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APPLICATION OF AI AND VR IN PRODUCTION MANAGEMENT

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Purpose: This paper investigates the use of Artificial Intelligence (AI) and Virtual Reality (VR) in production management. The goal is to identify research trends, integration models with MES/ERP systems, and key challenges associated with the implementation of these technologies in industrial practice, particularly in the context of Industry 4.0 and 5.0.
Design/methodology/approach: The research combines a Systematic Literature Review (SLR) with bibliometric analysis based on Scopus data up to May 1, 2025. The SLR focuses on peer-reviewed publications related to AI and VR in production. Bibliometric analysis includes publication dynamics, geographic distribution, institutional affiliations, authorship, and subject area classifications.
Findings: A marked increase in publication output has been observed since 2016, with a peak in 2023. AI and VR are increasingly used in production layout design, predictive maintenance, risk management, training, and system integration. Engineering and Computer Science dominate the field. China, the USA, and India lead in publication volume. However, few studies focus on integrated AI–VR systems or real-world implementations.
Research limitations/implications: The study is limited to English-language publications indexed in Scopus and focused solely on production (excluding quality management). Future research should address real-case studies, ROI/KPI evaluation, and organizational challenges in AI/VR adoption.
Practical implications: Results support industrial decision-makers in selecting, integrating, and scaling AI/VR tools. Emphasis is placed on improving interoperability, process flexibility, and workforce training within digital production systems.
Social implications: The research highlights how immersive and intelligent technologies can enhance safety, competence, and human-centered design in production, contributing to sustainable development and smart work environments.
Value: This is the first study to provide a focused, bibliometric SLR on AI and VR applications in production management. It offers a structured synthesis useful for scholars, practitioners, and policy designers seeking to align digital transformation with operational needs.
Keywords: Artificial Intelligence, Virtual Reality, Production Management, MES/ERP Integration, Industry 5.0.
Category of the paper: Literature review.

1. Introduction

The contemporary industrial environment is undergoing a profound transformation driven by the integration of advanced digital technologies under the umbrella of the Industry 4.0 paradigm. A pivotal aspect of this transformation is the redefinition of production management-shifting from a sequential and reactive approach toward adaptive, data-driven, and AI-supported systems. At the core of this shift lie cyber-physical systems (CPS), the Internet of Things (IoT), real-time data analytics, and intelligent decision-making algorithms, all of which are revolutionizing the planning, supervision, and continuous improvement of manufacturing processes (Zeqiri et al., 2025; Saranya et al., 2025).

In this context, Artificial Intelligence (AI) and Virtual Reality (VR) technologies play an increasingly significant role as tools supporting integrated production management. AI is applied in failure prediction, schedule optimization, adaptive resource control, and operational data analysis, thereby enhancing decision-making at both strategic and operational levels. VR, in turn, facilitates the creation of immersive environments for testing production systems, conducting employee training, designing ergonomic workstations, and simulating operational and emergency scenarios (Bolbotinović et al., 2025; Muralidhar et al., 2025).

With the transition toward the Industry 5.0 concept-which emphasizes human-machine collaboration, personalization, and sustainable development-the importance of human-centred design in production management is growing. AI and VR not only support automation but also serve as tools for enhancing workforce competencies, increasing operational safety, and building work environments that enable seamless transitions between physical and digital activities (Shabur et al., 2025).

In industrial practice, these technologies are increasingly implemented through Digital Twin concepts, integrating data from real-world processes with dynamic simulation models. This enables optimization of material flows, scenario-based planning, validation of decision alternatives, and comprehensive support in production and quality management (Uhlmann et al., 2025; Ma et al., 2025).

Despite the growing number of implementations and scientific publications, significant limitations remain, including the lack of comprehensive models for integrating AI and VR with production management systems (e.g., MES, ERP), the limited number of studies based on real operational data, and insufficient methodologies for assessing the added value of implementations (e.g., ROI, KPIs, VR training effectiveness). Furthermore, there is a noticeable shortage of systemic approaches that take into account not only technological but also organizational, normative, and cultural dimensions (Shee et al., 2024; Sharma et al., 2024).

In light of these observations, there is a justified need for an in-depth analysis of the scientific literature aimed at identifying dominant application areas of AI and VR in production management, classifying existing integration models, and diagnosing research gaps in the context of implementing these technologies in real industrial environments.

The objective of this article is to conduct a systematic review of the literature concerning the use of AI and VR in production management, with a particular focus on their impact on operational efficiency, process flexibility, and the development of integrated decision-making environments. The study addresses the following research questions:

- What are the dominant directions in the use of AI and VR in production management?
- What models of integration with operational management systems are identified in the literature?
- What limitations and challenges accompany the synergistic use of AI and VR from a managerial perspective?

Answers to these questions will allow for the systematization of current scientific knowledge, the identification of research needs, and the formulation of recommendations for future studies and implementation practices in the domain of intelligent production management.

