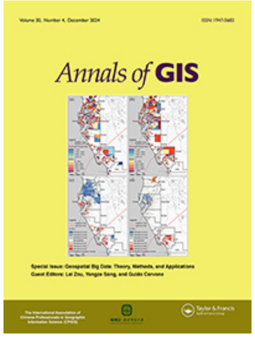

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REVIEW

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Progress in understanding human-COVID-19 dynamics using geospatial big data: a systematic review

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ABSTRACT
The COVID-19 pandemic has dramatically changed human daily life. To mitigate the pandemic's impacts, different countries and regions implemented various policies to contain COVID-19 and residents showed diverse responses. These human responses in turn shaped the uneven spatial-temporal spread of COVID-19. Such human-pandemic interaction is complex, dynamic, and interconnected. Delineating the reciprocal effects between human society and pandemics is crucial for preparing for and managing future epidemics. Geospatial big data acquired through mobile applications and sensor networks have facilitated near-real-time tracking and assessment of human responses to the pandemic, enabling a surge in researching human-pandemic interactions. However, these investigations involve inconsistent data sources, human activity indicators, relationship detection models, and analysis methods, leading to a fragmented understanding of human-pandemic dynamics. To assess the current state of human-pandemic interactions research using geospatial big data, we conducted a synthesis study based on 67 selected publications between 25 March 2020, and 9 January 2023. We extracted information from each article across six categories, i.e. publication details, research context, research area and time, data, methodological framework, and results and conclusions. Results reveal that the influence of stay-at-home policies on mobility decrease varied regionally, showing limited effectiveness in Europe compared to the US. The positive correlations between human mobility and COVID-19 case rates evolved through time and were highest in the initial outbreak in 2020. Public awareness generally peaked prior to the peaks in COVID-19 cases, with varying intervals of 0 to 19.8 days observed across different countries. This study summarizes the research characteristics of selected articles and highlights the need for future research to spatially and temporally model the long-term, bidirectional causal relationships within human-pandemic systems to inform evidence-based, hyperlocal pandemic mitigation strategies.

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Literature review; geospatial big data; human responses; COVID-19; pandemic

1. Introduction

The COVID-19 pandemic has dramatically changed human daily life and affected societies in much of the world. To tackle the uneven impacts of the pandemic, different countries and regions implemented distinct policies to contain the pandemic (e.g. lockdown, business closure, and distance education). Residents showed diverse responses and compliance with COVID-19 policies (e.g. wearing masks, maintaining social distancing, etc.) (Jun, Yoo, and Lee 2021). The discrepancies in responding policies and behaviours in turn shaped the disparate patterns of COVID-19 spread across space and time (Bryant and Elofsson 2020). Therefore, human-pandemic interaction is a complex, dynamic, interconnected system with feedback across social, economic, environmental, and health dimensions. It is essential to delineate the reciprocal effects between human society and pandemics. Given the similarities in the spread mechanisms of pandemics, understanding the reciprocal interplay between human behaviours and COVID-19 and its spatial temporal pattern can shed light on formulating localized strategies to mitigate the risk of future epidemics.

Geospatial big data collected from remote sensing, social media, cell phone apps, vehicles, and sensor networks enable near-real time, multi-dimensional tracking and evaluating human perceptions, sentiments, and behaviours towards the pandemic (Effenberger et al. 2020). Incorporating human-centric information derived from geospatial big data into spatial epidemiology can facilitate the visualization, analysis, and prediction of the impacts of the pandemic on human societies and the ensuing influences of human dynamics on epidemics.

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Nevertheless, interpreting human behaviours from geospatial big data is challenging. First, geospatial big data contain a sheer amount of noise information irrelevant to human behaviours during the pandemic. Second, geospatial big data collected from diverse sources have varying formats, structures, and standards, making it difficult to integrate them for analysis. Third, different research adopted various indicators based on geospatial big data to measure human activities, leading to inconsistent analysis methods and sometimes contradictory results (Razzaq et al. 2022). This discrepancy hinders reliable knowledge discovery and comparative studies. Fourth, only a small proportion of geospatial big data are embedded with precise locations, leaving the majority of the data unusable for spatial analysis directly. Ultimately, geospatial big data cannot represent the entire population (Lin et al. 2024), leading to biases and inaccurate estimations of human activities.

Uncovering the dynamics of the human-pandemic system poses additional challenges. First, the human-pandemic system is a complex adaptive system with multiple interacting factors such as COVID-19 policies, human behaviours, socioeconomic and demographic characteristics, healthcare availability and accessibility, and environmental conditions (Hsiang et al. 2020). It is difficult to consider all these factors in epidemiological modelling. Second, the relationships in this complex system vary across epidemic stages and geographic regions (Cinarka et al. 2021; Wallin Aagesen, Järv, and Gerber 2022), and contain numerous feedback loops. Quantitatively describing, analysing, and interpreting these complex casual relationships necessitates advanced spatial-explicit models. Third, two prominent issues exist in spatially and temporally analysing human-pandemic dynamics, the Modifiable Areal Unit Problem (MAUP) (Wong 2004) and the Modifiable Temporal Unit Problem (MTUP) (Cheng, Adepeju, and Preis 2014). These issues underscore the sensitivity of analysis outcomes to variations in spatial-temporal scales hierarchy and zonal systems. Finally, the emergence of vaccinations and new variants can further complicate the human-pandemic relationships.

This study conducted a synthesis study on research trends and gaps using geospatial big data to understand human-COVID-19 interactions. Publications between the 25 March 2020, and 9 January 2023, were included and analysed to answer two key questions. First, how did existing human-COVID-19 dynamics research leverage geospatial big data? Second, how did COVID-19 and human responses interact across different pandemic phases and space? To address these questions, we outlined four objectives: (1) to summarize the common geospatial datasets and indicators for monitoring the COVID-19 spread and human responses; (2) to identify traditional and advanced models for detecting relationships in human-pandemic dynamics; (3) to elucidate the evolving interactions and geographical disparities of human-pandemic dynamics; and (4) to highlight gaps in the current frameworks and knowledge and propose future research directions that can advance human-pandemic research with geospatial big data and improve pandemic management.

2. Methods of literature retrieval and analysis

The conceptual framework of human-pandemic interactions is illustrated in Figure 1. Initially, the spread of COVID-19 substantially affected human behaviours, triggering the implementation of COVID-19 policies, raising public awareness and concerns towards COVID-19, and changing human mobility. These human responses interacted with each other, and in turn, shaped the spatial-temporal spread of COVID-19. A robust literature has uncovered the dynamic human-pandemic interactions across different regions and pandemic phases using geospatial big data (Wellenius et al. 2021). This

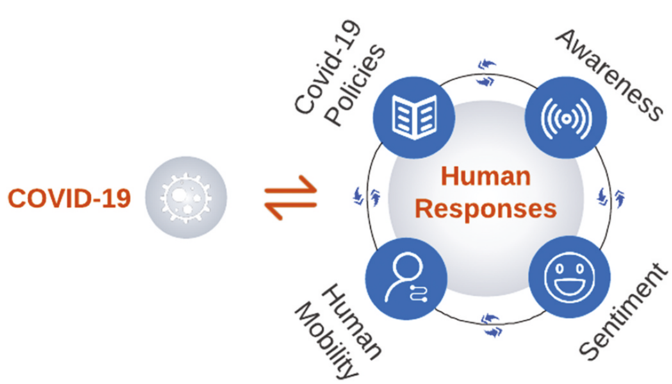

Figure 1. Conceptual framework of human-pandemic interactions.

study focused on published, peer-reviewed journal articles retrieved from the Web of Science.[1] Web of Science is a subscription-based citation indexing service originally developed by the Institute for Scientific Information (ISI) and currently maintained by Clarivate Analytics. The platform is commonly used to access scientific literature and research papers with features including citation searches and analysis, author and institutional profiling, and research trend identification.

The literature retrieval and analysis contain four steps. First, we opted for a keyword-based search restricted to article titles to retrieve the most relevant literature. We used three categories of keywords, COVID-19, human responses, and relationship, as shown in Table 1. One article's title had to contain at least one keyword from each category to be included. The search was limited to English articles published between 2020 and 9 January 2023, with the document type as 'article'. We acknowledge that this focus on English-language publications may exclude relevant studies published in other languages, which could influence the comprehensiveness of our analysis. Meanwhile, English is the predominant language for scientific publications. Relevant articles published in English are considered sufficient to cover the majority of studies to reflect the global research trends and findings on the topic. To avoid retrieving irrelevant articles, we excluded several research areas, such as Chemistry, Microbiology, and Meteorology Atmospheric Sciences. This resulted in 890 articles (Figure 2).

