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A systematic literature review of low-cost 3D mapping solutions

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ABSTRACT

In "low-cost" solutions, ensuring economic accessibility and democratizing the availability of emerging technologies stand as pivotal considerations. This study undertakes a systematic literature review of low-cost 3D mapping solutions. Leveraging SCOPUS as the primary database, a comprehensive bibliometric analysis encompassing 1380 publications was conducted, subsequently narrowing the focus to 87 recent publications for detailed review. This research endeavors to delineate the defining characteristics of low-cost systems, elucidate their principal applications and preferred platforms, assess accessibility level, gauge the extent of innovation in both hardware and software development, explore the contributions of Deep Learning and data fusion, evaluate the consideration of data quality, and examine the contemporary relevance of photogrammetry within low-cost context. The findings demonstrate that many authors subjectively use the term low-cost to highlight qualities of a technology, methodology or sensor, but challenges arise from data quality comparisons with high-cost systems.

1. Introduction

1.1. Context

In an increasingly globalized and competitive world, the implementation of low-cost 3D mapping solutions has acquired unprecedented relevance in the industry [1]. In response to growing competitive pressure and the constant pursuit of resource optimization, companies have been forced to reassess and rethink their product and service development strategies. The prioritization of economic efficiency and consumer accessibility has taken a central place in the formulation of effective business strategies [2]. In this sense, low-cost solutions have not only allowed companies to maintain healthy profit margins in an environment of constantly increasing costs, but also facilitated penetration into previously inaccessible markets, opening new opportunities for growth and expansion [3]. This paradigm shift has led to a more inclusive and consumer-centric approach, in which economic viability is sought alongside customer satisfaction [4].

Technological advancements and the evolution of efficient production practices have primarily facilitated the transition toward low-cost solutions. Implementing cutting-edge manufacturing techniques [5], developing more affordable materials [6], and optimizing processes [7] have allowed companies to significantly reduce operational and production costs, paving the way for greater profitability and scalability. Moreover, the democratization of technology and its widespread accessibility have leveled the playing field not only for companies of all sizes [8,9] but also in different global contexts, i.e., developing countries, fostering innovation and the development of affordable, high-quality products. In this context, the strategic focus on low-cost solutions has become a crucial differentiator [10] for technology and marketing [11]. However, it is important to recognize that there is always a trade-off between low-cost, quality, and user/customer support. While low-cost solutions can make technology more accessible, they may sometimes result in compromises in product quality, or the level of customer support provided. Addressing these trade-offs is essential to give a comprehensive and objective view of the impact and potential limitations of low-cost technological solutions.

In this context, this study presents a comprehensive analysis of the phenomenon of low-cost solution development, with a specific focus on the field of 3D mapping. As technology has advanced and become more accessible, low-cost 3D mapping solutions have emerged as a key tool for a wide range of applications and enhancing the establishment of sensor

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networks [12].

1.2. Terminology

Sensors to acquire 3D data are often grouped into active and passive sensors, where active sensors emit the energy required for the sensing themselves, and passive sensors use some other energy source (e.g., the Sun, ambient light, or thermal radiation). In the 3D domain, active sensors are typically lidar (light detection and ranging) sensors, where a direct distance measurement is carried out through time-of-flight or phase-shift methods, whereas passive sensors are typically cameras, where depth information is inferred through geometric intersection of image rays [13]. The combination of a lidar unit with a deflection mechanism and - in the case of mobile platforms - equipment to record platform position and attitude is called a laser scanner [14].

While price reduction in 3D sensors is clearly driven by the development of autonomous vehicles within the automotive industry [15,16], low-cost 3D mapping sensors are present in multiple disciplines and have given rise to new solutions and terminologies [17], for example Backpack Laser Scanning (BLS), Handheld Mobile Laser Scanning (HMLS) or Unmanned Aerial Vehicle (UAV) Laser Scanning (ULS). For a more complete overview, we refer the reader to [13]. In this manuscript, the term *solution* is used to indicate a method or physical device that allows 3D mapping of the environment. Consequently, a *sensor* is a single device that may be combined with other sensors into a hardware *system*. Sensors that are tightly coupled together (e.g., a laser scanner and an Inertial Measurement Unit (IMU)) may be considered as a single sensor. A *method* describes an algorithmic framework to achieve 3D mapping from some data, for example from images (photogrammetry) or laser returns (laser scanning). The literature survey (Section 2) contains contributions in terms of both low-cost solutions and methods.

1.3. Motivation

Multiple reviews have been conducted on the utilization of spatial 3D data, focusing on the analysis of specific platforms, such as Mobile Mapping Systems (MMS) [18] or indoor Mobile Mapping Systems (iMMS) [17], exploring advanced processing techniques including Deep Learning (DL) [19–21] or segmentation methods [22], or specialized applications such as Simultaneous Localization and Mapping (SLAM) for autonomous driving [23]. In contrast, comprehensive reviews concerning data acquired from low-cost sensors remain limited. In [24], the authors extensively investigate 2D Light Detection And Ranging (lidar) sensors, exploring assembly strategies and addressing the constraints associated with 3D map generation. In [25], the authors briefly provide insights into diverse types of solid-state lidar sensors, considered affordable. In [26], the authors concentrate on affordable solutions tailored for people with disabilities, highlighting the utilization of perception sensors and open-source software.

A review of low-cost sensors for 3D mapping is crucial to democratize access and promote innovation. Starting from the need to know what are considered low-cost sensors, as well as their main applications and data quality achieved, it is also important to know their feasibility to process low-cost data using Deep Learning techniques (the state of the art in 3D feature extraction and modelling), and to study the integration of low-cost sensors in more complex systems, merging information from other sensors and data sources. In addition, photogrammetry has always been a cheaper alternative to using lidar sensors, but it is important to know to what extent photogrammetry is still a viable alternative today in the face of the price reduction of 3D sensors.

1.4. Objective and research questions

The aim of this work is to address the growing need for a comprehensive and in-depth review in the field of low-cost 3D mapping solutions. As technology continues to evolve and costs remain a determining factor in the widespread adoption of these solutions, it is necessary to critically evaluate the effectiveness, feasibility, and limitations associated with the use of low-cost sensors in 3D mapping. The proposed review not only focuses on identifying emerging trends and recent innovations in this area but also aims at addressing existing gaps in the current literature and providing a holistic perspective on the applications, challenges, and potential opportunities presented by these low-cost solutions. This work will complement previous reviews and answer the following research questions:

1. What defines a low-cost 3D mapping sensor?
2. What are the primary application domains and platforms utilized for integrating low-cost 3D mapping sensors?
3. How accessible and user-friendly are "low-cost" 3D mapping sensors?
4. To what extent do current publications prioritize the development of novel 3D low-cost mapping solutions over comparative analyses?
5. What role does Deep Learning play in low-cost 3D mapping applications?
6. How is data fusion used to improve the capabilities of low-cost 3D mapping sensors?
7. Do low-cost 3D sensors produce poorer quality data than survey-grade 3D sensors?
8. What are the key differentiating factors between photogrammetric and low-cost lidar approaches for 3D mapping?
9. What are the current challenges in adopting and implementing low-cost 3D mapping solutions, and what future trends can be expected?

