engagement (Certoma, 2020; Ribeiro et al., 2024). DSI initiatives have matured from foundational mapping toward governance implications and ecosystem performance, often catalysed by a combination of public sector challenges, economic pressures, and persistent social problems (Misuraca and Pasi, 2019;

Certoma, 2020). These factors collectively stimulate innovation and the development of solutions that address social inequalities, with digital technologies amplifying the reach and impact of such efforts (Ribeiro et al., 2024). However, a critical point in the development and implementation of DSI is the digital divide, characterized by disparities in access to digital technologies due to geography, socioeconomic status, and education. This divide presents a substantial barrier, particularly in rural areas where limited mobility and inadequate infrastructure further restrict digital literacy and engagement (Sommer et al., 2025; Zerrer & Sept, 2020). Overcoming these barriers requires hybridization strategies that integrate digital and non-digital approaches, targeted DSI education, and the empowerment of local actors to drive bottom-up innovation (Marzano, 2020; Sommer et al., 2025).

Recent comprehensive studies have begun to explore the intersection of these social and digital components. A consistent emphasis on citizen science and low-cost sensor deployments as pathways to expand spatial coverage and public engagement is evident across the literature (Mahajan et al., 2021). For example, Mahajan et al. (2021) developed “AirKit” a social-IoT toolkit integrating hardware and data storytelling to support citizen sensing. Similarly, Daepf et al. (2023) proposed a “three-legged stool” framework emphasizing balanced participation of city agencies, communities, and researchers to produce credible, actionable data. Other works have analyzed engagement mechanisms in technology-mediated citizen science (McCroory et al., 2017) and developed community-empowered systems that integrate heterogeneous digital data to support advocacy (Hsu et al., 2017). These studies suggest that air quality governance increasingly requires not only advanced sensing and analytics but also digitally mediated participation and organizational designs that can convert data into legitimate action (Rodrigues et al., 2021).

Despite the potential synergy demonstrated in these specific cases, research integrating these fields remains limited, leaving a gap in understanding how DSI can address both the technical and social challenges of AQPM holistically. Existing reviews note limited empirical evidence on how citizen-generated data directly influences policy decisions and insufficient long-term evaluations of social and institutional impacts (Mahajan et al., 2021; Hsu et al., 2017). Furthermore, many deployments are project-based rather than sustained infrastructures, constraining longer-term institutional uptake and failing to fully address equity considerations regarding unequal sensor coverage (Daepf et al., 2023). Bridging these fields offers both theoretical insights and practical benefits, particularly in creating inclusive, data-driven, and community-centered solutions.

Consequently, the objective of this study is to map and analyse the thematic connections between DSI and AQPM as reflected in scientific literature. To achieve this, the research applies bibliometric analysis and topic modelling as its primary methodological approaches. These techniques enable the identification of key topics and conceptual relationships at the intersection of DSI and AQPM, providing a comprehensive overview of the field. Guided by these methods, the study addresses the following research questions: What are the main thematic connections between DSI and AQPM? What research gaps emerge from this intersection that can inform future studies?

## 2. Materials and methods

### 2.1. Data

A structured bibliometric and topic modelling approach was employed to map the research intersections between DSI and AQPM, aiming to capture both thematic interplay and methodological trends within these domains. As a source of bibliometric data, the Web of Science (WoS) was selected for its reliable and structured document repository, which facilitates a broad yet detailed analysis. The search equation applied on 14 July 2025 was as follows: “Digital Social Innovation\*” OR “air quality management” OR “air pollution

management' (Title) AND English (Languages). This targeted search initially yielded a total of 546 documents. After deduplication and verifying the completeness of title and abstract metadata, 442 documents were included in the final dataset, covering the period from 1975 to 2025 (Fig. 1).

## 2.2. Bibliometric analysis

Bibliometric analysis was conducted using the Bibliometrix R package in R version 4.3.3, an open-source tool designed for comprehensive science mapping (Aria and Cuccurullo, 2017). The analysis workflow comprised data preprocessing, network matrix construction, and the application of five complementary visualization techniques: Callon's strategic diagrams, Multiple Correspondence Analysis (MCA), historiographs based on bibliographic coupling, countries' production over time, and the countries' collaboration world map.

Keyword-based bibliometric coupling was implemented to infer thematic connections, following Kessler (1963) and Marshakova (1981). Author keywords were preprocessed with Natural Language Toolkit (NLTK) by lowercasing, removing punctuation with hyphen normalization, applying part-of-speech-aware WordNet lemmatization, and filtering out standard English stopwords plus a small domain list (using, based, approach, method, analysis); tokens shorter than two characters were discarded. Processed keyword lists were deduplicated and sorted to ensure reproducibility. A bipartite network linking documents to keywords was constructed and restricted to cross-group links between DSI-AQPM; documents were considered cross-coupled when they shared at least one author keyword across these group pairs (Armenia et al., 2024).

## 2.3. Mapping techniques

### 2.3.1. Callon's strategic diagrams

Strategic diagrams were employed to map and classify thematic clusters according to their development and importance (Callon et al., 1983; Ghura et al., 2022). This technique positions themes in a two-dimensional space defined by centrality (external connection strength) and density (internal cohesion), categorizing them into motor themes, basic themes, niche themes, or emerging/declining themes (Chen et al., 2023).

### 2.3.2. Multiple correspondence analysis (MCA)

MCA was applied to reveal the conceptual structure underlying the research domain (Aria and Cuccurullo, 2017; Khangar and Kamalja, 2017). As a dimensionality reduction technique, MCA decomposes associations among keywords to extract orthogonal dimensions representing latent conceptual patterns. Spatial proximity between keywords on the resulting map indicates stronger co-occurrence patterns (Khangar and Kamalja, 2017).

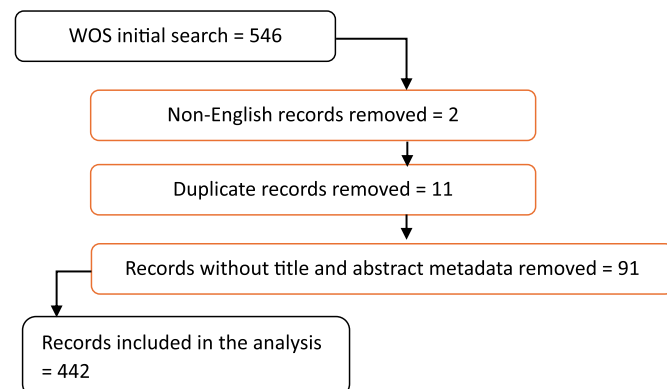


Fig. 1. Flowchart of database search and screening.

### 2.3.3. Historiograph based on bibliographic coupling

To visualize the historical development of the field, historiographs were constructed based on the bibliographic coupling of documents (Aria and Cuccurullo, 2017; Garfield, 2004). In this visualization, author keywords are represented as nodes positioned along a temporal axis according to their average publication year. Node size encodes citation impact, highlighting how specific research themes emerge and evolve chronologically within the scientific landscape.

### 2.3.4. Geographical indicators

The geographical and temporal distribution of scientific output was analyzed using the countries' production over time and countries' collaboration world map functions (Aria and Cuccurullo, 2017). These tools allowed for the identification of leading producer countries and the intensity of international co-authorship ties, highlighting major hubs of global knowledge exchange.

## 2.4. Topic modelling

Latent Dirichlet Allocation (LDA) was used to model latent themes, treating each document as a mixture of topics (Blei et al., 2003). For each record, the title, abstract, and author keywords were concatenated and preprocessed by lowercasing, removing URLs/emails and non-alphabetic characters, tokenizing, lemmatizing, and filtering against NLTK English stopwords augmented with 18 domain stopwords (for example, study, research, analysis). Documents with fewer than three retained tokens were excluded from modeling. Texts were vectorized using a CountVectorizer limited to the 1000 most frequent terms. The optimal number of topics was selected using R package "ldatuning" (Nikita and Chaney, 2020). The final model used scikit-learn's batch LDA with max iterations = 20, and random state = 42. Outputs included top words and weights per topic and per-document topic probabilities, recorded alongside model parameters to ensure full reproducibility (de Vasconcelos Gomes et al., 2018).

## 2.5. Analytical process

The analytical process involved a dictionary-based classification to profile the documents associated with each LDA topic. A specialized lexicon was constructed, originating with a set of seed terms related to social and digital concepts and later enriched with terms extracted from the corpus. This curated lexicon (see Appendix A) was then used to apply a classification scheme to each document's title and abstract, categorizing it as 'Digital', 'Social', 'Both', or 'Neither'. The classification was based on technical terms such as 'GIS' (Geographical Information Systems) and 'machine learning' and social terms like 'governance' and 'participation'. To identify cross-cutting connection areas, a qualitative synthesis of keyword groups and topics consolidated recurrent conceptual linkages into coherent areas of convergence between DSI and AQPM (Asmussen and Møller, 2019; Gürcan and Çağiltay, 2019; Mo et al., 2015).

## 3. Findings

### 3.1. Descriptive characteristics of the dataset

The bibliometric analysis involves a dataset spanning a fifty-year period. The collection was disseminated across 274 distinct sources (journals, books, and conference proceedings). An analysis of authorship patterns reveals a strong tendency toward collaborative research. The average number of co-authors per document is 3.75 and the social network exhibits a moderate degree of cross-border cooperation, with international co-authorships accounting for 20.04% of the total output.

### 3.2. Author productivity

A domain-specific analysis of author productivity reveals striking

**Table 1**  
Top 10 most productive authors by field.

Air pollution management		Air quality management		Digital social innovation	
Author	Number of documents	Author	Number of documents	Author	Number of documents
Chandrappa, R	5	Longhurst, JWS	48	Kaletka, C	3
Kulshrestha, UC	5	Beattie, CI	22	Misuraca, G	3
Cui, L	2	Woodfield, NK	18	Palacios, M	3
Wang, Y	2	Irwin, JG	13	Pelka, B	3
Yang, L	2	Elsom, DM	12	Rodrigo, L	3
Ye, F	2	Hayes, ET	10	Buck, C	2
Albinovic, S	1	Gibbs, DC	9	Davide, F	2
Asif, Z	1	Huang, GH	9	Drews, P	2
Batterman, SA	1	Jefferson, CM	8	Eckhardt, J	2
Belgiorno, V	1	Leksmono, NS	8	Gebken, L	2

structural disparities that reflect the varying developmental stages of the identified research clusters (see Table 1). Air quality management exhibits the characteristics of a highly mature and consolidated discipline, driven by a ‘‘star scientist’’ phenomenon where a single dominant figure (Longhurst, JWS) accounts for 48 publications. In sharp contrast, the Digital Social Innovation (DSI) domain displays the fragmentation typical of a nascent field, characterized by a flat, egalitarian hierarchy where the most prolific authors have produced only three documents each. Situated between these extremes is the air pollution management cluster, which follows a dual-leadership model headed by two primary contributors (Chandrappa and Kulshrestha) before tapering into a long-tail distribution of one-off contributions.

