



# Reducing Project Uncertainty through Data-Driven Management: A Bibliometric Analysis

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## ABSTRACT

In the context of accelerated digitalization and increasing complexity of project activities, research in the field of Data-Driven Project Management (hereinafter – DDPM) remains fragmented, which limits a holistic understanding of its intellectual structure and development dynamics, despite the active introduction of digital technologies. The purpose of this study is to identify the intellectual structure, development dynamics, and dominant research trajectories of DDPM based on a bibliometric analysis of scholarly publications. The methodological basis of the study was the bibliometric analysis of scientific publications using the tools Bibliometrix and Biblioshiny. The empirical database includes 1,149 articles and reviews indexed in the Scopus database for the period 2000-2025. The results of the study showed that with an average annual growth rate of 18.83%, articles account for 1,012 documents (88.1%), reviews – 137 (11.9%). The average number of citations per publication was 25.13, and the analysis of co-citations and keywords revealed the dominance of clusters related to machine learning, predictive analytics, and risk management. The results confirm that DDPM is fundamentally changing project management by improving decision support and maximizing resource efficiency, which directly reduces financial risks and uncertainty. The prospects for further research are related to the use of the results obtained by researchers when planning future scientific work, as well as practitioners and decision makers, for the strategic implementation of data analysis tools aimed at creating more sustainable, cost-effective and high-performance projects.

**KEYWORDS:** Digital Economy, Economics of Management, Strategic Project Management, Project Efficiency, Intellectual Evolution, Artificial Intelligence, Data Analytics, Bibliometric Analysis

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# Снижение неопределённости в управлении проектами на основе данных: библиометрический анализ

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## АННОТАЦИЯ

В условиях ускоренной цифровизации и усложнения проектной деятельности исследования в области Data-Driven Project Management (далее – DDPM) остаются фрагментированными, что ограничивает целостное понимание его интеллектуальной структуры и динамики развития, несмотря на активное внедрение цифровых технологий. Целью данного исследования является выявление интеллектуальной структуры, динамики развития и доминирующих исследовательских траекторий управления проектами, ориентированного на данные (DDPM), на основе библиометрического анализа научных публикаций. Методологической основой исследования послужил библиометрический анализ научных публикаций с использованием инструментов Bibliometrix и Biblioshiny. Эмпирическая база включает 1149 статей и обзоров, проиндексированных в базе данных Scopus за период 2000-2025 гг. Результаты исследования показали, что при среднем годовом темпе роста 18,83%, при этом на статьи приходится 1012 документов (88,1%), на обзоры – 137 (11,9%). Среднее число цитирований на публикацию составило 25,13, а анализ со-цитирования и ключевых слов выявил доминирование кластеров, связанных с машинным обучением, прогнозной аналитикой и управлением рисками. Результаты подтверждают, что DDPM фундаментально меняет управление проектами за счет улучшения поддержки принятия решений и максимизации эффективности ресурсов, что напрямую снижает финансовые риски и неопределенность. Перспективы дальнейших исследований связаны с использованием полученных результатов исследователями при планировании будущих научных работ, а также практиками и лицами, принимающими решения, для стратегического внедрения инструментов анализа данных, направленного на формирование более устойчивых, экономически эффективных и высокопроизводительных проектов.

**КЛЮЧЕВЫЕ СЛОВА:** цифровая экономика, экономика управления, стратегическое управление проектами, эффективность проектов, интеллектуальная эволюция, искусственный интеллект, анализ данных, библиометрический анализ

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## INTRODUCTION

Project management today is undergoing a significant shift, shaped by rising levels of complexity and uncertainty, as well as the accelerated technological progress associated with the Industry 4.0 and 5.0 eras (Hashfi & Raharjo, 2023). Modern projects increasingly operate in automated, interconnected, and information-intensive settings, requiring advanced methods for decision-making, risk control, and efficient resource utilization (Vergara et al., 2025). As a result, traditional step-by-step project management approaches, which emphasize structured planning and process control (PMI, 2021) are becoming less effective at handling the uncertainty and instability of modern projects, which can contribute to wasted resources, greater exposure to risk, and weaker performance outcomes. Although data-driven methods and artificial intelligence (hereinafter – AI) have become vital tools for addressing project challenges, the literature still provides only a fragmented view of their combined influence on project management, especially in relation to emerging trends, uncertainty mitigation, and efficiency improvements (El Khatib & Falasi, 2021). This gap necessitates a focused investigation to consolidate current knowledge and chart future research directions.

The scientific novelty of this research is grounded in its targeted structural-functional approach, which addresses the limitations inherent in existing literature reviews on this topic. The growing body of systematic and bibliometric reviews in this area is acknowledged. For example, Salimimoghadam et al. (2025) consolidated knowledge on the general opportunities, enablers, and barriers of AI in project management, while Adebayo et al. (2025), and Hanafy and Hanafy (2025) provided valuable, yet sector-specific, examinations of AI/ML applications across the construction project life cycle. However, these existing works, by prioritizing technological trends and specific phase applications, lack a focused structural analysis of the Data-Driven Project Management (hereinafter – DDPM) field itself. A twofold contribution is articulated. First, the study provides the first functional alignment of bibliometric network analysis (co-citation and keyword co-occurrence) explicitly aimed at examining the specific contributions of DDPM to two critical project success drivers: uncertainty reduction and

efficiency improvement. This systematic approach shifts the analytical focus from descriptive trend mapping toward actionable performance-oriented insights. Second, the intellectual evolution of DDPM is firmly situated within the framework of a strategic economic imperative, addressing the pressing need to enhance productivity in the construction sector and thereby linking micro-level project technology adoption with macro-level economic objectives.

The relevance of this study is underscored by the general interest in leveraging advanced analytics and AI for operational excellence across industries (Dhamija & Bag, 2020). However, current research still lacks thorough explanations regarding the conceptual structure and thematic progression of DDPM as a distinct area of study (Hashfi & Raharjo, 2023). This study demonstrates its theoretical significance by mapping the evolving field to establish foundational knowledge, and its practical significance by offering insights that can enhance real-world project execution and strategy formulation for researchers, practitioners, and policymakers.