The remainder of this paper is structured as follows. Section 2 shows the methodology of the review and the bibliometric analysis. Section 3 focuses on answering the research questions previously formulated. Section 4 examines the current challenges and future trends. Section 5 concludes this paper.

2. Methodology

2.1. Search criteria

The literature review used SCOPUS as a primary data source. As one of the largest abstract and citation databases, SCOPUS encompasses a vast array of scholarly publications, conference proceedings, and books across multiple disciplines. Moreover, it provides advanced search functionalities, citation analysis tools, and the ability to track the impact of publications, thereby facilitating a meticulous and systematic review process.

The keywords used in the search were “Low-cost AND (lidar OR 3D-mapping OR 3D-sensors)" within article titles, abstracts, or keywords. These specific terms were selected due to their prominence as primary representatives within the 3D data acquisition domain. They encapsulate a wide array of mapping-centric systems, including - but not limited to - lidar sensors and depth cameras. These technologies are relevant in fields that require 3D mapping and analysis. The timeframe was limited to the period between 2018 to 2023 to focus the review on the current state of technology.

2.2. Bibliometric analysis

The proliferation of publications focusing on 3D low-cost mapping and sensors has exhibited a consistent upward trajectory over the years (Fig. 1). The initial instance of continuous search terms tracing back to 1975 highlights the mention of a low-cost dedicated processor for a lidar acquisition system [27]. Until 2010, the volume of low-cost literature remained minimal. Subsequently, there has been a significant increase. Notably, over the past decade, the term ’low-cost’ has featured in approximately 3 % to 4 % of all 3D sensor-related publications. In 2023, there was a reduction in the number of publications dedicated to 3D mapping during that year and the upward trend plateaued.

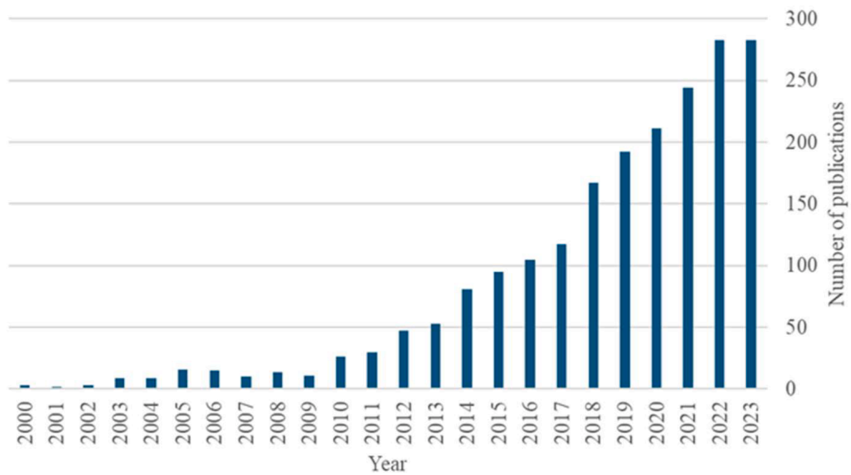

Fig. 1. Evolution of the number of publications since the year 2000 according to search criteria.

Between 2018 and 2023, a total of n = 1380 documents were identified, primarily sourced from scientific journals (50.5 %) and conference proceedings (42.8 %). English emerged as the predominant language, representing 1302 publications, followed by Chinese, comprising 63 publications.

VOSviewer, a specialized software employed in qualitative research and textual data analysis, was utilized to visualize, and discern the frequency and interrelationships among keywords or terms within the textual corpus [28]. This tool generates graphical representations, enabling the identification of prevalent patterns, recurring themes, and emerging trends within the analyzed text. Specifically, the titles and abstracts of the 1380 identified publications were entered into VOSviewer for analysis. From this dataset, the 200 most frequently occurring terms and their associations were curated and visually represented (Fig. 2).

Upon analysis, VOSviewer delineated three significant clusters of relevance. The blue cluster encapsulates publications directly correlated with sensor functionalities and design, focusing prominently on technical specifications such as range, resolution, and speed. Conversely, the red cluster pertains to publications revolving around autonomous navigation, encompassing subjects like autonomous vehicles, robotics, as well as complementary concepts essential to navigation such as GNSS (Global Navigation Satellite System), SLAM, IMU and object detection. Lastly, the green cluster predominantly focuses on studies centered around measurement and monitoring methodologies, encompassing topics such as UAVs, airborne lidar, photogrammetry, and satellite application in geospatial measurement and observation.

The collection of publications showcases a diverse distribution across various subject areas, as illustrated in Fig. 3.a. Predominantly, the significant fields encompass engineering, computer science, physics and astronomy, and mathematics. Interestingly, when the search parameters are broadened beyond the specific term 'low-cost' (Fig. 3.b), a comparable trend persists in the primary focus on engineering and computer science. However, this broader scope prompts an increased relevance in the field of earth and planetary sciences within the first two subject areas, suggesting an expanding thematic emphasis in these domains.

Geographically, as illustrated in Fig. 4, the leading contributors to publications were notably affiliated with institutions from China and the

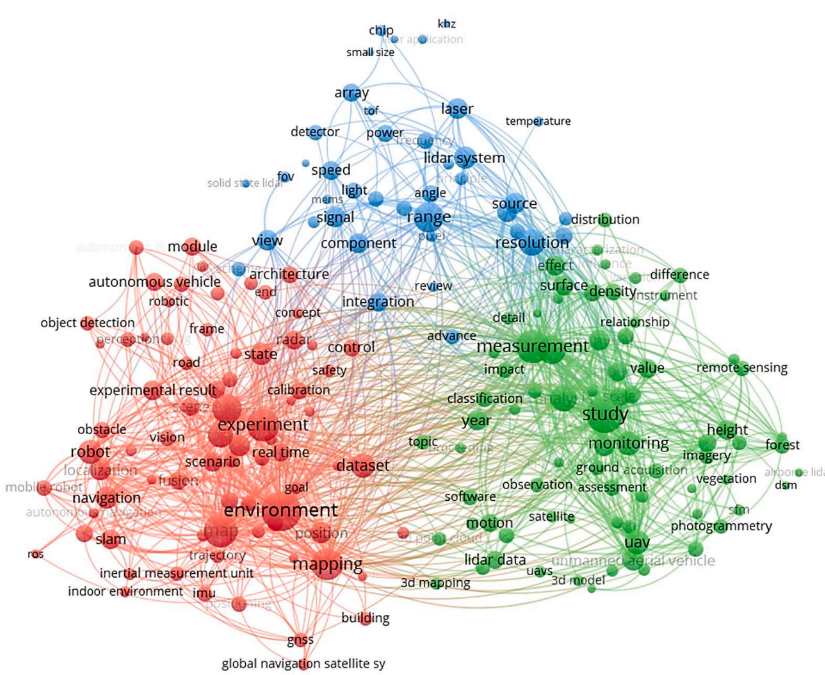

Fig. 2. VOSviewer Network analysis on terms contained in title and abstracts of the reviewed studies.

