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Unmanned Ground Vehicles (UGVs)-based mobile sensing for Indoor Environmental Quality (IEQ) monitoring: Current challenges and future directions

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ABSTRACT

The deployment of Unmanned Ground Vehicles (UGVs) offers a promising solution for addressing spatial inefficiency and non-detection zone challenges of the Indoor Environmental Quality (IEQ) monitoring area. Nevertheless, it is crucial to assess the current state of research development in this area, identify persistent challenges, and outline future directions. This review examines previous studies to identify current challenges and prospects. The data on four classified clusters (UGV structure and components, Monitoring and data capturing, Data analysis and validation, and Future directions) were extracted from 30 studies out of a total of 111 studies. The analysis results suggested that UGV navigation could benefit from the integration of 3D environmental models, its sensing reliability and performance can be further and better evaluated by including human behaviour into research, developing practical approaches for mitigating sensor response time error and calculating optimal velocity for UGV during particulate matter capturing enable to enhance data acquisition stage. Furthermore, leveraging the strengths of this approach can advance research domains such as integration of this sensing method with Building Automation System (BAS), source apportionment, IEQ predictive models, IAQ simulation area, and air pollutants concentration spikes capturing and analysis. The findings of this study offer valuable insights to researchers interested in implementing UGV-based mobile sensing for effective IEQ monitoring and assessment.

1. Introduction

The tendency of people to work from home has been on the rise since the COVID-19 pandemic, which has led individuals to spend more than 90% of their time indoors [1,2]. Consequently, ensuring a comfortable indoor environment has become a critical service provided by buildings to enhance occupant comfort [3,4]. Human interaction with buildings has emerged as a fundamental requirement for performing tasks, managing the built environment, and capturing valuable data [5,6]. In response to this, the field of Human Building Interaction (HBI) research has developed, aiming to create innovative technologies that enhance indoor environments by leveraging various sets of information [7].

At the core of HBI lies the concept of multi-domain Indoor Environmental Quality (IEQ), encompassing domains such as Indoor Air Quality (IAQ), thermal comfort, lighting, and acoustic comfort, all of which significantly impact occupant health, well-being, and productivity [8,9]. The comprehensive and accurate capture of environmental data across a wide range is essential for effectively managing and automating indoor environments [10]. Despite the availability of various monitoring techniques for measuring envi-

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ronmental data at different points, their deployment within buildings remains challenging. Consequently, undetected zones and spatial inefficiency pose significant challenges in evaluating IEQ and advancing research in the field of HBI [11,12].

The conventional method for addressing the issue of spatial inefficiency in buildings involves the implementation of single-point sensing methods, whether through wired or wireless sensing networks. In this approach, multiple sensing devices are strategically placed in different locations to capture environmental data [13]. However, several challenges arise when deploying a large number of these devices within a building. The primary challenges include initial costs, passive sampling (inability to capture environmental data in proximity to individuals), absence of clear guidelines for sensor density and placement within the building, and practical difficulties in calibrating a vast number of installed sensors [14,15].

Alternative approaches have been developed to introduce mobility into sensing, such as utilizing wearable sensors and Unmanned Aerial Vehicles (UAVs). Wearable sensors offer the potential for improved spatial coverage in sensing; however, determining the optimal location on the human body for sensor installation and ensuring the accuracy of data capture while accounting for emissions from the human body present significant obstacles in implementing this sensing strategy [16–19]. The use of UAV represents a novel approach, providing 3D sensing capabilities. Nevertheless, navigating and controlling UAV in indoor environments, as well as addressing sensing errors resulting from wing movements, remain substantial scientific challenges when applying this approach to improve spatial data gaps in IEQ within buildings [20,21].

In the current era of rapid robotics and autonomous systems development, utilization of Unmanned Ground Vehicles (UGVs) equipped with IEQ measurement sensors has emerged as a prominent and versatile approach for measuring and optimizing IEQ [22,23]. UGV is a robotic-based vehicle that operates while in contact with the ground through the wheels and without an onboard human presence. Various types of sensors are needed to couple with this platform for performing desired tasks for built-environment applications. This tool aims to provide mobility into the sensing to explore the surrounding environment. Indoor environment quality sensors along with other sensing devices (e.g., camera or lidar) mounted onboard enable the robot to interact with the environment and complete multiple tasks such as monitoring indoor environment parameters. UGV serve as active and dynamic sampling tools, as they autonomously navigate indoor environments, capturing real-time data. One of the key advantages of UGV is their ability to traverse various building configurations and locations, allowing them to cover areas that may be otherwise undetected by stationary sensors [24]. This capability not only enhances the collection of IEQ data but also opens up new possibilities for bridging the gap between human occupants and building interaction. In essence, UGV equipped with IEQ sensors represent a cutting-edge solution for the efficient and comprehensive assessment and enhancement of indoor environmental quality [9,25] (Fig. 1).

This paper aims to conduct a systematic literature review focused on the utilization of UGV for mobile sensing in IEQ monitoring. The primary objective is to assess the level of development in various aspects covered in the existing literature and identify future challenges and opportunities in this field. To address these research gaps, this review aims: i) to examine what are the main components of UGV-based mobile sensing structure, ii) What are the key segments or components in the environmental monitoring and data capturing process, iii) What are the primary methodology for data analysis and validation and iv) What are the forthcoming gaps and potential research directions that have been identified. The review findings provide valuable insights into the current state of mobile sensing technology, documenting both the challenges faced and the prospects for applying UGV-based mobile sensing to IEQ monitoring. The review is based on a comprehensive examination of academic literature sources, encompassing academic papers, conference papers, and review papers. Then, in section 2, the search strategy, data extraction, and classification from the literature are demonstrated. Section 3 discusses the 4 developed clusters and sections encompassing UGV structure and components, monitoring and data capturing, data analysis and validation, and future directions. We summarized our conclusions in section 4.

2. Methods

2.1. Literature search and filtering

A structured search was conducted in Scopus for peer-reviewed articles published in English until September 2023, covering all disciplines. The search focused on the "article title", "abstract", and "keywords". The following search terms were used for the query: ("indoor environmental quality" OR "IEQ" OR "indoor air quality" OR "IAQ" OR "indoor pollutant" OR "indoor contaminant" OR "indoor thermal" OR "indoor temperature" OR "indoor relative humidity" OR "indoor illuminance" OR "indoor acoustic") AND ("mobile sensing" OR "Robot" OR "autonomous mobile sens*" OR "robot sens*" OR "mobile monitor*" OR "robotic monitor*"). Initial database searches generated 109 articles, and 2 additional studies were sought from reference lists of retrieved studies. Regarding the filtering process, first, the literature source that represents different meanings from the defined concepts was eliminated. The publications whose target of applying robot-based mobile applications in other areas of the built environment, without full articles, and not written in English were eliminated. As a result, 38 studies were selected for further assessment for the inclusion and exclusion process. Based on the study scope and data acquisition requirements, the main articles were eligible for inclusion in this review when the study 1) focused on using UGV-based mobile sensing for IEQ monitoring, not platforms with other robot bases; 2) Specified IEQ measurable variables by the IEQ sensor. Consequently, a total of 30 studies met all the inclusion criteria and were included in the final data synthesis of this review (Fig. 2). Relevant publications were collected and organized in Endnote 20.