Furthermore, the economic relevance of this research is further underscored by the critical role of the construction sector. While construction significantly contributes to the Gross Domestic Product (hereinafter – GDP) and the formation of societal welfare, it globally remains one of the least digitized and most fragmented industries, struggling with low labor productivity (Bühler et al., 2025; Cucos & Turcan, 2025). This deficiency directly hinders broader economic growth and limits the potential for commensurate wage increases, thereby impacting overall societal prosperity. Consequently, the adoption of DDPM and AI is not merely a technological upgrade but a strategic economic imperative aimed at radically boosting labor productivity and, as a result, stimulating macroeconomic progress and enhancing national competitiveness.

Therefore, the object of this study is the body of academic literature on DDPM. At the same time, the subject is the intellectual structure, key trends, impact on uncertainty reduction, and contribution to efficiency improvement within this field. The purpose of this study is to identify the intellectual structure, development dynamics, and dominant research trajectories of DDPM based on a bibliometric analysis of scholarly publications. To achieve this aim, the study sets forth the following objectives: (1) to identify and analyze the key publication

trends, influential authors, and prominent research outlets in DDPM; (2) to map the intellectual structure through co-authorship, co-citation, and keyword co-occurrence networks, revealing collaboration patterns and thematic clusters; (3) to define the specific ways data-driven approaches contribute to uncertainty reduction in project environments; (4) to assess the role of data-driven methods in improving project efficiency and overall performance.

## LITERATURE REVIEW

Project management has evolved progressively in response to changing business environments, technological advancements, and increasing market demands. Early research emphasized the growing complexity, uncertainty, and dynamism of project environments, calling for a fundamental rethinking of how projects are conceptualized, planned, and executed (Lenfle & Loch, 2010). Historically, dominant project methodologies were largely linear and sequential, prioritizing predictability and control (Oseneike et al., 2024). More recent studies highlight the continued adaptation of project management practices to digital transformation and shifting market conditions (Marnewick & Marnewick, 2022).

For decades, traditional project management approaches, such as the Waterfall model, dominated various industries. While effective for projects with well-defined requirements, stable environments, and predictable outcomes, these linear models show significant limitations in today's volatile, uncertain, complex, and ambiguous (hereinafter – VUCA) world (De Meyer et al., 2002). The essential assumption of stable requirements and predictable development often clashes with the reality of modern projects, which frequently face rapid technological shifts, dynamic market conditions, and complex interdependencies (Jørgensen & Wallace, 2000). These methodologies are characterized by a sequential progression through distinct phases, initiation, planning, execution, monitoring, and closure, with a strong emphasis on upfront planning and documentation (Leong et al., 2023).

In response to the limitations of traditional models, especially in software development and innovation-driven sectors, agile and adaptive methodologies gained importance. Frameworks like Scrum, Kanban, and Lean project management prioritize

flexibility, iterative development, continuous feedback, and collaboration (Moniruzzaman, 2013). Agile principles emphasize delivering value incrementally, adapting to change over adhering strictly to a plan, and fostering self-organizing teams (Koi-Akrofi et al., 2019). This shift allowed projects to respond more effectively to evolving requirements, manage risks more dynamically, and deliver products that better meet user needs in rapidly changing contexts. The iterative nature of agile approaches permits continuous learning and adjustment, making them particularly well-suited for environments where requirements are fluid or difficult to define entirely at the outset (Steegh et al., 2025).

While Agile provides the necessary procedural and cultural flexibility, the actual advancement in managing complexity and risk comes from leveraging computational power to understand and mitigate uncertainty systematically. Managing uncertainty in projects, particularly in safety-critical environments such as civil-nuclear and aerospace, is crucial due to the potentially catastrophic consequences of failure. Project managers in these complex socio-technical environments must understand the sources of uncertainty and navigate them effectively to achieve successful outcomes. One approach to managing uncertainty is the “uncertainty kaleidoscope”, which helps identify and understand the sources of uncertainty in projects (Saunders et al., 2015). Additionally, strategies such as pre-defined semantics and incremental process program development can help manage process uncertainty in software projects by preventing code duplication and handling both predictable and unpredictable uncertainties (Chou, 2008). Furthermore, employing evidence-based software engineering principles and systematic literature reviews can identify methods and practices to reduce uncertainties, thereby improving project performance and success (Marinho et al., 2018).

In construction and infrastructure projects, managing uncertainty involves creating a flexible working environment and fostering learning among team members (Ranasinghe et al., 2021). Project-oriented organizations must balance structure and autonomy to handle complex and uncertain situations effectively (Nachbagauer & Schirl-Boeck, 2018). In the context of project portfolios, managers should frame uncertainties as opportunities or threats and use a combination of rational, structural, and cultural mechanisms to manage them dynamically (Martin-

suo et al., 2014). Additionally, integrating advanced methodologies such as fuzzy linguistic models and scenario network-based approaches can enhance adaptability and decision-making in cybersecurity projects (Tynchenko et al., 2024). Overall, effective uncertainty management requires a combination of structured frameworks, proactive strategies, and adaptive mechanisms to navigate the complexities and risks inherent in various project environments.

The second primary imperative driving the adoption of data-driven methods is the demand for greater efficiency. This shift is propelled by the need to optimize workflows, reduce inefficiencies, and enhance overall productivity. This paradigm shift necessitates a reevaluation of traditional decision theory and models to effectively integrate emerging technologies such as big data analytics, machine learning, and automation (Siddiqui et al., 2024). By harnessing empirical evidence and sophisticated data analysis techniques, organizations can make informed decisions that steer projects towards optimal outcomes (Pantović et al., 2024). Such data-driven approaches enable project managers to analyze large datasets and extract actionable insights, facilitating proactive risk mitigation and outcome optimization (Ajirotutu et al., 2024). The integration of AI and data analytics, particularly predictive analytics, fundamentally transforms decision-making by enabling project managers to foresee potential issues and develop tailored mitigation strategies, thereby minimizing delays and cost overruns (Adeniran et al., 2024). This analytical capability allows for real-time adjustments and resource re-allocation, leading to more efficient project execution and higher success rates across various project lifecycle stages (Vergara et al., 2025).

The ongoing digital transformation, driven by phenomena such as Industry 4.0 and emerging Industry 5.0, has fundamentally reshaped the operational landscape for projects. Industry 4.0, characterized by the integration of cyber-physical systems, the Internet of Things, big data, and AI, has ushered in an era of hyper-connectivity and automation (Cabeças & Marques da Silva, 2021). Project environments are increasingly data-rich, generating vast amounts of information from connected devices, sensors, and digital platforms (Iqbal et al., 2020). This proliferation of data, coupled with advanced computational capabilities, offers unprecedented opportunities for enhanced project insights (El Khatib et al., 2023).