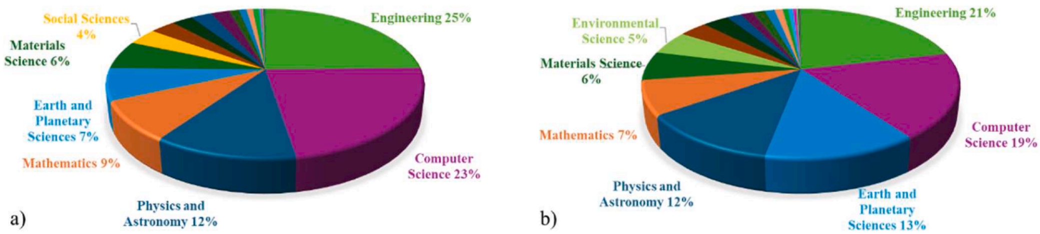

Fig. 3. Subject areas pertaining to the search categorized under 'low-cost' (a) and those not encompassing 'low-cost' (b).

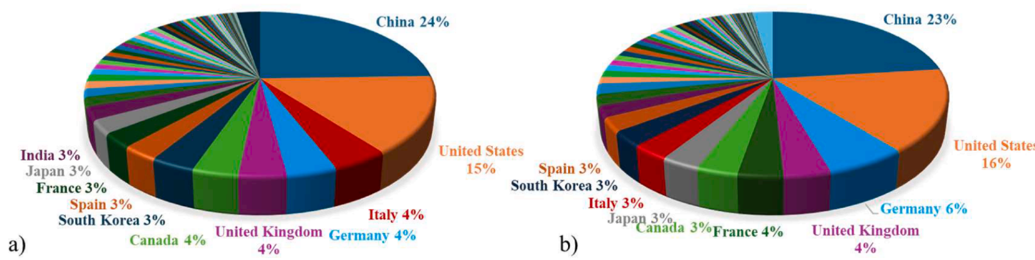

Fig. 4. Distinction between countries in the context of 'low-cost' search (a) and those without 'low-cost' constraints (b).

USA, followed closely by institutions from several European nations, Canada, South Korea, Japan, and India. This distribution is explicable given that the foremost contributing institutions were predominantly China-based. Specifically, the Chinese Academy of Sciences emerged as the most prolific institution, producing 65 publications, followed by the Ministry of Education of the People's Republic of China and the University of Chinese Academy of Sciences, each contributing 38 publications, and Wuhan University with 34 publications. Following the Chinese lead, the CNRS (Centre National de la Recherche Scientifique) of France ranked next with 17 publications.

This sequence remains consistent when considering the entirety of publications on 3D sensors and mapping. However, a notable trend emerged regarding an enhanced interest among researchers affiliated with institutions from Italy towards implementing low-cost solutions. While globally, low-cost solutions constituted around 3 % of publications, Italian institutions showcased a distinct focus, with 4.5 % of their publications dedicated to low-cost solutions, indicating a specialized interest and dedication towards cost-effective methodologies within this field.

2.3. Screening, eligibility, and appraisal criteria

To streamline the comprehensive biographical review process, the initial 1380 publications underwent a significant reduction, culminating in a final selection of 87 publications. This reduction was primarily achieved by excluding publications that delved into subject areas distant from the focal point of 3D mapping, such as veterinary, medicine, pharmacology, and chemistry, among others. Additionally, publications that did not align with applications related to 3D mapping of the as-built environment, such as those centered around atmospheric measurement, were omitted from consideration.

Furthermore, publications closely associated with the fundamental principles of sensor operation and setups, as identified within the blue cluster in VOSviewer analysis, were excluded from the final selection. This decision was motivated by the existence of a recent review closely addressing this specific facet [24], rendering such publications redundant. Publications categorized as preprints or short proceedings were also omitted, ensuring a focus on publications that provided in-depth and substantive content essential for the biographical review process answering the research questions.

2.4. Research constraints overview

The primary limitations encountered during the search process can be broadly categorized into database, string, and timeframe constraints. The SCOPUS database served as the primary resource for this study, although potential future endeavors might benefit from an expansion utilizing databases such as Web of Science and Google Scholar to enhance comprehensiveness. This literature review is based solely on academic publications, excluding information from private companies and industry sources.

The utilization of a concise search string aimed to encapsulate a broad spectrum of publications aligned with the research objectives. However, this approach led to the omission of certain publications that employed techniques or sensors relevant to the study's focus but did not explicitly feature the term 'low-cost'. For instance, traditional cost-effective methodologies like photogrammetry or sensors integrated into commercial devices like iPads and Azure Kinect might not always explicitly mention the 'low-cost' adjective, consequently eluding inclusion within the search results.

Moreover, the timeframe chosen for the study spanned the last 6 years, considering it as the most recent and prolific period in terms of article publications. Nonetheless, it's noteworthy that the pertinence of 'low-cost' in the context of this study extends back to around 2010. Consequently, this timeframe limitation might overlook earlier seminal works or developments related to cost-effective approaches within 3D mapping and sensor technologies.

3. Findings

3.1. Low-cost definition

In the analysis of 87 reviewed publications, only one definition of "low-cost" pertaining to 3D mapping was found. Bi et al., (2021) delineate two pivotal aspects integral to the definition of "low-cost" for 3D laser scanning:

- "Low-cost" is a relative term denoting a price significantly lower than that of comparable products, often achieved at the expense of certain specifications. This definition holds common ground beyond the domain of 3D laser scanning.
- The concept of "low-cost" may align with a consumer-grade or economically accessible product. However, the authors highlight

that existing laser scanners do not meet the criteria for being considered low-cost due to their lack of affordability for the public. They draw a comparison between the pricing of complete vehicles and lidar devices like the Velodyne VLP-16, HDL-32E, and HDL-64E. Their analysis concludes that the cost of low-cost lidar devices surpasses even the price of expensive consumer goods, such as a car, for example.

While the aforementioned definition stands as the sole delineation of "low-cost" within the reviewed literature on 3D mapping, several recurring patterns substantiate the usage of “low-cost” term across various works. The following enumeration presents these patterns in descending order of significance:

(1) Sensors regarded as inherently low-cost without extensive justification by the authors primarily encompass devices like the Velodyne VLP-16 or VLP-32, prominent in 20 of the reviewed works [29–33], with a starting price of approximately 5000 EUR. Indeed, sensors with similar capabilities are utilized across various applications and publications without necessarily being labeled specifically as "low-cost". Additionally, other manufacturers such as Livox [34,35], SICK [36,37], Garmin [38], and SureStar [39,40] are mentioned to a lesser extent, offering devices within a comparable price range. In the realm of consumer-grade technology, the Azure Kinect [41], the Apple iPad, and Apple iPhone [42–45] are also deemed as low-cost alternatives.

(2) Instances of low-cost techniques and technologies are highlighted in publications that do not specifically designate a sensor as low-cost (in contrast to the prior point), but rather justify a technique or technology as being economically advantageous. This pertains to:

3.2. Remote sensing, photogrammetry, or lidar: These techniques and technologies are deemed “low-cost” due to their efficiency in data acquisition compared to traditional approaches [46,47], such as total stations and manual surveys.
3.3. Simulations: Simulations are acknowledged as “low-cost” [48] as they enable data acquisition without necessitating investment in hardware or survey time.
3.4. UAVs. UAVs are considered a cost-effective alternative to traditional ALS for data collection purposes [49]. However, UAVs represent a highly specialized solution tailored for operations on a smaller scale with increased temporal resolution, rather than being inherently categorized as a low-cost solution.
3.5. Wearable devices. Although some wearable lidar devices might be more expensive than conventional devices, J. Li et al., (2022) regards wearable devices as low-cost.

