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AUTOMATED PROGRESS MONITORING IN PIPELINE CONSTRUCTION: A SYSTEMATIC REVIEW

Muhammad Hassaan Farooq KHAN[1], Wesam Salah ALALOUL[2]✉, Muhammad Ali MUSARAT[3], Abdul Hannan QURESHI[4]

[1]Department of Civil and Environmental Engineering, Universiti Teknologi PETRONAS, 32610 Bandar Seri Iskandar, Perak, Malaysia
[2]Department of Civil and Environmental Engineering, College of Engineering, United Arab Emirates University, Al Ain, United Arab Emirates
[3]Faculty of Civil and Mechanical Engineering, Riga Technical University, Kipsalas Street 6A, LV-1048 Riga, Latvia
[4]Department of Building and Real Estate, Faculty of Construction and Environment, The Hong Kong Polytechnic University, Kowloon, 999077 Hong Kong, China

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Abstract. Automated progress monitoring for pipeline construction is an evolving research domain among researchers which can provide effective visualisation and control of related projects. Although automation has been widely reviewed in building construction, a focused review on pipeline construction is lacking despite unique challenges and a growing need for automated monitoring. Hence, a systematic review of available methodologies and technologies was necessary to assess the achievement level of automation attained in progress monitoring practice in pipeline construction. Using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses statement, relevant studies in the area were identified by using five databases: Scopus, Web of Science, ScienceDirect, American Society of Civil Engineers, and Emerald. Keyword analysis was performed by developing a keyword network, and descriptive statistics were provided. The review examines a wide range of technologies and methods for automated progress monitoring, with a focus on data acquisition tools, monitoring techniques, and their integration within unnecessary article pipeline construction scenarios. A technological process overview was developed to outline the complete monitoring workflow, while a conceptual visual representation illustrated the potential impact of tools selection and integration strategies on successful project completion, and its broader impact on sustainability and economy.

Keywords: pipeline construction, MEP, automated progress monitoring, BIM, data acquisition tools, integration technologies.

✉Corresponding author. E-mail: *wesam.alaloul@uaeu.ac.ae*

1. Introduction

Monitoring progress in construction projects is critical for spotting gaps between planned and actual progress and executing remedial actions on time (Golparvar-Fard et al., 2011a; Mantel & Meredith, 2009). Timely actions are required to ensure that a construction management system runs smoothly and efficiently (Dave et al., 2016; Turkan et al., 2012). Maintaining a continual flow of actions requires collecting feedback signals to track the system's status during maintenance and assessment (Dave et al., 2016). Construction site data is used for a variety of objectives, including progress measurement (Kim et al., 2013; Turkan et al., 2012), tracking of equipment and materials (Memarzadeh et al., 2013; Yang et al., 2010), safety planning (Chi & Caldas, 2012), and productivity monitoring (Gong & Caldas, 2011). Construction site information is often divided into three categories: financial data, quality evaluations, and progress reports (Scott & Assadi, 1999). Having a precise understanding of the construction site's present progress is critical for making intelligent choices and equipping the management team to provide a final product that closely fits with expectations, even if the project timeframe has fluctuated (Lin et al., 2019; Turkan et al., 2013). Ineffective and inaccurate progress monitoring contribute significantly to construction project delays and budget overruns (Raykar & Ghadge, 2016; Shah, 2016). Approximately 10% of industrial project construction expenditures are spent on rework due to the late discovery of site issues. Human mistakes account for over half of the rework costs associated with faulty components, whereas material faults account for around 10% (Nahangi & Haas, 2014). Moreover, the inability to achieve real construction progress has resulted in over 53% of projects falling behind schedule, with more than 66% experiencing cost overruns (Han et al., 2018). Automating the process is the most cost-effective and efficient way to track progress and assess performance on construction projects (Navon & Sacks, 2007; Omar & Nehdi, 2016; Turkan, 2012). For this purpose, researchers have investigated a variety of innovative field data acquisition methods to automate project inspections. This involves using both single and combined technologies to improve the inspection process (Alizadehsalehi & Yitmen, 2016; Asadi et al., 2021; Rasoolinejad et al., 2020).

The emergence of Industry 4.0 creates a realm in which all automated machinery and methods smoothly interconnect through technological advancement, allowing them to work independently and exchange data without human intervention, hence increasing efficiency (Alaloul et al., 2016, 2020). Computer technologies that incorporate automated performance recognition and visualization of the as-built status of projects are critical for improving the efficiency of monitoring operations (Alizadehsalehi & Yitmen, 2016; Dib et al., 2013; Li & Liu, 2019; Sami Ur Rehman et al., 2022). Construction progress may be monitored using a wide range of data collection and detection technologies. Geospatial technologies, such as the Geographic Information System (GIS) and Global Positioning System (GPS), are commonly used for spatial data acquisition and location tracking. Object identification and tracking technologies, including barcode scanning, Ultra-Wideband (UWB), and Radio Frequency Identification (RFID) is primarily utilized to identify and monitor the movement of materials, equipment, and personnel in real time. Imaging techniques, such as laser scanning, photogrammetry, and videogrammetry are widely used for capturing as-built conditions and generating 3D models. Additionally, Unmanned Aerial Vehicles (UAVs) are increasingly utilized for aerial imaging and video capture, which are further processed for terrain modeling, progress tracking, and visual inspection. Extended reality technologies, including Virtual Reality (VR) and Augmented Reality (AR), enhance the visualization, simulation, and analysis of construction environments by integrating digital models with real-world contexts (Rahimian et al., 2020). However, many researchers see 3D laser scanning as the most dependable method for obtaining 3D data in construction projects. Its appeal arises from its superior speed and precision when compared to other existing technologies (Perez-Perez et al., 2021). Building Information Modelling (BIM) has fostered tremendous innovation in construction, transforming project management. BIM, particularly 4D models, helps measure progress by evaluating building activity sequences (Kropp et al., 2018).

Pipeline construction involves establishing linear infrastructure to transport resources such as oil, gas, and water over long distances, frequently in remote locations. These projects are essential for resource accessibility, economic expansion, and global energy distribution (Miao et al., 2021). Pipelines contribute to energy security by ensuring a continuous flow of resources and minimizing dependency on inefficient transportation methods such as trucking or shipping (Parpulova & Zinoviev, 2021). According to market reports, the global pipeline construction market was valued at approximately USD 45.7 billion in 2021, and expected to grow to USD 73.1 billion by 2030, reflecting a Compound Annual Growth Rate (CAGR) of 4.8% between 2022 and 2030 (Allied Market Research, 2022), and global oil and gas pipeline construction market alone is projected to reach USD 44.01 billion by 2032, growing at a CAGR of 5.8% from 2024, driven by rising energy demand and infrastructure expansion. Significant financial losses, supply chain interruptions, and environmental hazards can arise from delays or inefficiency (Ekanayake et al., 2022). Although progress monitoring can theoretically be quantified by measuring linear completion (e.g., kilometers of pipe laid), monitoring progress in pipelines construction remains inherently challenging due to the dispersed nature of worksites, diverse terrains, and the need for real-time coordination among multiple mobile crews (Azzahra et al., 2024; Jalilian et al., 2024). For instance, simultaneous activities such as trenching, welding, lowering-in, and backfilling often occur at different segments, making integrated progress tracking difficult (Prasad, 2024; Xu et al., 2024). Traditional approaches to pipeline construction monitoring frequently rely on subjective evaluations and manual reporting or non-digitized methods, which can lead to error rates ranging from 5% to 15% due to human factors and limitations in the inspection process (Rachman et al., 2021). In addition, the absence of deploying digital technology in traditional pipeline monitoring results in a 25% increase in response time to incidents, and a 15% decrease in overall monitoring efficiency (Gómez & Green, 2017). Furthermore, a building includes structural, exterior, interior, and mechanical, electrical, and plumbing (MEP) systems. Among these components, MEP systems are the most complex since they must span the whole structure to work properly (Korman et al., 2003). In relation to this, MEP services need to strategically position their pipes and ducts within limited ceiling heights while adhering to project specifications (Barton et al., 1983; Mehrbod et al., 2019). All of these are closely monitored during construction progress to ensure seamless integration. Failure to address these issues may result in greater costs associated with MEP systems which are due to the necessity for reworking (Lopez et al., 2010) and cost overruns (Love et al., 2013), which exceeds the overall cost of the project (Riley et al., 2005; Teo et al., 2022).

To overcome these deficiencies in building construction projects, several technical studies focused on automated construction progress tracking through data acquisition technologies and other automation strategies. In connection with this, construction monitoring involves the application of various aerial and terrestrial technologies to a range of objects and project categories, such as buildings, infrastructure, worker tracking, landslide detection, heritage sites, and resource tracking (Wang & Kim, 2019). In this regard, several review papers have already been reported targeting construction progress monitoring in the field of building projects and tracked elements as building components. Omar and Nehdi (2016), have presented a comprehensive review of data acquisition technologies, while Alaloul et al. (2021) focused on close-range detection and data acquisition technologies for building elements. In this regard,, Reja et al. (2022) provided an extensive review of computer vision-based construction progress monitoring. On the other hand,, Kolaei et al. (2022), provided a review of the challenges and opportunities presented by augmented reality during the construction phase. However, there is a lack of a comprehensive review that provides automated progress monitoring technologies for pipeline construction. This leads to research questions, what are the current methodologies, tools, and technologies used for automated progress monitoring in pipeline construction? How can these be utilised in a unified process reflecting the practical applicability of the technology or technological process for pipeline automated progress monitoring? How can possibly technology choices and integration strategies define the critical decision points in a project regarding their possible implications for project performance? What factors can highlight future research opportunities? Therefore, to answer these research questions and close this gap, the following objectives have been determined:

1. To identify and classify innovative methodologies for automated progress monitoring in pipeline construction, examine commonalities and differences among approaches, and critically assess current limitations.
2. To discuss the various techniques and tools adopted in existing studies.
3. To develop a technological process overview that highlights the stages of automated monitoring in pipeline missing period.
4. To present a conceptual overview emphasizing decision points and integration strategies impact for successful pipeline progress monitoring.
5. To determine potential areas and approaches for future research in the field.

The study adopted a systematic review method. This comprehensive overview would offer researchers valuable insights for evaluating the extent of progress achieved in automating the processes involved in monitoring construction progress. The study also provides an in-depth analysis of various techniques adopted by researchers by discussing key findings, significance and the possibility of integrating these techniques and tools to obtain highly efficient and accurate results. Furthermore, construction managers must evaluate the effectiveness of pipeline monitoring instruments and processes. Understanding the unpredictability and uncertainty in project activities allows for rapid and accurate decision-making, resulting in cost savings, quick corrective measures, error avoidance, and project success.