Second, although we excluded articles from unrelated research domains, some were still retained due to the broad scope of their research areas. For instance, some studies investigating the impact of COVID-19 on economic policies, energy consumption, air pollution, and food resources were included in the initial collection. Some of these articles qualitatively demonstrated the relationships between human responses and COVID-19 spread without the necessary data support, which was not aligned with our research objectives. Consequently, we manually reviewed the titles and abstracts of each article to remove duplicates and irrelevant studies, resulting in the exclusion of 572 articles at this stage. Subsequently, we conducted a narrative synthesis by manually reviewing the full text of the remaining articles, selecting those that specifically involved geospatial data, which led to the identification of 67 articles most pertinent to our review. Despite the rigorous approach employed in the article selection process, some selection bias may be present due to the limitations of the keywords used and the manual review process. The results presented in this paper are based on the analysis of these 67 selected articles.

Third, we created a review table to extract and record information from each article to facilitate content analysis and future ontological framework development. Each

Table 1. Keywords used in the initial collection of literature on human-pandemic interactions.

Category	Keywords
COVID-19	COVID-19, pandemic, epidemic, coronavirus, SARS-CoV-2
Human responses	Nonpharmaceutical Interventions, NPI, policy, policies, mobility, awareness, search engine, Google search, Baidu search, emotion, sentiment, attitude
Relationship	relationship, correlation, association, effect, impact, predict

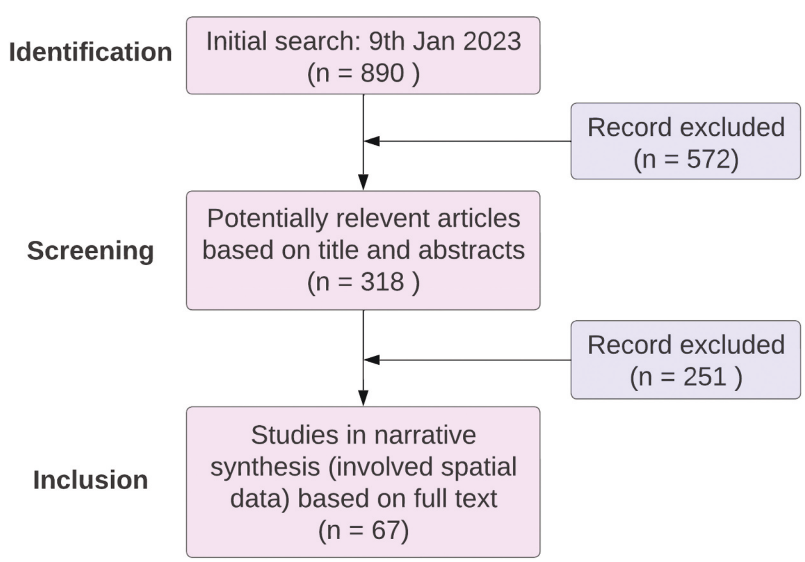

Figure 2. Inclusion criteria.

article was assigned a unique ID number. The review table consisted of six categories of information: (a) publication details, (b) research context, (c) research area and time, (d) data, (e) methodological framework, and (f) results and conclusions. Table 2 provides a detailed list of items under each category.

Utilizing data from the review tables of these 67 articles, we conducted five analyses: (1) a statistical summary concerning publication information; (2) a summary of indicators pertaining to human responses and COVID-19; (3) delineating the scopes of relationship analysis; (4) enumerating the models employed by these articles to discern relationships among human-COVID-19 dynamics; and (5) encapsulating the findings regarding relationships over space and time.

3. Results

3.1. Overall Summary

We gathered and organized publication data to obtain insights into three key aspects: the publication year, the country of origin of the first author, and the publication journal (Figure 3). All articles analysed in our study were published between 2020 and 2022, with 9, 31, and 27 papers in 2020, 2021, and 2022, respectively. Notably, 26.87% of the first authors were based in the United States, while 16.42% were affiliated with institutions in China. The *International Journal of Environmental Research and Public Health*, *PLOS ONE*, *Scientific Reports*, and *BMC Public Health* emerged as the top four popular publishers for human-pandemic interactions research, accounting for approximately 8.96%, 7.46%, 5.97%, and 5.97% of the 67 papers.

Figure 4 presents an overview of the study areas at the national level and the analysis temporal scopes. In human-COVID-19 dynamics investigations, 70 countries were chosen as the focal points of analysis. United States was the most frequently studied and featured in 26 (38.8%) papers. Italy, France, and China were the study areas in 12 (17.9%), 11 (16.4%), and 11 (16.4%) papers, respectively. Conversely, many countries in Africa, Eastern Europe, Western Asia, and Central Asia were absent within this research domain, possibly due to

Table 2. Review table.

Category	Information Item
Publication information	ID Authors Publication year Paper title First Author's affiliation First Author's country Journal name Number of citations as of Jan 2023 (Web of Science)
Research context	Abstract Keywords Objectives
Research area and time	Study area Country Geographic scale Time period Temporal scale
Data	Data name Data source
Methodological framework	Human response variables and indicators Pandemic health impact indicators Model name Model Source (• Existing model, • Improved models, • New model)
Results and conclusion	Types of relationships (• Spatially varying or unified, • Dynamic or statistic, • Causal or non-causal, • Compounding or single chain, • Bidirectional or one-directional) Scope of relationships (• The relationships among human responses, • The effects of COVID-19 on human, • The impacts of Human responses on COVID-19, • The bidirectional relationships between COVID-19 and human responses) Relationships Other findings Conclusion

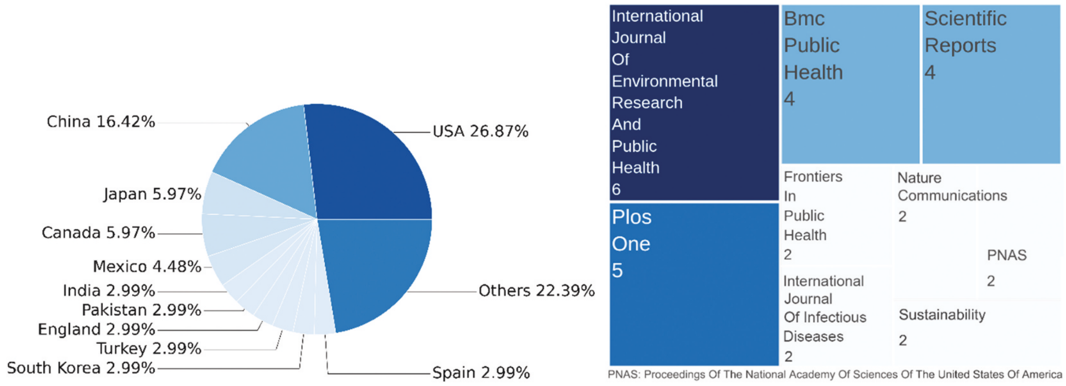

Figure 3. An overview of the countries of first authors' affiliations and the primary journal distribution.

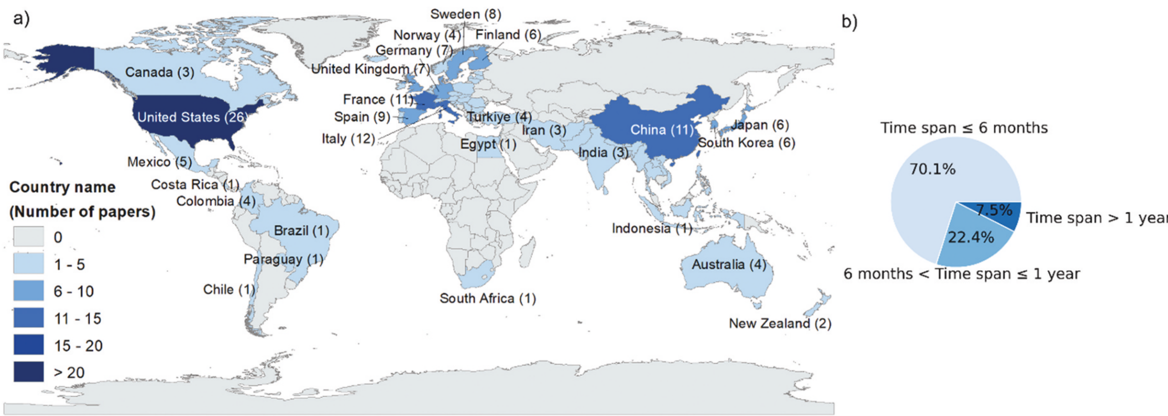

Figure 4. Summary of study area at country level and study time span.

data unavailability. Given COVID-19's global impacts, future efforts could explore human-pandemic dynamics in these under-investigated regions to inform local pandemic control strategies. Regarding the temporal dimension, most studies (47/70.1%) adopted a duration of no more than six months (Figure 4b). Approximately 22.4% of the papers analysed data over a period from six months to one year, while 7.5% of the papers extended their investigation to one year or longer.