(1) Solid state lidar [51–54] technology is deemed low-cost and encompass [25]: Microelectromechanical systems (MEMs) lidar [55], Flash lidar, Optical phased array (OPA) lidar, or Frequency-modulated continuous wave (FMCW) lidar systems.

(2) Custom-built sensors classified as low-cost by the authors, typically tailored to address highly specific issues, such as integrating multiple sensors for urban mapping [33,56] or indoor navigation [57]. An illustrative instance is provided in [58], where the cost of a 3D lidar within the 8 to 12-meter range is stated as USD 100, while the authors’ prototype is notably lower at USD 49. However, many works lack a detailed breakdown of component costs, hindering the assessment of their final pricing. Only one of the works gave a detailed breakdown of the cost of their system, at USD 12,700 [30]. A total of five publications presents the cost of the sensor they consider to be low-cost, with a range from USD 306 to USD 12,700 and a mean value of approx. USD 3500 [24,30,34,57,58]. Direct comparisons, however, prove difficult, as some publications give the cost of the sensor only, and others give the cumulative cost of the entire mapping system.

In broad terms, it is crucial to underscore the relative nature of "low-cost" concerning price comparisons, highlighting its extension beyond the realm of 3D mapping to align with widespread notions of affordability. While the term "low-cost" typically pertains to the initial purchase price of a device, certain authors also underscore its significance in device maintenance [59] or operational methods [60,61], particularly in utilizing free [26] or open source software [62] where the source code is either closed or modifiable and distributable, respectively. This multifaceted perspective reveals that "low-cost" encapsulates not only the acquisition cost but also encompasses the broader spectrum of expenditure and operational efficiencies within the device’s lifecycle and workflow implementation.

3.2. Low-cost 3D mapping: Platforms and applications

We reviewed the publications to examine the use of low-cost 3D sensors in relation to the platforms they are integrated with and the applications they are used for. As such, we aim to understand how low-cost 3D mapping systems have evolved and have been applied in real-world settings. Only publications addressing low-cost sensors combined with a specific application or platform are considered. Those solely addressing the development of low-cost sensors or evaluating their quality are discarded. The remaining 78 publications are classified into five platforms and four application categories. These distinctive categories provide insights into the different usage of low-cost sensors across the different studies. The platform categories are manned aerial, terrestrial mobile, terrestrial static, UAV, and wearable; and the application categories are autonomous driving, cultural heritage, forestry and monitoring and inspection. Table 1 shows how often a combination of platforms and applications is addressed in this review.

3.2.1. Manned aerial

Aerial platforms, typically airplanes, are combined with lidar sensors to form an Airborne Laser Scanning (ALS) system [63]. ALS systems typically fly at higher altitudes allowing them to cover larger spatial scales and collect high-point density data. Therefore, ALS is used for forestry [47] or urban mapping and monitoring applications, such as building footprint extraction [63] or 3D building modelling [64]. Manned aerial data acquisitions are typically more costly than using other platforms. This could explain why only five publications were found using our search strategy. Low-cost in these studies refers to making the information-extraction algorithms more efficient on lower point densities, reducing the needed amount of overpasses or sensor quality, [63,64] or making manned flights obsolete by using an ALS simulator [48].

Table 1
Combination of platform and application usage in the selected publications.

Platform	Application				
	Autonomous driving	Cultural Heritage	Forestry	Monitoring and Inspection	Total
Manned aerial	0	0	1	4	5
Terrestrial Mobile	7	1	0	23	31
Terrestrial Static	1	0	3	7	11
UAV	0	0	10	8	18
Wearable	0	2	9	2	13
Total	8	3	23	44	78

3.2.2. Terrestrial mobile

Terrestrial mobile platforms are the most common across the 78 publications. This category can be further subdivided into various sub-platforms, each with distinct uses for different applications. Several publications use lidar sensors integrated into rail trolleys or wagons for railway inspections [65,66]. Others combine them with robotic ground systems for indoor mapping [29] or with vehicles for autonomous driving applications [67]. However, most integrate them on vehicles for infrastructure inspection or asset management applications, such as traffic sign inventory measurements or road marking and pavement extraction and degradation detection [32,68–71]. Qiu et al., (2023) are the only authors to use depth sensors (Azure Kinect) for pavement monitoring. A vehicle equipped with lidar sensors for inspection purposes is commonly referred to as a Mobile Laser Scanning (MLS) or Mobile Mapping System (MMS). However, these terms are used interchangeably to denote a variety of non-vehicle platforms, such as those mentioned here or wearables (Section 4.5).

3.2.3. Terrestrial static

All publications in our review equip static terrestrial platforms with a lidar sensor to form a Terrestrial Laser Scanning (TLS) system. None equip them with photographic systems. The TLS systems are used for pavement inspection, high-definition map creation, or traffic monitoring [72–74]. Other authors use TLS systems for deriving forest structure parameters [75]. A special type of static terrestrial application includes those that fix 3D sensors to static structures. An example can be found in [73], where a lidar sensor is fixed alongside a road to measure the distance between vehicles moving in traffic.

3.2.4. Unmanned aerial vehicles (UAVs)

Typical use cases for low-cost 3D mapping with UAVs are forestry, cultural heritage or monitoring and inspection applications. UAVs are an ideal platform for carrying out monitoring of infrastructures that cover large linear infrastructures, such as roads [76], or for inspecting (industrial) assets or forests that are hard to reach or that need to be inspected from various perspectives that are outside the field of view of humans [77]. Laser sensor on UAVs have been investigated for 3D forest mapping by [30] and for 3D UAV bridge inspection by [78]. Surprisingly, our search strategy (see section 2.1) returns zero publications that use UAVs for low-cost cultural heritage applications. However, when adding the terms “UAV” and “cultural heritage” and removing “low cost” to the search term, more examples of low-cost photogrammetric 3D bridge mapping and cultural heritage applications are found. This suggests that the domain of cultural heritage is operating from a low-cost baseline and therefore does not emphasize the word low-cost in the manuscript or its tags. Examples of photogrammetric 3D bridge mapping and cultural heritage applications can be found in [79–83].

3.2.5. Wearables

A relatively novel platform is wearables. A wearable system allows low-cost 3D sensors to be carried in hand, such as Apple devices (iPhone or iPad) or attached to helmets or backpacks. Examples include helmets in industrial monitoring applications [50], assistance technologies for disabled persons [26] or custom-made backpacks for indoor 3D mapping [84,85]. However, most publications addressing wearables use commercial devices for cultural heritage or forestry applications [35,85–88]. The generally constrained budget for cultural heritage projects makes these affordable and accessible devices especially appealing although the level of detail is not always satisfactory compared to high resolution TLS data [86].