During a systematic literature review, a trend was observed with several publications over the years. To understand the trends and interest of research studies in this field, historical data are evaluated using five research databases; Scopus, Web of Science (WoS), ScienceDirect, American Society of Civil Engineers (ASCE), and Emerald, indicating that there has been a notable development in the published research articles in this sector. Figure 1 shows the trend of automated progress monitoring in pipeline construction from 1968 to 2024 across five databases. Between 1968 and 2004, there was minimal research activity on this topic, indicating a significant lack of interest in research during this period. Additionally, there may have been fewer instances of identifying critical issues related to pipeline construction and monitoring, which could

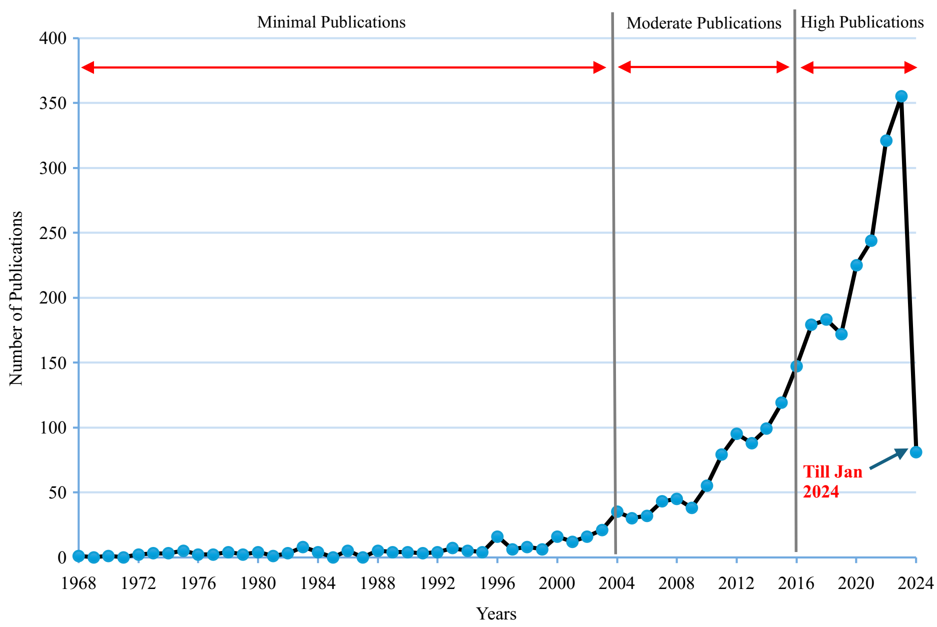


Figure 1. Publications on automated progress monitoring in pipeline construction (1968–2024) (Five databases)

have deterred research efforts. Furthermore, the absence of technological advancements in the monitoring process might have contributed to the limited interest and development in this field. After 2004, a shift in research studies can be seen with moderate publications and gained momentum with intensive research advancement in this area after 2016 for pipeline construction subsections such as MEP, industrial plant pipelines, long-distance pipelines, oil and gas pipelines, and pipelines used in infrastructure projects.

2. Methodology

The objective of this study was to evaluate related studies on progress monitoring techniques specifically focusing on automated approaches within construction domains such as pipeline construction and MEP systems. A systematic approach of the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) (Alaloul et al., 2022; Moher et al., 2009; Regona et al., 2022; Sarkis-Onofre et al., 2021) protocols guideline was considered.

A systematic review employs a methodical, comprehensive, and standardized approach to evaluate and comprehend all the prior research conducted on a specific research question, area, or phenomenon (Oates & Capper, 2009). The systematic framework can examine a specific field by adhering to technical and smart procedures, ensuring clarity and impartiality (Charlton, 2012). A systematic review can effectively address the constraints of a restricted methodology commonly utilised in literature reviews by providing a complete picture and combining different components to systematically summarise findings (Denyer & Tranfield, 2009). Figure 2 illustrates the flowchart for the PRISMA Statement.

Under the PRISMA statement methodology, the study has been divided into four distinct stages, namely, 1) Identification of articles, 2) Screening of relevant articles, 3) Eligibility of studies, and 4) Articles inclusion for interpretation.

2.1. Identification of articles

The initial step was designed to collect data from each database, including previous research studies. It was designed to retrieve past literature on automated progress monitoring techniques for pipeline construction. Pertaining to the aligned objective, the scope of the study was defined which covers, ‘progress monitoring’, ‘building engineering’, ‘infrastructure’, ‘Oil and Gas sector’, ‘construction domains’, ‘pipeline construction’, ‘MEP’, ‘plumbing’, and ‘automated technologies’.

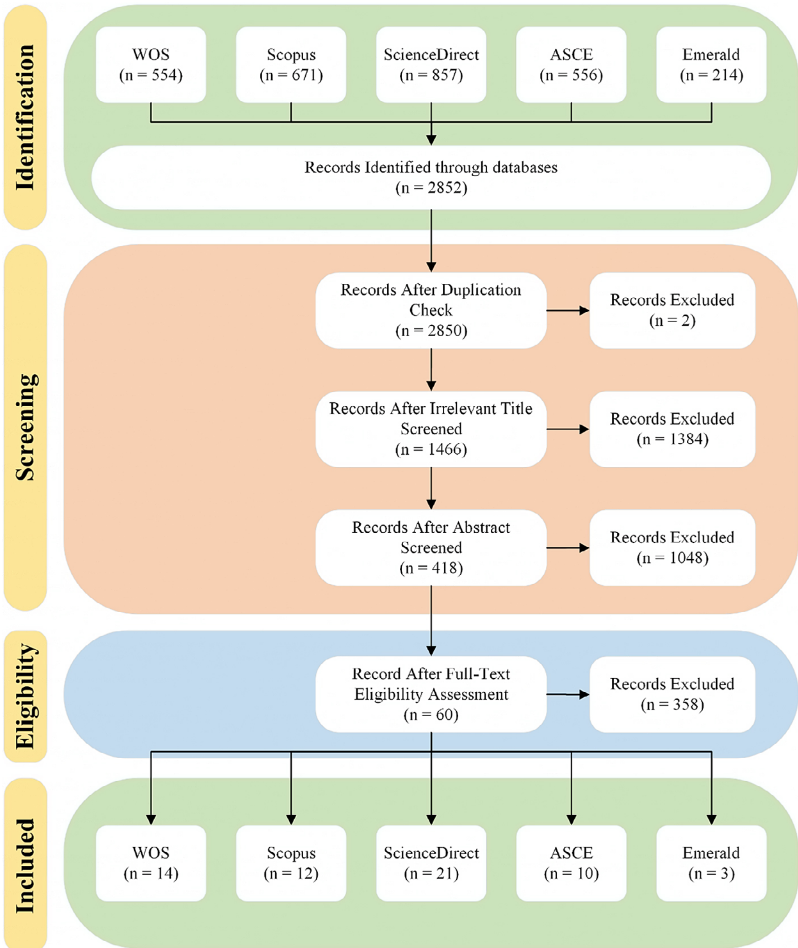


Figure 2. PRISMA flowchart

2.1.1. Selection of databases and keywords

Electronic databases were used as sources in the initial stage of identifying articles. Gathering information from current literature is critical because it aids in the selection of scientific research and findings that affect the outcomes of a review (Bramer et al., 2017; Yin et al., 2019). For data collection, five databases were selected. Web of Science (WoS), Scopus, ScienceDirect, ASCE, and Emerald were the databases for literature extraction purposes. These are some of the databases that are mostly adopted by researchers (Alaloul et al., 2021; Ng et al., 2021). However, most researchers focus on WoS and Scopus (Karimi & Iordanova, 2021; R. Khallaf & M. Khallaf, 2021; Mongeon & Paul-Hus, 2016). WoS is a diverse and selective database that includes specialized indexes organized by content type or subject. The main section, Core Collection (WoS CC), consists of six primary citation indexes: Science Citation Index Expanded (SCIE), Social Sciences Citation Index (SSCI), Arts & Humanities Citation Index (A&HCI), Conference Proceedings Citation Index (CPCI), Books Citation Index (BKCI), and the newly established Emerging Sources Citation Index (ESCI) (Pranckutė, 2021), it provides an extensive collection of quality studies for literature review. On the other hand, the Scopus database also provides a wide range of multidisciplinary journals, and their content is integrated and equally accessible (Gharbia et al., 2020; Pranckutė, 2021; Valderrama-Zurián et al., 2015). Other databases such as ScienceDirect, ASCE, and Emerald are also used by many researchers to keep the data acquisition process more extensive and thus provide a comprehensive review, by covering studies from various journals which were not published under WoS or Scopus (Altaf et al., 2023).

The keyword combinations were designed for each database by considering the importance of retrieving the relevant studies of the subject matter. Each query is created by keeping the scope of the research in consideration as described in Section 2.1. While searching for publications in each database no year filtration was applied, to include every possible study targeting our research scope. In WoS, the search elements were "TS=((Automated) AND (construction OR project OR progress OR technique OR technolog*) AND (monitor* OR updat* OR track* OR measurement) AND (MEP OR plumbing OR pipeline OR pipework*))" which showed 554 documents. These studies were refined after considering the scope of the research. For the Scopus database, the keyword combinations strategy designed a query, "TITLE-ABS-KEY((Automated) AND (construction OR project OR progress OR technique OR technolog*) AND (monitor* OR updat* OR track* OR measurement) AND (MEP OR plumbing OR pipeline OR pipework*))". The search provided 671 documents, which were refined under the defined scope and relevant limitations for the search. Considering the ScienceDirect database, the combination of keywords "((construction OR project OR progress) AND (monitor OR track OR measurement) AND (MEP OR pipeline OR pipework))" was used and 857 publications were found, several limitations were applied to refine the search within the defined scope. ASCE database, search was performed by utilizing the keyword combination "(construction progress monitoring) AND (construction project updating) AND (construction progress tracking) AND (construction progress measurement) AND (MEP OR plumbing OR pipeline OR pipework)", which provides 556 publications after the refining process within the defined scope of the study. Emerald database used with the keyword combination of "(construction progress monitoring) AND (construction project updating) AND (construction progress tracking) AND (construction progress measurement) AND (MEP OR plumbing OR pipeline OR pipework)". In this database, no limitations were applied considering the scope of the study. The search revealed 214 studies.

2.2. Screening of relevant articles

During the second step, publications were screened based on duplication, title, and then abstract. After assessing all the databases and performing screening for duplication checks, 2 studies were excluded for repeated publications in databases. In irrelevant title and abstract-based screening, 1384 and 1048 studies were excluded respectively. This screening was performed after careful assessment by keeping in mind the scope of the research.

2.3. Eligibility of studies

The third step, a full text-based screening, which was conducted to ensure the inclusion of only the most relevant studies. This step involved a detailed review of the text of each shortlisted article to assess its alignment with the study's objectives. Articles focusing on pipeline health monitoring through sensor applications, structural health monitoring (SHM) unrelated to construction progress, purely theoretical models without practical validation, manual or semi-automated tracking methods, and unrelated domains such as oil and gas reservoir monitoring or pipeline maintenance strategies were excluded at this stage. This leads to a total of 358 excluded publications, and 60 publications included.