2.2. Information extracted from the literature

Profile and content analysis was performed for the 30 studies identified based on the filtering phase. Based on the structure of studied, 4 clusters or sections were identified for data extraction and review. The extracted scientific information or data from these publications included.

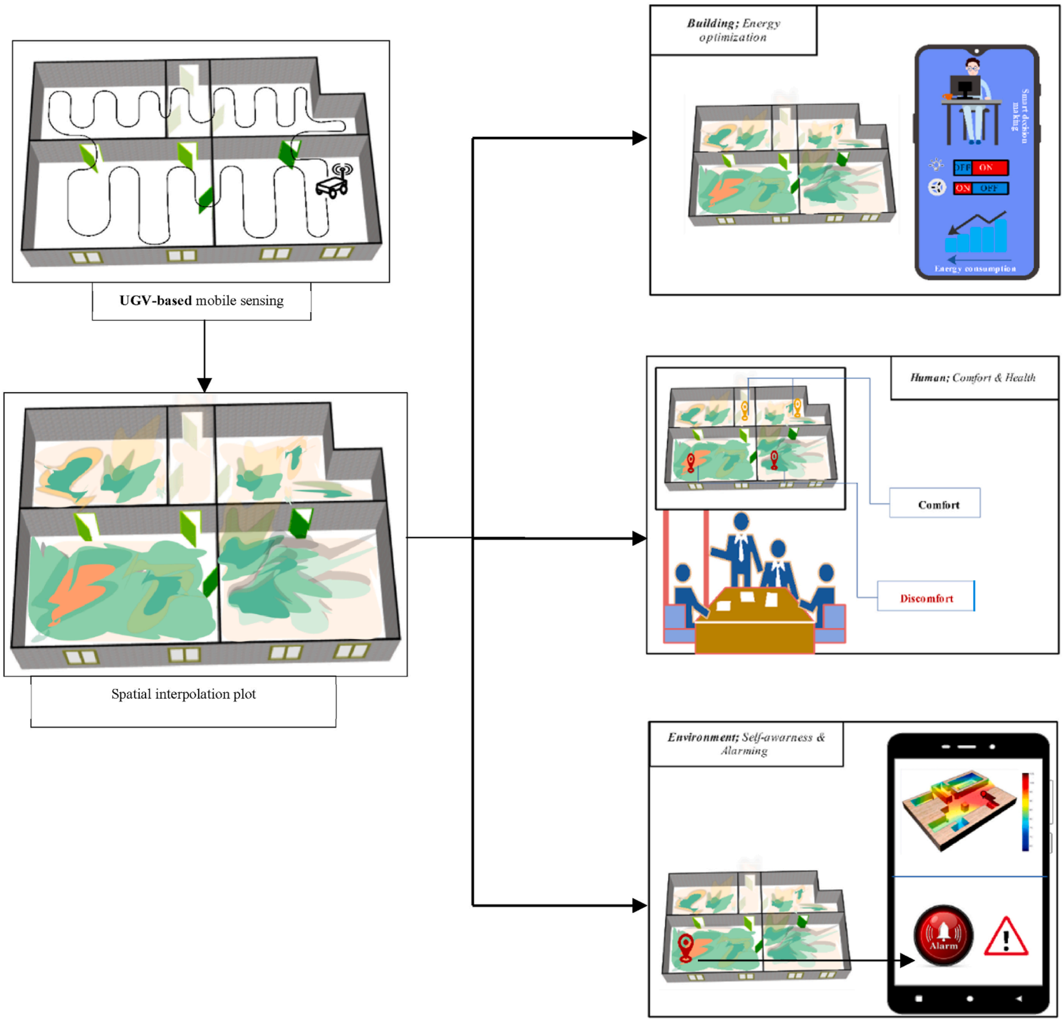

Fig. 1. UGV-based mobile sensing and its opportunities for monitoring IEQ.

(i) *UGV structure and components.* In this section, we have verified the type of robot suitable for the development of navigation. Additionally, we classified the localization techniques that will facilitate navigation tasks on the platform and enable the capturing of spatial data for the analysis section. We discussed the key onboard accessories and sensing devices, along with the appropriate height of placement for IEQ sensors for data capturing.

(ii) *Monitoring and data capturing.* In this section, we extracted and classified several critical components. These components include the experimental environment in which the research experiments were conducted, the primary domains within the research area, and the specific IEQ parameters selected for monitoring purposes. Furthermore, we delved into the various moving approaches employed by the UGV, encompassing both navigation modes and path-planning abilities. We also discussed the methodologies employed for capturing data throughout the experiments, while simultaneously addressing the challenges encountered in this process.

(iii) *Data analysis and validation.* In this segment, we systematically extracted and categorized the data analysis methods according to the dimensions of synthesis, specifically 2D or 3D, as highlighted in section 2. For each research domain, we scrutinized and organized the applicable techniques. Moreover, within this section, we detailed the principal validation techniques adopted for assessing the data collected through UGV monitoring. These techniques were sourced from relevant literature and were presented.

(iv) *Future directions.* In each respective section, we meticulously highlighted the gaps that were identified, setting the stage for subsequent investigation and exploration. We expounded on both the strengths and limitations of the UGV-based mobile sensing method for IEQ monitoring, providing a nuanced understanding of its capabilities. Towards the conclusion, we shed light on potential avenues for research and deployment of this sensing approach's advantages. By doing so, we demonstrated the applicability and potential impact of this methodology across various domains.