To sum up, this evolution has culminated in a landscape where project management is increasingly reliant on data-driven approaches and AI to navigate complexity, mitigate uncertainty, and optimize efficiency (Daraojimba et al., 2024).

A review of the scientific literature shows that project management has undergone a significant transformation over the past two decades, influenced by digitalization and increasing uncertainty. An analysis of the publications shows that the key drivers of this transformation are AI, machine learning, big data analysis, and predictive analytics, which form the basis of data-driven approaches in project management. Nevertheless, the issues of the dynamics of the development of the DDPM scientific field, its key thematic clusters, dominant research vectors, and intellectual turning points remain insufficiently studied. This work will allow us not only to fill in the identified gaps.

## MATERIALS AND METHODS

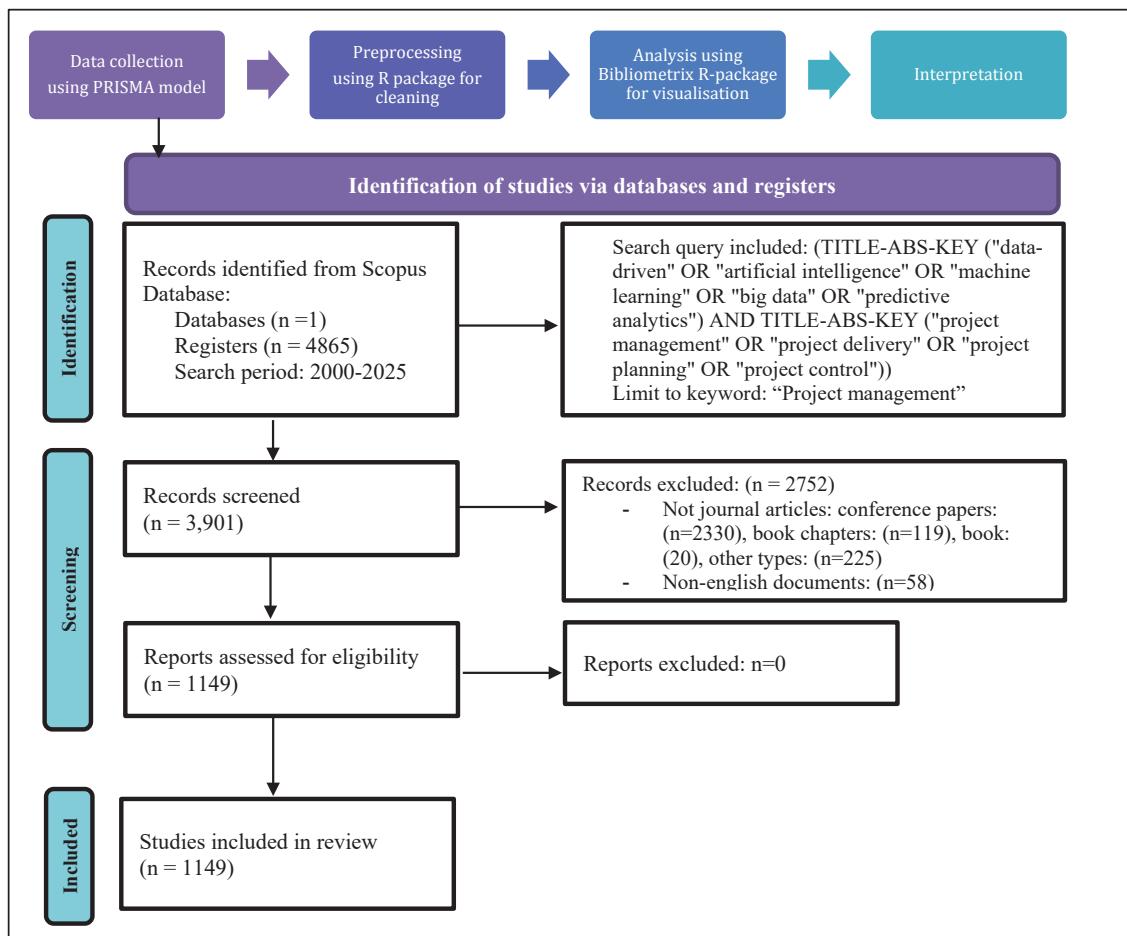
This study employs a bibliometric analysis to systematically map the scholarly literature on DDPM, identifying publication trends, key contributors, and the field's intellectual structure. Bibliometric analysis, a quantitative methodology, has increasingly become a cornerstone in academic research for assessing publication patterns, trends, and scholarly impact (Hoang, 2025). This analytical approach systematically evaluates scientific literature by applying statistical and quantitative techniques to academic publications to identify influential authors, map collaboration networks, and uncover emerging research trends (Kumar, 2025). The growing popularity of this analytical approach is mainly due to several factors, including the advancement and increased accessibility of bibliometric tools such as VOSviewer, CiteSpace, and Bibliometrix, as well as the widespread availability of scientific databases like Google Scholar, Scopus, and Web of Science.

The choice of bibliometric analysis over a meta-analysis is based on the study's exploratory and structural objectives. While a meta-analysis is ideal for synthesizing specific quantitative effect sizes (e.g., measuring the financial impact of a particular AI tool), it is unsuitable for achieving our primary goals: charting the intellectual evolution and mapping complex network relationships (co-citation, co-occurrence) that define the field's academic structure.

The novelty of this study lies in its focused analytical scope, which extends beyond a general bibliometric overview to specifically investigate how DDPM literature addresses the critical project success drivers of uncertainty reduction and efficiency. By aligning the analysis and interpretation of key bibliometric networks (co-citation and keyword

co-occurrence) with these two performance dimensions, this research offers a targeted and actionable intellectual roadmap for future research and practice.

The research process was divided into main stages: data collection, preprocessing, analysis, and interpretation, which is illustrated in Figure 1.