3.2.6. Platforms and applications over time

Table 2 shows how often applications or platforms were addressed between 2018-2023. Most notable is the sharp increase in monitoring and inspection applications for infrastructure and urban environments. Several factors could increase the need for automated and large-scale monitoring. Aging and degrading infrastructures and increased traffic volumes and loads lead to accelerated degradation of infrastructures. Climate change-induced prolonged weather extremes have a similar accelerated degradation effect [89]. Another reason for the increased interest in monitoring and inspection applications could be the increased computational capacity that is available or the relative ease and low-cost at which data can be collected. This presents the opportunity for urban planners to start scanning their assets from an asset’s design to construction and, eventually, the service life phase. Digital twinning requires extensive 3D information collection and storage at various stages of an asset’s life cycle and is increasingly becoming standard practice. Integrating Building Information Modeling (BIM) into this process further enhances the precision and utility of digital twins by providing a detailed digital representation of the physical and functional characteristics of a building or infrastructure, facilitating better decision-making throughout the entire lifecycle [90].

Table 2
Occurrence of publications grouped by application and platform in selected publications over the review period.

Application	Year						
	2018	2019	2020	2021	2022	2023	Total
Autonomous driving	0	0	2	3	2	1	**8**
Cultural Heritage	0	0	0	2	0	1	**3**
Forestry	2	3	3	6	6	3	**23**
Monitoring and Inspection	2	1	5	4	12	20	**44**
Platform							
Airplane	0	1	2	1	0	1	**5**
Terrestrial Mobile	1	1	3	4	7	15	**31**
Terrestrial Static	1	0	1	1	4	4	**11**
UAV	2	2	4	4	5	1	**18**
Wearable	0	0	0	5	4	4	**13**

Forestry is a domain that has seen a steady usage of low-cost 3D sensors due to the scale at which forestry studies are usually conducted. Especially interesting is the recent rise of wearables. Low-cost aerial mapping using UAVs is traditionally appealing because the spatial scale at which forestry studies need to be conducted would be too expensive to carry out at large scales without aerial remote sensing platforms. Now the usage of wearables seems driven by the need of practitioners to obtain detailed 3D metrics at tree stand level, which can inform them about their forest’s health. In addition, there is a rising consensus that highly detailed laser systems that provide millimeter-level resolution are overdone and that metrics such as Diameter at Breast Height (DBH) can also be derived from lower-resolution data, making wearables more appealing [87].

We see a steady but small number of autonomous driving applications that use low-cost sensors. Automotive applications require relatively high-detail data, something that low-cost sensors cannot provide [86]. Similarly, we find a relatively low number of cultural heritage applications in the review period. This could be explained by the prevalence of survey-grade sensors, which were already widely used in cultural heritage studies.

Regarding the types of platforms, it is noticeable that traditional platforms, such as static or airplane platforms, are steadily used. Surprisingly, the number of publications using UAVs in combination with low-cost 3D sensors is stable for the reviewed period. UAVs have the disadvantage of being sensitive to vibrations and weather conditions, which influences the range of errors in their 3D measurements and makes them unappealing to be used for precise measurements. The usage of terrestrial and mobile systems increased. Mobile terrestrial solutions are relatively low-cost for applications such as road and rail inspections where repeated detailed measurements are required at large spatial scales. It is interesting that although terrestrial platforms are traditionally used for applications where high-resolution data are needed, both mobile and static terrestrial platforms are used to address similar monitoring and mapping applications in the industrial, cultural heritage and forestry domains. While some authors advocate for using high-resolution TLS data to characterize environments such as forest features [36], others aim for an efficient trade-off between data resolution and data acquisition speed using wearables.

Overall, the publications rarely mention the effectiveness or generalizability of their method over different study sites, let alone geographic regions with different visual characteristics. We conclude that the variety and range of applications covered in the publications are often at lower development levels and not mature enough to draw conclusions on their usability and scalability in real-world settings.

3.3. Low-cost accessibility and user friendliness

As shown above, our review covers a diverse range of low-cost 3D mapping systems, some commercially fabricated, and some custom-made. The way in which data are recorded and processed is distinctively different for both types.

For most commercial systems, the way hardware and software interface and the way data are recorded, processed, or presented to the customer is determined by the manufactures. An example is a commercial wearable system. In this review, they often make use of RGB-D sensors, e.g. Azure Kinect, Zed2 or Apple sensors. Azure Kinect and Zed2 sensors are accompanied by proprietary developer kits to process data, which are free and open source. Data acquired by Apple devices can be processed with third-party applications such as Sitescape or AppleAR kit which are not always free or open source. Commercial TLS systems in this review are Trimble or Riegl-based systems. Although their data can be retrieved by free software, such as RiVlib[1], processing them requires using paid and closed software that is proprietary to these brands. Commercial UAV platforms in this review mostly use DJI systems. Some of them are sometimes customized by authors themselves or by third parties [30,34,40,91]. Other commercial reviewed brands are Zenmuse [91] and Applanix [92], however, these are used less than DJI drones.

Custom-made wearables are for example helmet [35], backpack [84], or railway inspection systems (Rahman, 2023). These solutions have in common that they are built as robotic systems. Data recording and hardware-software interfacing are achieved using the free and open-source Robotic Operating System (ROS)[2]. An exception is custom built UAV solutions where data collection and system integration is achieved using on-board computers, such as PX4[3] [93].

Most UAV mapping systems use the commercial software Pix4D[4] to perform Structure from Motion (SfM) [79,82,91,94]. In addition, most lidar-based system use commercial software to process data, such as LiAcquire and LIDAR360[5] (Hu, 2020) or MATLAB[6] scripts. CloudCompare[7] is the only free and open-source software that is used across all types of systems to classify or filter point cloud data [65].

Finally, most publications do not mention what training is needed to operate the system, what the user experience is while using the system, or publish their code or solutions online. Only [87] explicitly state that Apple systems provide the best user experience. Nonetheless, it is presumed that a high level of training is required due to the complexity of the workflow. Each stage, from acquisition to processing, requires a deep understanding of the system properties or of which parameters work best [66].

[1] http://www.riegl.com
[2] https://www.ros.org/
[3] https://px4.io/
[4] https://www.pix4d.com/
[5] https://www.greenvalleyintl.com//software
[6] https://www.mathworks.com/products/matlab.html
[7] https://www.danielgm.net/cc/

3.4. New low-cost research methods

The reviewed publications were categorized based on whether their primary objective presents a novel contribution in terms of methodological development (software and/or hardware) or if the publications are centered around technical comparisons between mapping solutions. The quantification of publications is depicted in Fig. 5, followed by an explanation of the findings for each category.

- Development of new algorithms: This category encompasses 34.5 % of publications and focuses on the development of novel software, typically centered around feature extraction, object detection and segmentation [88], as well as complex algorithmic developments for data fusion from multiple sensors [95] or simulations [48].
- Development of new systems: This category comprises 24.1 % of publications and focuses on descriptions of hardware setups and sensor calibrations that collectively provide a new system for 3D low-cost mapping [58]. The complexity of the setups varies depending on the application. The sensors are usually installed on a vehicle [37], robotic bases [96] or UAVs [30]. These publications are complemented by visualizations of the captured data and quality analyses.
- Development of new systems and algorithms: This category comprises 23.0 % of publications and provides complete mapping solutions to problems, from the design and installation of low-cost sensors to calibration and software development [32,70,97,98].
- Comparative quality analysis: This category encompasses 16.1 % of publications and compares different low-cost sensors, systems, or mapping solutions within their respective case studies. Some of these publications focus on analyzing the data quality [45,46,99], while others compare methodological developments using low-cost data [55]. It is also common practice for these comparisons to be conducted by juxtaposing consumer systems, with the iPad Pro being the most frequent [42,43], either with other low-cost devices or with well-established solutions in the field. Recently, comparative analysis went beyond technical specifications and also compared different apps (software) on commercial systems, since apps also influence data acquisition and quality [100].
- Survey: This category includes 2.3 % of publications and consists of reviews without conducting studies or comparisons on real use cases.