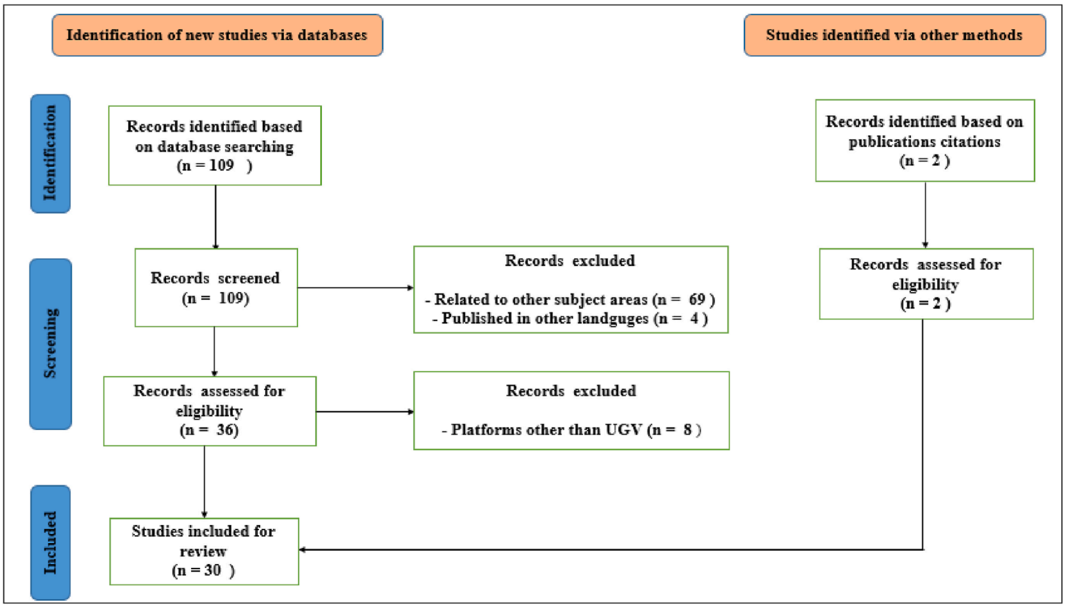

Fig. 2. Literature search and filtering.

2.3. Data classification

In this review, a variety of keywords and phrases were used to classify and extract data from the published studies, as previously outlined in the presented clusters. The review process involved four segments for localization techniques, followed by three sections dedicated to navigation rules and experimental environments. Additionally, 5 sectors were devoted to the evaluation of various domains, two sections covered data capturing methods, and the applied approaches for data analysis and synthesis were also examined.

1) The *robot localization techniques* have been categorized into four areas based on their specific abilities for estimating robot positions:

   Non-Vision-Based Methods: This category includes techniques that rely on emitted waves not within the visual spectrum, such as Wireless Local Area Network (WLAN), Radio-Frequency Identification (RFID), Ultra-Wideband (UWB), and Bluetooth.

   Map-Based Methods: These techniques enable robots to scan the environment and generate maps for position estimation. Examples in this category comprise Simultaneous Localization and Mapping (SLAM), Light Detection and Ranging (LIDAR), Cameras, and Laser Range Finders (LRF).

   Landmark-Based Methods: This category encompasses both active landmarks like beacons and passive ones such as fiducial markers or tapes. Landmark-based techniques use these reference points for position estimation.

   Robot Inertial Sensors and Encoders and algorithms: This category involves the use of robot inertial sensors like odometry and developed algorithms to estimate robot positions.
2) The *navigation techniques* are categorized into autonomous (the ability of the robot for obstacle detection and avoidance), semi-autonomous (the robot is capable of moving into the environment without an ability to detect the obstacles), and teleoperated (an operator dives the robot remotely by a controller). Regarding path-planning approaches, moving based on a pre-defined map (robot needs a path for traverse between the start and end points), without pre-defined path for navigation, and manually selected points concept that match with the teleoperated technique were selected as a examined approaches.
3) Based on the *IEQ-measured parameters* and the *objectives of the studies*, we classified IEQ-evaluated domains as follows: Thermal conditions (temperature and relative humidity), IAQ including source identification, detection of pollutant spikes, and routine monitoring of contaminants, comfort analysis encompassing thermal and illuminance factors, sound levels, and gas concentrations. Additionally, the applied predictive models for these areas were presented. In this context, the experimental environment was classified into three categories, namely dynamic (with high fluctuations), static (at a laminar level), and studies that implemented both strategies (D&S).
4) *Data-collecting methods* are considered (i) Continuous data collection, where data is acquired without stopping the robot during monitoring, and (ii) the move-stop-move (MSM) concept, which involves the sensing platform pausing at certain points for data collection.
5) *Data analysis techniques* were classified as 2D (temporal or spatial variation vs. time) and 3D (temporal and spatial variation vs. time).

This type of presentation initially serves as a guideline for data extraction and offers the potential for developing comparisons between methods and approaches. Subsequently, it facilitates the feasibility assessment of recognizing the developmental levels within each cluster and identifying gaps for future directions.

3. Characteristics of the reviewed literature

3.1. Cluster 1: UGV structure and components

In order to facilitate the development of mobile sensing, it is imperative to design an appropriate mobile sensing platform. This platform serves as a versatile tool capable of operating in a wide range of indoor environments, including those that are unknown and unpredictable. To achieve this, it must possess the capability to navigate seamlessly without disruption and maintain its position while traversing the environment. Consequently, the fundamental components of a mobile platform encompass the type of robot and its related locomotion system, with wheels being the most popular locomotion mechanism in mobile robotics by far, and localization components. Additionally, an integral component of the platform is the elevation of IEQ sensor, which plays a critical role in providing users with the essential data. It is evident that the overall effectiveness of mobile sensing hinges on the seamless integration of these three pivotal segments.

In this phase of the study, we aim to verify the most selected types of robots and locomotion mechanism for the development of the mobile sensing platform, evaluate localization techniques, and discuss about the IEQ sensor installation height.

3.1.1. Type of robot and locomotion mechanism

Based on a review of existing studies, Turtle bots emerged as the most commonly deployed robot in experiments (n = 6) [22,23,26–29], followed by Trolley-based robots (n = 3) [24,30,31], Assistant mobile robots, iRobot, and Airscop robots (n = 2 each) [32–36]. The majority of investigations (n = 22) opted for robots equipped with three or more wheels, with 4-wheeled robots being the most prevalent (n = 18), and 3-wheeled robots being used in 4 instances. This choice is primarily driven by the consideration of stability, a critical factor in mobile robot design. The placement of the Center of Gravity (COG) at the center between the wheels makes four-wheeled robots inherently more stable compared to three, two, and one-wheeled alternatives [37].

Considering the types of robots employed in the literature, Turtle bots offer promising prospects for the development of an Autonomous Mobile Sensing (AMS) system with the capability to navigate real environments. They are noted for their advantages, including remote control capabilities and the ability to make decisions based on real-time data [23] affordability, facilitated by their low-cost kit [22,28], ease of development for various complex robotic software, and the ability to accommodate additional required sensors [28]. Furthermore, they are well-suited for deployment in built environments and on flat floor surfaces [34], making them a preferred choice over other robot types.

3.1.2. Localization techniques

Localization is defined as a robot's capability to determine its current position within a given space, either in a global coordinate reference system or within a defined indoor environment. Localization is a crucial factor in the implementation of mobile sensing. It not only enables the development of autonomous mobile sensing systems but also plays a significant role in addressing spatial data gaps in IEQ monitoring [22]. Various indoor localization techniques have been explored in the literature, as depicted in Fig. 3.

Based on the review of publications, the following methods for monitoring IEQ using mobile sensing were identified: map-based techniques (n = 10) [38–41], robot inertial sensors and encoders (n = 9) [28,42–45], landmark-based techniques (n = 8) [22,26,46–48], and non-vision-based techniques (n = 2) [34,36].