Figure 5 shows the word cloud derived from the preprocessed (stemming and lemmatization) abstracts of all 67 articles. The words of higher frequency are displayed in larger fonts. The most frequently appearing words are disease, COVID-19, coronavirus, and outbreak.

Figure 5. Word cloud derived from the abstracts of the reviewed 67 articles.

The middle-size words are second-most frequently used and include behavioural, mitigate, prevent, intervention, and clinical. The smaller-size words include human, Wuhan, prevent, real-time, mobility, restriction, and population, offering additional insights into the thematic overview.

3.2. Indicators of human responses and COVID-19

Previous efforts employed a range of indicators at different spatial-temporal granularities to assess human responses to COVID-19. Figure 6 provides the distribution of articles by the geographical and temporal scales of data they used. Most articles (49.3%) gathered data at the national level, followed by 22.4% at the state or provincial level, 14.9% at the county level, and 9% at the city level. Regarding temporal scales, most articles (74.6%) collected daily data, while 14.9% focused on weekly data.

A total of 52 papers analysed COVID-19's health impacts (Table 3). These studies utilized various indicators, including raw and population-normalized daily (cumulative) confirmed cases or deaths, the reproduction number (Rt), doubling time, infection growth rate, incidence rate ratios, and the logarithm of total COVID-19 cases. They were derived from diverse data sources: 10 papers (19.23%) relied on data from Johns Hopkins University COVID-19 Dashboard, while 8 papers (15.38%) utilized data from official reports issued by provincial, municipal, or national health authorities. Additional data resources included the WHO Coronavirus Disease (COVID-19) Dashboard, Our World in Data, et al.

Table 4 outlines COVID-19 policy indicators and data sources, as referenced in 38 papers. The Oxford COVID-19 Government Response Tracker (OxCGRT) is the primary data source for COVID-19 policies and has been utilized in 17 papers (44.74%). The stringency index, one of the OxCGRT indexes, offers a composite strictness

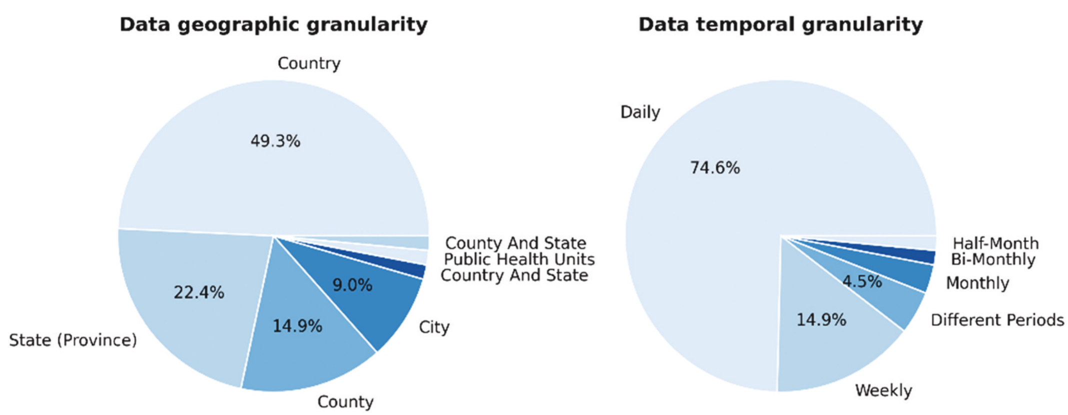

Figure 6. Spatial-temporal granularity of data.

Table 3. Summary of COVID-19 health impacts data sources (total number of papers analyzing COVID-19 health impacts: 52).

Data Sources	Number of papers	References
Johns Hopkins University COVID-19 Dashboard	10 (19.23%)	Badr et al. (2020); Buesa, Pérez, and Santabárbara (2021); Chang et al. (2021); Elitzur et al. (2021); He et al. (2021); Hsiang et al. (2020); Khan et al. (2021); Tu et al. (2021); Wellenius et al. (2021); Xiong et al. (2020)
Official reports from provincial, municipal, or national health governments	8 (15.38%)	Dainton and Hay (2021); Guo et al. (2022); Jung et al. (2021); Kraemer et al. (2020); Paternina-Caicedo et al. (2022); Poppe and Maskileyson (2022); Vega-Villalobos et al. (2022); Wang, Liu, and Hu (2020)
WHO Coronavirus Disease COVID-19 Dashboard	4 (7.69%)	Chung, Chan, and Hemida (2021); Cinarka et al. (2021); Tu et al. (2021); Wang et al. (2021)
Our World in Data	4 (7.69%)	Rahman and Thill (2022); Sözen, Sarıyer, and Ataman (2022); Tao et al. (2022); Widyasari et al. (2022)
The New York Times	4 (7.69%)	Gottumukkala et al. (2021); Guo et al. (2021); Kaufman et al. (2021); Zeng et al. (2021)
Control and Prevention (CDC)	4 (7.69%)	Abbas et al. (2021); Chung, Chan, and Hemida (2021); Effenberger et al. (2020); Jun, Yoo, and Lee (2021)
Oxford COVID-19 Government Response Tracker (OxCGRT)	3 (5.77%)	Bouzouina, Kourtit, and Nijkamp (2022); Chen, So, and Liu (2022); de la Rosa et al. (2022)
Others	15 (28.85%)	e.g., GitHub (Li et al. 2021), USAFacts (Yang et al. 2021), and China Data Lab (Chen et al. 2021)

Table 4. COVID-19 policy indicators and data sources (total number of papers analyzing COVID-19 related policies: 38).

Indicators	Data Sources	Number of papers	References
• Stringency Index • C (containment) indexes (C1-C8) • H (health system policies) indexes (H1-H5) • E (economic) indexes (E1-E4) • Combination of C, H, E indexes	Oxford COVID-19 Government Response Tracker (OxCGRT)	17 (44.74%)	Bouzouina, Kourtit, and Nijkamp (2022);Chen, So, and Liu (2022); Chung et al. (2021); Chung, Chan, and Hemida (2021); de la Rosa et al. (2022); Gordon, Grafton, and Steinshamn (2021); Kallidoni, Katrakazas, and Yannis (2022); Khan et al. (2021); Kumar, Nataraj, and Kundu (2022); Kuster, Overgaard, and Pujo-Menjouet (2021); Li et al. (2021); Rahman and Thill (2022); Sözen, Sarıyer, and Ataman (2022); Sukhwal and Kankanhalli (2022); Tao et al. (2022); Wang et al. (2021); Wu and Shimizu (2022)
• Composite policy index • Policy implementation date • Policy implementation area • Others	Government websites and various news websites	10 (26.32%)	Chang et al. (2021); Díaz-Castro, Cabello-Rangel, and Hoffman (2021); Guo et al. (2021); Hsiang et al. (2020); Jun, Yoo, and Lee (2021); Nguyen et al. (2021); Poppe and Maskileyson (2022); Wellenius et al. (2021); Yang et al. (2021); Zhang et al. (2021)
	Others	11 (28.95%)	e.g. Boston University School of Public Health COVID-19 US State Policy Database (Kaufman et al. 2021), the Global Database of Events, Language, and Tone (GDELT) (Gong et al. 2022), and the Institute of Health Metrics and Evaluation (IHME) (Elitzur et al. 2021)

measurement of COVID-19 policies based on nine response indicators, including five health system policy indicators (H1–H5, e.g. the COVID-19 testing regime and emergency healthcare investments) and four economic policy indicators (E1–E4, e.g. income support for citizens and foreign aid provision). The stringency index scales from 0 to 100 with 100 indicating the strictest measures. Other policy data sources encompass government websites, news websites, et al. These sources were employed to calculate composite policy indexes, policy implementation dates, and effective areas.