**Figure 1.** Research design flow

Data was exclusively sourced from the Scopus database on the 25<sup>th</sup> of August 2025. The search query used the TITLE-ABS-KEY operator to maximize the retrieval of relevant documents, as it captures information across the title, abstract, and author keywords, ensuring the identified studies are centrally focused on DDPM. The final limit on the keyword "Project management" was applied to ensure the focus remained strictly on project management literature, effectively filtering out studies that used AI/data-driven concepts in general manufacturing or supply chain processes. The period

of 2000-2025 was chosen, because it captures the entire modern evolutionary arc of project management, beginning with the rise of the Agile Manifesto and the mainstream adoption of digital tools in the early 2000s, and extending through the full emergence of data-driven and predictive analytics as central paradigms, especially in the most recent years leading up to and projecting toward 2025 trends (Hohl et al., 2018; Krasteva & Ilieva, 2020). Scopus database was chosen for its comprehensive, interdisciplinary coverage and its superior handling of citation networks compared to other platforms,

ensuring the reliability of co-citation analysis. The document selection process rigorously followed the PRISMA guidelines to ensure transparency and reproducibility, with the flow from initial identification to final inclusion meticulously detailed in a PRISMA Flow Diagram (Page et al., 2021). After the initial retrieval from Scopus, the preprocessing phase used the R package software to remove duplicates and standardize data, aligning with PRISMA's systematic approach to evidence synthesis.

The rigorous exclusion of conference papers (n=2330) and book chapters was a deliberate methodological choice aimed at mapping the field's established, peer-reviewed intellectual structure, which is most reliably captured by full-length journal articles. The excluded category "other types" (n=225) primarily consisted of editorials, letters to the editor, and short survey responses that do not represent primary research output.

The bibliometric analysis was performed using the Biblioshiny tool, a web-based graphical user interface for the Bibliometrix R-package, which enabled both quantitative analysis and network visualizations (Aria & Cuccurullo, 2017). It was selected over alternative tools for its comprehensive capability to conduct both performance analysis and diverse science mapping within a single, statistically robust framework. For quantitative analysis,

key metrics, including annual publication trends, the most prolific authors and journals, and the most influential countries and institutions, were calculated. For network mapping, three types of visualizations were created: co-authorship networks to map collaborative relationships, keyword co-occurrence networks to identify key research themes, and co-citation analysis to pinpoint the most influential publications and the field's intellectual foundations. This combined approach of quantitative and network-based analyses provides a comprehensive and structured overview of the research landscape.

## RESULTS AND DISCUSSION

The dataset comprises 1149 documents published between 2000 and 2025, inclusive, reflecting 26 years of scholarly output. The annual growth rate of publications within this field is notably high at 18.83%, suggesting a rapidly expanding area of research. The document's average age of 5.62 years indicates that the collection primarily consists of relatively recent publications. The dataset includes 1012 articles and 137 reviews. This systematic literature review employed a bibliometric approach to analyze a dataset extracted from the Scopus database (see Table 1).

**Table 1.** Main information about the data

No.	Description	Result
1	Timespan	2000 - 2025
2	Sources (Journals, Books, etc)	466
3	Documents	1149
4	Annual Growth Rate %	18.83
5	Document Average Age	5.62
6	Average citations per doc	25.13
7	References	59367
9	Keywords Plus (ID)	7598
10	Author's Keywords (DE)	3310
11	Authors of single-authored docs	146
12	Single-authored docs	155
13	Co-Authors per Doc	3.55
14	International co-authorships %	27.24
15	Article	1012
16	Review	137

Note: visualization retrieved by authors from the Biblioshiny software tool

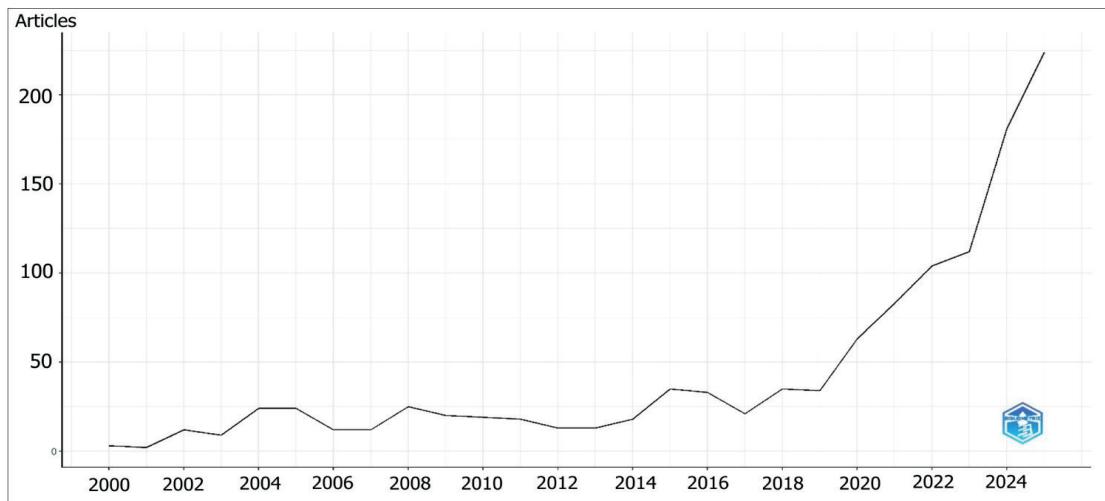
The collection encompasses contributions from 3311 distinct authors, with 146 authors contributing solely to single-authored documents. The cal-

culation of documents per author yields a ratio of approximately 0.35, reflecting the collaborative nature of research in this field. The co-authors per

document stands at 3.55, substantiating this collaborative trend and indicating that, on average, each publication involves multiple researchers. Furthermore, 155 papers were single-authored. An analysis of international collaboration reveals that 27.24% of publications involve international co-authorships. This figure suggests a substantial degree of global

engagement and knowledge sharing within the research area, highlighting the interconnectedness of researchers across different countries. Finally, the average citations per document is 25.13.

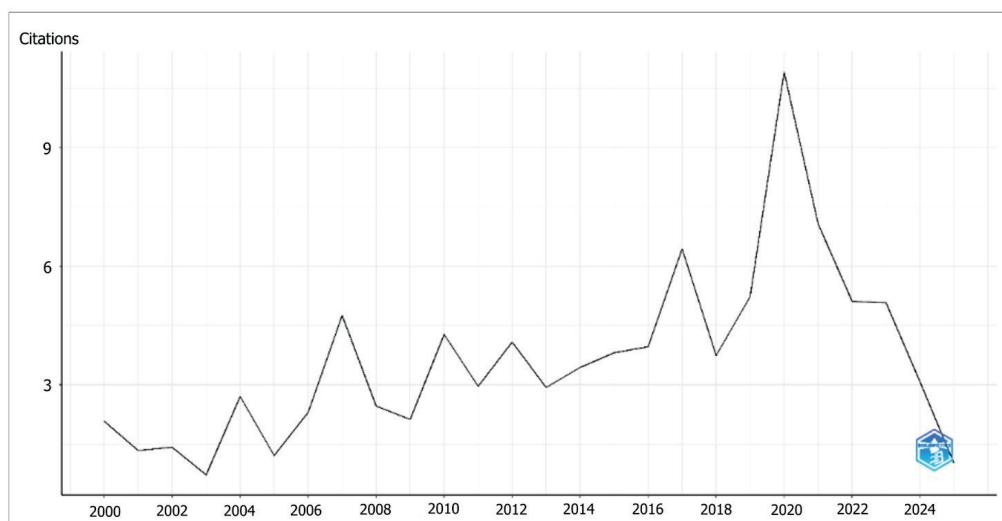
Scientific production, as shown in Figure 2, remained relatively stable until 2017, after which it increased exponentially, culminating in a substantial peak in 2024.