### 3.3. Geographic evolution and collaborative networks

Fig. 2 illustrates the dynamic evolution of the scientific output of the most productive countries, characterized by the United States’ sustained dominance, reaching a cumulative total of 208 articles through consistent growth since 1976. While the United Kingdom established an early foothold to secure third place (131 articles) despite stabilizing growth, the most defining trend is the dramatic shift toward Asian research hubs. China exhibited aggressive exponential growth post-2010, surging from negligible output to 169 articles and rapidly narrowing the gap with the USA, while India demonstrated a significant inflection point around 2016, skyrocketing to 79 articles. Meanwhile, Canada and Italy maintained moderate, steady trajectories.

Complementing these productivity trends, the analysis of international collaboration reveals a highly asymmetric and Canada-centric network structure, characterized by strong Trans-Pacific and North American integration (Fig. 3). The network identifies the United States and China as the primary ‘‘engines’’ of cooperation, yet with distinct strategic roles. The USA functions as a diversified global connector, bridging North America (Canada) with major Asian economies (China and India). Conversely, China acts as a high-volume specialist, establishing the single strongest bilateral link in the dataset with Canada (13 interactions). Canada emerges as the central focal point of convergence, receiving the highest volume of inbound partnership from the two global superpowers. While the Pacific Rim serves as the primary theater of activity, evidenced by the robust USA-China and China-Canada axes, a secondary, self-contained cluster of intra-European partnerships (e.g., Italy-Greece, UK-Italy) persists at lower frequencies.

Fig. 4 displays the most frequent author keywords across thematic clusters, dominated as expected by ‘‘air quality management’’ and related terms like ‘‘air pollution’’. Beyond these core concepts, the analysis highlights the emergence of significant sub-keywords including ‘‘indoor air quality’’, ‘‘big data analytics’’ and ‘‘social innovation’’.

### 3.4. Conceptual structure map

Fig. 5 presents the conceptual structure of the field through a multiple correspondence analysis of the most relevant author keywords,

revealing six distinct clusters that define the research landscape. The map is anchored in the lower-left quadrant by a technically oriented cluster that represents the discipline’s methodological foundation, grouping quantitative terms such as ‘‘emission inventory’’, ‘‘source apportionment’’, ‘‘particulate matter’’, and ‘‘modelling’’ to emphasise the physical measurement and assessment of pollution. Near the centre, a second, bridging cluster brings together general management and policy concepts, ‘‘air pollution’’, ‘‘air quality’’, ‘‘policy’’, ‘‘health’’, and ‘‘indoor air quality’’, capturing the core discourse that links governance concerns to human well-being.

Beyond these central groupings, several specialized outlying clusters appear. At the top of the vertical axis, a distinct cluster organised around ‘‘digital social innovation’’ and ‘‘social innovation’’ stands relatively isolated, highlighting an emerging, human-centric niche focused on societal engagement. In contrast, at the bottom of the map, a mathematically intensive cluster concentrates on ‘‘optimization’’ and ‘‘uncertainty’’ in decision models. Along the horizontal axis, another cluster links the administrative focus of ‘‘local air quality management’’ to the broader environmental context of ‘‘climate change’’. Finally, a single-term cluster defined by ‘‘public health’’ sits at the far right, underscoring health outcomes as both a key driver and a distinctive consequence of air quality management strategies.

### 3.5. Thematic evolution and emerging research topics

#### 3.5.1. Callon’s diagram

Fig. 6 utilizes Callon’s strategic diagrams to classify the field’s research topics into four distinct quadrants based on their centrality and density: motor, basic, niche, and emerging themes (Callon et al., 1983). The analysis identifies ‘‘air quality management’’ as the dominant motor theme, driving the research front. This cluster is the most developed and central, integrating high-frequency core concepts like ‘‘air pollution’’ and ‘‘particulate matter’’ with technical methodologies such as ‘‘optimization’’ and ‘‘source apportionment’’ as well as impact-related terms like ‘‘public health’’ and ‘‘policy’’.

Supporting this core are the basic themes, which represent the foundational, transversal structures of the field. These include ‘‘urban air quality’’, ‘‘indoor air quality’’ and ‘‘local air quality management’’. This quadrant anchors persistent, underlying challenges such as ‘‘uncertainty’’ and ‘‘climate change’’ indicating these are established concerns that permeate the broader discourse.

In the upper-left quadrant, niche themes represent highly specialized or isolated topics. These include specific technical tools and distinct management phrasings, such as ‘‘modelling’’, ‘‘GIS’’ and ‘‘air pollution management’’ which are well-developed internally but have lower centrality to the main research network.

Crucially, ‘‘digital social innovation’’ is identified as the sole emerging theme, containing keywords like ‘‘social innovation’’ and ‘‘health’’ this cluster appears in the lower-left quadrant, signifying that while it is a growing area of interest, it is currently weakly connected to the central ‘‘air quality management’’ motor theme.

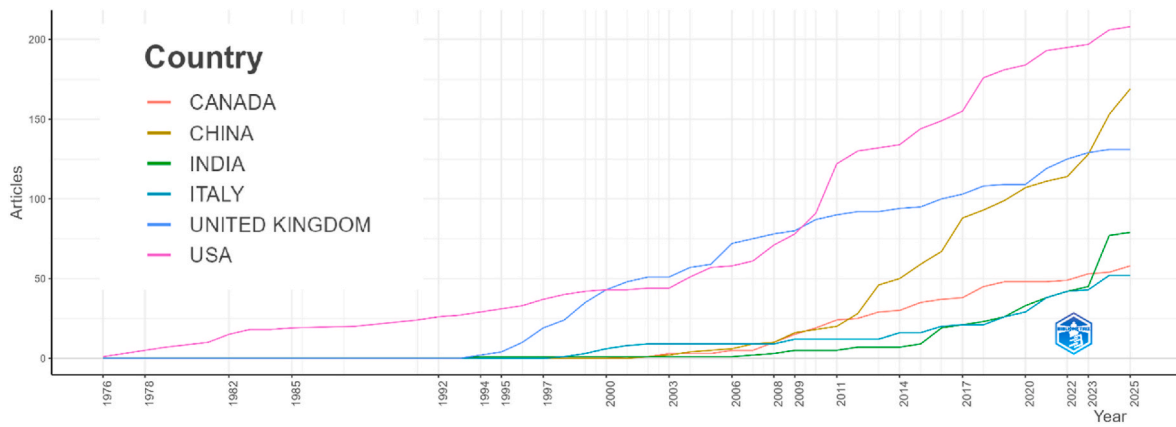


Fig. 2. Countries' production over time.

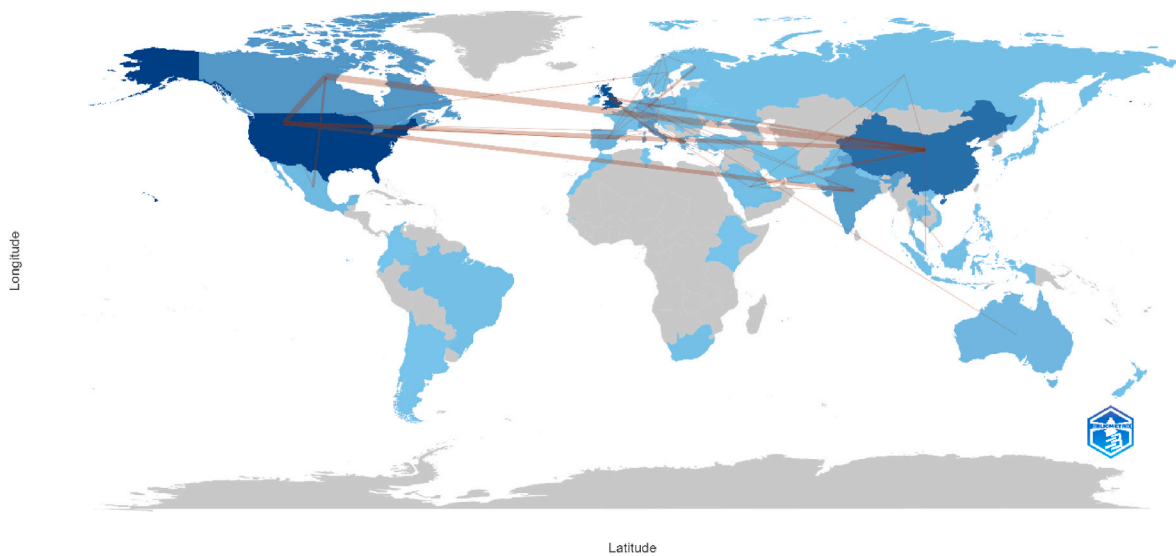


Fig. 3. Countries' collaboration world map.

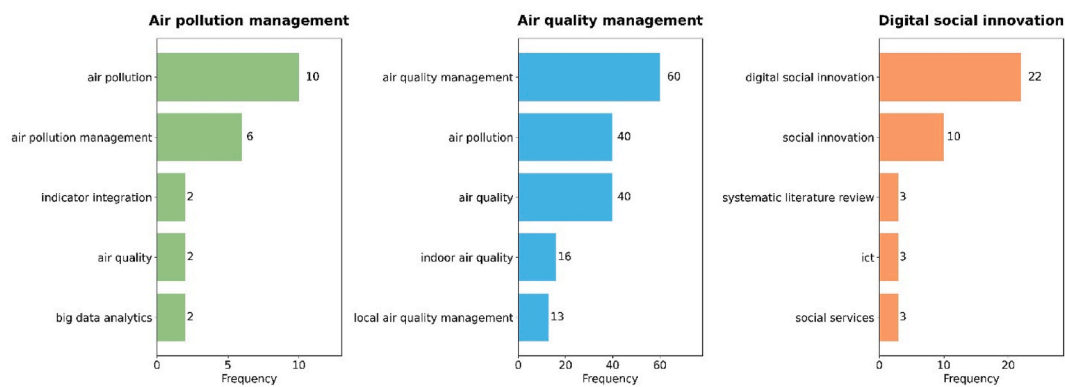


Fig. 4. Frequency distribution of the top five author keywords across thematic clusters.

### 3.5.2. Historiograph

The historiograph synthesizes the evolution of air quality management and allied domains through the temporal appearance and relative prominence of author keywords across the fifty years period, with bubble sizes indicating keyword salience (Fig. 7). Two high-level thematic neighbourhoods organize the map. The first, and most persistent, is the regulatory–managerial core in which “air quality management”,

“local air quality management”, and “air pollution” appear as dominant nodes, indicating that the literature is structured primarily around management and governance problem framings rather than single-pollutant atmospheric science alone. The second neighbourhood emerges later, concentrates toward the most recent years, and is anchored by “digital social innovation” together with “digital inclusion”, “digital innovation”, and “social innovation”.