Human mobility indicators and data sources concluded from 44 papers are summarized in Table 5. Most human mobility indexes were derived from locational data collected by map applications such as Google Maps, Apple Maps, and Baidu Maps (a widely used map service in China). The Google Mobility Indexes from Google's COVID-19 Community Mobility Reports are the most frequently employed, featuring in 21 papers (47.73%). The Google Mobility Indexes comprise users' direction requests volume changes compared to the baseline across six location types, i.e. grocery and pharmacy, transit stations, retail and recreation, residential, parks, and workplaces. The Apple Mobility Report offers human mobility indexes categorized by travel modes, including transit, walking, and driving. Apple mobility indexes were used in 3 papers (6.82%). Migration Scale Index and Inter-city and Intra-city Mobility Indexes from Baidu were applied in 2 papers (4.55%). Twitter/X, a popular social media platform, provides location tagging for users' tweets, enabling tracking users' movements and analyse their geographical mobility. In the reviewed papers, two indexes, Cross-border Mobility and Daily Weighted Mobility Inflow received by county, were constructed using Twitter/X data. Additional datasets assessing human mobility encompass Teralytics (mobile phone tracking data in Switzerland), mobile terminal network operational data, AccuTracking software on cell phones, and taxi-trip datasets of Chicago.

Public perception of COVID-19 encompasses public awareness and sentiment, traditionally assessed through surveys. With the rise of social media, residents have begun sharing observations and thoughts online, making it possible to gauge public perception from a digital perspective. During the pandemic, partially due to social distancing and lockdowns, many people turned to search engines to seek information about the virus, shared pandemic-related experiences and information on social media, and expressed their emotions. Researchers can assess public awareness and sentiment towards COVID-19 not only through surveys but also by examining pandemic-related search trends or social media posts. For public awareness, 6 out of 10 studies (60%) utilized relative

Table 5. Summary of indicators and data sources of human mobility (total number of papers analyzing human mobility: 44).

Indicators	Data Sources	Number of papers	References
• Six Google mobility indexes (grocery and pharmacy, transit stations, retail and recreation, residential, parks, and workplaces) • Average of six Google mobility indexes or five Google mobility indexes (exclude the residential) • Partial Google mobility indexes by dimensionality reduction method, e.g. PCA	Google's COVID-19 Community Mobility Reports	21 (47.73%)	Abulibdeh and Mansour (2022); Bouzouina, Kourtit, and Nijkamp (2022); Bryant and Elofsson (2020); Dainton and Hay (2021); Devaraj and Patel (2021); Díaz-Castro, Cabello-Rangel, and Hoffman (2021); Gong et al. (2022); Guo et al. (2021); He et al. (2021); Jewell et al. (2021); Jung et al. (2021); Kumar, Nataraj, and Kundu (2022); Li et al. (2021); Méndez-Lizárraga et al. (2022); Paternina-Caicedo et al. (2022); Rahman and Thill (2022); Sözen, Sarıyer, and Ataman (2022); Wang et al. (2021); Wellenius et al. (2021); Widyasari et al. (2022); Zhang et al. (2021)
• Three Apple mobility indexes (transit, walking, driving) • Average of three Apple mobility indexes	Apple Mobility Report	3 (6.82%)	Chung, Chan, and Hemida (2021b); Kallidoni, Katrakazas, and Yannis (2022); Wang, Liu, and Hu (2020)
• Migration scale index • Inter-city and intra-city mobility indexes	Baidu Inc.	2 (4.55%)	Chen et al. (2021); Kraemer et al. (2020)
Three mobility indexes (road, train, and plane)	Teralytics (Mobile phone tracking data in Switzerland)	2 (4.55%)	Badr et al. (2020); Vinceti et al. (2022)
• Cross-border mobility • Daily weighted mobility inflow received by county	Twitter API	2 (4.55%)	Wallin Aagesen, Järv, and Gerber (2022); Zeng et al. (2021)
• Community Activity Score (CAS) • Social Distance Index (SDI) • Citymapper Mobility Index • Time out of home • Median daily activity living space • Travel distance • Air travel passenger count • Traffic volume • Others	Others	14 (31.82%)	e.g., Mobile terminal network operational data (Wu and Shimizu 2022), AccuTracking software on cell phones (Pfeiffer et al. 2022), and taxi-trip datasets of Chicago (Mukherjee, Jain, and Ribeiro 2022)

Google search volume as an index to estimate public awareness (Table 6). Two (20%) derived awareness indexes from surveys, namely a Likert scale-based Public Awareness Index and Time Spent in Reading or Searching for Pandemic-Related Information. Public sentiment towards COVID-19 were investigated in 8 papers, and surveys were the primary data source and used in 4 (50.00%) studies. These surveys employed psychological distress assessments and gauged various emotions using Likert scales. Natural language processing techniques enabled the capture of sentiment from text content on social media. Sentiment indexes and percentages of positive, neutral, and negative sentiment were common indexes derived from social media data. Google search trends for emotion-related keywords, the Anxiety, Depression, Hopelessness, and Helplessness Index, and total sentiment indexes from the Global Database of Events, Language, and Tone (GDELT) were also utilized as alternative methods for evaluating public sentiment.

3.3. Scopes of relationships analysis

The influence of COVID-19 on human society is multidimensional, encompassing government responses, public perceptions, and shifts in public behaviours. These human responses interact and also exert reciprocal influence on the pandemic progression. Typically, scientific articles concentrate on a subset of elements within the system and explore their relationships. This section summarizes the current progress in researching these relationships within the Human-COVID-19 dynamics system, highlighting existing gaps that may serve as future research directions.

Figure 7 presents a breakdown of research pertaining to the relationships between COVID-19 health impacts and

Table 6. Summary of indicators and data sources of public perceptions towards COVID-19 (total number of papers analyzing public awareness/sentiment: 10/8).

	Indicators	Data Sources	Number of papers	References
COVID-19 Awareness	Relative Search Volume	Google/Baidu search trends for COVID-19 related keywords	6 (60.00%)	Abbas et al. (2021); Cinarka et al. (2021); Effenberger et al. (2020); Jun, Yoo, and Lee (2021); Kumar, Nataraj, and Kundu (2022); Tu et al. (2021)
	• Public awareness index with a Likert scale • Time in reading or searching for pandemic information	Survey	2 (20%)	Han et al. (2021); Peng et al. (2022)
	Public awareness based on the numbers of past epidemics and human incidence or COVID-19 trends	Others	2 (20%)	Emergency Events Database (Buesa, Pérez, and Santabárbara 2021) and Risk perception of COVID-19 linearly associated with the daily confirmed cases (Jung et al. 2021).
COVID-19 Sentiment	• Psychological distress with a Likert scale • Different types of emotions with a Likert scale	Survey	4 (50.00%)	Devaraj and Patel (2021); Han et al. (2021); Peng et al. (2022); Sibley et al. (2020)
	• Sentiment index (−1~1) • Percentages of positive, neutral, and negative sentiment	Twitter or Facebook	2 (25.00%)	Razzaq et al. (2022); Sukhwal and Kankanhalli (2022)
	Relative Search Volume	Google search trends for emotion related keywords	1 (12.50%)	de la Rosa et al. (2022)
	Anxiety, depression, hopelessness, and helplessness index, and total sentiment index	Global Database of Events, Language and Tone (GDELT)	1 (12.50%)	Gong et al. (2022)

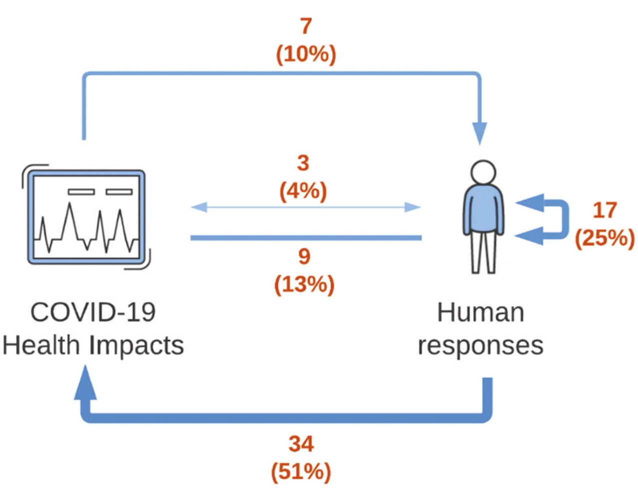

Figure 7. The breakdown of reviewed papers by relationship scopes.

human responses when considered as a holistic entity, as well as the internal dynamics of human responses. The total number of papers in Figure 7 is more than 67 because several studies investigated two or more relationships. The greatest research interest lies in understanding the influence of human responses on pandemic development (34 articles, 51% among all 67 papers). Exploring the internal relationships within human responses ranked second, accounting for 17 articles (25%). There are 9 articles (13%) investigating associations between human responses and COVID-19 health impacts without specifying causality. Seven articles (10%) focus on how COVID-19 health impacts affect human responses. Only three (4%) articles delve into the bidirectional interactions between human responses and the evolution of COVID-19.