2.4. Articles inclusion for interpretation

The fourth stage is the inclusion of relevant publications. After the screening process, 60 publications were dissected into each database, 14 studies in WoS, 12 studies in Scopus, 21 studies in ScienceDirect, 10 studies in ASCE, and 3 studies in Emerald.

3. Interpretation of articles and discussion

3.1. Descriptive statistics

An exploratory analysis was performed on the collected data taken from the selected papers. This research focused on the descriptive features of the collected data, aiming to uncover patterns, trends, and insights within the dataset.

Through this process, statistical techniques were employed to better understand the characteristics and distribution of the data. Following are the descriptive statistics used: 1) yearly-based distribution of publications, 2) source-based distribution of publications, and 3) geographical and pipeline category-based distribution of publications.

3.1.1. Yearly based distribution of publications

The distribution of 60 publications over the years is provided in Figure 3. In this distribution there are: 34 article papers, 10 review papers, 14 conference papers, and 2 papers in book series. Article papers generally outnumber review papers and conference papers, indicating a higher frequency of journal article publications compared to review articles and conference papers. There are years with significant variability in publication counts across all categories, indicating fluctuations in research output or possibly shifts in research focus.

3.1.2. Source-based distribution of publications

Table 1 provides a summary of the literature organized by the source of publication. It indicated that the journal *Automation in Construction* has the most significant number of articles, which accounted for nearly half (45%) of the total number of selected papers. The *Journal of Computing in Civil Engineering* and *Journal of Construction Engineering and Management* have a total of 9 publications. Meanwhile, the *International Pipeline Conference* accounts for 3.33% of all publications, while other conference proceedings were distributed across various conferences, each comprising no more than 1.67% or one paper per conference. In general, 73.33% of papers (44 out of 60) were published in scientific journals, while 14 articles (23.33%) appeared in conferences, and only two articles were published in book series.

Table 1. Articles distribution based on source of publication

Source	Publication Channel	Number	Percent
Journal	Automation in Construction	27	45.00%
	Journal of Computing in Civil Engineering	5	8.33%
	Journal of Construction Engineering and Management	4	6.67%
	Journal of Pipeline Systems Engineering and Practice	1	1.67%
	Journal of Information Technology in Construction	1	1.67%
	Procedia engineering	1	1.67%
	Computing in Civil and Building Engineering	1	1.67%
	Journal of Performance of Constructed Facilities	1	1.67%
	Smart and Sustainable Built Environment	1	1.67%
	Engineering, Construction and Architectural Management	1	1.67%
	International Journal of Building Pathology and Adaptation	1	1.67%
Journal Total		44	73.33%
Conference	International Pipeline Conference	2	3.33%
	Pipelines 2020: Condition Assessment, Construction, Rehabilitation, and Trenchless Technologies	1	1.67%
	Pipelines 2017: Condition Assessment, Surveying, and Geomatics	1	1.67%
	Pipelines 2021: Construction and Rehabilitation	1	1.67%
	Abu Dhabi International Petroleum Exhibition & Conference	1	1.67%
	Asian Conference on Remote Sensing (ACRS)	1	1.67%
	Tunnels and Underground Cities: Engineering and Innovation meet Archaeology, Architecture and Art	1	1.67%
	International Conference on 3D Vision	1	1.67%
	Conference of the Canadian Society for Civil Engineering (CSCE)	1	1.67%
	International Conference on 3D Imaging, Modeling, Processing, Visualization and Transmission (3DIMPVT)	1	1.67%
	American Institute of Aeronautics and Astronautics (AIAA)	1	1.67%
	Construction Research Congress 2012: Construction Challenges in a Flat World	1	1.67%
	Construction Research Congress 2020: Computer Applications	1	1.67%
Conference Total		14	23.33%
Book	Advanced Materials Research	1	1.67%
	Applied Mechanics and Materials	1	1.67%
Book Series Total		2	3.33%
Grand Total		60	100.00%

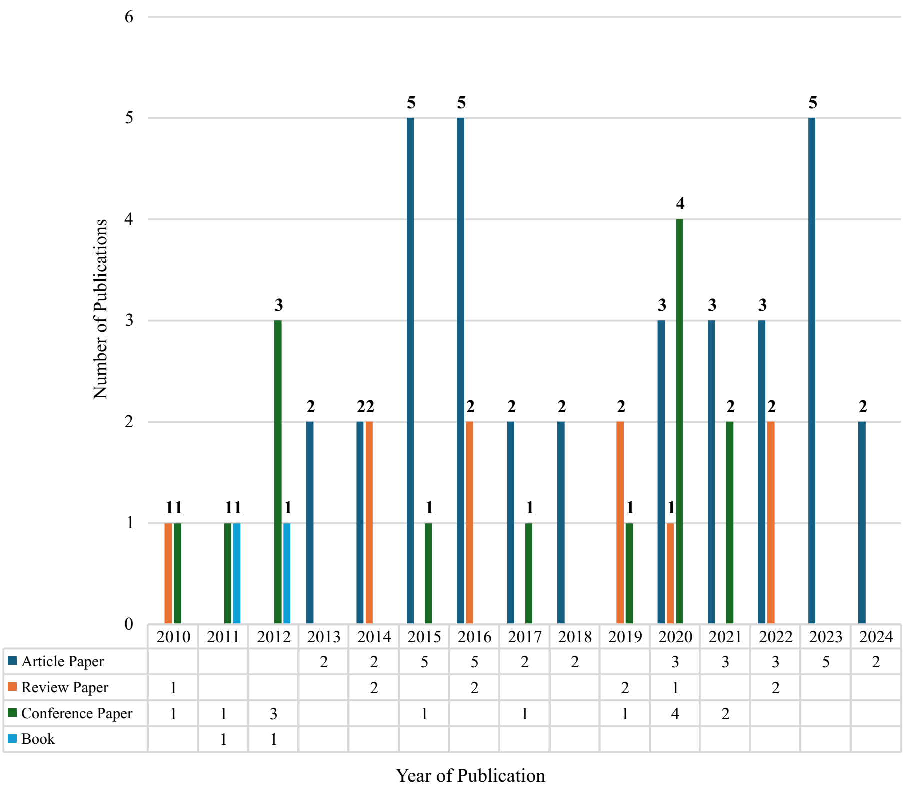


Figure 3. Articles distribution from 2010 to 2024

3.1.3. Geographical and pipeline category-based distribution of publications

Figure 4 illustrates the distribution of publications based on the geographical location of the first author's institute. Additionally, it depicts the particular pipeline types that were utilized as testbeds in relevant publications from each country. In general, most of the papers related to the topic were published by researchers in the USA (18 papers), followed by China (11 papers), South Korea (7 papers), and Canada and the UK (5 papers) each. In comparison, to the geographical distribution of papers related to automated progress monitoring in MEP, it was found that researchers in the USA and China led the research in this area (6 articles each), followed by the UK (4 articles). In the USA, researchers also concentrated on typical pipeline construction, with 8 articles in this category, 3 articles on water pipelines, and 1 article on oil and gas pipelines. Regarding the application of automated progress monitoring technology in industrial plant pipelines, South Korea produced 5 articles.

3.2. Keyword analysis

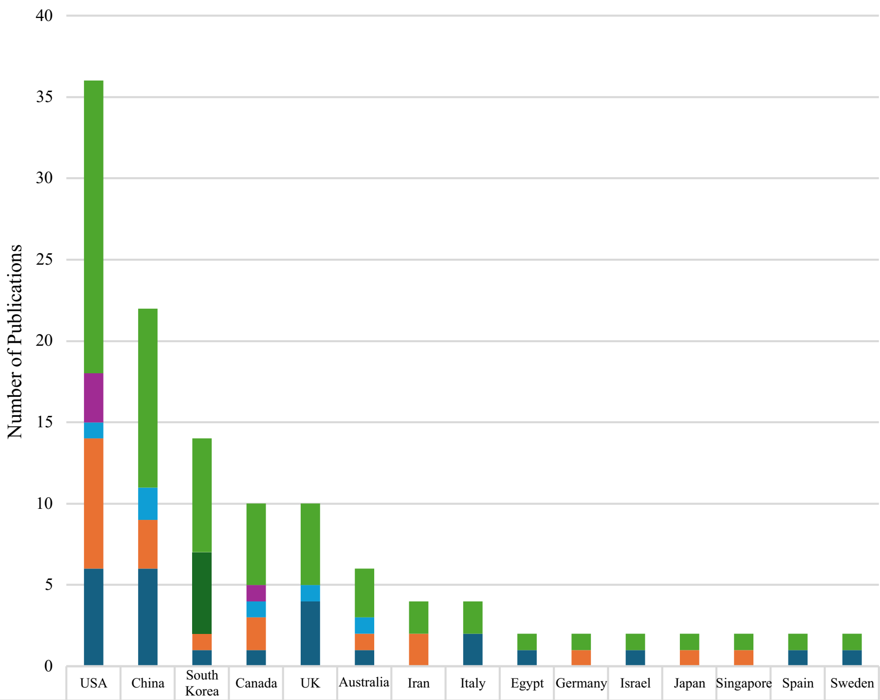
Keyword analysis offers a concise summary of the contents of a study and interprets prevalent research patterns within a specific field (Yin et al., 2019; Zhong et al., 2019a, 2019b). An organized examination of keywords in specific scientific fields can help to clarify the trends in growth and differences in research within that area. In many publications, the co-occurrence of keywords is used to determine how frequently different keywords are linked, demonstrating links between subjects. Mapping keyword co-occurrence and networks can help pinpoint new topics within a specific field of knowledge for a given timeframe. They also aid in tracking the advancement of research in that domain over time (Zhong et al., 2019b). This systematic review includes a network diagram showing the co-occurrence of keywords and how they are related to one another as shown in Figure 5. For this purpose, VOSviewer (version 1.6.20) software was used.

Keyword co-occurrence analysis was performed by considering the "full counting" option in the VOSviewer which helps to display explicit information of keyword linkage. The minimum occurrence is 4. This option enables VOSviewer to show only keywords having occurrences more than 4 times. It resulted in 2233 keywords, but only 113 qualified met the threshold. Furthermore, refinement in the selection of related keywords was performed by eliminating irrelevant keywords from the list. After elimination, 57 items were selected for mapping. The network visualization created 10 clusters with 57 related recurring keywords. The cluster nodes represent patterns and structures within the data by grouping items that are closely related to each other (Oyewola & Dada, 2022).