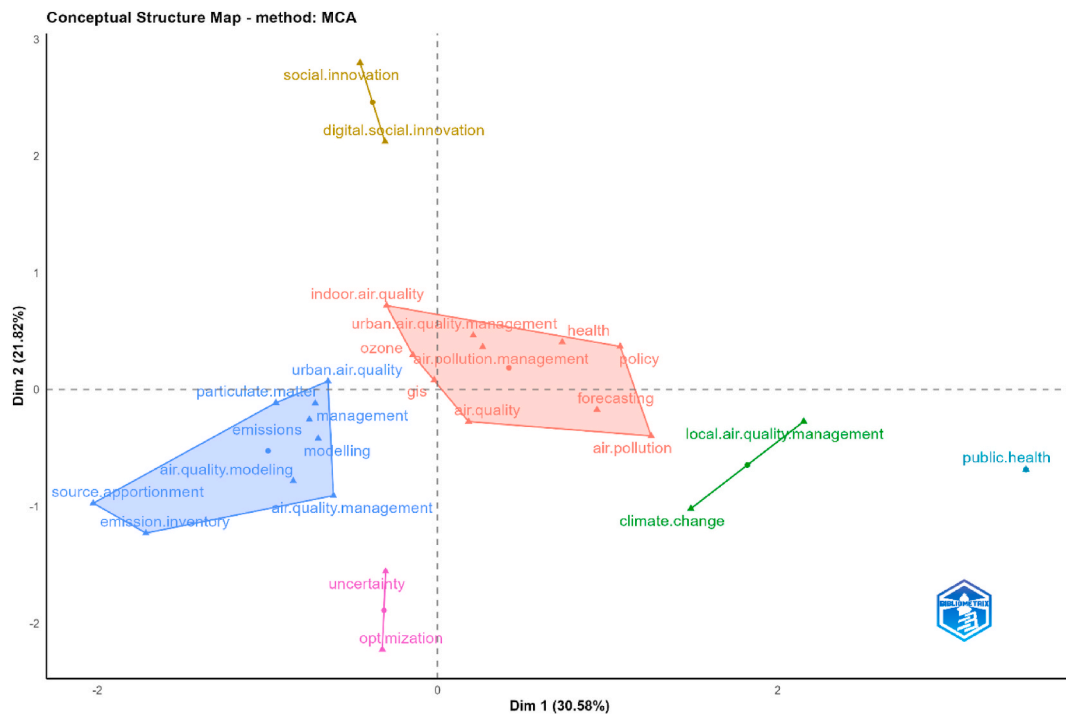


Fig. 5. Author keyword conceptual structure map.

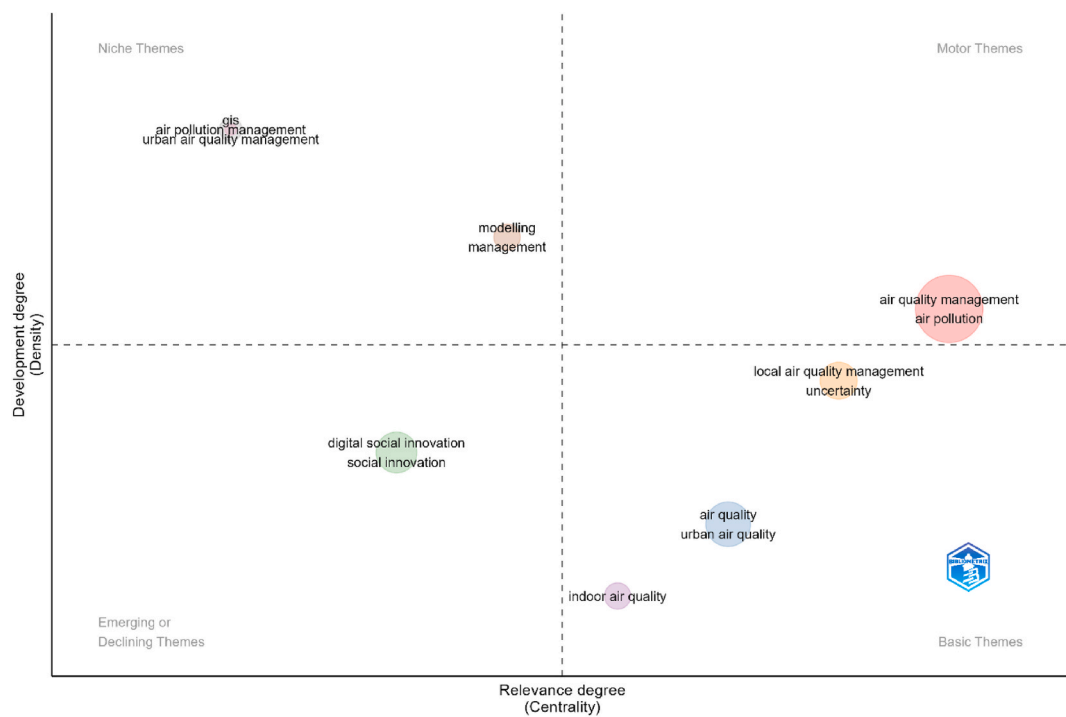


Fig. 6. Thematic evolution of author keywords.

The early conceptual foundations of the managerial core align with a decision-theoretic lineage that treats air quality management as constrained planning under structural and institutional constraints. Seminal optimization formulations such as optimal plant location with indivisibilities and economies of scale (Guldman and Shefer, 1977) and chance-constrained dynamic approaches to regulatory compliance (Guldman, 1988) establish a normative model-based view of management that is later generalized through stochastic programming

treatments of risk, strategies, and transport-related uncertainties (Watanabe and Ellis, 1993). Cooper's survey of mathematical programming in air pollution management (Cooper et al., 1997) consolidates this foundation by explicitly positioning optimization as central not only to control strategy design but also to monitoring network design and to constraints that are implicitly social and political (e.g., equity and risk considerations). In the historiograph, this foundational orientation is expressed by the rise of methodological keywords such as

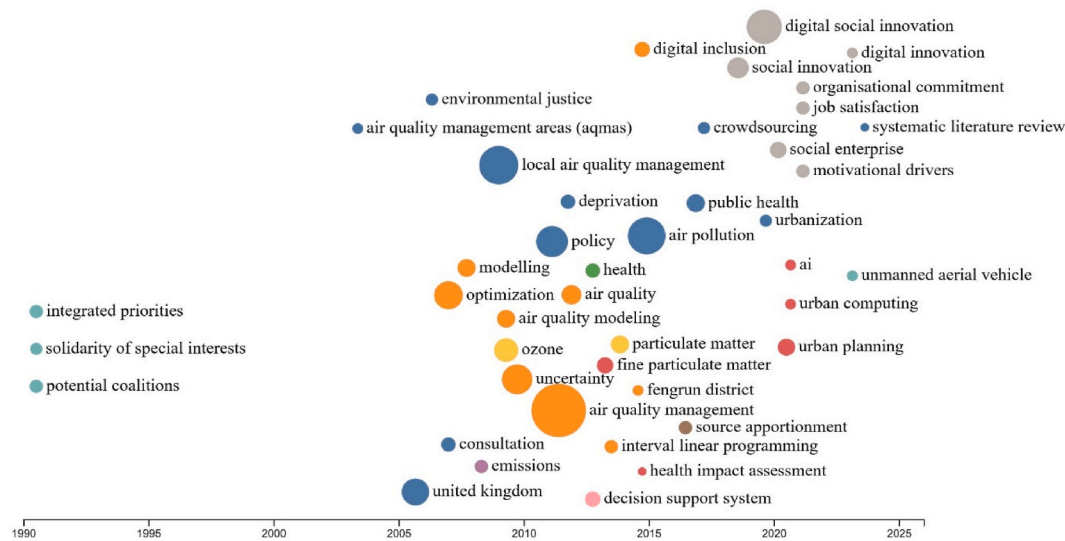


Fig. 7. Historiograph of author keywords (1975–2025).

“optimization” and “modelling”, which become closely associated with the expanding managerial core and anticipate later specialization in uncertainty-aware decision frameworks.

In parallel to these decision-analytic origins, the historiograph indicates that the field’s earliest visible governance emphasis is explicitly political and deliberative, represented by “integrated priorities”, “potential coalitions”, and “solidarity of special interests”. These keywords signal an initial research concern with collective choice and legitimacy: how preferences, coalitions, and integrated criteria shape which measures are selected and accepted. This strand becomes institutionalized and geographically grounded in the mid-to-late 2000s through the co-occurrence of “united kingdom”, “air quality management areas (aqmas)”, and “consultation” with the enlarging node “local air quality management”. This pattern mirrors the UK LAQM literature in which the object of analysis is the management regime itself—how statutory processes, designation of AQMAs, and consultation practices translate national objectives into local action (Longhurst, 1996; Beattie et al., 2001), and how barriers, organizational cultures, and behavioural factors produce a “strategic gap” between planning and remediation (Cannibal and Lemon, 2000). The continued visibility of “consultation” in the historiograph is consistent with later work arguing that LAQM functions as a risk management process requiring cross-sector integration and public engagement, particularly with public health actors (Longhurst et al., 2006; Brunt et al., 2016).

A pronounced methodological and decision-analytic trajectory becomes the defining technical signature from the late 2000s into the mid-2010s, structured in the historiograph by “air quality modelling”, “modelling”, “optimization”, and especially “uncertainty”. This configuration corresponds to the emergence of uncertainty handling as a core design object in regional AQM modelling, exemplified by influential fuzzy-stochastic robust programming formulations (Liu et al., 2003) and their subsequent development into two-stage hybrid methods (Li et al., 2006), interval-parameter and fuzzy-stochastic programming approaches (Lu et al., 2008), inexact fuzzy chance-constrained models (Xu et al., 2010), and joint-probabilistic, multi-pollutant extensions (Lv et al., 2011). The historiograph’s explicit appearance of “interval linear programming” adjacent to “air quality management” and “uncertainty” reflects the maturation of robust/inexact decision frameworks designed to negotiate trade-offs among abatement cost, feasibility, and tolerable risk of exceedance under incomplete or ambiguous information. The inclusion of place-based terms such as “fengrun district” indicates how these advanced formalisms are frequently legitimized through district or city-scale applications, consistent with a broader methodological culture

in which implementability and tractability become criteria of novelty, reinforced by work on screening and computational feasibility for complex chance constraints (An and Eheart, 2007).