Figure 8 provides a detailed breakdown of research discussing the relationships among variables within Human-COVID-19 dynamic systems. Studies that correlate two variables are summarized on the left, and articles exploring relationships among more than two variables are outlined on the right. Among two-variable relationship investigations, the impact of COVID-19 policies on health impacts and research on the influence of human mobility on COVID-19 spread were the most prevalent, each comprising 12 articles. The next popular relationshi was the influence of policies on human mobility (8 articles). Additionally, 6 articles explored the direct effects of COVID-19 on human mobility and 5 examined associations between COVID-19 and human mobility without specifying directions. Notably, there was a paucity of research on the roles of public sentiment and public awareness within the Human-COVID-19 system. Regarding studies involving multiple variables, 5 articles revealed the compounding influence of policies and human mobility on COVID-19 health impacts, while 4 articles delved into how

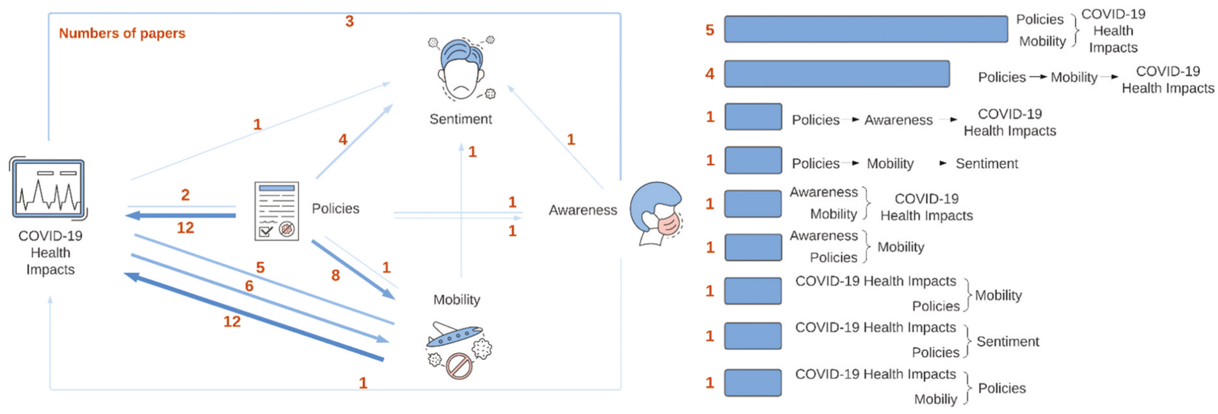

Figure 8. The amount and scope of papers analyzing two-variable relationships (left) and multi-variable relationships (right).

COVID-19 policies affected human mobility, subsequently impacting COVID-19 spread.

3.4. Relationship detection model

Diverse models have been employed to discern relationships within the Human-COVID-19 dynamic systems. These models can be classified into four categories: causal (15 papers, 22.39%), correlation (13, 19.40%), machine learning (3, 4.48%), and regression (45, 67.16%). Table 7 lists specific models in the first three categories, while Tables 8, 9 furnishes in-depth information regarding regression models.

Causal models operate under the assumption that, in the absence of intervention, the subject would

Table 7. An overview of models for relationship detection (proportion among all 67 papers).

Model Type	Model name	Number of papers	References
Models for evaluating causal effects or intervention impacts	Difference in Difference	8 (11.94%)	Abu-Rayash and Dincer (2020); Dainton and Hay (2021); Guo et al. (2022); Nakamoto et al. (2022); Nguyen et al. (2021); Pfeiffer et al. (2022); Razzaq et al. (2022); Wallin Aagesen, Järv, and Gerber (2022)
	Interrupted time series	3 (4.48%)	Chang et al. (2021); Kaufman et al. (2021); Poppe and Maskileyson (2022)
	Regression discontinuity approach	2 (2.99%)	Sukhwal and Kankanhalli (2022); Wellenius et al. (2021)
	Multivariate analysis of variance (MANOVA)	1 (1.49%)	Sibley et al. (2020)
	Segmented regressions	1 (1.49%)	Dainton and Hay (2021)
Correlation-based	Pearson correlation	4 (5.97%)	Abulibdeh and Mansour (2022); Gottumukkala et al. (2021); Sözen, Sarıyer, and Ataman (2022); Wu and Shimizu (2022)
	Time-lag correlation	2 (2.99%)	Effenberger et al. (2020); Tu et al. (2021)
	Cross Correlation	1 (1.49%)	Vega-Villalobos et al. (2022)
	Dynamic conditional correlation (DCC)	1 (1.49%)	Cinarka et al. (2021)
	Dynamic correlation	1 (1.49%)	Abbas et al. (2021)
	Functional canonical correlation analysis (FCCA)	1 (1.49%)	Abbas et al. (2021)
	Kendall's coefficient of rank correlation	1 (1.49%)	Chen, So, and Liu (2022)
	Spearman's rank correlation	1 (1.49%)	Chen, So, and Liu (2022)
	Sliding windows correlation models	1 (1.49%)	Cinarka et al. (2021)
Machine learning	XGBoost	1 (1.49%)	Yang et al. (2021)
	Random Forest	1 (1.49%)	Tao et al. (2022)
	Multilayer perceptron neural network algorithm	1 (1.49%)	Sözen, Sarıyer, and Ataman (2022)
Regression models	Details in Tables 8, 9	45 (67.16%)	Details in Tables 8, 9

Table 8. Categories of regression models for relationship detection.

Model Type		Basic	Panel data regression model Type 1	Panel data regression model Type 2	Time series model	Spatial model	Spatial-temporal model
Input data	Time-varying (√) or Static (×)	×	√	√	√	×	√
	Spatially varying (√) or Unified (×)	×	√	√	×	√	√
Spatial dependence	Considered (√) or not considered (×)	×	×	×	×	√	√
Output relationships	Time-varying (√) or Static (×)	×	×	√	√	×	√
	Spatially varying (√) or Unified (×)	×	×	×	×	√	√

Table 9. An overview of regression models in different categories (proportion among all 67 papers).