Keyword network visualization of co-occurrence analysis depicts the linkage between keywords adopted by the authors. Each point on the map has a color and combined points representing a cluster. The size of the circle/node represents the visual representation of the occurrence of the keyword. The intensity of interconnecting keywords can be determined by observing the thickness of the lines. The occurrence of the keywords, "pipelines", "pipeline", "model", "construction", "performance", and "monitoring" were the highest with 41, 37, 27, 18, 18, 12 instances respectably. A large portion of studies studied between these keywords shows the interest of researchers in this field.

3.3. Methodologies for automated pipeline construction monitoring

Automated project monitoring in the construction sector employs a complex procedure that delicately connects several sub-processes to accomplish effective project management (Alaloul et al., 2021). This automation implies the seamless collection of relevant project data (Vasenev et al.,



	USA	China	South Korea	Canada	UK	Australia	Iran	Italy	Egypt	Germany	Israel	Japan	Singapore	Spain	Sweden
Total	18	11	7	5	5	3	2	2	1	1	1	1	1	1	1
Water Pipelines	3			1											
Oil and Gas Pipeline	1	2		1	1	1									
Industrial Plant Pipeline			5												
Typical Pipeline	8	3	1	2		1	2			1		1	1		
MEP	6	6	1	1	4	1		2	1		1			1	1

Figure 4. Publication distribution building elementwise in each country

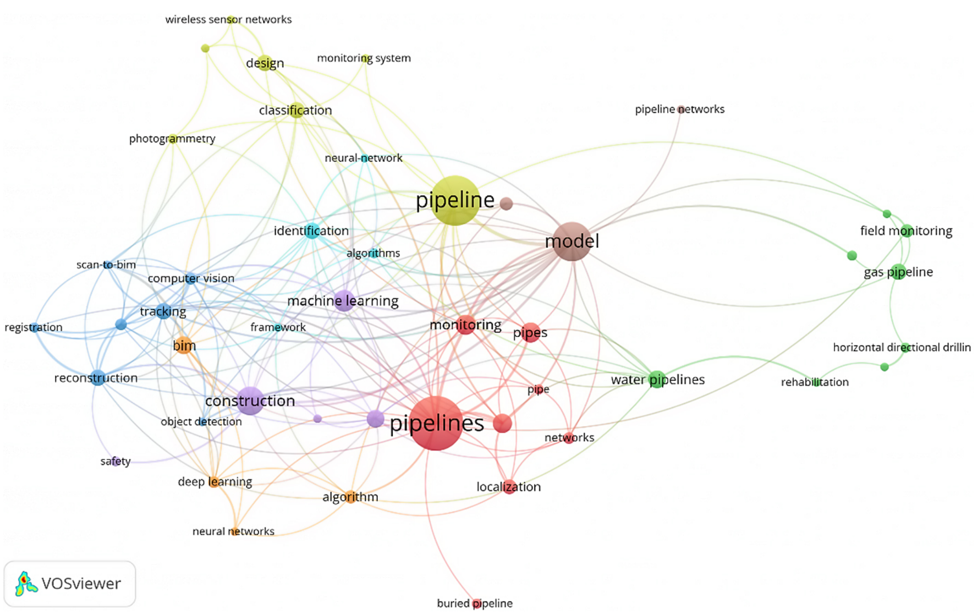


Figure 5. Network visualization of author keywords co-occurrence

2014), which includes a wide range of parameters such as progress earned, resource usage, and workflow dynamics (Zhang et al., 2022).

Traditional monitoring methods in construction may incorporate manual data collection and documentation processes that are prone to mistakes, delays, and inefficiencies (Kimoto et al., 2005). For example, getting progress reports from numerous stakeholders and entering them into spreadsheets or paper forms can be time-consuming and inefficient. Furthermore, the reliance on physical documentation makes it difficult to obtain real-time information, which may result in misunderstandings or inadequate data (Du et al., 2018). In contrast, new digital technologies provide automation and digitization solutions that improve monitoring operations and ease these issues (Mondejar et al., 2021). Sensors and IoT devices, for example, may automatically gather data, allowing for real-time insights on project progress and resource use (Tang et al., 2019). This automation lowers the need for human intervention, saving resources and time on labour expenditures while improving the quality and timeliness of data capture (Tyagi et al., 2020). Furthermore, high-capacity databases make it possible to store and analyze massive amounts of data, allowing for extensive monitoring and reporting capabilities (Hu et al., 2014). High-resolution cameras and drones provide visual recordings of construction sites by providing comprehensive imagery for analysis and documentation (Álvares et al., 2018; Bang et al., 2017; Choi et al., 2023; Fiz et al., 2022; Han & Golparvar-Fard, 2017; Rakha & Gorodetsky, 2018; Rao et al., 2022). Table 2 shows the summary of methodologies and analyses used in the studies, tracked components, key findings, and significance. Figure 6 presents the visualised mapping for automated pipeline construction methodologies including subsections. Detailed discussion can be found in each subsequent subsection.

3.3.1. Automated object recognition and modelling techniques

Pipes and elbows may be recognized automatically utilizing curvature information and CNN-based basic classification derived straight from laser-scanned points. While pipe detection is ubiquitous, elbow recognition is less so, as current approaches are indirect and subject to noise and obstruction. The proposed technique consists of four steps: pipeline extraction with noise filtering, elbow classification utilizing curvature information and CNN-based point filtering, direct elbow detection, and pipe classification. For pipe recognition, the average precision and recall were 91.81% and 94.51%. Furthermore, elbow recognition had an average precision and recall of 80.42% and 94.88%, respectively (Kim et al., 2020). An innovative approach to object verification in Scan-to-BIM processes use deep learning-based point feature comparison. It requires calculating point-level characteristics for possible point clusters derived from point clouds and BIM models. Feature distance maps and histograms are then generated for comparison, followed by binary classification using a tiny neural network to distinguish between positive and negative examples. This approach's efficacy was proven by validation with fake point clouds created from ModelNet40 and real-

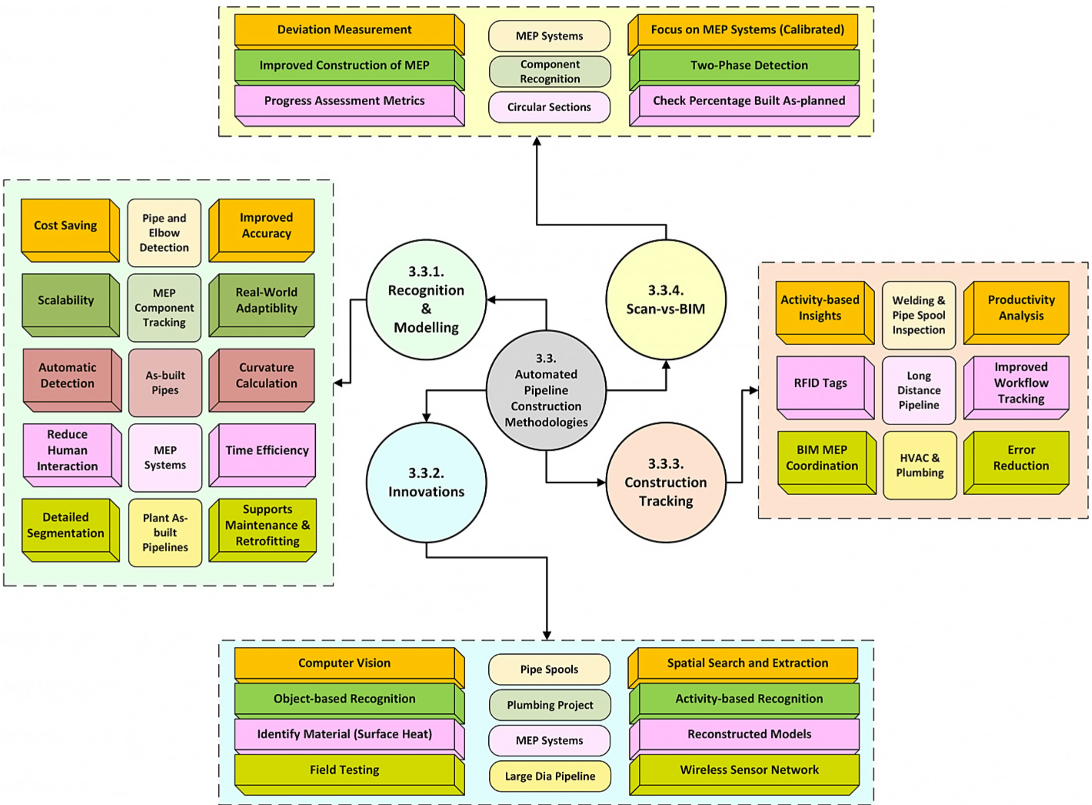


Figure 6. Visual mapping for automated pipeline construction methodologies

world data from an MEP room in a Hong Kong treatment facility (Wang et al., 2022). This article describes a method for automatically extracting 3D points representing as-built pipes from laser-scanned data within manufacturing facilities. A smoothness constraint is used to segment the data, which is then classified via curvature calculation. The algorithm was verified using real data, and it correctly distinguished pipeline points from other components. The algorithm only needs a portion of the surface data to compute radius, making it ideal for uses where pipes can be partially hidden, for example, in single-scan applications such as underground pipeline identification. The approach was evaluated on seven different pipeline types with diameters ranging from 76.2 to 304.6 mm (Son et al., 2015).