2. Literature Review

The aim of this study is to conduct a systematic analysis of the scientific literature concerning the applications of Artificial Intelligence (AI) and Virtual Reality (VR) in the domain of production management. Particular emphasis is placed on identifying dominant research directions, methods of integrating these technologies with operational systems (e.g., MES, ERP), as well as the challenges and limitations associated with their implementation in real industrial environments. To achieve this, the study adopts a Systematic Literature Review (SLR) approach, which enables a reliable and replicable synthesis of existing research findings and facilitates the identification of gaps and future development trajectories (Garcia-Peñalvo, 2022; Milner, 2015; Ramey, Rao, 2011).

The literature review process followed five key stages: (1) research design, (2) data extraction, (3) record selection, (4) analysis, and (5) interpretation of results. During the design phase, a research gap was identified concerning the integration of AI and VR into production management processes, and a set of research questions was formulated regarding application areas, types of technological solutions, and the factors facilitating or hindering their implementation.

In the data collection phase, publications were retrieved from the Scopus database-one of the most comprehensive bibliographic indexes for technical, engineering, and management sciences. The search criteria included English-language publications available up to May 1, 2025. Logical combinations of key phrases relevant to the research topic were used in the search queries, such as: “virtual reality”, “artificial intelligence”, “machine learning”, “production”, “manufacturing”, “smart factory,” “MES”, “process optimization”, “simulation”, and “training”.

The retrieved records were assigned to the thematic area of production management, excluding documents focused solely on quality-related aspects. Only peer-reviewed sources-including scientific articles, review papers, and conference proceedings-were included for further analysis.

Simultaneously, a bibliometric analysis was conducted using the "Analyze Results" function available in the Scopus system. The collected data covered the number of publications per year, countries of origin, institutional affiliations, authors, and subject classifications. These data were processed and presented in the form of tables and charts to illustrate the distribution of publications and to identify key research centres and emerging trends.

The application of the SLR approach-complemented by quantitative analysis-enabled a comprehensive exploration of the research topic, facilitating a systematic classification of AI and VR applications in production management, the identification of implementation barriers, and the formulation of potential directions for future research, development, and industrial deployment.

3. Methods

Contemporary applications of Artificial Intelligence (AI) and Virtual Reality (VR) in production management have evolved from experimental solutions to mature technologies that support the daily operation of industrial facilities. Based on a review of the literature and Scopus data, the main application areas have been identified, including: production layout and process design, operational planning, maintenance management, workplace safety, personnel training, and integration with MES and ERP systems.

3.1. Production Design and Planning

3.1.1. Virtual Modelling of Production Layouts

VR enables the creation of interactive 3D models of factory layouts-including machine placement, workstations, logistics zones, and transport paths. Thanks to its immersive nature, VR facilitates spatial simulations, ergonomic analyses, layout scenario testing, and the early detection of bottlenecks or accessibility issues. For instance, in the automotive industry, VR has been used to optimize component flow from warehouse to assembly line based on real production data. Choi et al. (2015) showcase VR applications for designing production cells, evaluating resource placement, operator load, and cycle times.

3.1.2. Process Modelling and Variant Analysis

VR also supports modelling of operational flows and technological sequences in a digital environment. Engineers and process designers can interact with virtual machines-simulating assembly, inspection, maintenance, or changeovers-without interrupting physical processes. These solutions enable testing of new technologies in terms of time, ergonomics, and disruption susceptibility. VR models, fed by CAD/CAM and real operational data (e.g., MTM measurements), allow for digital process prototyping and iterative optimization before physical production begins (Pöhler et al., 2021).

3.1.3. AI in Operational and Tactical Planning

AI is widely used in operational and tactical planning. Machine learning and metaheuristic algorithms (e.g., genetic algorithms, PSO, simulated annealing) support order scheduling, resource allocation, buffer and changeover management. AI can dynamically adjust production plans based on machine availability, operator performance, or demand fluctuations. Advanced predictive models forecast material needs from historical and real-time operational parameters to support real-time decision-making (Vrontis et al., 2022).

3.1.4. Integrated Planning and Simulation Environments

Digital Twin advancements enable integration of AI and VR into a unified decision- and simulation-support system. Operators may test layout changes in VR, while AI evaluates their impact on performance metrics (OEE), takt times, energy consumption, and throughput. These combined systems enhance deployment safety, expedite decision-making, and support ongoing improvement (Karaoglu et al., 2019; Stojadinovic, 2024).

3.1.5. Benefits and Implementation Challenges

Key benefits include:

- reduced time-to-market,
- lower design errors and modification costs,
- improved resource utilization,
- enhanced operator ergonomics and safety,
- enabling design for quality and maintainability.

However, challenges persist:

- the need for high-quality input data (CAD models, process data),
- lack of interoperable platforms linking AI, VR, MES/ERP,
- difficulty adapting AI to low-volume production,
- shortage of technical-analytical skills among engineers (Boopathy, Gurrammagari, 2025; Yüksel, 2024).

Despite these obstacles, growing literature and field observations highlight rapid development in sectors such as aerospace, automotive, home appliance, and contract manufacturing. AI–VR integration is becoming the cornerstone of modern production management strategies in the digital transformation age (Alamgir et al., 2025).

3.2. Maintenance Management and Failure Prediction

The modern approach to maintenance management is shifting from reactive and preventive models toward predictive strategies based on real-time operational data. AI and VR form complementary tools that enable early detection of failure symptoms, their visualization, root-cause analysis, and training staff in a safe digital environment.