Model Type	Model name	Number of papers	References
Basic	Simple linear regression	8 (11.94%)	de la Rosa et al. (2022); Devaraj and Patel (2021); Elitzur et al. (2021); Gordon, Grafton, and Steinshamn (2021); Jun, Yoo, and Lee (2021); Kraemer et al. (2020); Lison et al. (2022); Tokey (2021)
Panel data regression model_Type1	Generalized linear regression model	2 (2.99%)	Badr et al. (2020); Wang, Liu, and Hu (2020)
	Simultaneous equations model	1 (1.49%)	Xiong et al. (2020)
	Structural equation model	1 (1.49%)	Rahman and Thill (2022)
	Bayesian multilevel generalized structural equation model	1 (1.49%)	Zhang et al. (2021)
	Partial least square Structural equation model	1 (1.49%)	Widyasari et al. (2022)
	Poisson regression model	1 (1.49%)	Chung et al. (2021)
	Log-linear regression model	1 (1.49%)	Jung et al. (2021)
	Reduced-form analysis	1 (1.49%)	Hsiang et al. (2020)
Panel data regression model_Type2	Linear mixed-effects models (Multilevel linear regressions)	4 (5.97%)	Chung et al. (2021a); Han et al. (2021); Jewell et al. (2021); Kuster, Overgaard, and Pujo-Menjouet (2021)
	Pooled Mean Group–Autoregressive Distributed Lag (PMG-ARDL) model	2 (2.99%)	Bouzouina, Kourtit, and Nijkamp (2022); Khan et al. (2021)
	Fixed effects model	2 (2.99%)	Gong et al. (2022); Li et al. (2021)
	Panel Regression model	2 (2.99%)	Díaz-Castro, Cabello-Rangel, and Hoffman (2021); Kumar, Nataraj, and Kundu (2022)
	Panel Vector Autoregression model	1 (1.49%)	Wang et al. (2021)
	Mixed-effects Poisson model	1 (1.49%)	Méndez-Lizárraga et al. (2022)
	Hierarchical regression analyses	1 (1.49%)	Peng et al. (2022)
	Negative Binomial regression model	1 (1.49%)	Guo et al. (2021)
Time series model	Autoregressive integrated moving average (ARIMA) model	3 (4.48%)	de la Rosa et al. (2022); Jun, Yoo, and Lee (2021); Paternina-Caicedo et al. (2022)
	Autoregressive model	1 (1.49%)	Yang et al. (2021)
	Poisson count time series	1 (1.49%)	Zeng et al. (2021)
	Markov-Chain Monte-Carlo (MCMC) model	1 (1.49%)	Bryant and Elofsson (2020)
	Seasonal Autoregressive Integrated Moving Average with exogenous regressors (SARIMAX) time-series model	1 (1.49%)	Kallidoni, Katrakazas, and Yannis (2022)
	Seasonal Autoregressive Integrated Moving Average (SARIMA) intervention analysis model	1 (1.49%)	Meng et al. (2021)
	Newey-West linear regression model	1 (1.49%)	Vinceti et al. (2022)
Spatial model	Geographically Weighted Regression (GWR)	1 (1.49%)	Tokey (2021)
	Spatial regressions model	1 (1.49%)	Buesa, Pérez, and Santabárbara (2021)
	Spatial error model	1 (1.49%)	Tokey (2021)
Spatial-temporal model	Bayesian spatiotemporal generalized additive mixed model (GAMM) model	1 (1.49%)	He et al. (2021)
	Geographically and Temporally Weighted Regression (GTWR)	1 (1.49%)	Chen et al. (2021)

follow parallel trends over time. Causal inference is drawn from observed diverging trends following the intervention implementation. As indicated in Table 7, the most frequently employed causal model was *Difference in Difference*, which was used in 8 papers (11.94%). Additionally, 3 papers (4.48%) utilized the *Interrupted Time Series model*, and 2 papers (2.99%) applied the *Regression Discontinuity approach*. *Multivariate Analysis of Variance (MANOVA)* and *Segmented Regressions* were each utilized once in the reviewed literature. While these models can provide valuable insights, they may not always yield truly causal estimates if the underlying assumptions are not met or if uncontrolled confounding factors exist. In correlation models, the Pearson correlation was applied in 4 papers (5.97%), followed by *Time-Lag Correlation*. Machine learning models, including complex architectures like deep neural networks, can capture intricate non-linear relationships within Human-COVID-19 dynamics and have been adopted in three studies.

Regression models play a predominant role in the literature and were used in 45 papers (67.16%). To offer a comprehensive overview of regression models, we categorized them based on three criteria: the inclusion of spatial-temporal information in the input data, consideration of spatial dependence within the model, and the potential for output relationships to vary over space and time (Table 8). As indicated in Table 9, the foundational linear regression was employed in 8 papers. Simple linear regression uses input data devoid of spatial-temporal information, does not incorporate spatial dependence, and yields consistent results across time and space. The second category encompasses panel data regression models, which account for geographic and temporal variations in input data but do not explicitly incorporate spatial dependence into model structures. Consequently, output relationships remain constant regardless of geographical location. This category was further subdivided based on whether output relationships change over time. The first subcategory comprises models that output temporally static relationships, such as the *Generalized Linear Regression Model*, *Simultaneous Equations Model*, et al. The second subcategory includes models where output relationships evolve with time, including *Linear Mixed-Effects Models*, *PMG-ARDL Model*, et al.

The third category is time series models, where both input data and output relationships vary over time. These models do not consider geographic heterogeneity. Time series models include *ARIMA*, *Autoregressive Model*, et al. *ARIMA* was the most frequently employed and applied in 3 papers. The fourth category is spatial models, where both input data and output results vary across space, with consideration of spatial dependence. These models do not incorporate temporal variations. This category includes *GWR*, *Spatial Regressions Model*, and *Spatial Error Model*.

The fifth category is spatial-temporal models, which account for spatial-temporal heterogeneity, spatial dependence, and estimate relationships over space and time. Two papers employed models in this category, one utilizing the *Bayesian GAMM* and the other employing the *GTWR*.

3.5. Spatial-temporal relationships

3.5.1. The effects of COVID-19 policies on pandemic health impacts

Government responses to mitigate the COVID-19 spread have been at the forefront of pandemic management efforts. Numerous studies have assessed policy effectiveness in curbing pandemic impacts. Hsiang et al. (2020) evaluated COVID-19 policies' impacts in China, South Korea, Italy, Iran, France, and the United States, using a reduced-form econometric method. Without policy interventions, early COVID-19 infections exhibited an exponential growth rate of approximately 38% per day. Policy measures significantly reduced transmission rates, preventing an estimated 61 million confirmed cases.

Despite an overall positive assessment of COVID-19 policies' efficacy, varying policy types exhibited diverse effectiveness. The top three policies associated to second wave growth global scale were mandatory facial coverings in public, limitations on gatherings, and screening of foreign travellers on international flights (Tao et al. 2022). Chung et al. (2021a) categorized countries based on the number of pandemic waves and found that contact tracing and containment policies were effective in containing the pandemic for countries with two waves, while closure, economic, and health policies were useful for countries experiencing three waves. In Nordic countries, early-stage restrictions on international travels effectively reduced COVID-19 cases during the first half of 2020 (Gordon, Grafton, and Steinshamn 2021). Social distancing measures were linked to a 15.4% daily reduction in COVID-19 cases, preventing nearly 33 million cases within three weeks in the U.S (Kaufman et al. 2021). In the United States, school closures significantly reduced county-level basic reproductive numbers during the first half of 2020 (Yang et al. 2021).

The timing of policy implementation emerged as a critical factor affecting COVID-19's spread, as evident in data from 89 nations and states in the US (Elitzur et al. 2021). Stay-at-home policies became ineffective when implemented in the later phase of an outbreak. Delaying policy implementation by one week could nearly triple the infected population.

The effects of COVID-19 policies on the pandemic control varied in the short and long terms. Based on the analysis of South Asian countries from January 2020 to May 2021, economic support, stringency, and health and containment indexes (an expanded index builds on the Stringency Index) effectively reduced the pandemic's impact in the long term. While, in the short term, only the health and containment index effectively reduced the risk of resurgence (Khan et al. 2021).

3.5.2. The impacts of COVID-19 policies on human mobility

Since the outbreak of COVID-19 pandemic, governments worldwide have enacted diverse policies aimed at curbing virus transmission by regulating human movement, including stay-at-home orders, school and workplace closures, travel restrictions, event cancellations, and public transport suspensions. The effectiveness of policies in reducing human mobility is based on policy type and timing. Such relationships are geographically disparate and can be time-lagged. Wellenius et al. (2021) found that in the U.S., state-level emergency declarations reduced overall mobility by 9.9%, with additional reductions of 24.5% with social distancing policies (34.4%), and 29.0% additional reductions with shelter-in-place mandates (38.9%). Kallidoni, Katrakazas, and Yannis (2022) discovered that school closures had the greatest impact on reducing driving and walking mobility across twenty-five European countries from February 2020 to February 2021, while stay-at-home orders showed limited effects on mobility reduction. However, in the U.S., stay-at-home orders proved effective in mobility reduction from March to mid-July 2020 (Li et al. 2021). Workplace closures were also linked to notable decreases in overall mobility, while public information campaigns had minimal influence. In South Korea, mobility in retail and recreation, transit stations, and residential region correlated with the stringency of COVID-19 stay-at-home policies, while visitations to grocery and pharmacy, parks, and workplaces showed no significant relationship with policies from March 2020 to February 2021 (Sözen, Sarıyer, and Ataman 2022).

The impact of pandemic policies on human mobility varies across regions and phases. Nakamoto et al. (2022) studied the effects of two emergency declarations in Japan during different COVID-19 stages from 1 February 2020, to 30 April 2021. They found that while both declarations reduced human mobility, the impact of the second declaration was slightly weaker, suggesting the efficacy of emergency declarations in reducing mobility to control pandemic spread diminished over time. Chang et al. (2021) examined spatial heterogeneity in the effects of COVID-19 policies on human mobility in the U.S. at the county level. They concluded that socioeconomically disadvantaged counties were less affected by stay-at-home orders compared to counties with more resources.