**Figure 2.** Annual scientific production over last 26 years

This dramatic acceleration is primarily attributed to the mainstreaming of Big Data, Machine Learning, and AI tools post-2017. These technologies provided the necessary capabilities to move DDPM from conceptual discussion to practical application, driving

intense academic interest and output. The mean number of citations per year across the dataset is approximately 3.62, but this average is skewed by a period of low citations in the early 2000s and a very high-impact period more recently, as shown in Figure 3.



**Figure 3.** Average citations per year for all articles published

The standard deviation of 2.22 highlights the high volatility and lack of a consistent citation pattern across the years, which is a common characteristic of research in a developing field. Significant citation peaks (e.g., around 2020) likely correspond to the publication of highly influential or “breakthrough” articles that introduced new frameworks or successful empirical applications. The sharp rise

near 2020, in particular, reflects the growing impact of research during the period of accelerated digital transformation, where data-driven decision-making became crucial for managing project uncertainty. A three-field plot was generated in Figure 4 to visualize the interconnectedness between keywords ('DE'), corresponding countries of authors ('AU\_CO'), and cited sources ('CR\_SO') within the Scopus dataset.

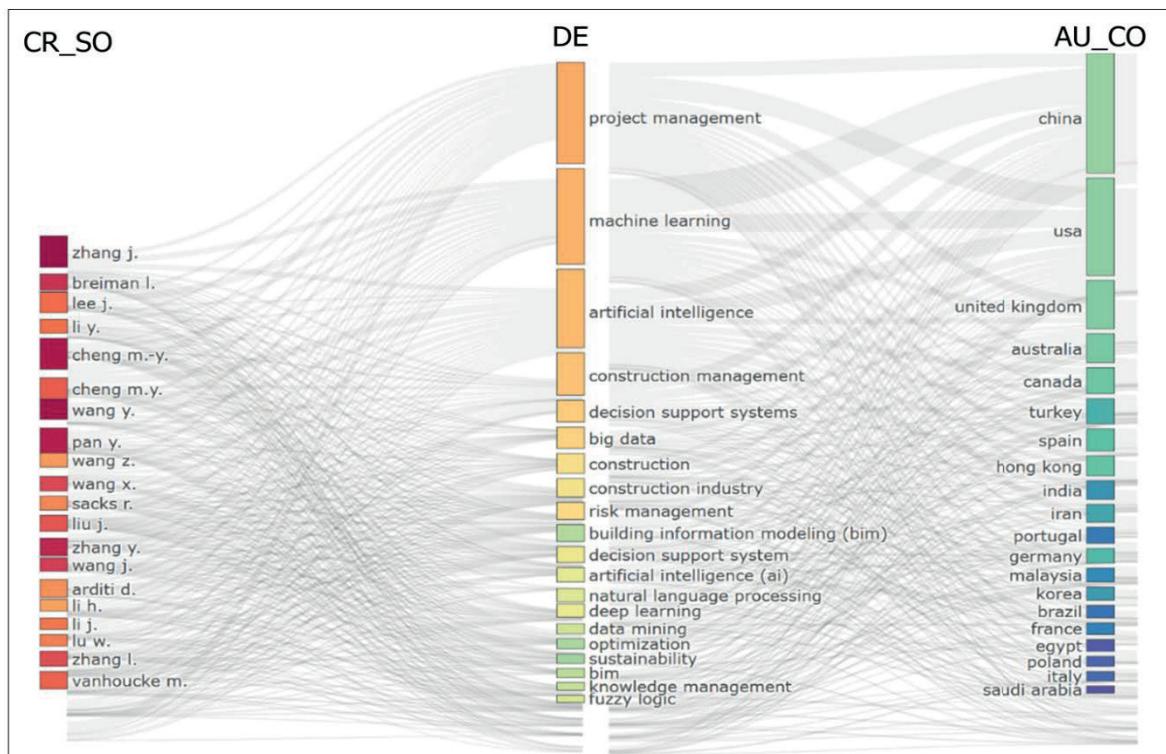


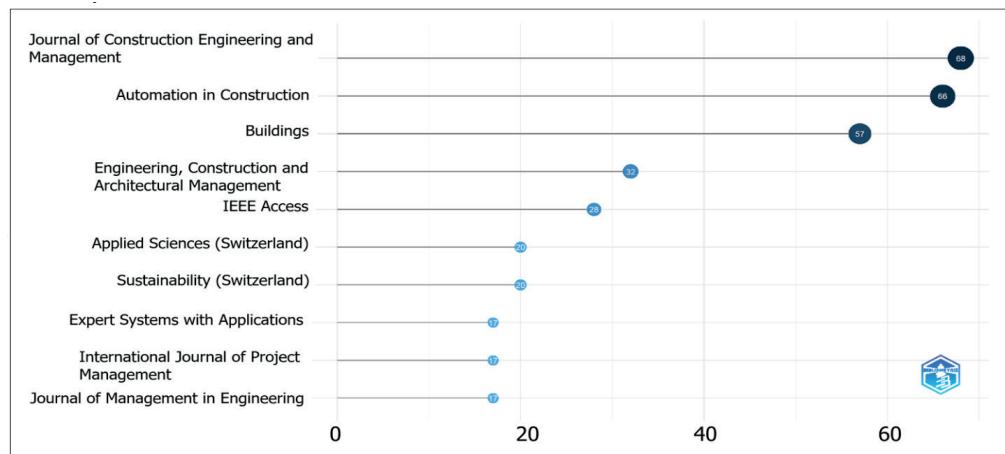
Figure 4. Three-field plot

The analysis revealed strong associations between specific research areas and geographical locations. Notably, ‘project management’, ‘machine learning’, and ‘artificial intelligence’ emerged as prominent keywords, with significant contributions originating from China, the USA, and the United Kingdom. These keywords also demonstrate a connection with the most frequently cited sources, such as Zhang J., Breiman L., and Lee J. The visualization further illustrates the global distribution of research efforts across diverse domains such as ‘construction management’, ‘big data’, and ‘building information modeling’, indicating varying levels of research activity across countries. The links stemming from

the cited sources highlight the foundational works underpinning these research themes and their relevance across geographical contexts. This provides an overview of the intellectual landscape and geographical concentrations in the identified research areas.