3.2.1. AI in Predictive Maintenance

AI powers Predictive Maintenance (PdM) systems that utilise data from sensors measuring vibration, temperature, flow, or voltage. Machine learning algorithms (decision trees, SVM, XGBoost) and deep neural networks (MLP, LSTM) detect anomalies, estimate remaining useful life (RUL), and recommend preemptive actions. With edge computing architectures, these systems facilitate low-latency responses and reduce network load. Benefits include reduced downtime, optimized service schedules, extended component lifespan, and failure prediction at component level (e.g., bearings, valves) (Cinar et al., 2020).

3.2.2. VR for Inspection Simulation and Service Training

VR complements AI by providing spatial visualization of machine conditions and immersive training for maintenance staff. Virtual line models replicate equipment layouts and diagnostics tools, allowing safe practice of procedures like component replacement in hard-to-reach areas, lubrication checks, or emergency responses. VR environments can be powered by predictive model outputs, enabling trainees to immediately respond to AI-identified anomalies (Kour et al., 2022).

3.2.3. Implementation Challenges

Key challenges include:

- integrating heterogeneous data sources (IoT, SCADA, CMMS),
- establishing adequate computing infrastructure,
- validating predictive models under variable operational conditions,
- overcoming organizational resistance to AI-supported decisions,
- addressing the shortage of technical-analytical personnel.

Nevertheless, maintenance systems are evolving toward proactive, integrated ecosystems combining AI, VR, IoT, and edge computing in unified predictive-decision frameworks (Sharma, Gupta, 2024; Uddin et al., 2024).

3.3. Safety and Risk Management

Workplace safety and operational risk management are crucial components of modern production systems. With the digital transformation in Industry 4.0 and 5.0, technologies supporting hazard identification, emergency scenario simulation, and safety culture maturity become increasingly important. AI and VR enable integrated warning, visualization, and training systems for comprehensive risk management in industrial settings (Uddin et al., 2024).

3.3.1. VR for Safe-Environment Design and Testing

VR allows for digital reconstruction of plant layouts and interactive hazard analysis. Safety engineers can identify blind spots, collision trajectories, evacuation obstacles, or signage errors. Emergency procedures-such as evacuation, e-stop activation, fire or chemical leak responses-can be tested in controlled virtual simulations, supporting ALARP principles at the design stage (Li, Yu, 2023).

3.3.2. AI in Monitoring and Predicting Dangerous Events

AI processes data from industrial cameras, environmental sensors, access control, and logistics logs. Object detection and behaviour recognition algorithms (e.g., YOLO, Faster R-CNN) identify individuals in restricted areas, missing PPE, or improper machine interactions. Predictive techniques detect patterns-like operator fatigue or sudden pace changes-preceding incidents. These systems can trigger safety alerts, initiate preventive protocols, or halt machinery automatically in automated settings (Johnson, 2019).

3.3.3. Integrated VR–AI for Training and Risk Assessment

Combined VR–AI environments enable realistic hazard training (e.g., fire, chemical leak scenarios), with AI evaluating decision accuracy, reaction time, and procedure adherence. AI compares behaviour against best-practice patterns, adjusting content and generating competency metrics-supporting continuous BHP (occupational health and safety) training (Mahmoudi-Dehaki, Nasr-Esfahani, 2024).

3.3.4. Implementation Barriers

Challenges include:

- high costs of creating realistic VR environments for niche industries,
- integration complexity with existing EHS/QHSE systems,
- organizational resistance to behavioural monitoring,
- absence of standard effectiveness metrics for simulations and training.

Despite these barriers, AI and VR deployment in safety brings resilience, proactivity, and reduced risk of production downtime, operational losses, and legal liabilities (Yüksel, 2024).

3.4. Operational Training and Onboarding

Effective training and onboarding in complex production settings are vital for ensuring safety, quality, and operational continuity. As technology complexity grows, traditional methods (lectures, shadowing) prove inadequate. VR and AI offer new possibilities for immersive, adaptive, and fully standardized training.

3.4.1. VR for Immersive Workplace Training

VR realistically replicates workplace environments, allowing trainees to perform assembly, inspection, or service tasks safely-without risk to equipment or health. Scenarios include machine operation, emergency response, quality control, and ergonomic assembly. VR training provides full repeatability, measurable performance metrics (time, error count, sequence accuracy), and independence from production availability or instructors. It is especially valuable in high-risk industries (Hecker et al., 2021; Dyck et al., 2022).

3.4.2. AI in Adaptive Teaching and Competency Assessment

AI personalizes training by analyzing movement patterns, reaction times, errors, and decision-making. Systems adjust difficulty, suggest repetitions, or offer additional modules-forming Intelligent Tutoring Systems (ITS)-and generate competency indices (e.g., Operational Readiness Index, OPRI). Integration with LMS or HRIS supports organizational competency tracking (Dudhee et al., 2024; Kushwaha, Sharma, 2025).

3.4.3. Onboarding and Competency Standardization

VR and AI facilitate smooth onboarding and periodic qualification checks by enabling:

- faster onboarding without production disruption,
- standardized competency across locations,
- reduction of subjective instructor assessments,
- multilingual, scalable training.