Table 2. Summary of methods used for automated pipeline monitoring

Authors	Methodology/Analysis	Tracked component	Key findings	Significance
Bosché et al. (2014)	Scan-vs-BIM, experimental analysis and comparative analysis	MEP	Assesses the effectiveness of Scan-vs.-BIM for tracking MEP works	Demonstrates efficiency in construction monitoring
Wang et al. (2021)	Scan-vs-BIM, algorithmic development, experimental validation, and comparative analysis	MEP	Develops an automated method for generating parametric BIM from laser scanning data	Facilitates accurate and rapid creation of BIM models
Bosché et al. (2015)	Scan-vs-BIM, algorithmic integration and enhancement, experimental validation, performance comparison	MEP	Extensive benefits of integrating Scan-to-BIM and Scan-vs-BIM approaches in construction monitoring	Enhances accuracy and efficiency in construction monitoring and management
Shahi et al. (2013)	Experimental and computational analysis	Typical pipelines	Demonstrates feasibility of 3D marking approach for tracking construction activities such as welding and inspection of pipe spools	Enables tracking of activities not associated with object movement
Lombard et al. (2020)	Critical comparison, review	Water pipelines	Provides insights into the use of drones for pipeline design and construction	Offers potential improvements and efficiencies in pipeline projects
Son et al. (2015)	Computational and algorithmic analysis	Industrial plant pipeline	Develops a method for automated extraction of as-built 3D pipelines from laser-scanned data	Enhances efficiency in pipeline data processing
Javadnejad et al. (2017)	Point cloud registration and parametric modelling	Typical pipelines	Evaluate the performance of UAS-based photogrammetry for CIM modelling of pipes compared to LiDAR	Assesses feasibility and accuracy of UAS-based photogrammetry for pipeline modelling
Norton Jr. et al. (2021)	Monitoring and measuring evaluation, comparing design and constructability	Water pipelines	–	Documenting design and construction steps for implementing pipeline renewal projects
Kim et al. (2020)	Experimental and computational analysis	Industrial plant pipeline	A noise and occlusion-resistant approach for automatically recognizing pipes and elbows	Improves the accuracy of identifying pipes and elbows in point cloud models
Wang et al. (2022)	Deep learning technique, dataset creation, and experimental validation	MEP	The method achieves more than 96% accuracy in object verification tasks	Enhances accuracy of automated BIM reconstruction process
Son and Kim (2016)	Experimental and computational analysis	Industrial plant pipeline	Providing more complete modelling results and explicitly incorporating domain constraints	Importance of automation in 3D modelling processes, as manual intervention can be time-consuming and prone to errors
Lee et al. (2023)	Semi-automated framework, experimental and computational analysis	MEP	The approach significantly reduces modelling time and human intervention in the Scan-to-BIM process while also facilitating automated progress monitoring	The proposed approach enables real-time construction progress tracking, facilitating efficient decision-making for stakeholders
Reja et al. (2022)	Systematic review	Typical pipelines	Importance of technology selection at each stage of progress monitoring	CV provides real-time, accurate, and reliable information for construction progress monitoring
Kalasapudi et al. (2014)	Relation-graph method, experimental analysis	MEP	Automating change detection in building systems composed of densely packed MEP components with interwoven geometries	Improving efficiency in MEP construction progress monitoring

End of Table 2

Authors	Methodology/Analysis	Tracked component	Key findings	Significance
Shen et al. (2011)	Monitoring and measuring evaluation, quantitative analysis	Typical pipelines	ZigBee-based WSN prototype provides signal reliability, accuracy of tracking, and system robustness	Cost-effective solution for automated resource tracking
Kim et al. (2012)	Pipeline extraction, segmentation, and surface-model reconstruction, algorithmic or computational analysis	Industrial plant pipeline	Automation in reconstructing 3D as-built plant pipeline model for automated construction monitoring	Potential to improve efficiency and accuracy for plant pipeline construction, operation and maintenance
Zhao et al. (2023)	Integrating robot-based techniques for construction progress monitoring, algorithmic analysis, and experimentation	Typical pipelines	The BIM-based checklist update approach eliminates false detections, enhancing progress tracking accuracy in construction monitoring	Potential to prevent quality deficiencies, reducing time and cost overruns in construction
Wang et al. (2016)	BIM-based MEP layout design and constructability, comparative analysis	MEP	BIM-based coordination helps with proper MEP construction monitoring, thus cost reduction of 16% in pipes	–
Omar and Nehdi (2016)	Literature review and comparative analysis	Typical pipelines	3D sensing technologies are recommended for large, non-congested projects like pipelines due to their high accuracy and speed in data acquisition	Improving decision-making, enhancing collaboration, adapting to industry trends, and meeting regulatory requirements
Kolaei et al. (2022)	Systematic review	Typical pipelines	Smartphones and tablets are commonly used for augmented reality (AR) implementation in construction due to their cost-effectiveness and accessibility compared to AR glasses and projectors	Potential for augmented reality (AR) technology to enhance real-time tracking and management of construction activities
Nahangi et al. (2015)	Point cloud registration, computational analysis, and Iterative feedback loops analysis	Water pipelines	The methodology autonomously plans realignment based on detected discrepancies, enhancing automated construction progress monitoring	The model provides high efficiency and accuracy of discrepancy quantification for pipe spools and modules
Czerniawski et al. (2016)	Recognition or detection analysis	Typical pipelines	Effective extraction of pipe spools from point clouds and differentiation of identical pipe spools within the same cloud	The study promises enhanced progress tracking and component inspection in pipeline construction projects via advanced information extraction methods
Yin et al. (2021)	Point-cloud segmentation, comparative, integrative, and evaluative analysis	Typical pipelines	ResPointNet++ outperforms the conventional method PointNet++ by 42% in mIoU and 23% in overall accuracy	The release of the dataset and ResPointNet++ fosters innovation in DL-based semantic segmentation for industrial point clouds (such as pipes)
Shahi et al. (2012)	Experimental analysis, data fusion modelling, comparative analysis	MEP	Fusing object recognition with activity tracking improves construction progress estimation, crucial for piping and industrial projects with high design changes	The method expands project management capabilities by tracking diverse construction activities beyond physical movements
Taneja et al. (2011)	Technology comparative analysis	Typical pipelines	Field capturing technologies must be assessed in terms of contextual factors which affect project progress monitoring, such as earthwork and pipeline	Automated field data capture improves construction decision-making
Huang et al. (2020)	Image-based 3D reconstruction and infrared thermography for updating as-built BIM, comparative analysis	MEP	Thermal images outperform traditional 3D reconstruction in capturing MEP data	The potential for cost-effective BIM updating and future advancements in semantic information reasoning
Alizadeh-salehi and Yitmen (2021)	Integration of reality-capturing technologies, statistical techniques, qualitative analysis	MEP	Promising applications of DRX in capturing accurate real-time data, providing semantic construction information, etc.	The DRX system tackles construction progress monitoring challenges by offering real-time, transparent, and digital data

Experimental and computational analysis strategies were adopted by the authors. The strategy described in this work uses scripts and CloudCompare to retrieve critical modelling data. While most information is automatically collected, CloudCompare may help users manually determine different family types and orientation angles. Dynamics helps parametric modelling by providing efficiency and versatility with built-in functions and the ability to launch Python scripts for advanced operations. When compared to manual approaches, this methodology significantly lowers modelling time and human interaction, demonstrating promising results for MEP systems (Lee et al., 2023). This research proposes to automate the reconstruction of as-built pipelines in plant facilities using laser-scanned data. The proposed method consists of three steps: first, cylindrical pipelines are extracted using random sampling consensus (RANSAC), then pipelines are segmented into components such as straight pipes and elbows using medial axis extraction and curve skeletonization, and finally, surface models are rebuilt using parametric modelling (Kim et al., 2012). For indoor hanging pipeline detection, the strategy developed by the authors is tracking-based monitoring which can be used in a variety of platforms, including mobile robots, phones, and drones, to record photographs of pipes during construction. For data acquisition purposes, goal points are located beneath the pipes with cameras pointing above. To acquire photographs, the drone rose to the same height as the pipes while staying within preset distances. Laboratory testing has shown that this technology can be adapted to various robot platforms. To increase the usage rate of construction robots by repurposing them for interior installation progress monitoring. This adaptability increases productivity in building operations where specialist robots are generally underutilized (Zhao et al., 2023).

Most methods focused on laser-scanned data for precision in pipeline recognition, the effort put to reduce manual intervention, often integrating tools like CloudCompare and RANSAC for parametric modelling segmentation. Several methods were designed to function in complex or partially obstructed scenarios, such as industrial or MEP settings. Some methods emphasized curvature-based pipe and elbow detection (Kim et al., 2020) while others focused on the reconstruction of entire pipeline geometries (Kim et al., 2012). While CNN-based classification offers high automation, they demand dense data and computational resources, limiting their scalability. In contrast, flexible tracking based systems (Zhao et al., 2023), using robots or drones, offer adaptability in dynamic environments but compromise on geometric precision. Additionally, many methods struggle with noise, occlusions, or lack real-time capability, especially in congested MEP or underground settings. Future work should focus on hybrid approaches that combine the accuracy of curvature-based models with the mobility of lightweight tracking systems to enable scalable, real-time pipeline recognition.

3.3.2. Emerging technologies and methodologies

The combination of 3D imaging methods with building information models (BIM) improves the detection and location of possible inconsistencies. To correctly mimic building site settings, the strategy uses point cloud registration approaches as well as a limited registration technique. This technique facilitates construction progress tracking (Nahangi et al., 2015). Automating dimensional compliance control and progress tracking with computer vision (CV) is a significant improvement perspective in construction. The authors provide an automated technique for recovering pipe spools from crowded point clouds, utilizing upcoming sensor networks and communication technologies. The method includes a spatial search and extraction methodology that relies on local data-level curvature estimate, clustering, and bag-of-features (BoF) matching. The sensitivity study demonstrates the effect of filter strength and sample density on extraction performance (Czerniawski et al., 2016). This study examines research and methods for automated estimation of construction progress. It emphasizes the difficulties existing automated object identification algorithms encounter, particularly in projects requiring plumbing and mechanical/electrical services with frequent design modifications. Concrete constructions undergo little alterations after construction begins, with structural parts remaining unchanged after around 20% completion. Steel constructions allow for more dynamic changes during construction, while design changes are rare after 50% completion. In contrast, plumbing projects frequently deviate significantly from the initial design, particularly during construction. Field routing and adjustments are typical to accommodate structural or service conflicts, leading to significant departures from the intended course. The research suggests combining object-based recognition with activity-based progress monitoring to improve estimation accuracy (Shahi et al., 2012).

Several authors have also utilized Simultaneous Localization and Mapping (vSLAM) technology because of its potential for automation. In one case, the strategy is to update as-built Building Information Modeling (BIM) models by combining vSLAM technology with semantic improvement approaches. By implementing a visual-based localization mechanism, the article investigates the possibilities of reconstructed models. The practicality of this localization approach is successfully proved. Furthermore, it suggests a semantic improvement method for automated component recognition and BIM updating. It explores how thermal cameras can identify materials based on surface temperature, allowing MEP systems to be separated from ceilings (Huang et al., 2020). The research presents the digital extended reality (DRX) technology, which allows for automated building progress monitoring. It brings together Building Information Modeling (BIM), reality capture technologies, Digital Twin (DT), and Extended Reality (XR) technology. These technologies are integrated using IDEF0 modelling, which uses boxes and arrows to simplify difficult ideas. The system's aims include producing high-quality designs, optimizing planning scenarios, properly collecting real-time construction data, precise data analysis, and enabling stakeholder communication (Alizadehsalehi & Yitmen, 2021). This study offers a ZigBee-based wireless sensor network (WSN) for automating resource tracking on construction sites, hence improving project control. Field testing in Hong Kong, which included a high-rise building and an open trench for laying down a 315 mm-diameter polyethylene (PE) pipeline, validated its feasibility, including fixed nodes and a received signal strength indicator (RSSI) for mobile node location (Shen et al., 2011).