Alongside this optimization–uncertainty axis, the historiograph highlights a complementary modelling-to-policy bridge through the growing prominence of “source apportionment”, “emissions”, and “decision support system”. This cluster corresponds to a shift from modelling as abstract prediction to modelling as operational attribution and policy justification. Dispersion modelling is articulated early as a practical tool for local management (Ekinci, 1998), and later work increasingly couples meteorology and chemistry to quantify source contributions for regulatory prioritization (Huang et al., 2012) and to support apportionment in complex urban contexts (Wu et al., 2018). Integrated assessment approaches that explicitly compare technical and non-technical measures and evaluate plans as policy portfolios (D’Elia et al., 2009; Miranda et al., 2015) align with this trend, while practice-improvement initiatives such as the FAIRMODE pilot (Pisoni et al., 2019) represent a late-stage implementation frontier in which the central problem becomes standardization, benchmarking, and comparability of AQM practices across jurisdictions.

From the early-to-mid 2010s onward, the historiograph displays a clear outcome and equity-oriented turn through the emergence of “health”, “public health”, and “health impact assessment” in close temporal proximity to “deprivation” and “environmental justice”. This pattern maps onto representative studies that reframe air pollution management toward health-anchored accountability and distributive justice. Environmental equity is explicitly positioned as central to air quality management, linking local and international implications for human health and climate (O’Neill et al., 2008), while health impact metrics provide evaluative scaffolding for comparing strategies in terms of disability-adjusted life years and monetized outcomes (Martens et al., 2015). The historiograph’s continued attention to pollutant-specific terms: “particulate matter”, “fine particulate matter”, and “ozone”, suggests that this outcome-oriented shift does not replace pollutant control concerns but reorganizes them around exposure mixtures and health relevance. This is consistent with the multipollutant paradigm articulated around 2010, which argues for management frameworks that move beyond single-pollutant logic and toward integrated risk-based strategy design (Chae, 2010; Hidy and Pennell, 2010), and with later accountability-oriented evaluations linking policies to measurable reductions in mortality or hospitalizations (Han et al., 2018; Rose et al., 2021).

In the later years of the timeline, the historiograph captures a state-

of-the-art shift toward digitalized management infrastructures through the clustering of “urban planning”, “urban computing”, “ai”, and “unmanned aerial vehicle” around the managerial core, alongside persistent “decision support system”. This pattern reflects the transition from model-centric decision support toward data-centric governance ecosystems in which sensing networks, analytics, and computational infrastructures are integrated into planning and operational workflows. Representative work in this lineage begins with GIS and optimization-enabled decision support (Fedra and Haurie, 1999), extends through environmental telematics and web-enabled tools (Karatzas and Mousiopoulos, 2000) and user-requirement-driven integrated information systems (Karatzas et al., 2003), and is institutionalized through municipal GIS-based decision support system implementations (Elbir et al., 2010). The more recent frontier is characterized by smart-city architectures that integrate IoT, AI/ML, and cloud computing as a unified service perspective (Kaginalkar et al., 2021) and by explicit attention to big data governance as a design constraint for urban air quality management (Kaginalkar et al., 2022). The appearance of “unmanned aerial vehicle” corresponds to an emerging monitoring frontier that expands the spatial-temporal resolution of evidence available for management, complementing broader trends toward low-cost sensing and high-resolution exposure mapping seen in the underlying corpus even when not explicitly rendered as keywords in the historiograph.

The historiograph also indicates that the most forward-looking operational frontier involves a compression of managerial tempo, moving from long-horizon plans to dynamic, near-real-time decision cycles. This is consistent with representative studies on operational forecasting and dynamic management (Odman et al., 2018) and with the emergence of integrated warning and decision support systems for megacities (Govardhan et al., 2024; Ghude et al., 2024). The transition becomes conceptually explicit in the appearance of control-oriented approaches in the broader corpus, where receding-horizon and model predictive control logics propose a constrained control framing for short-term air quality management (Sangiorgi and Carnevale, 2023; Sangiorgi et al., 2024). In historiographic terms, this frontier is reflected in the co-presence of decision support, advanced analytics, and urban computing keywords near the most recent years, suggesting that real-time management is becoming an identifiable sub-agenda.

The digital social innovation neighbourhood evolves in parallel and becomes denser toward the end of the timeline, where “digital social innovation” is surrounded by “crowdsourcing”, “systematic literature review”, “social enterprise”, “motivational drivers”, “organisational commitment”, and “job satisfaction”. This internal structuring indicates consolidation of DSI as a research domain that combines synthesis and evidence mapping with organizational and behavioural explanations for adoption and impact. Representative work demonstrates an early methodological concern with linked-data crowdmapping and interoperable participation (Halpin and Bria, 2015), the development of frameworks for designing DSI (Fu and Huang, 2015) and platforms grounded in co-creation and open systems (Dinant et al., 2017), and a later maturation toward landscapes, taxonomies, and success-factor research agendas (Misuraca and Pasi, 2019; Buck et al., 2023, 2025; Buyannemekh, 2024), including scenario-based consideration of socio-political implications in urban governance (Certoma, 2022). When interpreted together with the contemporaneous rise of citizen-centered air quality approaches in the broader AQM literature, the historiograph suggests an emergent convergence: state-of-the-art air quality governance increasingly depends not only on improved models and richer sensing infrastructures, but also on digitally mediated participation, interpretive frameworks for public meaning-making, and organizational designs capable of converting heterogeneous data into legitimate and equitable action.

### 3.6. Keywords coupling

Bibliographic authors’ keyword coupling facilitates the

identification of documents that share similar concepts across different contexts. Author keywords were lemmatized and normalized to ensure consistency during the analysis. This preprocessing step enabled the identification of author keywords that appeared across multiple documents. A total of 17 author keywords were identified as being present in both DSI-related and AQPM documents (Fig. 8). The analysis revealed the following convergent categories of keywords.

- Digital technologies and smart cities: This group encompasses keywords such as “Artificial Intelligence”, “Big Data”, “Big Data Analytics”, “ICT”, “Education”, “Information Technology”, “Smart City”, “Sustainability” and “City” and “Indicator”. These keywords were identified in 29 documents.
- Inequality: This group considers keywords such as “Inequality” and “Social Medium”, which were found in five documents.
- Policy development: This group includes keywords such as “Transport Policy”, “Policy”, “Evidence-Based Policy” and “Strategy”, which were identified in 17 documents.
- Regional approaches: This category surges by only one shared author keyword “Latin America”, which appeared in two documents.

#### 3.6.1. Digital technologies and smart cities

Digital technologies have fundamentally reshaped AQPM by enabling real-time monitoring, decision-making, and participatory governance. For instance, ICTs, including IoT and AI, are shown to facilitate the real-time collection and analysis of environmental data, which in turn supports more responsive and adaptive governance structures (Cannibal and Lemon, 2000; Chen et al., 2023; Kaginalkar et al., 2021; Shahbaz et al., 2021). In industrial settings, such as Tangshan’s iron and steel sector, the deployment of ICTs allows for the precise identification and targeted mitigation of pollutant sources, demonstrating a direct link between technological adoption and improved environmental outcomes (Chen et al., 2023).

In smart cities, data-driven strategies and advanced technologies improve governance and sustainability, while DSI enhance collaboration (Alshbatat, 2023; Myeong and Shahzad, 2021). Ensuring digital inclusion, particularly for marginalized groups, is essential to equitable democratic participation, as it provides access to digital tools and platforms that empower communities to engage in decision-making processes (Chompunth, 2013; Mehmood and Imran, 2021; Rodrigues et al., 2021). DSI leverage ICTs to foster inclusive and participatory approaches in both social and environmental governance, thereby empowering individuals and communities to engage actively in AQPM (Eckhardt et al., 2016; Zerrer & Sept, 2020). This participatory dimension is further supported by evidence that IT enables dynamic simulations for pollutant monitoring, integrating technical precision with broader societal benefits (Fu and Huang, 2015; Li and Shue, 2004; Rosa-Bilbao et al., 2025). AI, as a subset of digital technologies, is particularly notable for its capacity to combine prediction and mitigation functions, thereby supporting the development of sustainable solutions within participatory frameworks (Davide et al., 2021; Myeong and Shahzad, 2021).

DSI includes open data portals and open knowledge repositories that support community mapping and urban planning; low-cost open-hardware sensor kits that enable citizen science (e.g., crowdsourced air-quality monitoring); crowdsourcing platforms for reporting mobility and public safety issues; gamified civic apps that incentivize recycling or public transport use; participatory budgeting and co-design hackathons for local policymaking; and crowdfunding initiatives for community gardens and cultural preservation (Buyannemekh, 2024; Devlin, 2020). These innovations empower local governments and communities to address urban challenges collaboratively, generating economic value and enhancing community interaction (Buyannemekh, 2024).

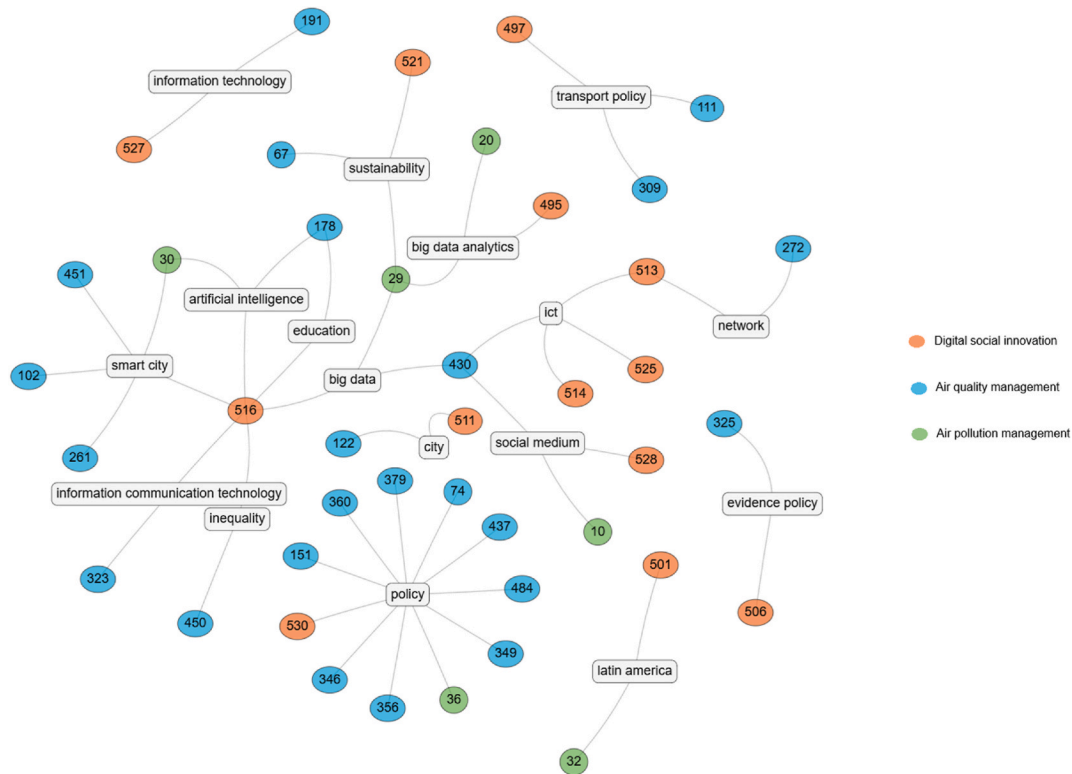


Fig. 8. Bibliographic coupling network based on author keywords.