Quantifying the possible delayed effects of policy on reducing human mobility is crucial for determining the optimal timing for policy enactment. The implementation of pandemic policies involves several steps, including proclamation, information dissemination, compliance adaptation, and eventual observable changes in behaviour. This process often entails a temporal delay in the impact of pandemic policies on human mobility. Sözen, Sarıyer, and Ataman (2022) found no delay in the impact of COVID-19 stay-at-home policies in Poland, Turkey, and South Korea from March 2020 to February 2021. Conversely, Wellenius et al. (2021) observed a 24.5% mobility reduction occurred one week after the implementation of social distancing policies in the U.S. between January and March 2020 utilizing data from Google COVID-19 Community Mobility Reports.

3.5.3. Relationships between human mobility change and COVID-19 spread

A notable human mobility decrease has been discovered after the COVID-19 outbreak, partially due to the implementation of relevant policies. Amidst the COVID-19 pandemic, human mobility decreased in China (Guo et al. 2022), the United States (Pfeiffer et al. 2022), and Nordic countries (Wallin Aagesen, Järv, and Gerber 2022). Wallin Aagesen, Järv, and Gerber (2022) further demonstrated that decreases in cross-country-border mobility ranged from − 35% (Iceland) to − 82% (Finland). Mukherjee, Jain, and Ribeiro (2022) found a sharp decline in travel-related demands in regions with high economic activities, e.g. airports, downtown areas, and business zones, in Chicago from March to November 2020.

These human mobility reductions subsequently influenced the spread of COVID-19. The cumulative number of cases outside Wuhan, China, was positively correlated with population inflow from Wuhan (Chen et al. 2021). Xiong et al. (2020) highlighted a positive relationship between mobility inflow and the number of infections, which indicated the efficiency of limiting inflow mobility to mitigate pandemic spread. This phenomenon became increasingly stronger in partially reopened regions in the U.S. from March 1 to 9 June 2020. In the state capitals of Colombia, case rates decreased as mobility in retail stores reduced (Paternina-Caicedo et al. 2022). Jewell et al. (2021) found that in the U.S., the positive relationships between human mobility and COVID-19 cases were significant in Spring 2020, decreased in summer and fall 2020, and then increased in late 2020 and early 2021.

Some studies indicate varying delays in the positive impacts of reduced human mobility on controlling COVID-19 spread. For instance, New York and Madrid experienced a 14-day and 18-day delay, respectively, in the declining deaths after the reduction of public transport mobility from March to October 2020 (Vega-Villalobos et al. 2022). A delay of approximately 3 weeks was observed in increased infections following mobility increases at the county level in the U.S. from January to April 2020 (Badr et al. 2020). Longer delays of 5–7 weeks in case number growth were observed following mobility growth in 20 U.S. states from July to September 2020 (Gottumukkala et al. 2021), as well as at the county level in the U.S. from February to July 2020 (He et al. 2021).

Conversely, reductions in human mobility have been observed to correlate with increased transmission of COVID-19 in some studies. In Mexico City, although a reduction in daily trips taken via public transport was observed, the daily COVID-19 deaths increased from March to October 2020 (Vega-Villalobos et al. 2022). In the U.S., infection rates were negatively correlated with average travel miles per person and out-of-county trips from March to August 2020 (Tokey 2021). Additionally, a few studies found insignificant relationships between some types of human mobility and COVID-19 spread. For instance, visitation to parks was tested irrelevant to COVID-19 spread in the U.S. at the county level from February to July 2020 (He et al. 2021). The relationship between visitation to Grocery and infections was also insignificant in European countries from 12 March 2020 to 31 August 2021 (Bouzouina, Kourtit, and Nijkamp 2022).

3.5.4. Associations between COVID-19 awareness and pandemic

Public awareness of disasters plays a critical role in shaping human behaviours in responding to disasters. Previous work has attempted to estimate public awareness of COVID-19 and decipher its relationship with the pandemic spread. Cinarka et al. (2021) utilized Google search trends of COVID-19 symptoms to gauge public awareness in Turkey, Italy, Spain, France, and the United Kingdom from January 1 to 31 August 2020. The study revealed that symptoms like fever, cough, and dyspnoea correlated well with new cases during the first wave, but correlations began fluctuating after May 2020. Effenberger et al. (2020) examined the link between public awareness and COVID-19 cases in different countries using Google search trends for 'Coronavirus' compared to reported cases by the European Center for Disease Control. Their analysis showed a consistent positive correlation, with peak interest occurring 11.5 days before the peak in reported cases, observed across European countries and the US. In Brazil and Australia, peak correlations occurred 7 days prior, while in Egypt, there was no lag. Tu et al. (2021) examined search trends for common COVID-19 symptoms on Baidu from January 11 to 22 April 2020. Spearman's correlation analysis revealed strong positive correlations between daily confirmed cases and Baidu search trends for each symptom. The average delay of increased confirmed cases after the search peak was 19.8 days. Jung et al. (2021) used public awareness, human mobility, and temperature to predict the effective reproduction number of COVID-19 in Japan during 16 January 2020 to 15 February 2021. Their analysis suggested that the model including public awareness performed better than models without public awareness, and public awareness was negatively associated with COVID-19 transmission.

3.5.5. Influential factors shaping COVID-19 sentiment

COVID-19 policies significantly influence public sentiment towards the virus. During the nationwide lockdown in New Zealand, residents experienced higher rates of mental distress compared to the pre-lockdown phase, as indicated by the New Zealand Attitudes and Values Study (Sibley et al. 2020). In Singapore, public sentiment evolved over time, with an increase during the lockdown period, a further rise after partial lifting of restrictions, and a subsequent decrease following further easing of measures (Sukhwal and Kankanhalli 2022). In Shenzhen, China, populations in lockdown areas exhibited more negative emotions compared to other regions, as revealed by a survey examining social emotions across four zones, i.e. lockdown, control, prevention, and safe zones, during a week-long lockdown during March 13–20, 2020 (Peng et al. 2022).

The COVID-19 health impacts were also found to be a determinant of public sentiment. Through analysing the 'Quarantine Life' dataset, which contain thousands of tweets from India, Ireland, Midrand, the United States, and South Africa from January to September 2020, Razzaq et al. (2022) revealed that individuals experienced distress and fear during the COVID-19 pandemic. COVID-19 sentiment was closely linked to COVID-19 awareness. A significant link was observed between higher risk perception of COVID-19 and more negative public sentiment in the PsyCorona Survey which involved 54,845 participants across 112 countries (Razzaq et al. 2022). Human mobility is another determinant of public sentiment. Devaraj and Patel (2021) investigated how psychological distress changed in response to reduced mobility during the early stages of the 2020

COVID-19 outbreak in the United States. They analysed data from 5,132 individuals who participated in the Understanding America Study (UAS) and found that a one standard deviation decline in mobility was associated with a 3.02% higher psychological distress.

4. Discussion

This synthesis analysis presents a comprehensive overview of past efforts in investigating the dynamics of human-pandemic systems using geospatial big data. In addition to highlighting the collective efforts and outcomes, this review points out existing challenges across different domains that necessitate further research attention to bridge knowledge gaps.

First, the multitude of human responses to COVID-19 are interconnected factors that give rise to numerous closed influencing loops. For example, prolonged adherence to human mobility restrictions may induce fatigue and reduce compliance with safety measures, potentially fostering negative sentiments towards the pandemic. Diminished awareness and negative sentiments might prompt individuals to be less compliant with stay-at-home policies, thereby increasing human mobility. Despite these interconnected dynamics, limited attention was dedicated to exploring these feedback loops among human responses. Moreover, the emergence of COVID-19 has instigated interactions among human reactions, which, in turn, impact the spread of the virus. Understanding these reciprocal relationships is crucial for comprehending the pandemic's effects on human society and grasping effective pandemic control. However, our findings reveal a scarcity, with only three articles (4%) delving into bidirectional interactions between human responses and the evolution of COVID-19. Future research could expand the scope of relationship analysis, adopting a more comprehensive perspective and conducting analyses of the interconnected, closed-loop influencing, bidirectional relationships among various elements within human-pandemic dynamics. This will enable more efficient and effective response efforts for future pandemics.