Map-based techniques eliminate the need for physical instruments and space, as they create a map of an unknown environment to facilitate navigation for mobile sensing. By equipping the system with obstacle avoidance capabilities, it can be applied effectively in real-world environments with changing levels of occupancy. However, this technique has significant drawbacks, including high costs,

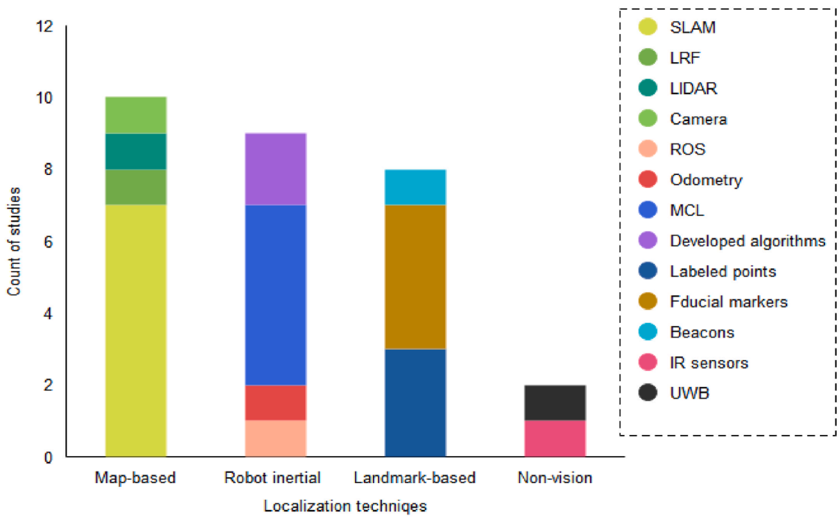

Fig. 3. Indoor localization methods for UGVs-based mobile sensing.

demanding computational requirements, and sensitivity to various types of obstacles in dynamic environments (both movable and static) [49,50].

Localization based on robot inertial sensors relies on combining information from different sensors to estimate the robot's orientation and position. This form of localization, known as relative localization, provides accurate position estimation. In localization systems accuracy or location error is defined as differentiate between the estimated location and actual mobile location [51]. Despite this type of localization technique being renowned for its high level of accuracy and solely to calculate the position and orientation of the device, it can only be employed for short durations which means it is not reliable for loge-term and permanent monitoring situations and most proper for short-time experiments or situations with specific objectives, making it a major limitation [37].

Landmark-based localization tools can be categorized as active-based (using beacons) and passive-based (utilizing fiducial markers, tape, or other natural and artificial markers). These approaches offer advantages such as simplicity, easy setup, and high accuracy. However, they face limitations, including the need for adequate lighting in the environment and the deployment of a large number of markers for extensive spaces. Beacons, despite providing high localization accuracy, are unsuitable for environments with frequent occupancy changes due to their interference with robot navigation and large spaces, which result in significant positioning and navigational errors [52,53].

Non-vision techniques, such as WLAN, RFID, UWB, and Bluetooth, present benefits such as easy to carrying out due to the lightweight and small size and can cover large area because of their waves can penetrate through obstacles. On the contrary, they encounter challenges in terms of localization accuracy, as they are prone to meaningful location errors (above 30 cm difference between robot actual position and estimated one) [51]. Additionally, they require sufficient infrastructure, have constraints related to indoor space because wireless communications such as routers, access points, or antennas need to set up within the building, are time-consuming to implement, and come with additional costs and budget considerations [54,55].

3.1.3. IEQ sensor installation height

The positioning of sensors is a critical factor in IEQ monitoring. Understanding the proper placement of sensors can enhance control over indoor environments and mitigate unnecessary energy consumption by Building Automation Systems (BAS) [56,57]. Several studies have reported the height at which IEQ sensors are installed on robots. For instance Ref. [25], positioned sensors at 0.75 m for temperature [47],1.55 m for thermal measurements [39], at 0.85 m for illuminance [23], at 1.5 m for comfort [58], at 0.8 m for thermal and Volatile Organic Compounds (VOCs) [41], at 2 m for thermal measurements [59], at 0.5 m for temperature, and [34] at 0.15 m for thermal and illuminance measurements.

It's important to note that the positioning of sensors can vary depending on the objectives of the studies and experiments. The optimal sensor placement remains a topic of discussion among researchers because IEQ is significantly influenced by factors such as space type, ventilation strategy, and occupancy dynamics [56]. Green building certification schemes, such as WELL v2 and RESET v2, specify that fixed sensors should be installed at heights ranging from 1.1 to 1.7 m and 0.9–1.8 m, respectively, with certain specific conditions. Considering established standards for sensor height in buildings and the height of the Breathing Zone (BZ) as defined by ANSI/ASHRAE standard 62.1 (ranging from 0.8 to 1.8 m above the floor), it is advisable to position sensors on robots within the BZ range (0.8–1.8 m) to comprehensively evaluate occupants' health and ventilation effectiveness in terms of IAQ parameters [60]. Regarding developing predictive models, Zang. et al. (2023) confirmed that chosen of mobile sensing location has a strong correlation with the prediction accuracy for real-time temperature monitoring [61]. Then, developing principles for choosing optimal sensor height in different environments for producing accurate exposure models is essential in this field.

For other comfort parameters like thermal conditions, sound levels, and illuminance, the choice of sensor height may depend on the specific application area. For example, a sensor height of 0.85 m above the ground might be suitable for an office environment [62], while a height of 0.45 m could be chosen for preschool facilities [48]. Additionally, sensor height may be determined based on waist, head, or ceiling height. For studies focused on investigating the impact of daylight on productivity, measuring illuminance at head height is a reasonable choice [34].

3.2. Cluster 2: Monitoring and data capturing

In this section, the experiment design parameters such as conducting area, navigation methods, type of captured data and evaluated domains, and data-acquisition approaches were presented.

I. *Experiment environment.* In accordance with our classifications, the majority of experiments were conducted in static environments (n = 19), followed by dynamic environments (n = 8), with only one study opting to perform experiments in both types of environments. University buildings emerged as common spaces for testing and validating mobile sensing approaches in static environments. The level of occupancy changes was reported in only two studies conducted in static environments, while seventeen investigations were carried out in conditions akin to laboratory settings. For dynamic environments, laboratory settings (n = 3) were the predominant choice, followed by chamber environments (n = 2), factory settings (n = 2), and school environments (n = 1). Notably, a few studies had the specific objective of generating pollutant hotspots, which required worker intervention to create a dynamic environment with pollutants (n = 2) [40,63]. Laboratory and chamber environments were deemed suitable for conducting experiments related to IAQ parameters, as they enabled control over experimental conditions and minimized the influence of uncontrolled variables. Conversely, university buildings and larger spaces were selected for experiments focused on occupant comfort monitoring, encompassing parameters such as temperature, relative humidity, sound levels, and illuminance.