### 3.6.2. Policy development

Policies integrating DSIs align technology with societal needs for sustainability. Traditional policies focus on coordination and compliance, while DSIs use tools like crowdmapping to enhance engagement and decision-making. Clear communication drives behavioral change, amplified by participatory platforms (Cannibal and Lemon, 2000; Halpin and Bria, 2015). Combining DSIs with policy frameworks fosters evidence-based policy development in air quality complexities (Munoz-Pizza et al., 2022). DSIs, leveraging ICT tools, promote citizen welfare and social investments (Misuraca and Pasi, 2019). For instance, transport policy impacts urban air quality by shaping mobility and reducing emissions (Kliucininkas et al., 2005). DSIs democratize transport planning and enhance participation via ICTs (Mehmood and Imran, 2021). Combining predictive modeling with participatory platforms could create responsive, equitable policies addressing pollution (Kliucininkas et al., 2005; Mehmood and Imran, 2021).

### 3.6.3. Inequality

The health burden of environmental exposures is not equally distributed, a fact that is receiving increased attention in environmental research (Davos et al., 1991). Inequality shapes pollution exposure and access to decision-making, which disproportionately affects disadvantaged populations (Brunt et al., 2017; DAVOS et al., 1991). Frameworks such as SmartAirQ could beneficially integrate urban services and technology to foster more collaborative approaches to these issues (Kaginalkar et al., 2022). To achieve equity, it is essential that strategies integrate public health priorities with robust stakeholder engagement (Brunt et al., 2017; Davide et al., 2021). By enhancing resource efficiency and community involvement, DSIs can support the development of scalable and inclusive solutions (Milwood and Roehl, 2019).

### 3.6.4. Regional approaches

Air quality challenges are deeply shaped by regional socio-economic, environmental, and policy contexts. In Latin America, for example, urbanization, industrial growth, and socio-economic disparities create

significant obstacles to effective AQPM (Riojas-Rodriguez et al., 2016). DSI offer promising avenues for addressing these challenges by leveraging technology and new governance models to tackle social, environmental, and economic issues (Bonina et al., 2021). However, the effectiveness of such innovations is often constrained by fragmented monitoring systems and uneven regulatory frameworks, which hinder the integration of scientific evidence into policy and limit the capacity for coordinated action (Munoz-Pizza et al., 2022).

This fragmentation is not unique to Latin America; similar barriers are observed in other regions, where institutional capacity, legal frameworks, and knowledge transfer remain persistent challenges to evidence-based policy development. Studies across Europe reveal that regional AQPM is most effective when it incorporates participatory and collaborative approaches. For instance, the SHERPA-Cloud model (SHERPA: Screening for High Emission Reduction Potential on Air) enables policymakers, citizens, Non-Governmental Organizations (NGOs), and industries to quantify the impacts of emission reduction strategies and thus inform more robust governance decisions (Pisoni et al., 2024). In the United Kingdom (UK), the Local Air Quality Management framework, demonstrates the value of structured, multi-level governance and the integration of DSI to enhance urban planning and AQPM under fiscal constraints (Devlin, 2020; Longhurst, 1996; Beattie et al., 2001). These examples underscore the importance of capacity building, stakeholder dialogue, and localized governance in improving data collection, policy effectiveness, and ultimately public health outcomes (Brunt et al., 2017; Ndou and Aigbavboa, 2023; Davos et al., 1993).

### 3.7. Topic modelling

In the process of applying topic modelling to scientific literature or other large text collections, it is necessary to define a set of topics to organize and analyse the documents (Armenia et al., 2024). However, the literature does not provide a definitive guideline for selecting the ideal number of topics (Zhao et al., 2015).

To address this, the R package “ldatuning” (Nikita and Chaney,

2020), recognized for its robustness (Ballester and Penner, 2022), was employed. The selection of the optimal number of topics followed the approach described by Kunc et al. (2018), which involves identifying the intersection point of two maximization metrics. In this case, the metrics proposed by Griffiths and Steyvers (2004) and Deveaud et al. (2014) were used. The intersection of these metrics, as illustrated in Fig. 9, indicated that six topics should be considered for the chosen set of terms. This data-driven approach ensured a balanced and meaningful topic structure for subsequent analysis (Armenia et al., 2024).

### 3.7.1. Labelling topics

The process of assigning labels to each identified topic began with a review of the top 5 articles with the highest topic probability, as determined by Latent Dirichlet Allocation (LDA). Titles and abstracts of these top articles were examined. This strategy ensured a thorough understanding of the main themes associated with each topic. After selecting the most representative documents, collective discussions were held to interpret the central ideas and recurring concepts within each group of articles. Potential topic labels were proposed and refined through group deliberation, with open dialogue used to resolve any differing viewpoints until consensus was achieved on the most appropriate label. The final set of topic labels, established through this collaborative and consensus-driven process, is presented in Table 2. This method ensured that each label accurately reflected the underlying themes of the research areas, providing a clear and organized structure for further analysis and interpretation (Armenia et al., 2024).

After obtaining these labels, an in-depth analysis of each topic will follow. Each topic includes a subsequent step that applies a social–digital classification dictionary. Using this dictionary, papers are categorized as digital, social, both, or neither. Priority will be given to papers with the highest posterior probability of membership in each topic according to LDA, as well as to papers in which both social and digital elements are identified within the same document, since such papers serve as connectors between DSI and AQPM.

### 3.7.2. Topic 1: digital social innovation

Several documents exhibit a very high probability of belonging to the DSI topic, including research on European welfare systems (Davide et al., 2021), landscaping the DSI evidence base in the EU (Misuraca and Pasi, 2019), and designing DSI platforms (Dinant et al., 2017). Recent publications also show high topical relevance, such as studies on healthcare ecosystems (Cosimato et al., 2024), a taxonomy of DSI (Buck et al., 2023), and success factors for DSI initiatives (Buck et al., 2025).

Across the 40 documents assigned to this topic, there is strong integration of social and digital elements. Most; 37 of 40 (92.5%); contain both social and digital keywords. A single document (2.5%) is classified as digital-only, and none are social-only. The remaining two documents (5%) contain no keywords from either dictionary. This distribution indicates that research in this area predominantly addresses

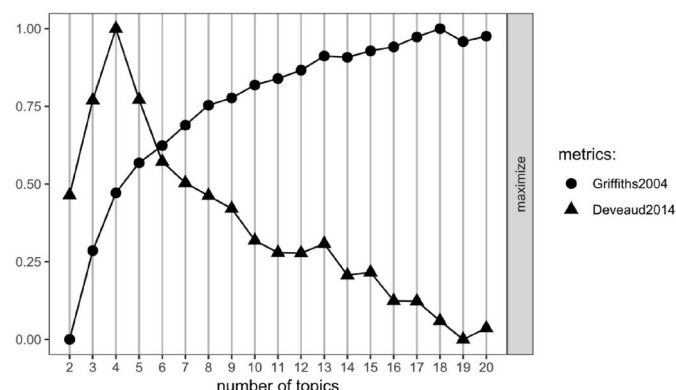


Fig. 9. Determination of the optimal number of topics.

Table 2  
Root words and topic labels.

Topic Labels	Root Words
Digital social innovation	social, innovation, digital, technology, DSI, smart, development, service, design, ecosystem
Urban air quality	air, quality, management, system, urban, pollution, model, concentration, health, city
Air quality management	air, quality, management, local, pollution, policy, process, authority, area, environmental
Emissions	emission, source, air, quality, traffic, model, urban, area, pollution, concentration
Indoor air quality	air, concentration, quality, indoor, management, pollutant, particulate, carbon, vehicle, source
Programming and decision-making models	air, management, quality, model, system, control, decision, uncertainty, programming, cost

the interplay between technological and social dimensions. For instance, research on smart city air quality management connects technologies like artificial intelligence, big data, and the internet of things with social elements such as citizen engagement, collaboration, and governance (Kaginalkar et al., 2022). Similarly, studies on urban governance explore how DSI is linked to citizen participation and public sector activities (Certoma, 2022). Other examples include the use of digital platforms to address healthcare challenges through social innovation (Cosimato et al., 2024) and the connection of ICT with community engagement and policy for inclusive transport planning (Mehmood and Imran, 2021).

### 3.7.3. Topic 2 urban air quality

In the domain of Urban Air Quality, an analysis of 109 documents published between 1978 and 2025 reveals a strong focus on management and policy. The search term ‘Air quality management’ yielded 98 documents, while ‘Air pollution management’ returned 11, and no documents were found for ‘Digital social innovation’. The relevance of these documents to the core topic, as measured by dominant topic probability, ranges from 0.333 to a very high 0.994. Exemplifying this strong thematic focus are studies on the public health benefits of management policies (Han et al., 2018), the design of comprehensive management systems (Kakarla et al., 2019), and the development of systems for policy support and decision-making (Moussiopoulos et al., 2012; Deserti et al., 2001).

In total, 67% of the documents contained keywords related to either social or digital aspects. Specifically, 24.8% of the documents focused exclusively on digital themes, 22.9% on social themes, and 19.3% integrated both. The most prominent digital keywords were decision support systems (13 mentions), sensors (12), and neural networks (10). On the social side, the most frequent keywords were policy/regulation (30 mentions), and human health (9).

These documents illustrate a connection where digital technologies are developed and deployed to serve social and governmental functions: For instance, data analytics and neural networks are used explicitly to aid in policy-making (Li and Shue, 2004), and sensor-based management systems are designed with stakeholders and policy/regulation in mind (Kakarla et al., 2019). This connection is consistently framed around the need for evidence-based governance; digital platforms and big data models are built to help policy-makers and citizens simulate and understand the effects of different policies (Pisoni et al., 2024).

### 3.7.4. Topic 3 air quality management

The corpus on air quality management spans 1983–2025 and comprises 149 documents. The model indicates topic probabilities ranging from 0.313 to 0.996. Retrieval by search terms shows 11 records under ‘Air pollution management’, 138 under ‘Air quality management’, and none under ‘digital social innovation’. Several papers exhibit near-maximal topic probabilities, including: public-health integration in Wales via a Delphi study (Brunt et al., 2018), a public health-driven risk assessment approach (Brunt and Jones, 2019), and science–policy interplay in the Pearl River Delta and Hong Kong (Zhong et al., 2013).