The top three sources, as shown in Figure 5 – Journal of Construction Engineering and Management (68 articles), Automation in Construction (66 articles), and Buildings (57 articles), are the most prolific and influential platforms for this research, collectively accounting for a significant portion of the total publications.

MANAGEMENT AND MARKETING

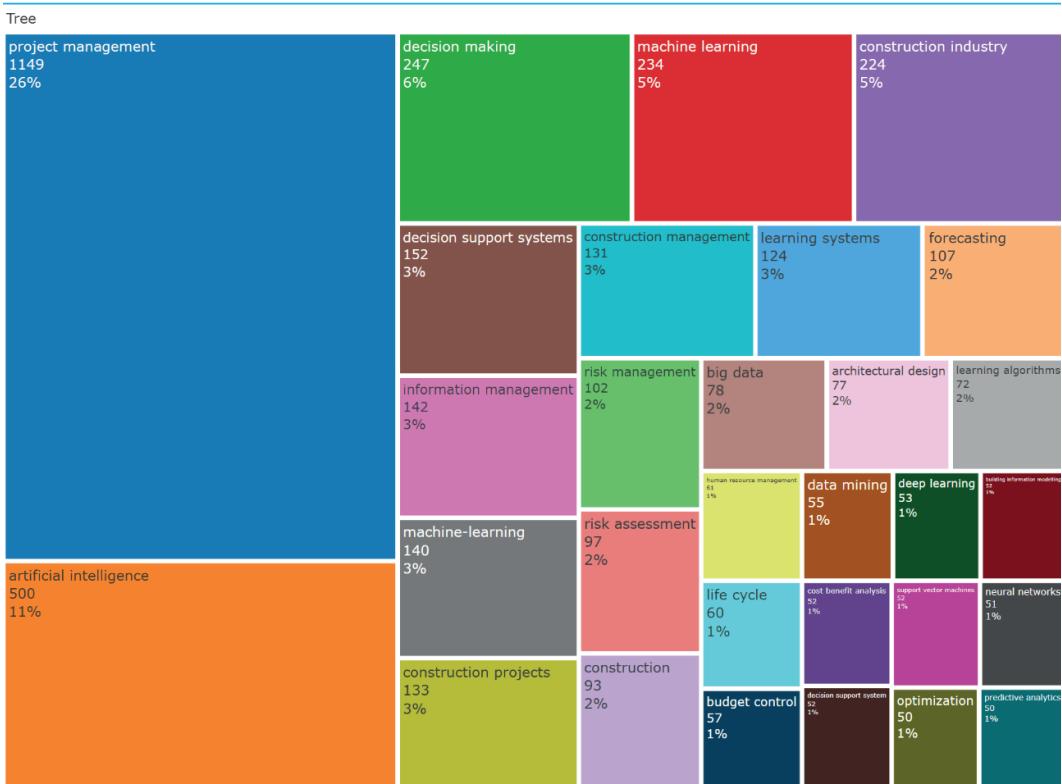


**Figure 5.** Most relevant sources

A steep drop-off in article count is observed after these top-tier journals, with the fourth-ranked source, engineering, construction and architectural management, publishing less than half the number of articles of the top journal (32 articles). This pattern suggests that while the research is concentrated in a few core journals, it also appears in a broader range of interdisciplinary and technology-focused publi-

cations, such as IEEE Access and Expert Systems with Applications. This distribution underscores the fusion of traditional project management with advanced technological and data-driven approaches, indicating the field's interdisciplinary nature.

The keyword frequency in Figure 6 provides a quantitative snapshot of the most prevalent topics within the analyzed literature on DDPM.



**Figure 6.** Keyword frequency tree

The term 'project management' has the highest frequency (1149), which is expected, as it defines the study's core subject area. The second most frequent term is 'artificial intelligence' (500), followed by 'decision making' (247) and 'machine learning' (234). This immediately highlights a central theme: the application of AI and machine learning techniques is the primary technological driver within this field. The high frequency of 'decision making' indicates that a key purpose of these technological applications is to provide enhanced support for project-related decisions.

Figure 6 also reveals a significant focus on a specific industry, with terms like 'construction industry' (224), 'construction projects' (133), and 'construction management' (131) appearing prominently. This suggests that the construction sector is a leading area for the practical application and research of DDPM methods. Other related technological and conceptual terms, such as 'information management' (142), 'big data' (78), and 'data mining' (55), further support the overarching theme of leveraging large datasets and advanced analytics to improve project outcomes. The presence of 'risk management' (102) and 'risk assessment' (97) demonstrates that traditional project management concerns remain central, but they are now approached with data-driven methods.

While the co-occurrence networks and frequency data establish the primary technological (AI/ML) and industrial (Construction) focus of the field, the subsequent analysis moves beyond description to address the core substantive objectives of this study: defining the role of data-driven approaches in Uncertainty Reduction and assessing their contribution to project efficiency and performance. The combi-

nation of the 'machine learning' cluster (prediction/optimization) and the high frequency of "risk management" and 'risk assessment' explicitly addresses the role of data-driven methods in uncertainty reduction. The shift toward AI and machine learning is not simply about automation but about transforming reactive risk management into a proactive, data-driven discipline. The literature, as evidenced by these keywords, focuses on providing early warning signals and improving the accuracy of forecasts for schedule and cost variables. The inclusion of 'decision making' as a high-frequency term confirms that the ultimate goal of reducing uncertainty is to enable project managers to make better-informed choices under dynamic conditions.