II. *Navigation methods.* Three distinct navigation approaches were examined: teleoperated, semi-autonomous, and autonomous (Fig. 4). The teleoperated mode (n = 6), which is operated remotely, was primarily applied in the development of IEQ predictive models (n = 3) [30,31], pollutant spike identification (n = 2) [46,63], and real-time data collection for building comfort and energy (n = 1) [27]. This approach is particularly suited for collecting sporadic data in large spaces, where the robot's path can be manually selected for specific sampling points.

The semi-autonomous mode (n = 6), which lacks obstacle detection capabilities, was designed for studies focused on comfort analysis (n = 6). It was predominantly used in settings with regular occupancy changes and relatively fixed layouts. In this mode, path-planning options for the UGV included pre-defined paths (n = 2) and without pre-defined paths (n = 4). These techniques were essential for guiding the UGV in the absence of obstacle avoidance capabilities. The truly autonomous mode, equipped with obstacle avoidance capabilities, was the focus of most studies (n = 13). It was primarily developed for monitoring comfort (n = 6), followed by thermal analysis (n = 3), IAQ monitoring and source identification (n = 2), temperature distribution (n = 1), and illuminance (n = 1). For path planning in this mode, both pre-defined paths (n = 6) and without pre-defined path models (n = 6) were preferred options. This mode of navigation was predominantly used in studies that aimed to assess parameters over extended periods of time. It's worth noting that some publications did not provide sufficient information about the navigation protocols they employed. The rationale behind using pre-defined paths or initial maps in the monitoring process was to ensure comprehensive coverage of the spatial domain related to the IEQ target parameter. In contrast, the without pre-defined path mode, in which the UGV seeks a path from the starting point to the endpoint, may potentially miss some data points and fail to provide a complete spatial view of the monitored parameter.

III. *Type of captured data and evaluated domains.* A significant majority of the studies conducted have focused on monitoring temperature (T) (n = 21) and relative humidity (RH) (n = 19), followed by carbon dioxide (CO2) (n = 10), particulate matter with a diameter of 2.5 μm or smaller (PM2.5), volatile organic compounds (VOCs), airspeed (AS), illuminance (I), and sound level (SL), each with fewer than 10 studies dedicated to them. The selection of temperature and relative humidity in a vast number of studies can be attributed to their simplicity in experiment development, their importance in achieving real-time building comfort and energy data, and their ability to collect data with minimal errors compared to other IEQ parameters.

As depicted in Fig. 5, the parameters monitored through UGV-based mobile sensing can be categorized into two sets: the first set includes T, RH, I, SL, and AS, which are crucial for assessing occupancy comfort levels in indoor environments. The second set comprises VOCs, PM2.5, and CO2, which are essential for capturing IAQ conditions. Within the first set, the dominant domains are the improvement of comfort level analysis (n = 11) and the development of predictive models (n = 4). In contrast, the use of a UGV-based mobile sensing system for the second set primarily focuses on enhancing source identification and localization, as well as providing high-resolution IAQ data spikes, all while striving for high-accuracy predictive models.

IV. *Data-acquisition approaches.* After categorizing studies based on data collection methods, it was observed that among those providing information on data collection approaches, 14 studies implemented the MSM strategy, while 8 investigations utilized continuous monitoring. The distribution of MSM-based studies was as follows: thermal (n = 6), IAQ (n = 5), IAQ + thermal (n = 2), and visual (n = 1). On the other hand, continuous monitoring

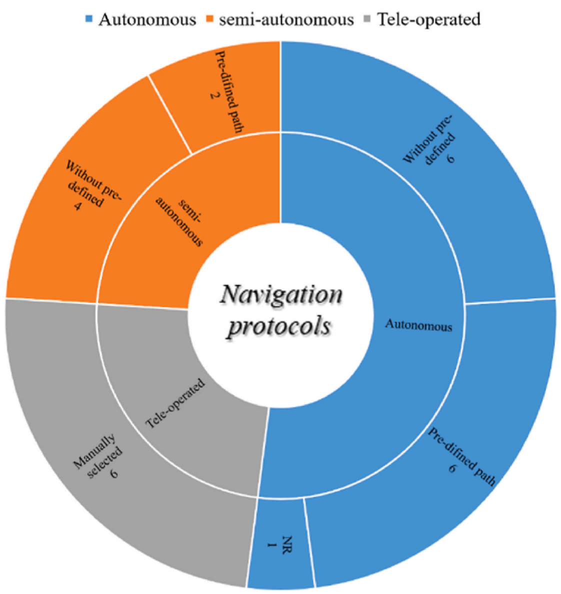

Fig. 4. Navigation protocols of UGV in the indoor environment.

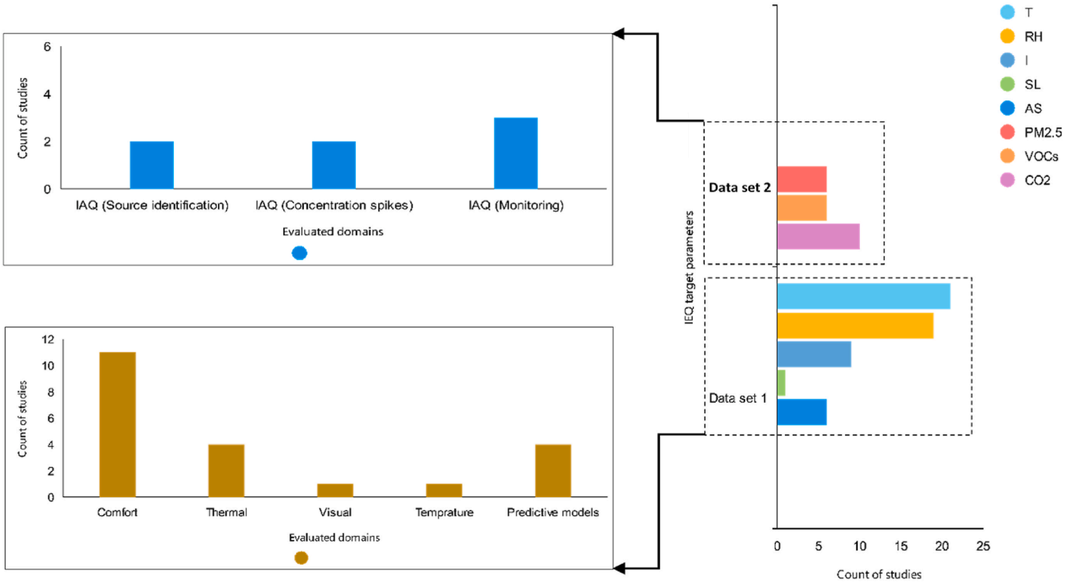

Fig. 5. Captured data and evaluation domains.

included thermal (n = 4), IAQ + thermal (n = 3), with a predominant focus on thermal, and IAQ (n = 1) (Fig. 6a). An overarching observation reveals that the MSM approach is particularly robust for capturing data related to IEQ parameters, especially IAQ. In contrast, continuous methods are primarily deployed to capture thermal parameters rather than IAQ. The rationale behind using the MSM approach is to mitigate errors stemming from Sensor Response Time (SRT) due to sensor mobility. SRT comprises three sections: 'sensor reaction or preheating time,' during which the sensor responds to concentration changes; 'sensor delay time,' when the sensor indicates 90% of the final value; and 'sensor recovery time,' during which 10% of the baseline value is achieved [64] (Fig. 6b). The absence of a solution to address SRT during mobile sensing can lead to errors in IEQ spatial and temporal data. In MSM methods, the typical solution is to halt the robot momentarily at specific points for sensor measurements.