Recent aligned contributions is a landscape assessment approach to AQPM in Maharashtra (Das and Ghosh, 2023), and a study translating research to policy recommendations in the Greater Bay Area, China (Chow et al., 2025).

Across the 149 connected papers, 127 documents contained at least one matched keyword from the digital or social dictionary (85.2%), while 22 had neither (14.7%). Class proportions show that socially oriented articles dominate at 113 of 149 (75.8%), combined social-and-digital at 10 of 149 (6.7%), and digital-only at 4 of 149 (2.6%). The most frequent digital keywords were GIS (9 mentions), sensors (2), and text mining (1). In contrast, social keywords were more prevalent, led by policy/regulation (87), and governance/public sector (39).

Social and digital elements were identified when digital methods are deployed in governance, community engagement, and policy design contexts. Studies that combine classes consistently pair specific tools with institutional and participatory keywords: GIS appears alongside community and policy/regulation in both national and local government settings (Martins, 2010; Birchall and Wood, 1997; Deacon, 1997), text mining is linked with collaboration, governance/public sector, and local government (Song et al., 2023), digital platforms are connected with policy/regulation (Badach et al., 2020), and big data or sensors co-occur with behavior/perception, community, and policy/regulation (Giri and Nagendra, 2024). Decision-support systems and predictive/statistical models explicitly connect technical analytics to policy and policy-makers (Fedra et al., 1996).

### 3.7.5. Topic 4 emissions

In the context of Emissions, an analysis of 35 documents published between 1983 and 2025 reveals a distinct focus within the AQPM literature. All documents were sourced using the 'Air quality management' search term. The alignment of these documents with the Emissions topic varied, with dominant topic probabilities ranging from 0.286 to a very high 0.996. Illustrating the upper end of this range are studies such as the application of an integrated modeling tool for source apportionment in Benxi, China (Wu et al., 2018), an assessment of PM10 (Particulate Matter) emission sources in urban AQPM (Huang et al., 2012), and an analysis of the spatiotemporal variability of particle number size distributions (Young et al., 2012). Recent and highly relevant examples include the application of a PM2.5 dispersion models, monitoring and source apportionment (Ratanavalachai and Trivitanurak, 2023; Li et al., 2017).

From this corpus, 22 documents (63%) contained keywords related to social or digital elements. The distribution shows a strong inclination towards social aspects, with 42.9% of the documents classified as social-only, compared to 11.4% as digital-only. An additional 8.6% of documents contained both social and digital elements, while 37.1% had neither. The most prominent social keywords identified were policy/regulation (appearing in 11 documents), policy (6), and regulation (3). On the digital side, top keywords included GIS (2), data analytics (1), and algorithms (1).

The intersection of social and digital elements leverages computational tools to inform policy and health assessments. For instance, research has combined data analytics with policy and regulations for health assessments (Hopke, 2008), used GIS to compare management strategies considering public behaviour and perception (Ying et al., 2007), and harnessed AI and machine learning to support data-driven approaches for human health protection (Lin et al., 2025). These connections are driven by the need to provide robust, data-informed evidence for policy-making (Wu et al., 2018).

### 3.7.6. Topic 5 indoor air quality

The corpus on indoor air quality spans from 1981 to 2025 and comprises 52 documents. Dominant-topic probabilities range from 0.314 to 0.991, indicating heterogeneous centrality of indoor air quality across the set. With respect to search-term coverage, 46 documents matched "air quality management", 6 matched "air pollution

management", and none matched "digital social innovation".

Across the 52 connected papers, 27 documents contained at least one keyword from the digital or social dictionaries, representing 51.9% of the corpus. Within this subset, 16 documents were classified as social-only (30.8% of the full set), 6 as digital-only (11.5%), and 5 as both social and digital (9.6%); the remainder were neither (48.1%). The most frequent digital keywords were sensors (n = 5), sensor (n = 4), and internet of things (n = 3). The most frequent social keywords were policy/regulation (n = 8), behavior/perception (n = 5), and social/qualitative methods (n = 4).

The highest dominant-topic probability was observed for an experimental study on combined ventilation and air cleaning (Ciuzas et al., 2016). Other highly aligned documents include an assessment of indoor air purifiers and ventilation in Dubai (Jung and Alshamasi, 2024), and a design study of CO2 sensor systems for indoor air quality (Abe and Tanaka, 2024) and a materials-focused efficiency study for indoor air quality control foams (Ji et al., 2023).

Documents categorized as both social and digital explicitly connect technological techniques with policy, collaboration, citizen engagement, or behavioural considerations. These include AI and machine learning aligned with policy and policy measures in India (Rautela and Goyal, 2024), a school-based citizen-science IoT framework emphasizing awareness, citizens, and community (Barros et al., 2024), a systematic review linking data analytics and sensors to human health (Zhang and Srinivasan, 2020), physics-informed neural networks paired with behavioural dimensions (Kim et al., 2025), and machine learning explicitly tied to policy/regulation during COVID-19 lockdowns (Brancher, 2021).

### 3.7.7. Topic 6: Programming and Decision-Making Models

The analysis of the topic Programming and Decision-Making Models reveals a substantial body of research spanning from 1982 to 2025, comprising 57 documents. Most of these documents were retrieved using the search term "air quality management" (54 documents), with a smaller subset from "air pollution management" (3 documents) and none from "digital social innovation". The dominant-topic probability ranges from 0.357 to 0.994. Documents with the highest probabilities often focus on complex optimization and modeling techniques, such as T-sets based optimization (Garai et al., 2017), inexact fuzzy-random-chance-constrained models (Xu et al., 2013), and modeling under stochastic and interval uncertainties (Liu et al., 2015; Lv et al., 2011). Recent publications continue this trend, exploring multi-domain models for sustainable management (Cebolla-Aleman et al., 2025), adaptive control systems for heritage buildings using digital twins (Zhang et al., 2023), and optimized management based on AI predictions (Guo et al., 2024).

From the 57 documents, a subset of 30 was identified as containing keywords related to social or digital dimensions. A classification of this subset shows a varied landscape: 21.1% of the documents focus exclusively on digital aspects, 15.8% on social aspects, and another 15.8% integrate both. A significant portion, 47.4%, did not contain keywords from either category, suggesting a core focus on purely technical or mathematical modeling. The most prominent digital keywords were algorithms (12 mentions), predictive/statistical models (3), and sensor (2). On the social side, the top keywords were policy/regulation (10 mentions), policy (4), and governance/public sector (4).

These studies connect computational methods to governance structures: For instance, one study combines predictive models with policy and regulation (Ye et al., 2020), while another discusses the use of decision support systems within the public sector (Elbir et al., 1997). The connection is also evident where algorithms are developed to support decisions involving multiple stakeholders (Cheng et al., 2015; Jin et al., 2018). The link between the digital and social is often driven by necessity, where computational tools are designed to meet the demands of policy and regulation. This connection is particularly crucial in long-term strategic planning, where digital platforms are used to

understand uncertainty within existing and future regulatory landscapes (Gamas et al., 2015).

#### 4. Discussion and implications

DSI and AQPM remain structurally and conceptually separate research domains: bibliometric coupling and LDA show minimal cross-field integration (only 17 of 1269 shared author keywords) and most publications align strongly with topics internal to their originating field. This divide is reinforced by differences in field maturity and organisation, AQM appears consolidated and star-scientist driven, while DSI is fragmented and emerging, alongside an uneven global geography where the USA dominates output, China and India surge in recent years, and collaboration is concentrated in a few brokerage corridors (notably USA–China, with Canada as a convergence node).

Conceptual and strategic mapping further indicate that AQPM is anchored in a technical measurement/modelling base linked to governance-and-health concerns, with “air quality management” as the central motor theme, whereas DSI forms an isolated, weakly connected emerging cluster.

Historically, AQPM evolves from optimization and uncertainty-aware decision frameworks toward decision-support, health/justice-adjacent accountability, and increasingly digital, near-real-time management infrastructures (AI, urban computing, UAVs), while DSI densifies around crowdsourcing, digital inclusion, and adoption/impact factors, suggesting a growing but still incomplete alignment where DSI’s socio-technical participation and legitimacy mechanisms could help translate AQPM’s expanding digital capacity into trusted, actionable governance.

Fig. 10 illustrates how social, digital, and combined (social + digital) keywords are distributed across the six LDA topics, highlighting clear differences in topical “lexicons”. The Air Quality Management topic is dominated by social keywords, consistent with its emphasis on policy, governance, and institutional decision-making. By contrast, digital keywords concentrate in more technically oriented topics; especially Programming and Decision-Making Models and Urban Air Quality, where computational methods, sensing, and data infrastructures are central. The Digital Social Innovation topic is distinctive because combined keywords prevail, indicating that social and digital elements are routinely co-articulated and reinforcing its inherently socio-technical character. Table 3 complements this overview by listing, for each topic, a recent representative document that explicitly includes both

social and digital keywords.

Despite DSI and AQPM structural independence, we identify five higher-order areas of convergence, derived through manual synthesis that integrates keyword groups and topics (Fig. 11).

##### 4.1. Digital infrastructures & smart urban systems

This convergent area arises where the keyword group “Digital Technologies & Smart Cities” intersects with the topics “Digital Social Innovation”, “Urban Air Quality”, “Programming & Decision-Making Models” and “Indoor Air Quality” because these components jointly require sensing, computation, and integration layers that enable end-to-end environmental intelligence (Bai et al., 2024; Certoma, 2020).

The results reveal a significant asymmetry: while AQPM literature demonstrates the use of digital tools, it lacks the integrated socio-technical framing characteristic of DSI. For example, within the “Urban Air Quality” topic, 24.8% of documents are digital-only and 19.3% integrate both social and digital elements, driven by keywords like “decision support systems” (13 mentions) and “sensors” (12). However, in the core “Air Quality Management” topic, a striking 75.8% of documents are social-only, with a mere 6.7% integrating both dimensions.

In contrast, 92.5% of documents in the “Digital Social Innovation” topic are inherently socio-technical, combining digital and social keywords. This suggests an opportunity: DSI can provide the “socio-technical glue” to connect AQPM’s established digital infrastructures, such as low-cost sensors, IoT nodes, and dispersion models; with participatory frameworks. The implication is that DSI offers a ready-made toolkit of engagement models, platform governance, and inclusive innovation methods that can transform the purely technical data streams of smart urban systems into socially legitimate and actionable environmental intelligence.

##### 4.2. Participatory data practices & governance

This convergent area is generated by the overlap of the keyword groups “Digital Technologies & Smart Cities” and “Policy Development” with the topics “Digital Social Innovation” and “Air Quality Management” because data platforms and governance mechanisms co-evolve to democratize access, interpretation, and actionability of air quality information (Halpin and Bria, 2015; Kaginalkar et al., 2022; Misuraca and Pasi, 2019).