Simulations can be aligned with standards (ISO 9001, 45001, IATF 16949) and internal procedures (SOPs), enhancing compliance with quality and safety management systems (Dudhee et al., 2024; Kushwaha, Sharma, 2025).

3.4.4. Organisational Benefits and Technical Limitations

Benefits:

- shortened training/adaptation time,
- fewer errors by new employees,
- improved safety and ergonomics,
- increased motivation (gamification elements),
- easier documentation of progress.

Limitations:

- high cost of creating realistic VR processes,
- need for domain experts for scenarios,
- difficulty modeling psychological factors (stress, fatigue),
- requirement for continuous simulation updates (Muszyńska et al., 2019; Zigart et al., 2023).

3.4.5. Future Prospects

The future points toward integration of VR, AI, haptics, Augmented Reality (AR), biometric analytics, and wearables-leading to "competency digital twins" that combine simulation, real work, and supervisor assessments, allowing precise human capital management (Mak et al., 2020).

3.5. Integration with MES/ERP Systems

Effective implementation of AI and VR in industrial environments requires integration with existing MES and ERP systems. A coherent, interoperable digital ecosystem allows full utilization of AI's decision support and VR's simulation capabilities via real-time data exchange and synchronized actions.

3.5.1. AI Integration: Architecture and Functionality

AI can be implemented as a layer over or inside MES/ERP architectures. Common applications include:

- cycle time, failure, and downtime prediction based on MES data,
- recommendations for job scheduling and changeovers using ERP data,
- detection of process and cost anomalies via unsupervised learning,
- assessment of operator decisions and competencies using production and HR data.

This integration requires middleware/API, data structure compatibility, metadata availability, and real-time updates (Malzer et al., 2022; Mamone, 2025).

3.5.2. VR Integration: Communication and Synchronization

VR draws data from MES and ERP for accurate reproduction of production states. This enables:

- automated VR training scenario generation from real operational cases (e.g., failures),
- dynamic model updates (layouts, machine statuses, production batches),
- interactive decision simulation (e.g., resource reallocation),
- synchronization with Digital Twins reflecting current operations.

Synchronization may be real-time or batch-mode, using OPC UA or MQTT standards (Curiel-Ramirez et al., 2024; Menck et al., 2012).

3.5.3. Implementation Challenges

Barriers include:

- lack of uniform protocols and data standards across vendors,
- legacy systems unable to handle unstructured data (e.g., VR visual streams),
- semantic inconsistencies (e.g., differing identifiers for batches, operators),
- organizational resistance to AI-based decisions,
- risk of data mismatches with partial synchronization.

Integrating VR with ERP often necessitates middleware or indirect MES-based integration (Curiel-Ramirez et al., 2024; MamiMekalai et al., 2024).

3.5.4. Strategic Importance of Integration

AI–VR integration with MES/ERP is strategically essential for building digital, flexible production environments. It enables:

- holistic optimisation of technical and managerial processes,
- automated, data-driven decisions,
- higher operational resilience,
- realization of smart factory and Industry 5.0 objectives.

A fully integrated environment for data, processes, and competencies underpins future-ready manufacturing organizations-boosting competitiveness, agility, and compliance (Curiel-Ramirez et al., 2024; Horbach, 2013).

4. Results

4.1. Objective and Scope of the Analysis

The aim of the conducted bibliometric analysis was to identify and systematize the structure and dynamics of scientific research concerning the application of Artificial Intelligence (AI) and Virtual Reality (VR) in the context of production management. Both technologies represent key enablers of industrial transformation under the paradigms of Industry 4.0 and 5.0. However, their effective implementation in industrial environments continues to face significant technological, organizational, and integration-related challenges. In this regard, bibliometric analysis of the scientific output provides a structured overview of the main research directions, identification of institutional and geographic leaders, evaluation of publication intensity, and the recognition of research gaps requiring further empirical investigation.

In contrast to traditional literature reviews, bibliometric analysis adopts a quantitative approach to the entire corpus of publications that meet predefined search criteria. This method allows for the identification of thematic development patterns over time, analysis of disciplinary distribution, mapping of relationships between authors and institutions, and the localization of interdisciplinary synergies. As a result, it offers an objective and replicable representation of the current state of knowledge, forming a foundation for further studies on the implementation of AI and VR in production management.

The temporal scope of the analysis covered publications from 1996 to 2025, including all documents indexed in the Scopus database as of May 1, 2025. The study focused exclusively on scientific publications addressing the use of artificial intelligence and virtual reality in the context of production-specifically, in areas such as process planning, production optimization, layout modelling, operational training, maintenance management, and integration with MES and ERP systems.

The data were retrieved from the Scopus database, recognized as one of the most authoritative sources of scientific literature in the fields of production engineering and management. The datasets were analyzed along selected dimensions: publication counts over time, thematic distribution, author country of origin, institutional affiliations, and most prolific authors. These findings serve as the basis for the detailed analyses presented in the following subsections.