Overall, the development of new methods (software and/or hardware) accounts for 81.6 % of the reviewed works. To assess the quality of these new methods results are often compared against survey-grade equipment, with TLS being the most representative [40,44,65].

3.5. Deep Learning in low-cost 3D mapping

The representation of Artificial Intelligence (AI) applications in the low-cost 3D mapping domain is limited. Most of the low-cost literature continue to use heuristic methodologies [37,63,71,101–104]. Only 13 works employ AI in segmentation or classification tasks. In [66], Machine Learning is integrated within a heuristic framework, specifically the unsupervised clustering algorithm k-means. Prioritizing the use of heuristic methodologies makes sense since AI-based approaches, especially DL, require significant computational resources for training and implementing Deep Neural Networks (DNN), resulting in higher operating costs. In addition, most heuristic approaches can be tuned to better suit a specific application by using threshold parameters. However, the risk is that these threshold values are typically set by hand, which makes it difficult to extrapolate, generalize or transfer the developed heuristic method to other geographic areas or tasks, even if they are similar.

Currently, the trend in DL is to employ end-to-end approaches with two input options: 2D images or 3D point clouds. Image-based DL has been around for a much longer time due to a larger interest from the computer vision community and reduced computational complexity.

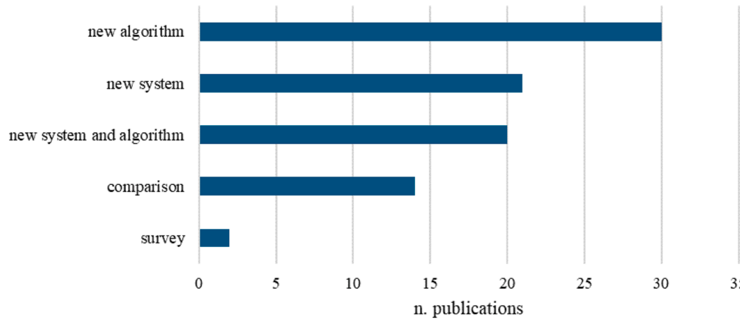

Fig. 5. Distribution of "low-cost" publications according to the development of new research methods.

Hence, DL approaches working directly on the 3D data are still sparse, as e.g. the first methods were developed not more than 8 years ago [105]. Therefore, approaches dealing with image manipulation, obtained either from cameras, or from rasterizing point clouds are currently typically more efficient. In the literature survey, many applications of DL focus on object detection [67,68,106] or semantic segmentation [41,56,69,107,108].

Applying DL directly to point clouds without rasterization is the alternative to using 2D input data. A U-Net-styled architecture built upon KPFCNN can segment objects in UAV lidar point clouds [54]. Point Transformer is another alternative, used for road inventory, although with lower accuracy rates in traffic sign classification compared to 2D-CNN [70].

Another crucial aspect is the creation of datasets for DL training and testing, as this process is laborious and costly. In most reviewed works, there is no low-cost strategy presented for data labeling, and this process is entirely manual [56,68]. Nonetheless, the computer vision domain has seen a growing interest in DL-assisted labeling approaches, using for example one-shot learning [109] or Segment Anything [110]. An exception is found in [47] where the samples were generated through Object-Based Image Analysis using thresholds in a Canopy Height Model (CHM) and the Normalized Difference Vegetation Index (NDVI).

In this context, low-cost works prioritize methodologies that require lower computational cost for data analysis. Among these methodologies, the most efficient 2D-CNN are the most relevant, such as Fast-SCNN, as they provide superior and faster results than using raw point clouds as input data in end-to-end approaches. While for post-processing tasks, computational power is less critical and is available through big providers in the cloud and at reasonable prices, online and real-time processing is more of an issue. This is especially true for low-cost systems, where expensive, high-throughput hardware like GPUs is not a feasible option or where they make use of computationally constrained edge-devices such as the NVIDIA Jetson's or the Raspberry Pi.

3.6. Data fusion in low-cost devices

Throughout the investigated publications, two main types of data fusion manifested: The fusion of imagery and lidar data (Section 3.8), and the fusion of lidar and IMU data. In the latter case, a SLAM approach is often used to find both the trajectory of the system and the resulting point cloud simultaneously [111]. IMU data are hereby used to aid in the trajectory estimation (localization) [112], especially in difficult geometries where the SLAM approach may be ambiguous.

Data fusion can - in general - be applied on multiple levels [113]: as a tight integration such as in SLAM approaches [114], where the original observations of the different sensors are combined to get an improved result [52,53,95,97], or at a later point, where information is first extracted from the data, and later fused together (loose coupling). Tight integration often makes use of the Kalman filter, which allows the combination of different measurements at different rates to obtain an estimate of, e.g., position [38,74,85]. The sensors used for data fusion are often common cameras, and -in the 3D mapping domain- laser scanners. However, these scanners are less common and, therefore, also comparatively expensive, albeit having a much lower price-tag than survey-grade laser scanners.

Many of the loose fusion approaches presented in the publications use DL approaches for tasks like image classification before carrying out data fusion, typically with lidar [68,96,106]. Data fusion approaches combined with low-cost sensors attempt to compensate for the - generally lower - data quality of these sensors. Especially in non-optimal conditions the quality of the result is improved significantly by this fusion. For example, [38] show variances in lidar and IMU data were reduced by almost a factor of two. [53] achieved similar results, with decreases in positioning Root-Mean-Square-Error (RMSE) by up to 70 % when fusing GNSS, IMU, and lidar data.

A similar concept to data fusion is Augmented Reality (AR), where data are overlaid on a real-time video stream to enhance the video with information. While AR is often reported as the main application for consumer low-cost sensors, such as the Apple iPad Pro [42,43], only one publication developed a tool where annotations and measurements can be input on the 3D sensed data and experienced through a smartphone display [88].

In summary, by combining multiple sensors in one system and fusing the data streams, developers of low-cost systems have managed to use comparatively cheap hardware like cameras [115] and IMUs and combined it with less common hardware like low-cost laser scanners. This combination allows either a transfer of methods existing for imagery and mapping it onto 3D data, or an improvement of the quality of the 3D data.

3.7. Low (cost) data quality

Data quality is an important topic, especially when discussing low-cost sensors. Three different groups were identified with regard to data quality management: (a) publications that investigate the quality of the target variables for a specific use-case (e.g., diameter at breast height (DBH) in forestry, [34]), often in comparison to survey-grade systems, (b) publications that repeat datasheet specifications and deduct some quality information, and (c) publications that do a full in-depth analysis of data quality and consider the - typically lower - quality of low-cost sensors in their method or analysis [38,40,116]. A small number of publications did not discuss data quality at all.