Most methods combine analytical models like BIM or digital twins with advanced data acquisition (e.g., point clouds (SfM), thermal imaging, wireless sensors). However, WSN targets resource tracking rather than structural progress monitoring. CV and DRX are methods that adapt to real-time changes and on-site dynamics. Despite growing application of DRX and vSLAM for real-time pipeline progress tracking, their adoption is limited by cost, integration complexity, and data fusion challenges. In pipeline specific context most implementations lack validation, which involve long distance pipelines, or application in variable topographies. Activity-based monitoring is an effective technique in the case of plumbing and MEP systems because these systems are prone to significant deviations and require dynamic approaches. Comparative performance benchmarking of DRX and WSN in dynamic, distributed pipeline environments remain an open gap in the literature. Additionally, vSLAM systems with semantic enhancement still need better training data to accurately recognize MEP components in crowded environments.

3.3.3. Construction activity tracking strategies

An Ultra-wide Band (UWB) positioning system can monitor structural and non-structural activity on building sites. Unlike previous approaches, which struggle to measure progress for non-physical operations such as welding or pipe spool inspection, this approach allows for activity-based monitoring. Incorporating this strategy into progress-tracking models gives a unique source of site information, hence improving automation efforts in construction progress monitoring (Shahi et al., 2013). Gathering exact, complete, and reliable field data is critical for successfully managing construction projects, which include activities such as material tracking, progress monitoring, and quality assurance. The use of field data-capturing technology in construction and facility management is of great importance. It includes technology for sensing entities, contextual surrounds, and tracking workflow in these tasks. These technologies serve two functions: they collect data on operations at construction and facility sites while also gathering information about the surrounding environment. They also monitor the flow of activity throughout these processes. These technologies are classified into several types, including image capture tools like laser scanners and video cameras, automatic identification systems like barcodes and RFID tags, tracking mechanisms like GPS and wireless LAN, and process monitoring tools like on-board instruments (OBI) (Taneja et al., 2011). This project created a realistic BIM framework for coordinating MEP layout from preliminary design to construction, which was divided into five detail levels and four coordination processes which are based on relevant activities during the project execution. The study found that BIM applications had considerable benefits, such as reduced errors, cost savings (16% in pipes, 14% between HVAC and plumbing, and 9% between plumbing and plumbing), and improved construction time schedules (Wang et al., 2016).

Most of these techniques focus on data integration to provide project managers with actionable insights. They are versatile and adaptable to different construction activities, including pipeline projects. While UWB-based systems allow detailed activity tracking for weld inspections and pipe spool assembly, their effectiveness decreases in steel-heavy environments due to signal interference. BIM-based coordination tools support visual planning but depend on the precision of as-designed models, which often diverge from as-built conditions in MEP-heavy projects. Few studies talked about using RFID and BIM in real-time with integrated approach.

3.3.4. Scan-vs-BIM application

Automated progress tracking for MEP systems in construction is sometimes disregarded when compared to structural work. When a Scan-vs-BIM framework is evaluated using utility corridor data, it discovers problems with item detection caused by deviations from design drawings. Despite the limits of employing 3D BIM models for operations and maintenance, the study proposes a potential confidence measure for calculating deviations that might improve performance tracking. However, validation is required to determine its suitability for automated evaluations of the percent built as intended (Bosché et al., 2014). In another study, authors proposed a novel methodology by using scan and BIM data, which comprehends better performance. This study describes a reliable approach for autonomously recognizing and recreating BIM models of MEP components using point cloud data. It classifies components according to geometric complexity and employs two-phase detection techniques: 1) preliminary geometric information extraction by detecting cross-sections from point cloud slices, and 2) refined geometric information extraction by integrating cross-section information in 3D space. Validation of Hong Kong scenes shows great retrieval rates and accuracy. The study adds value by automating the recognition of thin long items and objects with different forms, as well as the construction of MEP networks. The retrieval rate was 91.3%, showing a success rate in modelling the necessary components. The comparison of as-designed and modelled pipe radii yielded an RMSE of 2.45 mm and a relative error of 1.86%, suggesting acceptable geometric correctness (Wang et al., 2021). Furthermore, another study inferred to automatically detect items such as pipes with circular cross-sections in 3D data from building sites collected with a terrestrial laser scanner. It compares the data to the project's 3D design BIM model. The metrics used in the procedure not only aid in identifying items but also assess how well each component follows the original plan. These estimations can then be used to assess how well an entire system, region, or group fits the original design, often known as "percentage built as planned" (Bosché et al., 2015).

In order to track pipeline progress, studies place a strong emphasis on precise geometric reconstruction and identification of deviations between as-built and as-planned components. By identifying and assessing objects like pipes and fittings based on automated detection applications, the frameworks intend to overcome manual inspection procedures. Considering pipeline geometry detection during construction activities, one technique focused on detecting circular cross-sections and aligning built components with original BIM designs, establishing a "percentage built as planned" statistic, which is an effective and simplified approach. In another case, the method suggested a two-phase detection approach that makes use of geometric complexity to provide reliable MEP modeling. This is a significant and efficient practice in MEP systems providing reliable outcomes. However, these methodologies may struggle in large-scale activities compared to compact MEP systems. Under pipeline-specific circumstances, such as varied environmental consequences or complicated terrains, some of the studies lacked adequate real-world validation. Object detection techniques specifically focusing on circular cross-sections may obscure special and non-standard parts that are frequently utilized in pipelines.

3.4. Tools and techniques used for automated monitoring

Table 3 displays the tools utilized for automated pipeline monitoring. The most extensively used tool appears to be the laser scanner, which many researchers incorporate into their research. Laser scanning provides high-precision and comprehensive 3D imagery, making it ideal for pipeline monitoring. BIM is another widely used tool among academics. It gives a digital representation of pipelines' physical and functional features, allowing for more efficient planning, design, construction, and management.

Table 3. Tools and techniques employed in the monitoring of pipelines

Author	Tools/Technique													
	Laser Scanning	BIM	UWB	Barcodes	RFID	SfM	Robots	UAV	GPS	Computer Vision	Machine Learning	CNN	Infrared Thermography	Other
Bosché et al. (2014)	✓	✓	–	–	–	–	–	–	–	–	–	–	–	–
Wang et al. (2021)	✓	✓	–	–	–	–	–	–	–	–	–	–	–	✓
Bosché et al. (2015)	✓	✓	–	–	–	–	–	–	–	–	–	–	–	✓
Shahi et al. (2013)	–	–	✓	–	–	–	–	–	–	–	–	–	–	–
Lombard et al. (2020)	–	–	–	–	–	–	–	✓	–	–	–	–	–	–
Son et al. (2015)	✓	–	–	–	–	–	–	–	–	–	✓	–	–	–
Javadnejad et al. (2017)	✓	–	–	–	–	✓	–	✓	–	–	–	–	–	–
Norton Jr. et al. (2021)	✓	–	–	–	–	✓	–	–	–	–	–	–	–	✓
Kim et al. (2020)	✓	–	–	–	–	–	–	–	–	–	–	✓	–	–
Wang et al. (2022)	✓	–	–	–	–	–	–	–	–	–	–	–	–	✓
Son and Kim (2016)	✓	–	–	–	–	–	–	–	–	✓	✓	–	–	–
Lee et al. (2023)	–	–	–	–	–	–	–	–	–	–	✓	–	–	✓
Reja et al. (2022)	–	–	–	–	–	–	–	–	–	✓	–	–	–	–
Kalasapudi et al. (2014)	✓	✓	–	–	–	–	–	–	–	–	–	–	–	–
Shen et al. (2011)	–	–	–	–	–	–	–	–	–	–	–	–	–	✓
Kim et al. (2012)	✓	–	–	–	–	–	–	–	–	–	–	–	–	✓
Zhao et al. (2023)	–	✓	–	–	–	–	✓	–	–	✓	–	–	–	–
Wang et al. (2016)	–	✓	–	–	–	–	–	–	–	–	–	–	–	–
Nahangi et al. (2015)	✓	✓	–	–	–	–	✓	–	–	–	–	–	–	–
Czerniawski et al. (2016)	–	✓	–	–	–	–	–	–	–	–	–	–	–	–
Yin et al. (2021)	✓	–	–	–	–	–	–	–	–	–	✓	–	–	–
Shahi et al. (2012)	–	–	✓	–	✓	–	–	–	–	–	–	–	–	–
Taneja et al. (2011)	✓	–	–	✓	✓	–	–	–	✓	–	–	–	–	–
Huang et al. (2020)	–	✓	–	–	–	–	–	–	–	–	–	–	✓	–
Alizadehsalehi and Yitmen (2021)	✓	✓	–	–	–	–	–	–	–	–	–	–	–	–

Machine learning techniques are also widely used, demonstrating a rising interest in using artificial intelligence for pipeline monitoring. Ultra-wideband technology is used less frequently than other techniques. UWB can provide fine localization capabilities, but its use may be restricted for reasons such as cost, complexity, and application constraints. Infrared thermography, while effective for monitoring temperature fluctuations in pipelines, is used less commonly. This might be because it needs specific equipment and knowledge, and its performance is affected by environmental conditions. GPS technology is moderately adopted by researchers. While GPS provides accurate positioning data, its application in pipeline monitoring may be more limited compared to other tools that offer detailed spatial. Figure 7 presents a summarized visualization of trends in automated monitoring tools and techniques, highlighting target areas, tools, and their purposes for pipeline construction monitoring.

3.4.1. Trends in embracing advanced tools and techniques

The researchers' interest in the adopted tools reflects the ever-evolving context of pipeline monitoring technology, with a strong emphasis on using sophisticated imaging, modelling, and artificial intelligence approaches to improve the procedure for monitoring construction. Laser scanning and BIM are particularly popular, indicating a strong commitment to using advanced visualisation and data modelling tools for thorough process analysis. These technologies have unique capabilities in gathering comprehensive geographical information and accurately representing pipeline assets, allowing for better-informed decision-making throughout the construction process. Furthermore, the increased use of machine learning demonstrates an awareness of artificial intelligence's potential in dealing with huge and complicated datasets inherent in pipeline monitoring applications. Machine learning algorithms show promise for spatial change and anomaly identification, revealing underlying patterns and trends that traditional approaches may miss. However, the comparatively low adoption of technologies like UWB and infrared thermography indicates either a restricted application in specific pipeline monitoring contexts or the need for additional research and development activities to successfully solve implementation issues. These instruments may have unique capabilities, such as accurate localization or thermal anomaly detection. Furthermore, robot utilization is still limited in pipeline construction monitoring although it provides an efficient solution for manoeuvrability in complex environments such as industrial plant pipelines and oil and gas pipelines. Robotics provides an opportunity to develop unique building strategies to meet these challenges (Khoshnevis, 2004; Munoz-Morera et al., 2015). In addition, robotic accessibility in complex congested MEP environments shows its potential in plumbing construction monitoring with the help of mounted camera equipment or scanning devices which ease the whole process of monitoring (Nahangi et al., 2015; Zhao et al., 2023). On the other hand, researchers incorporated UAV technology in very limited studies in the context of pipeline construction. However, this technology is widely embraced by researchers in other construction projects of building and infra-