4.2. Quantitative Analysis of Publications

4.2.1. Publication Dynamics Over Time

The analysis of publication dynamics related to the use of Artificial Intelligence (AI) and Virtual Reality (VR) in production management reveals a clear and accelerated growth of interest in this area over the past decade. According to Scopus data (as of May 1, 2025), until around 2015, the number of publications on the topic remained relatively low, typically ranging from a few to a dozen entries per year.

A significant turning point occurred after 2016, with a noticeable intensification of scientific research, peaking in the period 2020-2023. This surge is strongly associated with the rapid advancement of Industry 4.0, the growing importance of production process digitalization, and the accelerated technological transformation triggered by the COVID-19 pandemic. Notably, the year 2023 marked a record high in the number of publications, confirming both the maturity of the topic and its firmly established status within academic and industrial communities.

Preliminary data for 2025, covering the period up to May 1, also indicate sustained high levels of research activity, although a full evaluation of the year's dynamics will only be possible after its completion. This trend is illustrated in Figure 1, which presents the annual distribution of publications during the analyzed period (1996-2025).

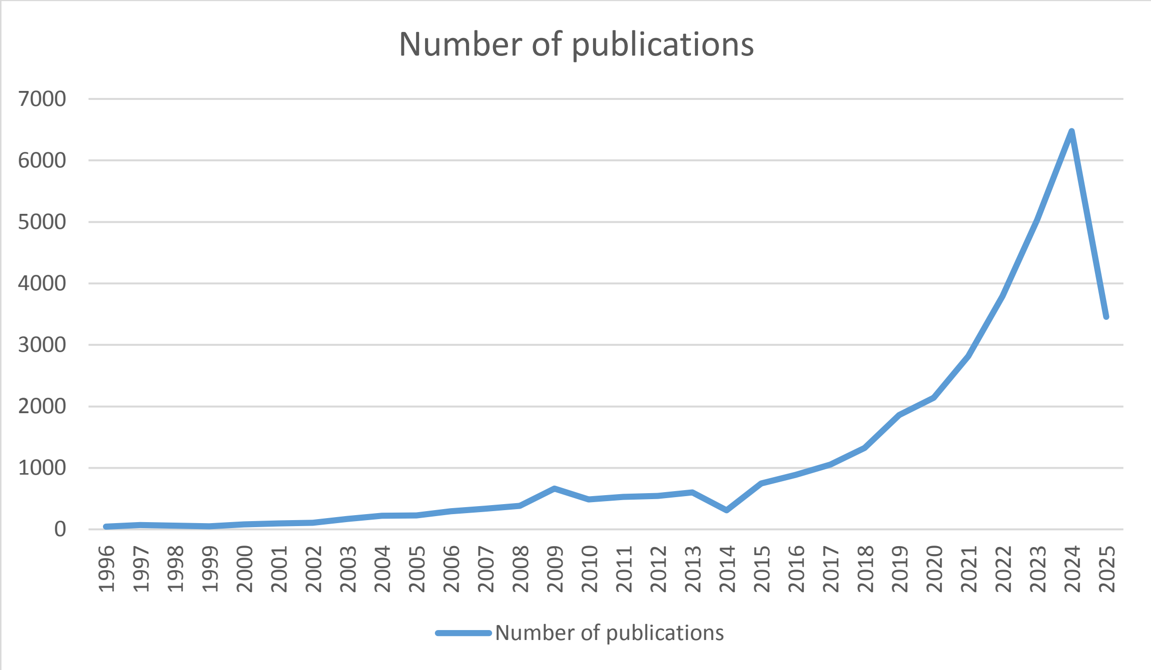

Figure 1. Publication trends on the use of AI and VR in production management (1996-2025).

Source: authors' elaboration based on Scopus data, as of May 1, 2025.

4.2.2. Publications by Country of Author Affiliation

The geographical analysis of scientific publications helps identify countries most actively contributing to the advancement of knowledge in the field of AI and VR applications in production management. According to data from the Scopus database (as of May 1, 2025), the leading contributors by volume of publications are China and the United States-both countries with well-established positions in industrial technology research and deployment.

China ranks first, with a total of 7500 publications in the analyzed domain, underscoring its dominant role in the digital transformation of manufacturing. The United States follows with 6581 publications, reflecting sustained activity in both theoretical research and practical implementations. Other prominent contributors include India (2626), Germany (2495), and the United Kingdom (2370)-all actively developing Industry 4.0 concepts and advanced digital production models.

The top ten also include European countries such as Italy, Spain, France, and Canada, whose contributions demonstrate growing interest in AI and VR integration, particularly in areas such as production planning, optimization, and operational training.