This area is also grounded in the high frequency of governance-related keywords across the AQPM corpus; for instance, “policy/regulation” appears 87 times in the “Air Quality Management” topic alone. Bridging studies show that digital infrastructures like open-source portals and blockchain-secured ledgers are not merely data repositories but mechanisms for institutionalizing transparency and traceability (Badii et al., 2016; Vaneeta et al., 2023).

These platforms operationalize DSI’s participatory ethos within established governance regimes by reducing expert–layperson asymmetries and building social capital (Cangiano et al., 2017). This connection is visible where digital tools are explicitly deployed to support policy processes, such as the use of GIS for public communication and regulatory management (Lindley and Crabbe, 2004; Martins, 2010). The assumption is that participatory data practices are a core feature of effective institutional design, converting raw data into collective sense-making and anchoring governance in public-facing, evidence-based accountability.

##### 4.3. Co-creative policy design & Evidence-Based Decision-Making

This convergent area results from connecting the keyword groups “Policy Development” with the topics “Emissions”, “Programming & Decision-Making Models” and “Digital Social Innovation” because model-based appraisal and participatory inputs must be integrated to

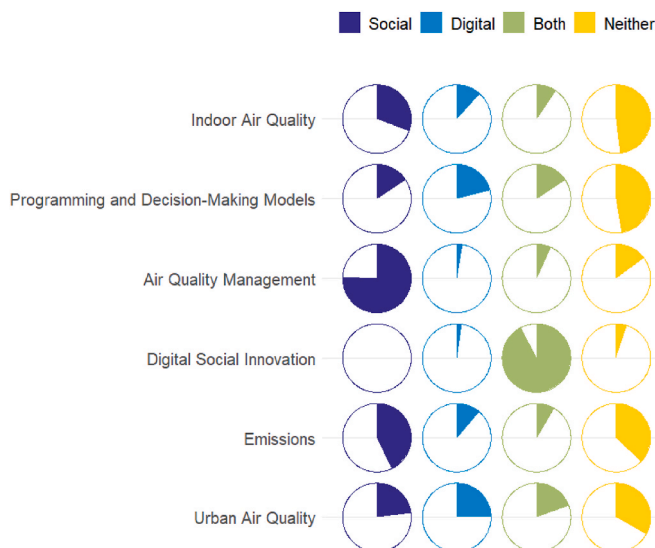


Fig. 10. Distribution of social, digital, and combined dictionary keywords across topics.

**Table 3**  
Recent topic exemplars with combined social and digital keywords (by LDA topic).

Article Title	Year	Digital Keywords	Social Keywords	Topic
Making the most of digital social innovation: An exploration into success factors	2025	digital social innovation; digital technology	digital social innovation; social innovation; social/ qualitative methods	Digital Social Innovation
Digital social innovations in rural areas - process tracing and mapping critical junctures	2025	digital social innovation; digitalization	collaboration; community; digital divide; digital social innovation; participatory; social innovation	Digital Social Innovation
Digital social innovation: how healthcare ecosystems face Covid-19 challenges	2024	digital platforms; digital social innovation; digital tools/ platforms	digital social innovation; social innovation	Digital Social Innovation
The role of digital social innovations to address SDGs: A systematic review	2024	artificial intelligence; blockchain; digital technology; internet of things	behavior/ perception; collaboration; community	Digital Social Innovation
Digital Social Innovation in Cities: A Systematic Literature Review and a Research Agenda	2024	digital social innovation	citizens; digital social innovation; social capital; social innovation; stakeholders	Digital Social Innovation
Optimizing the Architecture of a Quantum-Classical Hybrid Machine Learning Model for Forecasting Ozone Concentrations: Air Quality Management Tool for Houston, Texas	2025	deep learning; machine learning; neural networks; predictive/ statistical models	policy/ regulation; quality regulations; regulations	Urban Air Quality
SHERPA-Cloud: An open-source online model to simulate air quality management policies in Europe	2024	big data; digital platforms	citizens; policy; policy makers; policy/ regulation	Urban Air Quality
Decision Support System version 1.0 (DSS v1.0) for air quality management in Delhi, India	2024	decision support systems	policy/ regulation	Urban Air Quality
Exploring Temporal and Spatial Trends in PM2.5 Concentrations in the Klang Valley, Malaysia: Insights for Air Quality Management	2024	apis	governance/ public sector; government	Urban Air Quality

**Table 3 (continued)**

Article Title	Year	Digital Keywords	Social Keywords	Topic
Air pollution perception for air quality management: a systematic review exploring research themes and future perspectives	2024	big data; sensors	behavior/ perception; community; policy/ regulation; social networks/ media	Air Quality Management
The Evolutionary Game of Cooperative Air Pollution Management under Complex Networks	2023	text mining	collaboration; governance/ public sector; government; local government	Air Quality Management
Urban Vegetation in Air Quality Management: A Review and Policy Framework	2020	digital platforms	policy; policy/ regulation; regulations	Air Quality Management
Harnessing AI and advanced modeling for precision ozone control: A data-driven approach to air quality management	2025	artificial intelligence; artificial neural; machine learning; neural networks	human health	Emissions
The use of source apportionment for air quality management and health assessments	2008	data analytics	policy/ regulation; regulations	Emissions
Comparison of air quality management strategies of PM10, SO2, and NOx, by an industrial source complex model in Beijing	2007	gis	behavior/ perception	Emissions
Dynamic Estimation of PM2.5 Penetration and Removal Rates Using Physics-Informed Neural Networks for Indoor Air Quality Management	2025	neural networks	behavior/ perception	Indoor Air Quality
SchoolAIR: A Citizen Science IoT Framework Using Low-Cost Sensing for Indoor Air Quality Management	2024	citizen science; internet of things; sensors	awareness/ education; citizen science; citizens; community	Indoor Air Quality
A Systematic Review of Air Quality Sensors, Guidelines, and Measurement Studies for Indoor Air Quality Management	2020	data analytics; sensor; sensors	human health	Indoor Air Quality
Optimized air quality	2024	algorithms; machine	policy/ regulation	Programming Models

(continued on next page)

Table 3 (continued)

Article Title	Year	Digital Keywords	Social Keywords	Topic
management based on air quality index prediction and air pollutants identification in representative cities in China		learning; neural networks		
Neural circuit policies-based temporal flexible soft-sensor modeling of subway PM2.5 with applications on indoor air quality management	2022	neural networks; sensor; sensors	policy/ regulation	Programming and Decision-Making Models
Optimized Energy and Air Quality Management of Shared Smart Buildings in the COVID-19 Scenario	2021	internet of things	awareness/ education	Programming and Decision-Making Models
A new air pollution management method based on the integration of evidential reasoning and slacks-based measure	2020	predictive/ statistical models	policy; policy/ regulation	Programming and Decision-Making Models
An integrated bi-level optimization model for air quality management of Beijing's energy system under uncertainty	2018	algorithms	governance/ public sector; stakeholders	Programming and Decision-Making Models

align technological solutions with societal needs (Halpin and Bria, 2015; Misuraca and Pasi, 2019).

For instance, the “Programming & Decision-Making Models” topic, comprising 57 documents, is rich with advanced computational methods. However, the results show that only 15.8% of these documents integrate both social and digital elements, with a large portion (47.4%) remaining purely technical. This reveals a significant gap between modeling and its application in participatory contexts. Where convergence does occur, it points toward powerful hybrid approaches. Frameworks like SHERPA-Cloud and SmartAirQ exemplify how model-based appraisals (e.g., source apportionment, scenario analysis) can be coupled with crowdsourced data and deliberative inputs to co-produce a more robust evidence base (Kaginalkar et al., 2022; Pisoni et al., 2024). This moves beyond using models for communities to problem-solving with them.

#### 4.4. Addressing inequality & Promoting Inclusivity

This convergent area emerges where the keyword group “Inequality” and the keyword group “Regional Approaches” connect with the topic “Digital Social Innovation” because distributional and procedural justice concerns are intrinsic to both exposure burdens and voice in decision processes (Bonina et al., 2021).

The analysis reveals a paradox: while the “inequality” author keyword coupling is minimal (2 documents), a latent justice orientation is evident in the frequent appearance of social keywords like “human health” and “policy” throughout the AQPM literature. This suggests that while the consequences of unequal exposure are a concern, inequality is not yet a primary analytical lens, nor is it being systematically addressed with digital tools. DSI offers concrete mechanisms to operationalize both distributional and procedural justice by integrating marginalized communities into monitoring and planning through citizen science and other participatory methods (Brunt et al., 2017; Singh et al., 2022). However, the digital divide remains a critical barrier, as evidenced by cases from both developing and developed nations (Rautela and Goyal, 2024; Zerrer & Sept, 2020). The proposition is that equity must be a core design principle. Without targeted strategies, such as hybrid online-offline engagement and community-led capacity building, DSI-enabled AQPM risks exacerbating existing informational and social inequalities.

#### 4.5. Regional adaptation & Context-Specific Solutions

This convergent area follows from linking the keyword groups “Regional Approaches” with the topics “Digital Social Innovation” and “Air Quality Management” because air quality challenges are tightly coupled to local socio-economic, environmental, and regulatory contexts that demand tailored responses (Bonina et al., 2021; Misuraca and Pasi, 2019).

The bibliometric signal for regional approaches is weak, with only one shared keyword (“Latin America”). Yet, the analysis confirms that effective AQPM is profoundly context-dependent, from the UK's Local Air Quality Management framework to multi-pollutant control policies in Asia (Longhurst, 1996; Wang and Hao, 2012). DSI's utilitarian and collectivistic orientations are well-suited to tailoring digital solutions to these diverse local socio-economic, environmental, and regulatory contexts (Bonina et al., 2021). This points to a strategy of glocalization: developing interoperable digital infrastructures (e.g., standardized sensor protocols) that can be deployed through locally governed and culturally adapted platforms.

### 5. Conclusions, limitations and future directions

#### 5.1. Conclusions

This study provides a comprehensive mapping of the thematic intersections between Digital Social Innovation (DSI) and Air Quality and Pollution Management (AQPM), revealing a research landscape characterized by significant technical depth but persistent socio-technical fragmentation. Through bibliometric analysis and topic modeling of five decades of literature, several key conclusions emerge regarding the current state and future trajectory of the field.

First, the results confirm that DSI and AQPM remain structurally independent domains. While AQPM has matured into a consolidated, policy-driven discipline focused on technical measurement, optimization, and health-anchored accountability, DSI remains a nascent and fragmented field centered on participatory platforms and social ecosystems. The minimal overlap in author keywords and the isolation of DSI as an “emerging theme” in strategic mapping suggest that the potential for digital tools to foster social collaboration in air quality governance is recognized but not yet systematically integrated into mainstream environmental management.