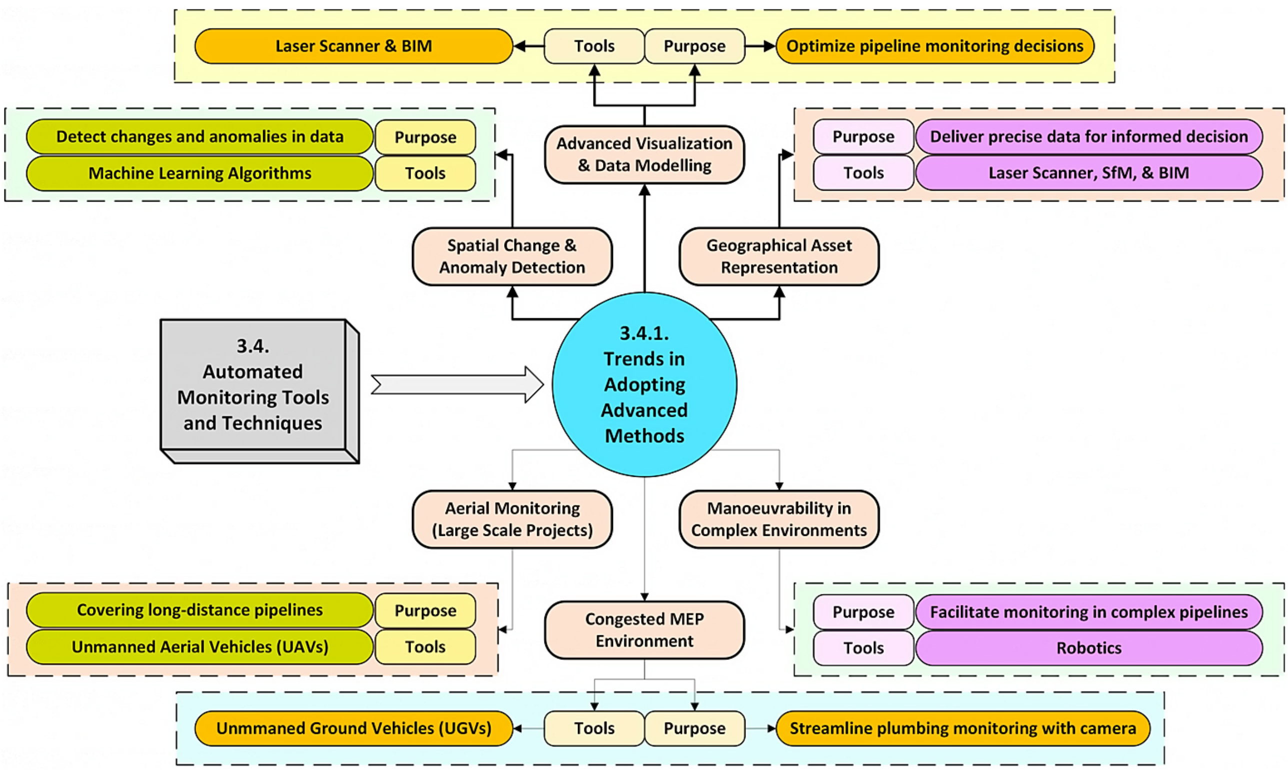


Figure 7. Visual summary of automated tools and techniques in pipeline monitoring

structure (Hamledari et al., 2017; Jacob-Loyola et al., 2021; Lin et al., 2015). UAVs can swiftly cover huge areas and access difficult-to-reach or hazardous spots, allowing for regular and thorough monitoring without disturbing existing construction activity (Albeaino & Gheisari, 2021; Chan, 2017). The exclusive aerial capture technology in the UAV system provides an enhanced capturing solution in the data acquisition process for pipeline construction monitoring in large-scale projects such as the oil and gas sector. For automation using advanced tools and techniques, continuous investigation and refining of these technologies are critical for realising their full potential and improving their utility in pipeline monitoring applications.

3.5. Overview of technology-driven process for pipeline monitoring

Figure 8 displays a visual overview of an automated progress monitoring process for pipeline tracking. A technology-based demonstration, to highlight the possible construction progress monitoring process for pipeline detection purposes. Furthermore, in the context of Construction 4.0, Building Information Modelling (BIM) has increased the construction industry's anticipation of the rapid shifts brought about by the digital era (Shahinmoghadam & Motamedi, 2019). Research on digital construction progress monitoring has switched its attention to technology integration, or Construction 4.0.

3.5.1. Data acquisition and 3D reconstruction

Sensing technologies are critical to the data acquisition process (Moselhi et al., 2020), with digital cameras (Golparvar-Fard et al., 2015), video cameras (Bognot et al., 2018), laser scanners (Bosché et al., 2015), and range imaging (or RGB-D cameras) (Kopsida & Brilakis, 2020) being the most common vision-based technologies used for data collection and monitoring. For this purpose, a framework is developed which receives inputs in the form of picture frames or point clouds that are acquired using different sensor mounting methods (Wang et al., 2020). These approaches include fixed equipment, portable devices, robotic systems mounted on unmanned ground vehicles (UGV) (Gharbia et al., 2020), unmanned aerial vehicles (UAV) (Jacob-Loyola et al., 2021), or a combination of these (Asadi et al., 2020). Each technique has distinct advantages depending on the individual needs of the building project, such as accessibility, coverage area, and resolution. Fixed devices provide constant monitoring from specified viewpoints, portable devices give flexibility for on-site inspections, and robotic systems mounted on UGVs or UAVs allow for dynamic data gathering in large or difficult-to-reach locations (Halder & Afsari, 2023). Several 3D reconstruction methods are used to create a point cloud model. Numerous photogrammetric progress tracking procedures make use of commercial software to turn optical or depth photos into a 3D point cloud.

3.5.2. As-planned and as-built modelling

Throughout the construction phase, these models aid in analyzing operations, enabling project managers to strategize site management, coordinate contractors, plan logistics, assess access routes, and evaluate schedule integrity and construction sequences (Golparvar-Fard et al., 2011b). Moreover, the use of these models during construction can increase if problems related to modelling detailed portions and site layouts are overcome, and further advantages of merging BIM with as-built data are investigated. In pipeline construction monitoring the most adopted strategy was Scan-vs-BIM modelling, having the use of laser scanners and BIM, which comprises the process for pipeline tracking by optimising and utilizing various methodologies as discussed in Section 3.4.1. In this process, MEP (mechanical, electrical, and plumbing) and other pipeline data are collected during this step using as-built modelling, resulting in a detailed depiction of the project's physical infrastructure at various stages of development (Bosché et al., 2014; Kalasapudi et al., 2014). This information may then be compared and evaluated to provide useful insights into project development. Discrepancies and deviations can be found by superimposing the planned design on the actual as-built circumstances.

3.5.3. Integration techniques

Machine learning (ML) approaches are considered essential for dynamic systems with automatic and continuous learning capabilities (Bhaddurgatte et al., 2019). Furthermore, there has been a rising trend of combining ML with construction detection and data-collecting technologies in recent years. ML approaches have been integrated into a variety of technologies, including laser scanners, photogrammetry, videogrammetry, augmented reality, and infrared thermography. However, laser scanners and photogrammetry have received the majority of attention in terms of machine learning integration (Braun & Borrmann, 2019). Limited study has been conducted on the inclusion of CV and augmented reality (AR) into the detection process (Ekanayake et al., 2021). Laser scanners have especially used ML in combination with CV, and more specifically with BIM, for mechanical, electrical, and plumbing (MEP) work and typical pipeline monitoring (Qureshi et al., 2020).

3.5.4. Progress visualisation and monitoring

Currently, the most commonly used approaches on construction sites are progress visualization and comparison-based monitoring. These approaches simply visualize the 3D as-built model created from on-site geographical data. On the other hand, a more advanced tactic involves thorough comparison and monitoring of the progress by visually assessing the planned and actual statuses at a specific point in time. This innovative method has gained traction in various projects and has been studied extensively in research papers.

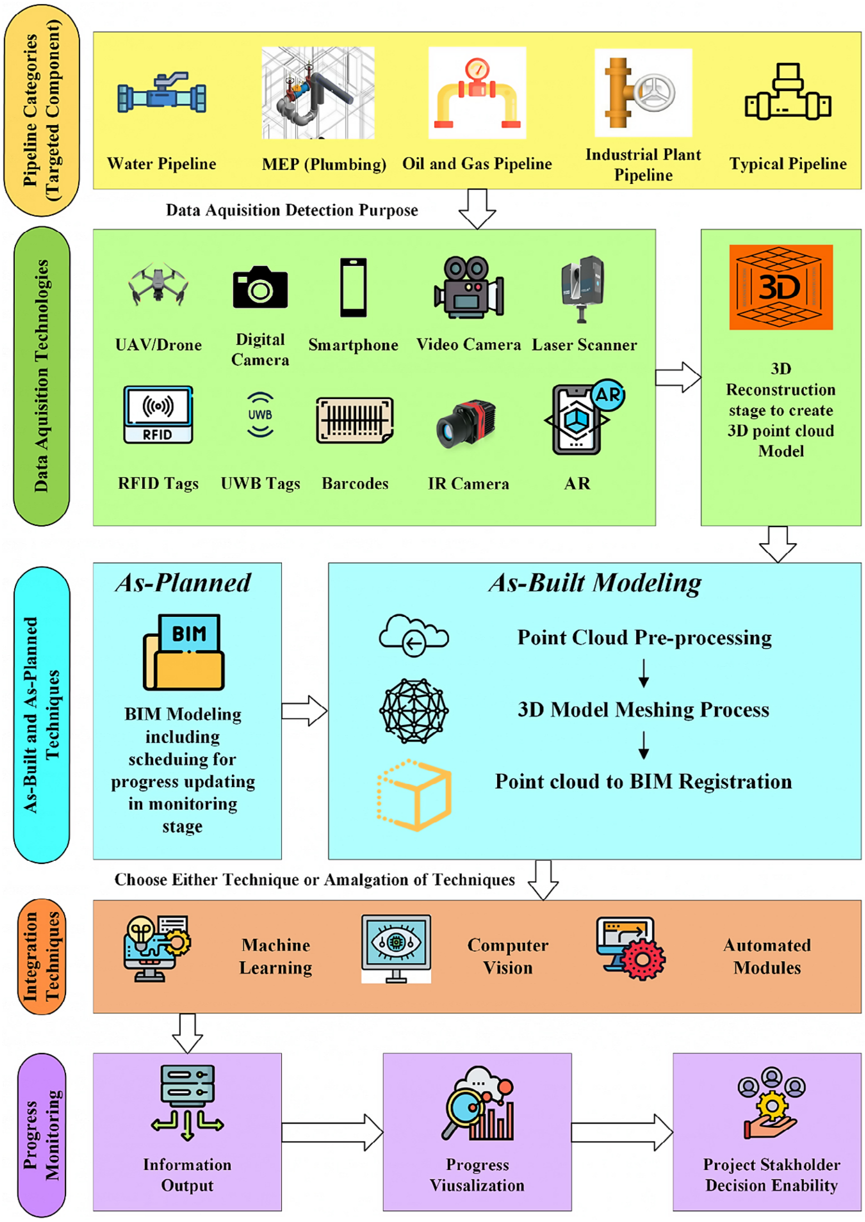


Figure 8. Visual process overview of automated pipeline monitoring systems

Visualisation can be interactive through Interactive user interfaces (UIs). UIs are becoming increasingly popular because of their potential to ease information sharing across stakeholders. They allow users to assign tasks or notes to the workforce and include capabilities such as adding annotations to PDF documents straight from the user interface. Advancements in game engines now allow for the integration and stacking of point clouds and BIM models into a single VR scene using Unity3D (Rahimian et al., 2020).