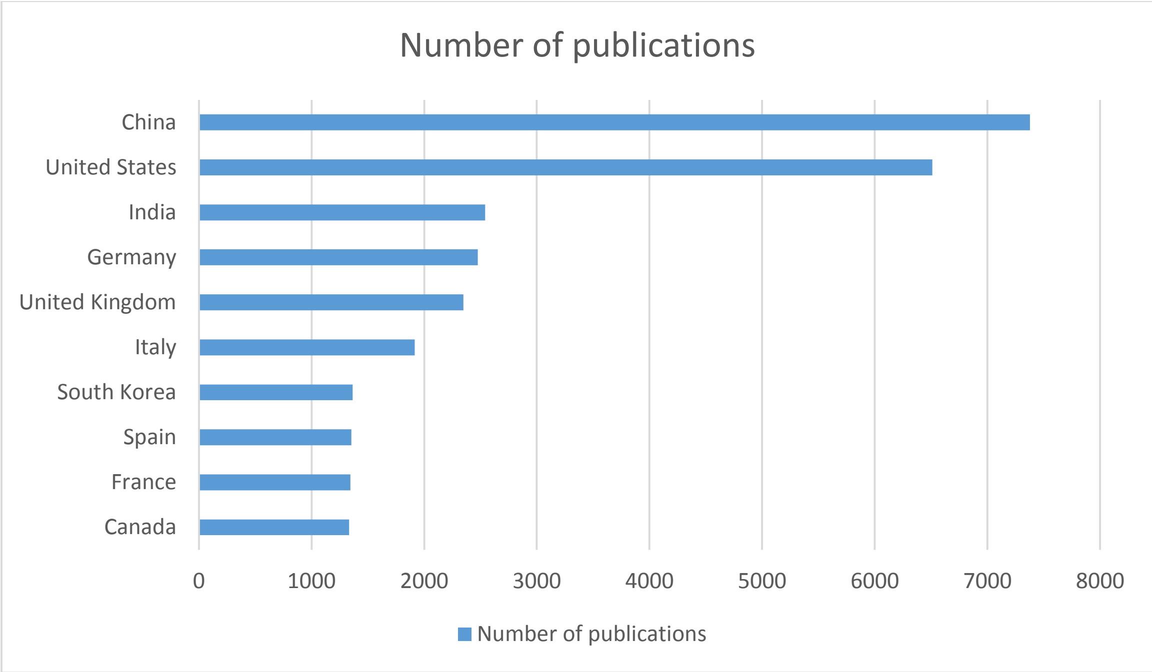

Figure 2. Number of publications on AI and VR in production management – Top 10 most active countries.

Source: authors' elaboration based on Scopus data, as of May 1, 2025.

These findings highlight the importance of geographical context in shaping research and implementation trajectories for immersive and intelligent technologies. At the same time, they suggest that a concentration of research activity in a few leading countries may result in asymmetries in technological adoption, driven by national industrial policies, R&D funding availability, and levels of infrastructure digitalization.

4.2.3. Leading Institutional Affiliations

The analysis of author affiliations identifies academic institutions playing a key role in the advancement of research on AI and VR applications in industrial contexts. Scopus data indicate that leading institutions are predominantly based in China and other Asian countries, reflecting a broader shift in digital technology research toward the East Asian region.

The Chinese Academy of Sciences ranks first, contributing 458 publications. Tsinghua University follows with 382 publications, and CNRS – Centre National de la Recherche Scientifique in France ranks third with 374, confirming the presence of active European institutions. Other notable institutions include the Ministry of Education of the People's Republic of China, Beihang University, Shanghai Jiao Tong University, and Zhejiang University.

Also represented are European and Singaporean universities such as Delft University of Technology, Technische Universität München, and Nanyang Technological University-indicating the rising importance of highly specialized international engineering centers.

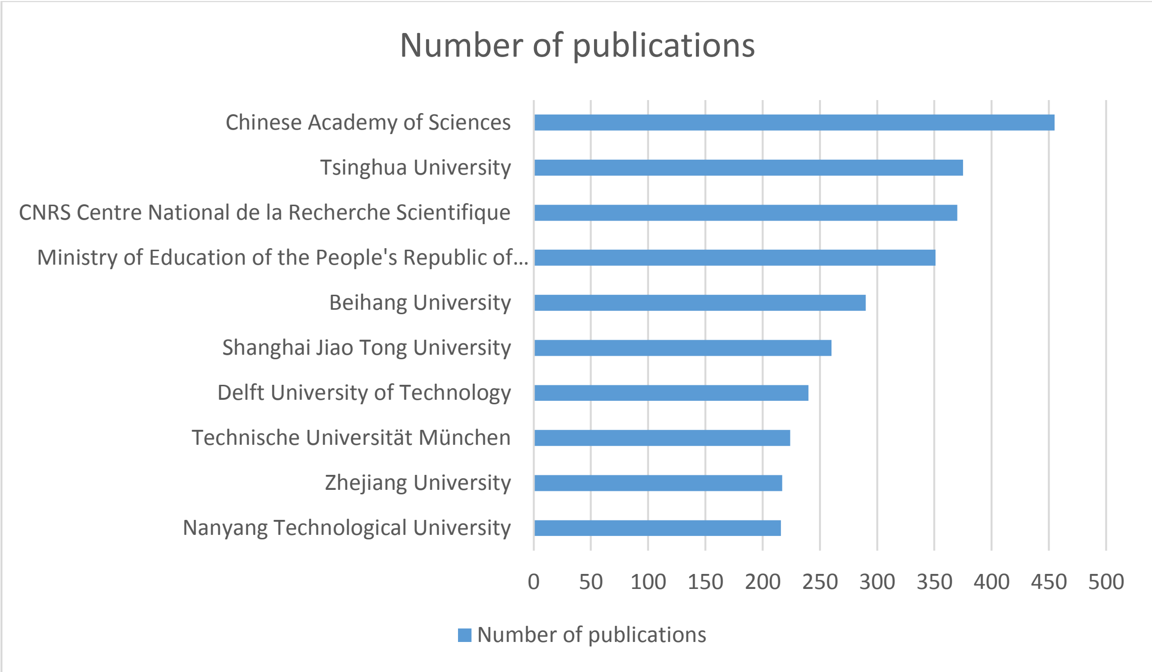

Figure 3. Top 10 most active research institutions in AI and VR for production management.