Data quality considerations also very much depend on the sensor type that is being investigated. When sensors are combined in more complex systems, e.g., a laser scanner with an IMU, data quality is more often discussed in terms of the final product than the individual components. For example, in a cultural heritage application, quality is investigated as mean surface roughness over the whole point cloud [60]. Furthermore, the discussion of quality also aligns with the intended use-case. For example, applications in forestry often discuss the obstruction of signals (GNSS or laser) by the canopy [30,117].

Overall, there is a consensus that more expensive survey-grade equipment is considered to have better data quality and can be used as a reference for low-cost systems, especially ones that combine several low-cost sensors [69]. Data quality is investigated in terms of (ranging and positioning) accuracy, occlusions, and data density. Most commonly the applicability of a method or system is evaluated for a specific use case, i.e., *fitness for use* [46]. While this is a valid approach when solving a specific problem, it makes comparisons between different methods, systems, and sensors difficult. Typical results of the investigations are that a certain system's quality suffices for a specific selected use-case.

When numeric comparisons are carried out, the quantification of a RMSE is prevalent. Fewer studies try to quantify precisions and bias values separately, only if they find a physical or geometric reason to do so [42,94].

Some publications compare different methods, such as laser-scanning point cloud with one obtained by photogrammetric dense image matching [49]. While these comparisons are indeed essential, it is important to account for the inherent differences in point density and occlusions caused by the sensing methods themselves. If these factors are not properly considered, the comparisons may become biased, leading to potentially misleading conclusions [118].

Publications that present the use of low-cost sensors together with DL approaches tend to quantify data quality by detection performance, i.e., the ability to detect objects of interest [29,67,106]. Accuracy, a term typically used to describe the distribution of differences from the measured values to the reference value, is then calculated by the ratio of correctly detected objects to all objects. Similarly, precision, commonly describing the repeatability of a single measurement, is the ratio of true positive detections to all positive detections. Consequently, when comparing such values across different publications, as one may give a precision of 3 mm (e.g., as a standard deviation), and another may give a precision of 95 %.

In general, there is little to no consensus on the usage of metrics for data quality, and authors tend to use metrics adapted to their field of study. Similarly, the use of terminology is not standardized and may lead to confusion when attempting direct comparisons. Publications that do attempt to characterize data quality allow experienced users to evaluate whether a sensor could be used for their use-case, albeit the transfer of such data quality considerations remains difficult. Interestingly, authors rarely mention a lack of intercomparability to other methods. While there is consensus among the publications that low-cost sensors typically exhibit lower data quality, most investigations merely show that it is sufficient regarding their application and do not quantify the difference to survey-grade equipment. If provided, datasheet values of sensor variances present parts of this reduced quality.

3.8. Photogrammetry vs low-cost lidar

Photogrammetry, particularly Multi-View Stereo (MVS) matching, and lidar represent two divergent paths in the realm of 3D surveying and documentation, each offering distinct advantages and drawbacks [119]. Photogrammetry, known for its cost-effectiveness and accessibility, leverages mainstream technology like digital cameras and smartphones. This democratizes the field of 3D surveying by enabling a broader audience to participate in digital documentation processes, without the need for specialized equipment. Additionally, the user-friendly nature of many photogrammetric software packages, i.e. Agisoft Metashape[8], Meshroom[9], 3DF ZEPHYR[10], Reality Capture[11], Autodesk ReCap Pro[12], which often include intuitive, plug-and-play functionalities, further lowers the barrier to properly performing photogrammetric acquisition and processing. These characteristics make the photogrammetric approach especially valuable in fields where budget constraints frequently limit documentation efforts.

Especially, in educational settings, photogrammetry facilitates hands-on learning by allowing students to use their personal devices for digital surveying exercises [120,121]. This approach is particularly beneficial in cultural heritage preservation, where the detailed 3D modeling of sites and artifacts is crucial yet often hindered by financial limitations. However, it is worth noting that, despite its accessibility and cost-effectiveness, photogrammetry is not universally applicable. Specific applications, in the forestry domain [122], underground archeology [123], or the presence of narrow spaces [124] or water bodies [125], are challenging for photogrammetric techniques due to the limitations in lighting conditions, and the need for discernible texture in the environment, such as the uniformity encountered with snow-covered landscapes [126].

Comparing photogrammetry to both conventional lidar and recent lidar-enabled devices like the iPad, it becomes clear that while photogrammetry can be more precise under the right circumstances due to its adaptable ground-sampling distance, lidar offers advantages in terms of intuitiveness and ease of use. For instance, lidar sensors, including those available for tablets, provide intuitive interfaces and can capture accurate 3D data even in challenging environmental conditions. On the other hand, photogrammetry offers high-resolution color textures and detailed visuals that low-cost lidar devices cannot, making it suitable for applications requiring detailed visual accuracy [127].

The integration of terrestrial photogrammetry with UAV imaging exemplifies an advanced approach to overcoming some of photogrammetry's limitations, enabling effective data capture from inaccessible or elevated locations.

In addition to photogrammetry, videogrammetry—where video footage is used to produce 3D models— remains a valuable tool in the digital documentation toolkit [128]. Videogrammetry can complement traditional photogrammetric techniques, offering dynamic data capture capabilities that are particularly useful in documenting large-scale events or moving objects [129]. Moreover, videogrammetry allows to shift work towards the post-processing phase, by acquiring videos during the survey and then selecting the frames for photogrammetry at a later stage, although this carries setbacks related to larger data storage requirements and increased processing time.

Photogrammetry remains a viable and accessible alternative, or valuable integration [130,131], to lidar for 3D surveying and documentation. Its cost-effectiveness and user-friendly interfaces support widespread use in both educational contexts and preservation projects. However, acknowledging its limitations and the necessity for integrated approaches in certain scenarios is crucial. As the field evolves, ongoing improvements and the inclusion of techniques like videogrammetry are essential for expanding photogrammetry's application range.

4. Discussion: Current trends and future challenges

4.1. Accessibility and affordability

The price and accessibility of low-cost solutions are still far from being accessible for the average consumer. The market lacks solutions specifically designed, marketed, and distributed for personal, familial, or household utilization, barring certain exceptions like Apple devices, which, while versatile, are not primarily dedicated to 3D mapping. Moreover, a substantial portion of systems remains overpriced, ranging from USD 300 [58] to USD 13,000 [30] and it is difficult to obtain complete information on prices and technical specifications without contacting distributors directly. This lack of transparency inhibits the democratization of remote sensing, where lower costs could serve as a catalyst for increased accessibility and adoption of novel techniques.

8 https://www.agisoft.com/
9 https://alicevision.org/
10 https://www.3dflow.net/
11 https://www.capturingreality.com/
12 https://www.autodesk.it/products/recap/

4.2. Mobile platforms and sensor networks

The increased usage of mobile platforms coincides with the increased number of monitoring applications, especially in the industrial domain (infrastructure monitoring and asset management). Rapidly deteriorating infrastructures, which drives the need for highly automated, precise, and scalable monitoring solutions [89]. Mobile platforms provide the flexibility and replicability that these applications require. These same needs could explain the increased interest in wearables. They are user-friendly and readily replaceable. The forestry sector is increasingly interested in wearable technology, prioritizing rapid and convenient data collection over high-resolution data. In the same vein, fast measurements using wearables, mobile platforms or UAVs can provide a tremendous advantage in applications such as disaster mapping. Surprisingly, we see no publications covering this type of application in this review.