The bibliometric evidence equally confirms the field's focus on improving Project Efficiency and Performance. The emphasis on terms like 'optimization' (within the ML cluster) and the prominence of specialized applications such as 'digital twin' and 'building information modeling' (focused on enhanced control and monitoring) are the key bibliometric indicators of this drive. The research implicitly leverages data-driven methods to achieve efficiency by enabling dynamic resource allocation, identifying and eliminating process bottlenecks, and automating routine monitoring tasks. Furthermore, the strong sectoral focus on the construction industry highlights the attempt to apply these efficiency gains in a domain traditionally characterized by high complexity and low productivity.

The author collaboration network represented in Figure 7, derived from the Scopus database, reveals a fragmented structure with several distinct communities, identified using the Walktrap algorithm.

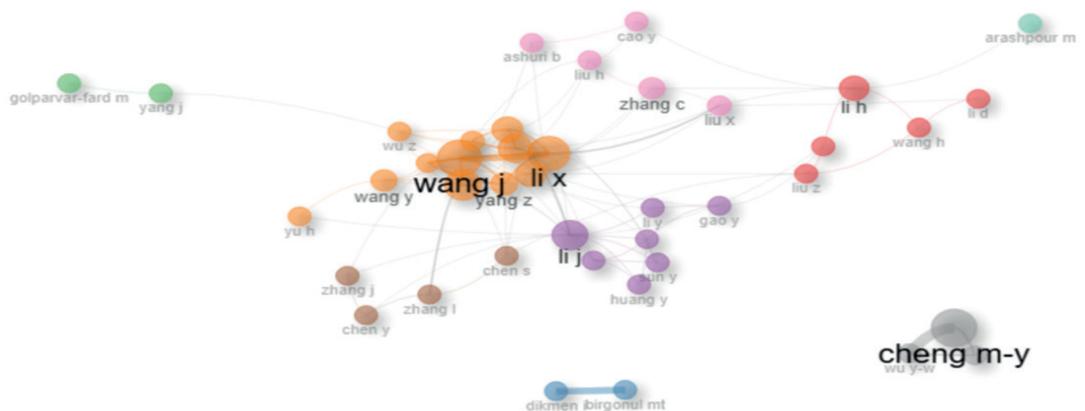
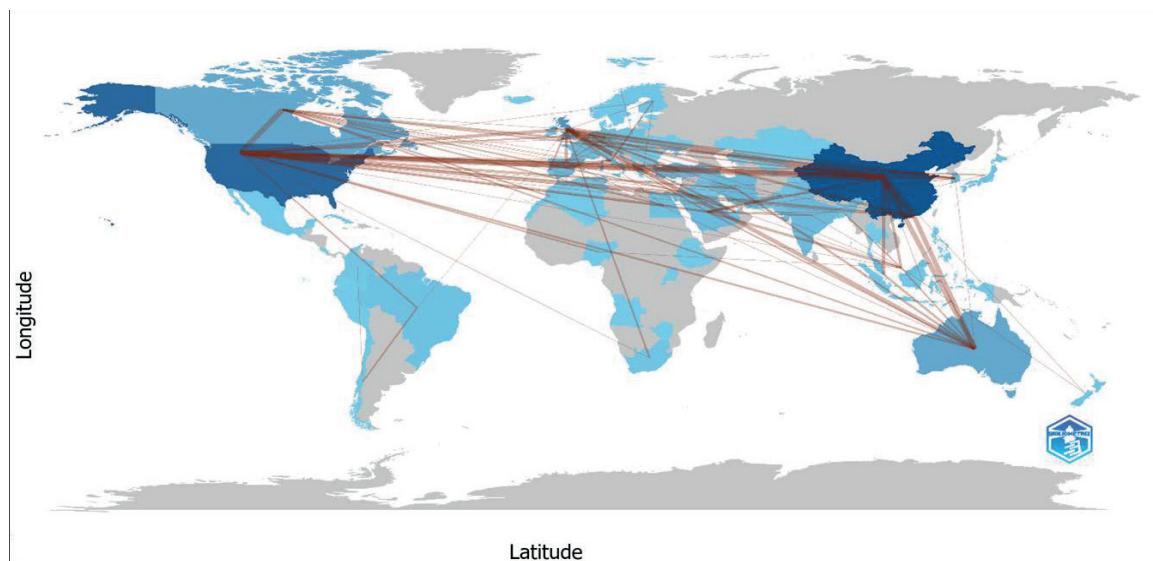


Figure 7. The author collaboration network

The network is characterized by a core group of highly connected authors, notably Wang J., Li X., and Yang Z., suggesting these individuals are central figures within this research area and likely drive collaborative efforts. Several smaller clusters are also apparent, indicating potentially isolated research groups or distinct sub-fields within the broader topic, with the names of other authors also mentioned. Some nodes appear isolated, which suggests either

single-authored papers or collaborations with authors outside the scope of this dataset. The visualization highlights the importance of core individuals in fostering cooperation and reveals potential opportunities to bridge existing communities.

A global collaboration network map, illustrated in Figure 8, derived from the SCOPUS database, highlights key trends in international scientific co-operation.



**Figure 8.** Country collaboration map

The intensity of the country's shading corresponds to its total research output, with the United States and China emerging as central hubs of scientific production, exhibiting the darkest shades. The lines connecting countries represent collaborative links established through co-authorship, independent of the author's order. Notably, strong collaborative ties are observed among the United States, European countries (especially the United Kingdom), China, and Australia, forming a global network anchored in these regions. Other countries showing significant research presence

(lighter shades) include Canada, Brazil, South Africa, and some Asian countries. This visual representation offers insight into the interconnectedness of the global research landscape in the studied field, illustrating patterns of knowledge exchange and collaborative research.

The list of highly influential papers presented in Table 2, ranked by Local Citations, strongly confirms that the intellectual core of DDPM lies in applying AI and machine learning techniques to improve project outcomes.