After evaluating the literature and actual implementations, this study discovered that visualization environments are underutilized for progress monitoring in pipeline construction. These systems can efficiently transmit real-time information because of increased computer capabilities, significant advances in immersive technologies, and the requisite bandwidth made possible by the 5G standard (Reja & Varghese, 2019). To develop interactive user interfaces and merge augmented reality (AR) and virtual reality (VR) environments effectively, dedicated research efforts are necessary, which enable users to have a more complete experience. Leveraging game engines can improve progress visualization, particularly in the context of pipeline tracking.

4. Potential impact of technology choices on pipeline progress monitoring

Figure 9 presents a conceptual overview illustrating how the adoption of automated progress monitoring in pipeline construction can potentially improve project efficiency in terms of cost, time, safety, and error reduction. It also highlights the possible economic benefits achieved through the implementation of efficient progress-tracking strategies during the construction phase.

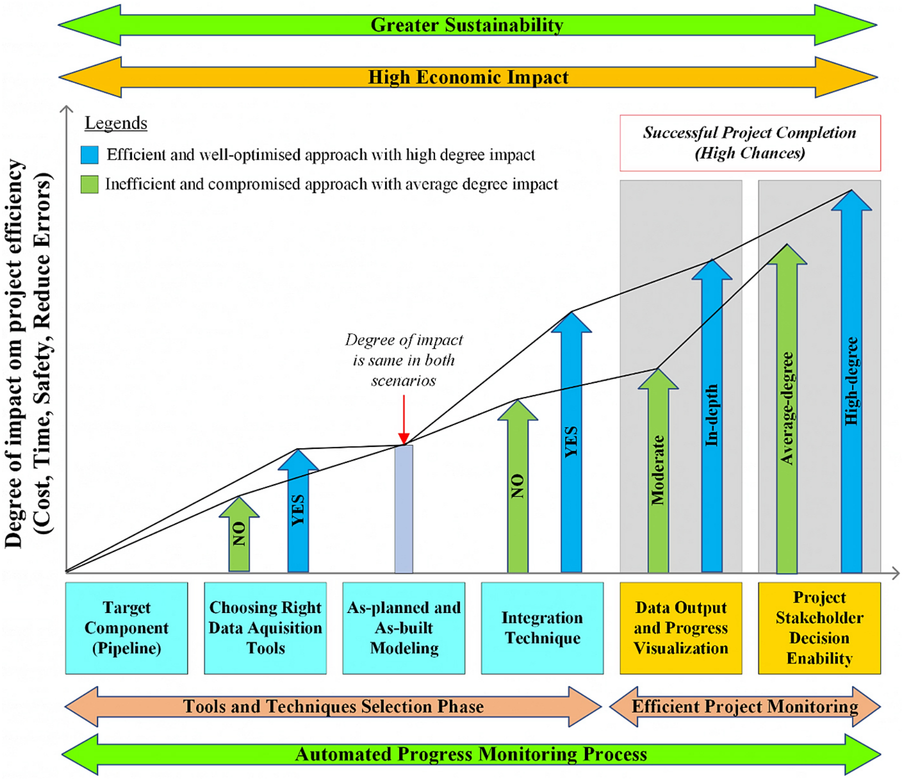


Figure 9. Conceptual visualisation of technology choices on pipeline progress monitoring

The main conceptualization is about appropriate tool selection and integration technique strategies. These two are the most critical stages of the whole process. Following an in-depth literature review of the selected studies and an analysis of the limitations and shortcomings of automated progress monitoring methodologies for pipeline construction, these two stages were chosen to enable effective and high-performance decision-making for project stakeholders during the construction project tracking process. For successful project completion, choosing the appropriate strategy is of utmost importance. It must be noted that utilizing automation techniques for construction progress tracking can provide decent data output and progress visualisation but might bring some loopholes because of the inability to provide complete information due to the incapacity of the tool chosen during the data acquisition stage. However, this can be overcome by adopting the concept of integration techniques that can provide an enhanced form of data by utilizing machine learning, CV, and AI algorithms. These combinations have already proven to be highly effective by many researchers in their studies.

For pipeline construction, the industry application scenarios are very broad and versatile. Indoor construction situations can present different challenges when compared to outdoor construction. MEP is one of the examples of indoor construction which incorporates plumbing. The pipeline network in MEPs is very congested, crowded, and complicated which might be difficult to track with simple techniques. For efficient tracking, laser scanners mounted on static tripods or mounted on robots or UGVs, are widely used in industry to track construction progress. This tool is used because it generates high-quality results and can be integrated with other techniques. However, the laser scanning technique is expensive which can impact the cost of the project. Outdoor pipeline construction, such as trenches and pipelines, is less congested. As a result, less expensive data acquisition tools and techniques can be used. Close-range data acquisition tools and strategies can be used for this purpose which are handy and provide a decent outcome for these kinds of scenarios. After all, project managers, engineers, and stakeholders must efficiently evaluate which tools should be used to monitor pipeline construction progress.

In a broader sense, using the appropriate modern technology and techniques to track building progress can significantly improve the efficiency of monitoring methods. This development provides accurate and real-time data collected from pipeline construction sites, allowing managers to make educated decisions quickly. Effective decision-making leads to cost savings, faster corrective actions, fewer mistakes, and better safety measures. As a result, the likelihood of successful project outcomes increases. Successful project completion improves the firm's market competitiveness, promotes economic development, and ensures customer satisfaction.

5. Future directions

A comprehensive review of selected 60 studies helped in devising the outcome providing information about current achievements in the adoption of automated technologies for progress monitoring of pipeline construction and highlighting the limitations, gaps, and challenges in this realm. As compared to building engineering the studies in pipeline construction engineering are very limited which is a significant problem that must be addressed by future researchers. It is required to focus more on this sector to develop enhanced studies which will ultimately benefit the industry in terms of optimum project performance.

Despite some research and studies on automated monitoring in pipeline construction, many challenges remain, some of which have been highlighted in this study.

1. After conducting an extensive literature review of the chosen studies, it was observed that many researchers adopted laser scanners for data acquisition purposes in pipeline construction monitoring i.e., typical pipelines or plumbing in MEP. The high acceptance of these tools by researchers reveals the efficiency and high performance of laser scanning technology. However, it must be noted that this technology is costly, and might be not feasible to apply in certain projects. For this reason, more research is required for the use of other data acquisition technologies which are more cost-effective and efficient at the same time.
2. Data interoperability and integration of automated techniques are a major problem which is noted in this study by the authors. Nevertheless, some studies implemented various integrated techniques such as Scan vs BIM, CV, Scan, and BIM, machine learning, convolutional neural networks (CNN), which develop more efficient automated modules as compared to the strategy in which non-integrated strategy is adopted. However, integration brings data interoperability issues. More studies and special efforts are required by the research community to overcome this issue.
3. The pipeline construction sector is a massive industry which is mostly comprised of mega projects, such as oil and gas pipelines, industrial plant pipelines, and long-distance pipelines, which involves extensive resources and budgets which is the main concern of the stakeholders. These projects have massive financial impacts which must be considered while construction progress monitoring. Furthermore, the use of automated technology has financial implications to ensure the success of the digital monitoring technology trend in the pipeline construction sector, the research community must include financial concerns in their studies.
4. The authors suggest that several conflicts in research results arise which are due to two factors: a lack of comprehensive perspective and varying complexity levels in studies. To mitigate these conflicts, it is recommended to examine automated tools from multiple perspectives and at more complex levels.

6. Conclusions

The study explored methodologies devised and tools adopted for automated progress monitoring in pipeline construction. For this purpose, a systematic literature review was performed on a total of 60 articles (including article, review, and conference papers) extracted from five databases; WoS, Scopus, ScienceDirect, ASCE, and Emerald. PRIMSA framework was adopted for systematic review purposes. A detailed analysis was performed on selected studies based on descriptive statistics and keyword analysis (authors' keywords co-occurrence analysis by using VOSviewer). The data analysis revealed important information about the distribution of studies in geographical regions and studies on targeted components considering pipeline categories. Among other countries, the USA tends to study more in these technological applications with 18 published papers (30% of the selected articles) on automated progress monitoring for pipeline construction. Furthermore, a discussion was conducted in considering the methodologies and analyses used in the studies by the authors, providing a comparative overview of all methodologies based on their key findings and significance presented in a single review.. The data analysis further revealed the tools and techniques adopted by the researchers for data acquisition and as-planned modelling purposes. For pipeline construction progress monitoring, tools such as UWB, barcodes, RFID, robots, UAV, infrared cameras, and techniques such as SfM, GPS, CV, Machine Learning, and CNN; Laser scanners and BIM are highly embraced by researchers for advanced visualization and as-built modelling. The study also presents a visual overview of the technology-driven process in automated progress monitoring for pipeline construction. It provides an integrated perspective of the end-to-end process, offering detailed technical insights specific to the pipeline context. A conceptual overview was developed to highlight the importance of choosing the right data-acquisition tools and implementing integration techniques strategies, as well as their impact on the likelihood of successful project completion. This was done after a thorough analysis of all the studies and consideration of the growing trend of automated progress tracking in pipeline construction.

Overall, the study offers a valuable glimpse into both the operational strengths and weaknesses of automated pipeline construction monitoring. The efficient use of automated progress monitoring technology in pipeline construction is still hampered by several technological constraints, despite the research community's best efforts. This research expands on the understanding of automated pipeline construction progress monitoring by evaluating and determining gaps, challenges, and opportunities for development. The study has several limitations. To begin, it gathered data from five databases, preventing some bibliometric analyses such as author co-citation, journal, and institutional analysis owing to data variability. Second, it only included English papers, which might exclude relevant items in other languages.

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Author contributions

All the authors contributed equally to this study.

Data availability statement

All data generated or analysed during this study are included in this published article.

Conflicts of interest

The authors declare that they have no conflict of interest.

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