However, among studies employing continuous sensing [65], attempted to mitigate SRT by using sensors with reaction times of less than 2–3 s. Nevertheless, they encountered issues related to sensor delay time, which became apparent in their results. Another approach involved trading off robot velocity, as introduced by Ref. [48] in temperature measurements. This solution is suitable for measuring thermal parameters due to the relatively low fluctuations in temperature and relative humidity indoors. However, it may not be a robust option for IAQ parameters due to their high variability. Furthermore, robot movement can trigger the resuspension of particulate matter (PM) during PM measurements, necessitating adjustments to the robot's velocity before commencing monitoring [46].

3.3. Cluster 3: Data analysis and validation

1. *Data analysis methods.* Data analysis is a pivotal component of research as it allows for the investigation of hypotheses using the specified approaches. Depending on the objectives of each research project, various data analysis methods may be

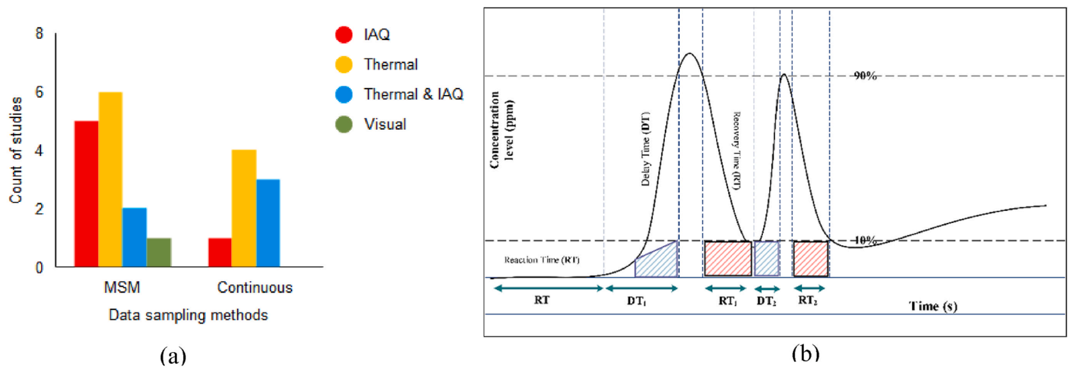

Fig. 6. (a) Data sampling methods by UGV-based mobile sensing, (b) SRT sections in data capturing.

employed. In this section, we outline diverse data analysis processes relevant to different research subjects, including comfort evaluation, thermal and IAQ monitoring, concentration spike detection, source identification and localization, as well as the analysis of predictive models.Given that the data generated by UGV-based mobile sensing typically assumes a time-series format, common approaches for analyzing these subjects involve both 2D analyses (variation vs. time or space) and 3D analyses (variation vs. time and space dimensions).

- In the context of comfort evaluation, several studies adopted various data analysis approaches. For instance Ref. [33], employed interpolation methods to process data generated by mobile sensing. They subsequently displayed this data on a building map to identify areas exhibiting uncomfortable patterns. Additionally [44], introduced a data visualization method for assessing occupancy comfort levels by synchronizing variation data with the trajectory of the UGV. This approach allowed them to correlate variation data with spatial data. Furthermore, graphic analysis over time was utilized as another method for presenting timely patterns and facilitating comparisons of changes over time (variation vs. time). Additionally [43], took comfort analysis to another level by classifying parameters into four categories: low, medium, good, and excellent. This classification took into account various comfort evaluation regulations."
- Thermal and IAQ: The prevailing method for visualizing data related to thermal and IAQ parameters was through observing variations over time. This approach leverages the advantages of real-time and continuous data capture. Researchers commonly employed 2D heatmaps with interpolation techniques such as cubic, kriging, and nearest neighbor to visualize data at different time intervals, typically aligned with the time it takes for the UGV to complete a lap. This approach facilitated the development of 3D analyses.

In a notable contribution [48], introduced a curve-fitting approach to address temporal data gaps in UGV-generated data. This method enabled the generation of high-resolution spatial-temporal temperature data.

- Concentration spikes detection: Applying the interpolation technique for creating plots on the monitoring area map was a preferable tool for presenting a 3D spatial-temporal analysis and identifying areas and times with high concentrations of IAQ parameters.
- Source identification and localization: Kalman filter was introduced by Ref. [65] for data pre-processing. The mean position of IAQ high values was calculated and developed on a 2D heatmap to estimate and localize the source (variation vs. space).
- Developing predictive models: A limited number of studies [25,30,31] have sought to leverage mobile sensing data to enhance predictive models, with a notable emphasis on the utilization of supervised machine-learning techniques. For instance Ref. [30], employed a genetic algorithm to estimate spatiotemporal domains of IEQ. They implemented a teleoperated mode of mobile sensing with adjustable height, enabling data collection at different heights and locations. This approach allowed them to gather sporadic data from various points, which, in turn, contributed to training and enhancing the accuracy of predictive models.

Additionally [48], employed an autonomous mode of UGV-based mobile sensing, featuring continuous monitoring capabilities, to capture data cluster locations (where fixed sensors will be deployed). This data was then utilized as training data for generating high-resolution spatial-temporal long-term temperature maps. Various predictive algorithms were applied in their study, including Support Vector Regression (SVR), K-Nearest Neighbor (KNN), Linear Regression (LR), Lasso Regression (Lasso), Decision Tree (DT), and Random Forest (RF). The Root Mean Square Error (RMSE) value served as the metric for evaluating the reliability and accuracy of these predictive models.

2. *Data validation techniques.* Most of the existing literature did not provide comprehensive validation methods for evaluating the outputs of UGV-based mobile sensing. However, among the limited number of studies that did report data validation techniques, stationary sensors were frequently employed to establish a robust ground truth.

For instance [65], conducted temporal comparisons between data collected by two sensing systems, presenting their findings through a 2D variation vs. time graph to highlight disparities between the datasets. Mean and variance values were calculated for both sets of data, offering a quantitative assessment of the differences.

[22] utilized a *t*-test hypothesis to statistically compare data collected by BAS sensors with data obtained through mobile sensing. They reported the corresponding p-values as a measure of the significance of the differences observed.

Spatial-temporal data comparison between stationary sensors and mobile sensing data was also carried out by Ref. [48] for validating the mobile sensing outputs.