Second, the evolution of the field indicates a clear shift from static, model-centric planning toward dynamic, data-centric governance. The integration of IoT, AI, and real-time sensing has compressed the managerial tempo, allowing for hyper-local monitoring and near-real-time

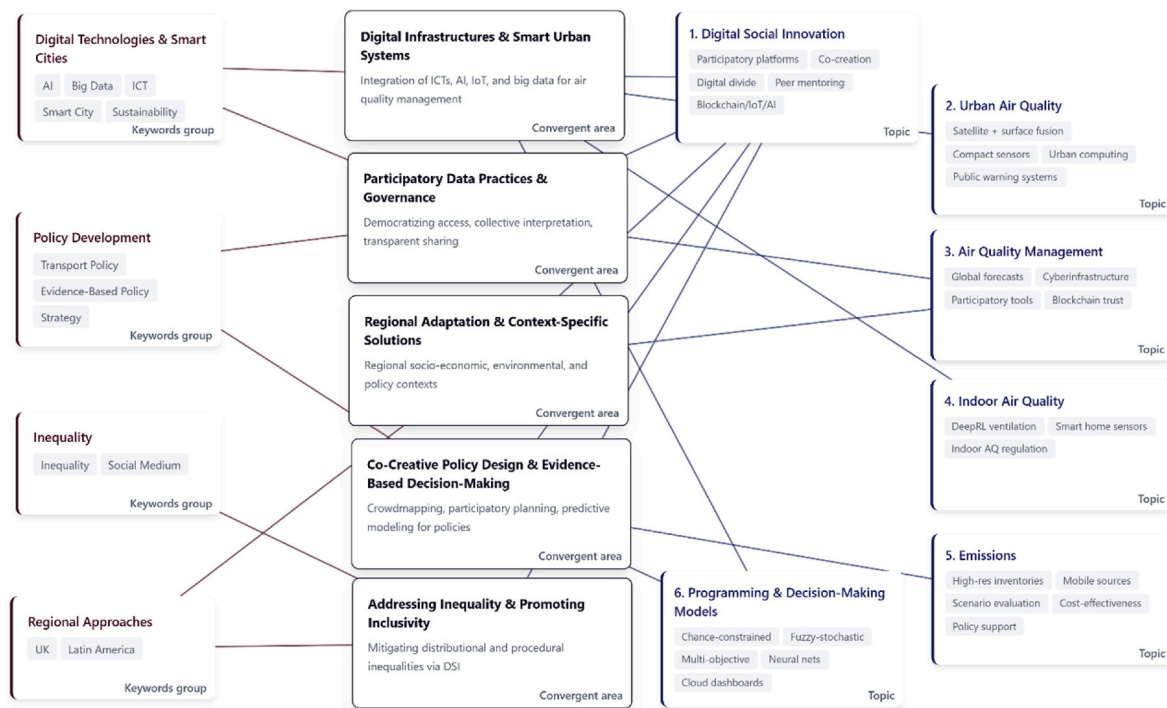


Fig. 11. Convergent areas in DSI and AQPM derived from author keyword groups and LDA topics.

decision cycles. However, the analysis highlights a “strategic gap”: while the technical capacity to generate data has exploded, the institutional and social mechanisms to convert that data into legitimate, equitable action remain underdeveloped. DSI offers the necessary “socio-technical glue” to bridge this gap by providing frameworks for citizen science, crowdsourcing, and co-creative policy design that can democratize air quality data.

Third, the study identifies environmental equity and the digital divide as critical challenges that demand urgent attention. Although literature increasingly reframes air pollution as a matter of distributive justice, the use of digital tools to specifically empower marginalized communities is still in its infancy. Without intentional design strategies that address disparities in digital literacy and sensor coverage, advanced technological interventions risk exacerbating existing social inequalities rather than resolving them.

Finally, the identified convergent areas: (1) Digital Infrastructures and Smart Urban Systems, (2) Participatory Data Practices and Governance, (3) Co-Creative Policy Design and Evidence-Based Decision-Making, (4) Addressing Inequality and Promoting Inclusivity, and (5) Regional Adaptation and Context-Specific Solutions, provide a roadmap for future research. To move toward a more holistic “Digital Social Innovation for Air Quality”, scholars and practitioners must move beyond project-based deployments toward sustained, interoperable infrastructures.

## 5.2. Limitations

The corpus is restricted to Web of Science, English-language, and title-field retrieval, likely excluding relevant work indexed elsewhere, published in other languages, or framed without target terms in titles; omission of grey literature and practitioner outputs underestimates real-world deployments and cross-sector collaborations. Keyword coupling depends on author-supplied terms; dictionary-based tagging of “social” and “digital” is a heuristic simplification; and topic modeling choices; preprocessing, a 1000-term vocabulary cap, model selection criteria; introduce parameter sensitivity. The convergent areas synthesis is descriptive and interpretive, mapping connections but not establishing

causal effects or comparative effectiveness across intervention types.

## 5.3. Gaps and future directions

### 5.3.1. Build integrated DSI–AQPM socio-technical frameworks (shared vocabulary, shared evaluation logic)

DSI and AQPM still operate largely as distinct research fields with separate vocabularies and conceptual frameworks, which constrains cross-disciplinary synthesis and cumulative learning. Future research should develop integrated socio-technical frameworks that connect technical system design, social engagement, behavioral interventions, and governance mechanisms from the outset. To make these frameworks actionable, studies should also adopt comparative designs (experimental or quasi-experimental where feasible) and standardized outcome measures to determine which combinations of tools and participation models work best under specific contextual conditions.

### 5.3.2. Design policy integration pathways that turn citizen-generated data into formal accountability

Although governance is frequently referenced in AQPM and DSI provides tools to democratize data, the institutional mechanisms that translate citizen-generated information into binding decisions remain under-specified. Future work should examine and test policy integration pathways, the organizational, political, and procedural processes through which participatory monitoring influences regulation, planning, enforcement, or investment. This includes designing and evaluating institutional arrangements such as data trusts, citizen assemblies, and formal advisory structures, and documenting why translation succeeds or fails across different jurisdictions and administrative cultures.

### 5.3.3. Advance “equity by design”: reduce digital divides and ensure fair participation and benefits

The AQPM literature often foregrounds health impacts, but inequality is not consistently used as a primary analytical lens; at the same time, the digital divide remains a major barrier to inclusive DSI. Future research should adopt equity-centered implementation approaches that explicitly measure and address disparities in access to

sensors, platforms, data literacy, and participation opportunities, especially in communities facing disproportionate pollution burdens. Priority strategies include hybrid engagement models (online + offline), community-led capacity building, and sustained educational programming (e.g., school/youth initiatives) that can strengthen long-term civic and technical capability.

**5.3.4. Develop “glocal” scaling strategies via standardization, interoperability, and replicability research**

Current AQPM approaches often skew toward either generic, one-size-fits-all interventions or hyper-local pilots that are difficult to replicate. Future research should develop “glocal” strategies that preserve local governance and cultural fit while enabling scale through interoperable infrastructures. This requires stronger evidence on scalability constraints (technical infrastructure, institutional capacity, funding models, and engagement design), including multi-site replication studies and documented scale-up pathways. A central enabling condition is standardization and interoperability; consensus protocols for low-cost sensor calibration, validation, data formats, and integration with regulatory monitoring networks.

**5.3.5. Strengthen evidence with longitudinal impact assessment, behavioral mechanism testing, and cost-effectiveness**

Across DSI-enabled AQPM studies, reported outcomes are often short-term (awareness, early behaviour change, proof-of-concept deployments), while rigorous evaluation of long-term impacts on air quality, health outcomes, policy change, and sustained behavioural shifts remains limited. Future work should support longitudinal research programs with comparison groups and standardized metrics to assess sustainability and lasting effects. In parallel, behavioural interventions should move beyond documenting outcomes to testing mediators and moderators (e.g., self-efficacy, social norms, perceived control; socioeconomic context), enabling more targeted intervention design. Finally, cost-effectiveness analyses are needed to compare monitoring architectures and engagement strategies to inform resource allocation and scaling decisions.

**5.3.6. Combine advanced analytics with multi-stressor monitoring, open science, and data ethics**

Future DSI-AQPM research should continue advancing AI/ML-

enabled calibration, data fusion, forecasting, and decision support, while ensuring transparency and interpretability so outputs can be trusted and used in governance contexts. Research should also expand from single-pollutant emphasis (often PM) toward multi-pollutant and multi-stressor approaches (e.g., NO<sub>2</sub>, O<sub>3</sub>, VOCs; and linked stressors such as heat/noise), improving environmental health relevance and local actionability. To accelerate replication and cross-city learning, the community should institutionalize open science and data sharing (open protocols, code, repositories). At the same time, expanding monitoring and participatory data infrastructures makes privacy, consent, ownership, and ethical reuse increasingly salient, requiring systematic research and governance models aligned with citizen science contexts.

**CRedit authorship contribution statement**

**Leonardo Triana:** Writing – original draft, Formal analysis, Data curation, Conceptualization. **Helinä Melkas:** Writing – review & editing, Supervision, Conceptualization. **Anne Pässilä:** Writing – review & editing, Validation, Conceptualization. **Eugenio Morello:** Writing – review & editing, Validation, Conceptualization. **Mikko Happonen:** Writing – review & editing, Formal analysis, Conceptualization.

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

**APPENDIX A – KEYWORDS DICTIONARY**

DIGITAL KEYWORDS	SOCIAL KEYWORDS
digital social innovation	policy/regulation
gis	policy
sensors	governance/public sector
algorithms	government
digital platforms	social/qualitative methods
decision support systems	community
neural networks	digital social innovation
sensor	social innovation
internet of things	collaboration
digital technology	stakeholders
data analytics	human health
smart technologies	regulations
ict	behavior/perception
predictive/statistical models	survey
artificial intelligence	citizens
big data	awareness/education
machine learning	local government
artificial neural	values/equity/trust
satellite-based	regulation
gis-based	quality regulations
micro-scale air	surveys
statistical/computational methods	environmental policy
cf-d-based air	policy making

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DIGITAL KEYWORDS	SOCIAL KEYWORDS
digital tools/platforms	questionnaire survey
information technology	co-operation
sensor-based	policy makers
cloud computing	protect public
deep learning	questionnaire surveys
digital twin	stakeholder
remote sensing	behaviour
apis	central government
blockchain	equity
citizen science	policy measures
crowdsourcing	public engagement/participation
digitalization	co-benefits
digitally-enabled	control policy
mobile applications	government agencies
text mining	human activities
wearables	justice
	participatory
	policy-makers
	publication
	regular
	social networks/media
	county government
	planning policy
	policy areas
	policy initiatives
	polycymaking
	science-policy
	social capital
	transport policy
	science policy
	citizen science
	co-creation/codesign
	crowdsourcing
	digital divide

## Data availability

No data was used for the research described in the article.

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