The usage of UAVs or manned aerial platforms remained steady over time, and we expect this trend to continue in the near future. We see a steady increase in low-cost sensors embedded into mobile platforms. This could be motivated by the intersecting domains of low-cost sensors and the Internet of Things (IoT) [33,53,132]. IoT increases the intelligence of mobile platforms by providing computing power, sometimes attuned with GPU edge-devices for DL applications, or by making them connected to a communication network. In this way, mobile platforms form a comprehensive system that can process and transfer data faster and more efficiently.

4.3. Open repositories and Deep Learning software

Low-cost mapping systems use a diverse range of closed and open-source software. Almost all systems utilize a piece of closed or proprietary software in their. There is no clear indication that the publications rely on the code of other authors in the scientific community nor do authors standard publish their code under open science practices. As such there is no evidence of an existing “community of best practices”.

The low-cost mapping systems reviewed here employ a variety of closed and open-source software with almost all utilizing some proprietary software. We believe this explains why the code on which they are built is not shared on public repositories. While ideas are shared in the publications themselves, it is difficult for outsiders to compare systems or learn from the system’s building blocks.

Significant advancements have been made in the development of novel neural network architectures tailored for point cloud data. However, despite these strides, the integration of point-based neural network architectures into low-cost data solutions remains largely unexplored. There is a noticeable gap in the attention given to enhancing automatic labeling processes, which is extensively researched in computer vision [133]. Open access initiatives and sharing code repositories have not been seen as a common practice in most publications, although collaborative efforts could accelerate progress in low-cost DL 3D mapping solutions. Additionally, the absence of dedicated low-cost hardware solutions for real-time DL applications poses a challenge. While edge GPUs and Tensor Processing Units (TPUs) have not yet surfaced prominently in low-cost literature, their potential incorporation hints at a prospective avenue for future research [134].

4.4. Data fusion with deep learning

Data fusion can be grouped into loose and tight coupling, where - in our context of low-cost sensors - loose coupling typically fuses data derived from imagery (e.g., class labels or detection results) with lidar data. Tight coupling is observed mostly though Kalman filters in location estimation using IMU and lidar data. Often, the combination ensures appropriate data quality even if one of the sensors provides degraded results, e.g. due to environmental conditions. This is especially common with GNSS devices. In the future, the use of neural networks for data fusion may solve current issues where a tight coupling is currently not possible due to a missing physical model, and a loose coupling does not fit the application. The use of neural networks for data fusion has been shown to be successful [135], and largely depends on available training data. In geospatial and 3D mapping applications, training data can be generated in large quantities using survey-grade instruments, directly observing the targeted high-quality results.

4.5. Need for comparative analyses

Many low-cost 3D mapping papers concentrate on the development of new hardware and software, which is propelled by two primary factors. Firstly, the specific demands generated necessitate the creation of novel systems to accommodate the 3D environments. Secondly, the unique properties of data captured by low-cost devices require the continual development of specialized algorithms to effectively harness this data for mapping purposes. However, there exists a notable scarcity of works solely dedicated to comparative analyses between different solutions, whether commercial or non-commercial, or comprehensive literature reviews. Such comparative studies and reviews play a crucial role in elucidating the strengths and weaknesses of existing solutions, guiding future research directions, and facilitating informed decision-making for practitioners and researchers alike.

A major challenge in evaluating the data quality in general is the difficulty in comparing given metrics. Even if the metrics are the same (e.g., RMSEs to a higher-order reference), the study objects differ by the required quality and how accurately they can be sensed. For example, the requirements for a sensor for documentation of cultural heritage are very different from those for applications in forestry. This is an issue for both low-cost and high-cost systems; and especially for the comparison between the two, where the comparability between sensor datasheets is further hindered by the fact that manufacturers give values adapted to their main customer base or use case (e.g., forestry vs. structural engineering in laser scanning). A solution to this could be a common, easily recreatable benchmark. While a 3D-printable object may offer such opportunities on small scales [136], the larger scales typically of interest for low-cost 3D topographic mapping tasks, make such an endeavor difficult.

4.6. Evolution of photogrammetry

In today’s rapidly evolving digital landscape, photogrammetry remains a viable and highly accessible option for generating detailed 3D models, thanks to its straightforward application and cost efficiency. Recognizing this continuous evolution, photogrammetry is increasingly complemented by advancements such as learning-based MVS [137–139] and Neural Radiance Fields (NeRF) [140]. While learning-based MVS aims to create depth maps through CNN approaches [141], NeRFs create 3D scenes from a limited set of images with an unparalleled level of detail and realism [142]. Another current trend is Gaussian splatting [143] which offers an innovative approach to 3D scene rendering and reconstruction. A smooth, continuous surface is produced by treating each point in the cloud as a multidimensional Gaussian entity and merging these points. This potentially address traditional photogrammetry challenges, such as effectively handling transparent or reflective surfaces. These advancements indicate that the domain of photogrammetry and its related fields is not just keeping pace but is at the forefront of blending traditional methods with the latest technologies to enhance and expand the capabilities of 3D modeling and virtual reconstructions.

5. Conclusions

This study has comprehensively examined low-cost 3D mapping solutions to shed light on their defining characteristics, applications, accessibility, technological advancements, and potential future directions. Through a systematic literature review and bibliometric analysis of a substantial number of publications, we can conclude that:

- Authors use the term "low-cost" to highlight that a sensor, system, or solution has a lower cost than an equivalent one, typically referred to as “survey-grade”.
- Various low-cost mapping systems and applications have been identified. Some publications on low-cost mapping are driven by the need for automated and improved monitoring, while others are simply exploring the use of increasingly available low-cost commercial platforms for their specific domains.
- All publications use, to some extent, a closed or proprietary piece of software in their system, making it increasingly difficult to replicate or compare solutions, especially in a low-cost manner.
- Although 81.6 % of the publications on low-cost 3D mapping present new hardware and software developments, comparisons of commercial systems are also relevant since they are much more accessible and attract more interest from potential buyers.
- The use of DL in low-cost 3D mapping focuses on end-to-end approaches with 2D images or rasterized point clouds and prioritizing efficient CNN for both 3D reconstruction and semantic labelling.
- Data fusion is employed on different levels in low-cost systems to leverage affordable cameras or IMU systems for enhancing results and augmenting the capabilities of more expensive sensors such as lidar units, thereby improving data quality.
- High-cost sensing systems discuss data quality, while low-cost systems often overlook it, leading to performance evaluations based on final reports or DL metrics, and making comparisons challenging due to the assumption of low-cost data adequacy.
- The integration of photogrammetry into low-cost 3D mapping solutions highlights its central role in democratizing the field, enabling widespread engagement in detailed digital documentation and modeling using common technology.

CRediT authorship contribution statement

Jesús Balado: Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Raissa Garozzo:** Writing – original draft, Investigation. **Lukas Winiwarter:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Sofia Tilon:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization.

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

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

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