In addition to these validation approaches, some studies explored the generation of ground truth through Computational Fluid Dynamics (CFD) simulations, enabling a thorough comparison of the mobile sensing algorithm's performance with established ground truth data [59].

A Sankey diagram was prepared to visualised the data synthesised. The provided labels and steps are matched with the evaluation factors illustrated in data extraction section (Section 2.3.) (Fig. 7). Also, Table 1 shows the summary of studies based on clustering sections.

3.4. Cluster 4: Future directions

The current review covers the implementation of the UGV-based mobile sensing approach for improving IEQ sensing. The literature shows this system is able to detect areas with discomfort patterns and unexpected discomfort events in specific locations and specific times which was not possible with traditional fixed sensors sensing in occupancy comfort evaluation studies. High potential performance in filling IEQ data gaps and providing high-resolution spatial-temporal maps. This sensing scheme achieved a fine spatial granularity of IAQ parameters than stationary sensing for the identification and localization of pollutant sources. Furthermore, using

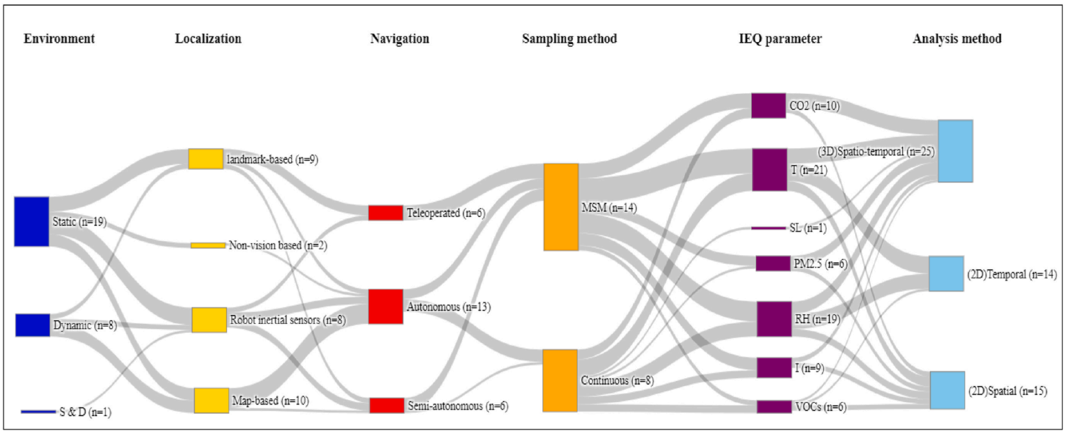

Fig. 7. Sankey diagram showing the main characteristics of 30 reviewed articles.

Table 1
Summary of studies that applied for clustering in this study.

Paper	Environment			Localization				Navigation			Sampling		IEQ parameter							Data analysis		
	S [a]	D [a]	S-D [a]	MP [a]	RI [a]	LMB [a]	NV [a]	A [a]	SA [a]	TO [a]	MSM	Conti	CO_2	T	RH	SL	$PM_{2.5}$	I	VOCs	S-T [a]	T [a]	S [a]
[22]	√					√		√			√		√	√	√			√			√	
[34]	√						√	√				√		√	√			√			√	
[66]	√							√						√	√		√				√	
[36]	√						√										√					√
[59]			√		√				√		√			√								√
[26]	√					√			√		√		√	√	√			√			√	
[41]	√			√				√						√					√		√	
[67]	√				√			√			√			√	√							√
[33]		√									√			√	√				√			√
[68]	√			√				√						√								√
[69]	√				√									√	√			√		√		
[27]	√					√				√	√						√				√	
[40]		√		√						√	√		√	√	√			√		√		
[23]		√		√		√		√			√				√		√					√
[28]					√			√					√					√	√			√
[46]	√				√					√	√	√		√	√						√	
[35]	√					√		√				√		√	√					√		
[38]		√		√					√			√		√	√					√		
[44]	√			√				√				√		√	√				√		√	
[65]		√			√			√			√		√	√	√			√		√		
[30]	√			√						√	√		√							√		
[62]		√				√		√			√		√	√	√							√
[31]	√			√						√	√							√				√
[47]	√					√			√				√	√	√						√	
[70]	√				√							√		√	√						√	
[42]	√			√					√			√	√	√	√		√	√	√	√		
[43]	√				√			√				√	√		√	√			√		√	
[48]		√			√			√			√			√						√		
[63]		√		√						√					√		√			√		
[61]						√			√					√								√

[a] **S**: Static, **D**: Dynamic, **S-D**: Static & Dynamic, **MP**: Map based, **RI**: Robot inertial, **LMB**: Land marker base, **NV**: Non vision, **A**: Autonomous, **SA**: Sime-autonomous, **TO**: Tele operated, S-T: Spatio-temporal, T: Temporal, S: Spatial.

mobile sensing data for capturing building energy data shows this sensing tool decreases energy consumption by 3% more than BAS sensors. Besides, incorporating mobile sensing data in developing predictive models shows its capability to generate high-resolution spatial-temporal IEQ maps. However, several directions and gaps seem to call for further investigations.

- *UGV localization and navigation:* While various localization techniques have their merits and drawbacks, they remain active research areas necessitating further investigations, particularly to ensure the safe movement of UGV. Recently, map-based methods, notably SLAM, have garnered increased attention due to their capability to operate effectively in unknown environments. However, UGV systems still face several challenges, such as object detection and avoidance limitations. Notably, UGV perception sensors struggle to detect and avoid objects positioned above and below their installed sensors.

Furthermore, the literature indicates that UGV-based mobile sensing is primarily in a testing phase, requiring enhancements to handle complex and cluttered indoor environments. Localization and navigation systems need to be rigorously tested in sophisticated scenarios that involve various object types, including movable objects. To achieve a fully autonomous mobile sensing system, it is essential to transition from 2D maps of indoor environments to 3D models or maps for improved localization and object recognition/detection.

Path planning is another critical factor contributing to uncertainty in indoor navigation. Effective action plans should be developed to address situations in which the robot inadvertently deviates from its intended path. To tackle these challenges, cross-disciplinary collaboration between robotics, environmental engineering, and building science is imperative to foster innovative solutions for implementing UGV-based mobile sensing in IEQ evaluation.

- *Experiment design and monitoring:* The emitted contaminant from occupants themselves is a main determinant of spatial-temporal variation of IAQ and personal exposure. Occupancy dynamics either the number of occupants and their activities is one of the pivotal factors influencing the spatial-temporal variation of IAQ in the buildings. According to the literature, human intervention was to a very low degree in the few studies related to comfort evaluation and thermal monitoring. Also, human intervention is restricted to static occupancy rather than dynamic. Human activities strongly contribute to the indoor air pollution burden associated with concentration spikes. Therefore, it requires the main pieces of the indoor environment "human behaviour" included in the studies and experiments. Investigations on occupant densities and activity patterns for checking UGV-based mobile sensing reliability into the sensing and its performance in capturing concentration spikes will be necessary before the mobile sensing system is implemented in real-life scenarios.
- *Data capturing:* As previously mentioned, SRT can introduce distortion errors in mobile sensing applications, particularly when capturing VOCs. Some studies have attempted to address this challenge by developing a Multi-Chamber Electronic Nose (MCE-nose) featuring a Metal Oxide Semiconductor (MOS) VOC sensor [71]. This innovation aimed to mitigate the issue of the sensor's prolonged recovery time. However, it's worth noting that this solution required the installation of an additional component on the mobile platform and was not easily extendable to other sensors or parameters.