Source: authors' elaboration based on Scopus data, as of May 1, 2025.

These results suggest that research on the integration of AI and VR into manufacturing processes is concentrated in selected academic and governmental institutions. At the same time, there is increasing international collaboration and growing European participation, which may support the global diffusion of knowledge and broader adoption of these technologies.

4.2.4. Most Active Authors and Co-authors

An analysis of the most prolific authors allows the identification of researchers contributing most significantly to the development of knowledge on AI and VR in production environments. Such rankings also help identify opinion leaders, the research institutions clustered around them, and potential directions for international collaboration and thematic specialization.

Based on bibliometric data from Scopus (as of May 1, 2025), a list of the top ten most publishing authors in this field was compiled and is presented in Figure 4. The most active researcher is clearly Andaluz, V.H., with 59 publications, followed by Du, J. (39 publications) and Wang, F.Y. (35 publications).

These authors are predominantly affiliated with institutions in China, South Korea, Turkey, and the United States, indicating a concentration of expertise in East Asia and selected centers in Europe and North America. Other highly active researchers include Cecil, J., Onur, M., Billinghurst, M., Sepehrnoori, K., Vale, Z., and Rossmann, J., all of whom significantly contribute to the study of immersive and intelligent technologies in production management.

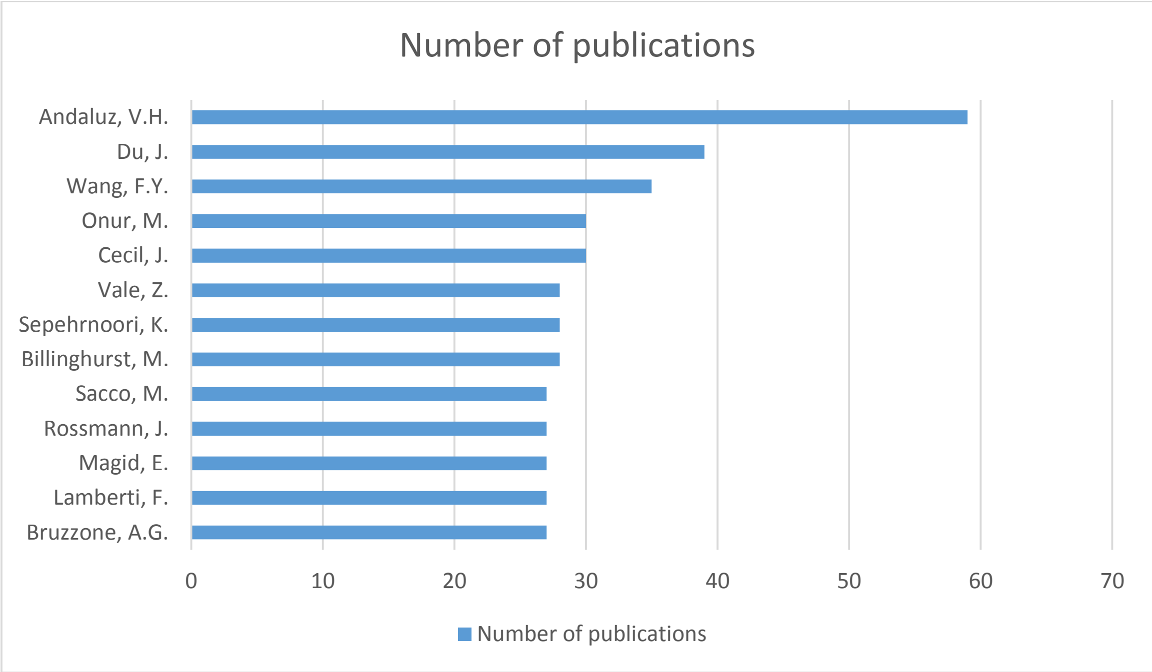

Figure 4. Top 10 most active authors in AI and VR in production.

Source: authors' elaboration based on Scopus data, as of May 1, 2025.

This analysis suggests that knowledge development in this field is largely shaped by a relatively narrow circle of experts, which may foster deep specialization but also carries the risk of limited methodological and thematic diversity. Therefore, initiatives aimed at internationalizing research teams and integrating diverse disciplines into interdisciplinary projects are strongly recommended.

4.2.5. Main Thematic Areas (Scopus Subject Classification)

To determine the disciplinary structure of research on AI and VR applications in manufacturing, an analysis of Scopus subject classifications was conducted. The analysis covered the ten disciplines with the highest number of publications, providing insight into the scientific foundations and interdisciplinary linkages of this research domain.