Second, the inclusion of COVID-19 awareness and sentiment in human-pandemic dynamic analyses is limited, with each considered in 10 articles (15%) and 8 articles (12%). Awareness and sentiment play a significant role in shaping individual behaviour and decision-making regarding preventive measures and adherence to public health guidelines, thus directly influencing the spread of the pandemic. Moreover, comprehending how individuals perceive and respond to the pandemic on a psychological level is crucial for developing interventions that not only effectively and sustainably curb the spread of the virus but also embody humanistic care.

Third, despite 15 papers (22.39%) identifying causal relationships utilizing classical statistical models, there exists an imperative for further exploration. Causal modelling entails the consideration and control of potential confounding factors, facilitating the inference and prediction of causal relationships between specific variables rather than mere correlations. Such models, compared to association models, can unveil deeper underlying mechanisms, evaluate the effects of specific interventions on COVID-19 spread, and more precisely forecast pandemics. This ensures that we can derive more accurate and reliable conclusions, thereby enhancing our comprehension of the intricate causal dynamics inherent in human-pandemic interactions.

Fourth, only two papers (2.99%) employ spatial-temporal models, which emerge as the most appropriate for analysing data imbued with inherent spatial-temporal information in human responses and COVID-19 health impacts. Incorporating spatial-temporal heterogeneity and spatial dependence into research methodologies enables a more sophisticated understanding of how human activities and COVID-19 spread vary and interact across regions and time periods. The ability to estimate spatial-temporally sensitive relationships enhances our predictive capabilities and responsiveness to COVID-19. Consequently, prioritizing the development and implementation of advanced spatial-temporal models is imperative.

Finally, our findings reveal that only 5 papers (7.46%) set the interest time window to one year or longer, despite the enduring nature of the pandemic. The choice of the research time frame significantly influences analytical outcomes, with longer temporal spans providing a more accurate portrayal of the temporal scale and yielding results closer to reality. Given that we have generated and collected sufficient data over the past four years since the beginning of the pandemic, extending the study period beyond two years is both feasible and necessary.

5. Conclusions

This synthesis study aims to deepen the understanding of human-pandemic dynamics using geospatial big data by analysing 67 selected articles from 25 March 2020 to 9 January 2023. Our findings reveal that various forms of geospatial big data were utilized in studying human-COVID-19 interactions, including location-based social media data, website data, and location-based usage/log data. Among the selected literature, 52, 44, 38, 10, and 8 articles considered the COVID-19 health impacts, human mobility, COVID-19 policies, public awareness, and public sentiment, respectively. Regression models were the most popular approach for detecting human-pandemic relationships (45 papers), and only two studies leveraged spatial-temporal models. Research on the impact of policies on COVID-19 health impacts and the influence of human mobility on COVID-19 spread was the most prevalent, each comprising 12 articles. Only 3 papers delved into the bidirectional interactions between human responses and the evolution of COVID-19.

Our examination of human-pandemic dynamics highlighted five key aspects, including the effects of COVID-19 policies on health impacts, the impacts of policies on human mobility, relationships between changes in human mobility and COVID-19 spread, associations between COVID-19 awareness and the pandemic, and triggers of COVID-19 sentiment. The principal findings of this study are as follows. First, although COVID-19 policies demonstrated overall positive effectiveness, their impacts were influenced by policy type, timing of implementation, and varied across immediate and long-term scenarios. Second, the impact of stay-at-home policies on mobility exhibited regional variation. These policies were less effective in reducing mobility in Europe during the first and second waves of COVID-19, whereas they showed effectiveness in the US during the first wave. Within the US, the effects of these policies varied regionally, with socioeconomically disadvantaged counties demonstrating less pronounced changes in mobility. Third, the relationship between mobility and COVID-19 health impacts exhibited temporal variation. In the US, a significant positive correlation between human mobility and COVID-19 case numbers was observed in Spring 2020. The significance of this relationship decreased during the Summer and Fall of 2020, and then increased in late 2020 and early 2021. Fourth, awareness peaks typically preceded COVID-19 case peaks, with a generally positive relationship between them. The intervals between their peaks varied by country, with gaps of 0, 7, 11.5, and 19.8 days observed in Egypt, Brazil and Australia, European countries and the US, and China, respectively. Finally, COVID-19 policies, health impacts, COVID-19 awareness, and human mobility are four critical determinants of public sentiment towards the virus.

These findings on the spatiotemporal heterogeneity of human-pandemic dynamics offer tailored insights for countries or regions in addressing future epidemics. Given the observed regional variation in the effectiveness of stay-at-home policies, future pandemic responses should incorporate localized strategies, adjusting interventions based on regional socioeconomic conditions, public compliance levels, and historical data on policy effectiveness. The temporal variation in the relationship between mobility and COVID-19 health impacts further underscores the need for dynamic and adaptive policy interventions. Continuous monitoring of mobility trends and health outcomes would enable policymakers to modify restrictions in response to evolving conditions, thereby avoiding both the premature relaxation of measures and delays in implementing necessary controls. Additionally, the less pronounced changes in mobility observed in socioeconomically disadvantaged U.S. counties emphasize the necessity of targeted support for these communities. Tailored interventions, such as economic assistance or alternative methods to reduce mobility, should be prioritized in future pandemic planning to mitigate the unique challenges faced by these populations.

While this study focused on a limited timeframe, it provided valuable insights into future directions for research on human-pandemic dynamics. The directions are as follows: extending the temporal scope of investigation beyond two years; broadening the scope of relationship analysis among more elements; delving into the examination of causal relationships; developing spatial-temporal modelling; and analysing the interconnected, closed-loop, bidirectional relationships within human-pandemic dynamics.

Note

1. https://www.webofscience.com/wos/woscc/basic-search.

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Data availability statement

The data used in this research were derived from the Web of Science database.

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Appendix

Table A1 compiles the highest-cited articles within the reviewed collection, with citation counts retrieved from Web of Science as of March 2024. The range of citations spans from 1641 to 48. The leading article, published in Science, employed real-time travel history data from Wuhan, China, to elucidate the role of case importation in transmission across various Chinese cities. The second-ranked study, featured in Nature and being cited 695 times, empirically evaluates the impact of large-scale anti-contagion policies on the growth rate of infections.

Table A1. Ten Most cited articles in the current collection.

Publication year	Paper title	Authors	Publication name	Number of citations as of March 2024
2020	The effect of human mobility and control measures on the COVID-19 epidemic in China	Kraemer, Moritz U. G.; Yang, Chia-Hung; Gutierrez, Bernardo, et al.	Science	1641
2020	The effect of large-scale anti-contagion policies on the COVID-19 pandemic	Hsiang, Solomon; Allen, Daniel; Annan-Phan, Sebastien, et al.	Nature	695
2020	Association between mobility patterns and COVID-19 transmission in the USA: a mathematical modelling study	Badr, Hamada S.; Du, Hongru; Marshall, Maximilian, et al.	Lancet Infectious Diseases	467
2020	Effects of the COVID-19 Pandemic and Nationwide Lockdown on Trust, Attitudes Toward Government, and Well-Being	Sibley, Chris G.; Greaves, Lara M.; Satherley, Nicole, et al.	American Psychologist	458
2020	Association of the COVID-19 pandemic with Internet Search Volumes: A Google Trends^{TM} Analysis	Effenberger, Maria; Kronbichler, Andreas; Shin, Jae Il, et al.	International Journal of Infectious Diseases	143
2020	Mobile device data reveal the dynamics in a positive relationship between human mobility and COVID-19 infections	Xiong, Chenfeng; Hu, Songhua; Yang, Mofeng, et al.	Proceedings of The National Academy of Sciences	181
2020	Analysis of mobility trends during the COVID-19 coronavirus pandemic: Exploring the impacts on global aviation and travel in selected cities	Abu-Rayash, Azzam; Dincer, Ibrahim	Energy Research & Social Science	119
2021	Associations of risk perception of COVID-19 with emotion and mental health during the pandemic	Han, Qing; Zheng, Bang; Agostini, Maximilian, et al.	Journal of Affective Disorders	84
2021	Impacts of social distancing policies on mobility and COVID-19 case growth in the US	Wellenius, Gregory A.; Vispute, Swapnil; Espinosa, Valeria, et al.	Nature Communications	82
2021	The Impact of Policy Measures on Human Mobility, COVID-19 Cases, and Mortality in the US: A Spatiotemporal Perspective	Li, Yun; Li, Moming; Rice, Megan; Zhang, Haoyuan, et al.	International Journal of Environmental Research And Public Health	48