Furthermore, it's important to recognize that SRT is not a static property of the sensor but can vary due to multiple factors, including the concentration of the target parameter, the sensor's absorption and diffusion characteristics, environmental conditions, sensor type, and more. To enable continuous monitoring, practical approaches must be developed to address the variability of SRT across different concentrations. Possible methods may involve the incorporation of mathematical models, such as curve-fitting, or the utilization of various algorithms to estimate and correct SRT errors. Validation techniques, such as quantifying SRT under different concentrations through designed experiments, can further enhance the accuracy of mobile sensing systems.

Additionally, the movement of mobile sensing systems can induce the resuspension of PM in indoor environments, akin to the effect of human activities. Thus, future research should consider calculating the optimal velocity of the robot to mitigate resuspension errors when monitoring PM concentrations.

- *Interacting with BAS:* While the literature has offered limited insights into the application of mobile sensing data, primarily focused on temperature, for evaluating building retrofit performance and estimating annual energy savings, it serves as a promising foundation. Future investigations should expand their scope to encompass more complex environments with a comprehensive array of IEQ parameters. This expansion will enrich our understanding of how real-time and intelligent data collection approaches can enhance building performance in multiple facets, including operational efficiency, sensing costs, and informed decision-making.

As a result, forthcoming studies are anticipated to evolve by exploring the integration of UGV-based mobile sensing with BAS to enhance intelligence and smart capabilities in building operations. However, this endeavor necessitates the establishment of robust communication infrastructures and protocols to enable seamless data exchanges. Additionally, it requires the development of effective human-robot interaction mechanisms and a thorough investigation of privacy concerns associated with robotic data collection.

- *IAQ evaluation areas (improve Source Apportionment (SA), improve predictive models and simulation methods, and spikes analysis):* As the trend of remote work, particularly following the COVID-19 lockdown, continues to grow, IAQ has emerged as a critical factor affecting overall health. Among the essential components of IAQ evaluation is SA, which aims to identify the sources of IAQ emissions and quantify their contributions to overall IAQ. However, SA studies face challenges due to limitations in monitoring resolution and source identification capabilities. To enhance indoor SA, modern monitoring techniques capable of providing real-time, high-resolution spatial and temporal data are required. The mobile sensing approach, as observed in our literature review, demonstrates the potential to offer real-time data, identify and quantify sources, and generate high-resolution spatial-temporal plots of IEQ parameters. Future studies can explore the integration of mobile sensing in SA methods, including Positive Matrix Factorization (PMF), which does not require prior knowledge of pollutant chemical profiles and has been widely applied in previous research.

Additionally, the literature has introduced supervised machine-learning methods for improving IEQ predictive models by incorporating mobile sensing data. The autonomous nature of mobile sensing, coupled with adjustable sensor heights, enables the collection of extensive data from various locations, enhancing the creation of high-resolution predictive models. However, further optimization of techniques like cure-fitting, particularly for scenarios with rapid and drastic IEQ fluctuations, should be considered in future works.

Simulation software, such as CONTAM, used for IAQ modeling and analysis, relies on defining contaminant sources. The capabilities of mobile sensing to locate and quantify unknown sources within a building environment can provide flexibility in modeling various indoor pollution scenarios, warranting further exploration.

Despite the rapid advancements in IEQ monitoring methods, the identification and analysis of indoor air pollutant spikes remain limited in the scientific literature. Mobile sensing features exhibit the potential to address this challenge effectively. Mobile sensing has demonstrated higher sensitivity in detecting IAQ fluctuations compared to fixed sensors, providing precise spike characteristics such as concentration magnitude, duration, frequency, timing, location, possible sources, and even occupancy patterns during spikes. This capacity opens up avenues for future research related to spike evaluation, exposure estimation, and health assessments, ultimately offering valuable opportunities for further investigations in the field of IEQ.

4. Conclusion

This work presents a review of the recent scientific literature on using UGV-based mobile sensing for IEQ monitoring. 30 papers were selected for further investigations on level of development in this research area, identify challenges and prospects. The data was extracted from four classified sections such as UGV structure and components, Monitoring and data capturing, Data analysis and validation, and Future directions. The main findings from the present study are.

- From locomotion based, more than half of studies (n = 22) preferred to use robots with three or more wheels. Also, among the type of robots, Turtle bots were dominant for IEQ monitoring (n = 6).
- The majority of studies favored testing UGV-based mobile sensing in a static environment (n = 19), indicating still is in testing stage and need for further experiments.
- Various navigation methods including autonomous (n = 13), semi-autonomous (n = 6), and teleoperated with or without predefined path were chosen based on objectives of studies.
- MSM technique for IEQ data capturing (n = 14) was more selected than continuous technique among studies.
- Data analysis involved various dimensions, including 2D temporal, 2D spatial, and 3D spatial-temporal analyses.
- Number of research gaps highlighted including integration of indoor environment 3D models for improving autonomous navigation of UGV, development of some principles for proper placement of IEQ sensor for increasing accuracy in prediction models in different environments, including human behaviour either static or dynamic into the research for further evaluating UGV-based mobile sensing reliability and performance, developing practical approaches for addressing SRT error in continuous data capturing technique, and calculating optimal velocity for robot during PMs measurements for mitigating resuspension error.
- Regarding future directions, leveraging the strengths of this approach can advance research domains such as integration of this sensing method with BAS, linking with Augmented Reality (AR) technique for increasing occupant's self-awareness, source apportionment, IEQ predictive models, IAQ simulation area, and air pollutants concentration spikes capturing and analysis.

The outcomes of this study have several important implications for research on utilizing UGV-based mobile sensing for IEQ. Firstly, addressing the highlighted gaps in this work reduces the level of error in experiments. Secondly, integrating the advantages of this novel technique into various research domains can enhance overall IEQ monitoring and evaluation. It's important to note that the limitations of this study include the exclusion of publications that were published after the preparation of my review and the reliance solely on the Scopus database for searching.

CRediT authorship contribution statement

Ebrahim Alinezhad: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. **Victor Gan:** Visualization, Methodology, Investigation, Formal analysis, Data curation. **Victor W-C Chang:** Writing – review & editing, Supervision, Resources, Methodology, Investigation, Conceptualization. **Jin Zhou:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Data curation, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used [Chat GPT] in order to [grammar check and academic style revision]. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Declaration of competing interest

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.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jobe.2024.109169.

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