**Table 2.** Highly cited articles in the field of DDPM

Author	Journal	Title	Year	Local Citations	Global Citations
Wauters & Vanhoucke (2016)	Expert Systems with Applications	A comparative study of Artificial Intelligence methods for project duration forecasting	2016	18	72
Pospieszny et al. (2018)	Journal of Systems and Software	A practical approach for software project effort and duration estimation with machine learning algorithms	2018	18	197

Wauters & Vanhoucke (2014)	Automation in Construction	Support Vector Machine Regression for project control forecasting	2014	16	116
Akhavian & Behzadan (2016)	Automation in Construction	Smartphone-based construction workers' activity recognition and classification	2016	13	238
Wang et al. (2012)	International Journal of Project Management	Predicting construction cost and schedule success using an artificial neural network ensemble and support vector machine classification models	2012	12	165
Zhang & El-Goheiry (2017)	Automation in Construction	Integrating semantic NLP and logic reasoning into a unified system for fully automated code checking	2017	11	214
Wauters & Vanhoucke (2017)	European Journal of Operational Research	A Nearest Neighbour extension to project duration forecasting with AI	2017	10	53
Costantino et al. (2015)	International Journal of Project Management	Project selection in project portfolio management: An artificial neural network model based on critical success factors	2015	10	168
Faghihi et al. (2015)	The International Journal of Advanced Manufacturing Technology	Automation in construction scheduling: a review of the literature	2015	10	88
David & Thaveeporn (2005)	Journal of Computing in Civil Engineering	Predicting the Outcome of Construction Litigation Using Boosted Decision Trees	2005	10	87

Note: compiled by the authors

The recurring prominence of research focusing on project duration forecasting and estimation (e.g., Wauters & Vanhoucke, 2014, 2016, 2017); Pospieszny et al., 2018) through algorithms like Support Vector Machines and Neural Networks highlights predictive accuracy as the field's dominant concern. This focus directly supports the goal of Uncertainty Reduction by replacing traditional subjective estimates with data-driven probabilistic forecasts. Furthermore, the significant presence of articles in Automation in Construction (e.g., Akhavian & Behzadan, 2016; Wang et al., 2012) immediately validates the construction sector as the primary real-world testbed and source of innovation for DDPM, demonstrating practical applications from automated code checking to worker activity recognition. This sectoral focus underscores the drive for Efficiency by applying automation and predictive control in a highly complex, resource-intensive environment. While the high Global Citations for these papers attest to their fundamental academic impact, the intense specialization in predictive modeling and construction also suggests a potential thematic imbalance or research gap in exploring data-driven

solutions for other crucial project lifecycle stages (such as initiation or benefits realization) or non-engineering, organizational industries.

The analysis of these highly cited papers establishes the foundational intellectual structure of DDPM: it is fundamentally a technology-driven field aimed at proactive control. Specifically, the dominance of forecasting research demonstrates that the primary mechanism for achieving Uncertainty Reduction is through superior temporal and cost prediction. Simultaneously, the focus on automation, activity recognition, and schedule optimization directly signifies the field's commitment to enhancing Project Efficiency. Consequently, the intellectual foundation of DDPM, as defined by these influential works, is built on leveraging AI/ML to increase predictive power, enable better resource allocation, and ultimately deliver more predictable and efficient project outcomes.

This robust intellectual foundation did not emerge instantaneously but rather through a clear, phased, substantive, and philosophical evolution over two decades, as illustrated in Figure 9.

					2020-2025 (YTD)		
					2015-2019	Advanced System Integration	
					2010-2014	Exponential AI Adoption	
2000-2004		2005-2009	Shift to Predictive Analytics				
Conceptualization of Need			Implementation of Machine Learning (ML): ANN, SVM. Focus on forecasting project cost and duration.		Sharp growth in publications (post-2017). Use of AI for automation of routine tasks and in-depth analysis of Big Data.		
Key Substantive Development							
	→	→	→	→	→	→	
Evolutionary Outcome							
Formation of a demand for adaptive, non-linear approaches.	Shift from theoretical discussion to pioneering modeling efforts.	Transformation of reactive risk management into proactive and precise uncertainty management.	DDPM becomes the dominant paradigm. Construction emerges as the leading industrial testbed.	Shift to comprehensive, end-to-end control of the project lifecycle in real-time (Industry 5.0).			

**Figure 9.** Intellectual evolution and substantive development stages of DDPM

The DDPM field's development began with a conceptual phase (2000-2009) that established the need for adaptive, non-linear approaches to project uncertainty. The decisive intellectual inflection point was reached in the 2010-2014 period, marked by the systematic implementation of Machine Learning techniques (ANN, SVM). This shift transformed the discipline by replacing traditional methods with a highly proactive predictive mechanism, thus solidifying the concept of data-driven uncertainty management. This core innovation fueled the subsequent exponential AI adoption (2015-2019), rapidly maturing the field, driving specialization, especially in the Construction industry, and establishing DDPM as the dominant research paradigm. Consequently, the field's current trajectory (2020-2025) is focused on Advanced System Integration, leveraging technologies such as digital twin and building information modeling to move beyond mere prediction toward comprehensive, end-to-end control of the project lifecycle in real-time, thereby aligning the future of project management with the demands of the Industry 5.0 era.

## CONCLUSION

The bibliometric analysis successfully achieved its aim of exploring the intellectual evolution of DDPM, it confirmed the thesis that data-driven approaches are fundamentally reshaping project management practice by effectively addressing contemporary challenges. The study fully met all set objectives: it mapped the field's rapid expansion (18.83% annual growth) and identified the most influential sources and authors (Objective 1); it defined the intellectual structure through network analysis, revealing the central role of the machine learning cluster and the emerging digital twin/building information modeling cluster (Objective 2). Crucially, the findings confirmed that the primary mechanism for Uncertainty Reduction (Objective 3) is the predictive power of AI/ML, as evidenced by the dominance of forecasting research in highly cited works. In contrast, Project Efficiency (Objective 4) is enhanced through automation, optimization, and specialization within the highly complex Con-

struction industry—all of which collectively define the field's intellectual core.

This article provides a significant scientific contribution on two fronts. In the domain of bibliometric analysis, the study introduces and visualizes a novel five-stage intellectual evolution model (Figure 9), providing a critical chronological framework that links the field's technological adoption directly to its substantive development. This approach moves beyond simple mapping. In the DDPM subject area, the study precisely identifies the 2010-2014 period as the intellectual inflection point, where the systematic implementation of machine learning established the field's foundation in proactive, predictive control. This analysis also projects the field's future trajectory towards the comprehensive Advanced System Integration enabled by digital twin and building information modeling. However, the study is subject to limitations, primarily the exclusive reliance on the Scopus database, which may introduce selection bias, and the systematic exclusion of conference papers during data screening, potentially underrepresenting the most recent technological innovations that often debut at conferences.

## AUTHOR CONTRIBUTIONS

Conceptualization and theory: LS and ZM; research design: LS and ZM; data collection: ZM; analysis and interpretation: LS and ZM; writing draft preparation: LS and ZM; supervision: LS; correction of article: LS and ZM; proofread and final approval of article: LS and ZM. All authors have read and agreed to the published version of the manuscript.

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