The highest number of publications was recorded in Computer Science (22,504), underscoring the central role of algorithms, machine learning, and software engineering in AI and VR system design. The second most dominant category is Engineering (17,007), encompassing studies on industrial applications, production system design, digital twin integration, and process automation.

Mathematics ranks third (7395 publications), reflecting the extensive use of mathematical modeling, optimization, and data analysis. Other notable disciplines include Social Sciences, Physics and Astronomy, Energy, Materials Science, Business, Management and Accounting, Decision Sciences, and Medicine.

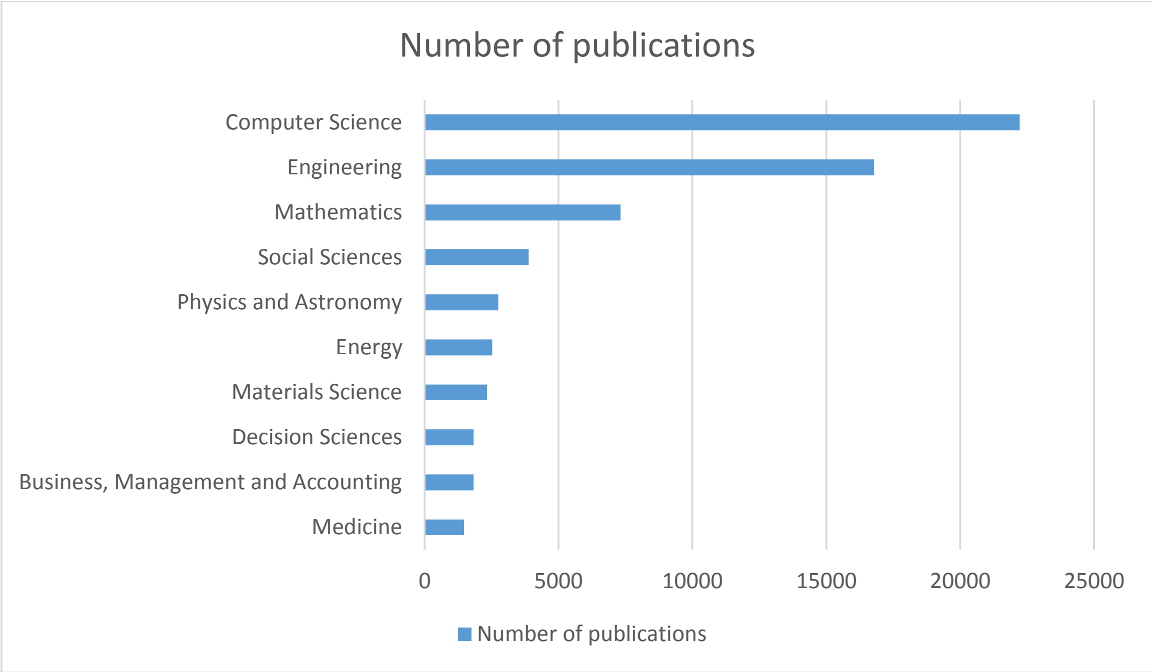

Figure 5. Ten most represented scientific disciplines (Scopus classification) in publications on AI and VR in production.

Source: authors' elaboration based on Scopus data, as of May 1, 2025.

These results reveal a strong dominance of technical and technological disciplines, while also highlighting the presence of organizational, managerial, and social perspectives. This diversity confirms the interdisciplinary nature of the field and the need to integrate engineering expertise with process analysis and technology implementation skills in complex industrial settings.

5. Discussion

The conducted bibliometric and systematic literature analysis allowed for a structured examination of the state of research on the application of AI and VR in production management. The results revealed not only the dynamics of publication growth and the concentration of contributions in specific countries and institutions, but also the prevailing thematic orientations of the field. Building on these findings, this discussion addresses three key aspects: comparison with prior studies, the identification of methodological and implementation challenges, and the formulation of theoretical, practical, and future research implications.

5.1. Key Contributions and Novel Findings

This study makes a significant contribution to the existing body of literature by presenting the first fully integrated bibliometric and systematic review on the applications of Artificial Intelligence (AI) and Virtual Reality (VR) in production management within the paradigms of

Industry 4.0 and 5.0. Unlike previous studies, which typically focused on one of these technologies or analysed their applications solely from a technological perspective, this research encompasses implementation, functional, and systemic dimensions.

The bibliometric analysis identified a sharp increase in research interest in AI/VR integration after 2016, particularly in countries such as China, the United States, India, and Germany. The highest number of publications were recorded in areas such as production layout design, predictive maintenance, immersive training, and operational planning. At the same time, a strong concentration of research was observed within the fields of engineering and computer science, while studies focused on organizational, decision-making, and systemic aspects remain relatively underrepresented.

The reviewed literature indicates that AI is predominantly used for failure prediction, schedule optimization, and adaptive process control, whereas VR is primarily applied in operational training, spatial modelling, and decision scenario testing. Both technologies are increasingly incorporated within the concept of Digital Twins; however, their actual integration with MES/ERP systems remains limited and is rarely analysed systematically.

This study also highlights key research gaps, such as the lack of empirical analyses based on real-world implementations, the insufficient use of effectiveness indicators (e.g., ROI, KPI), and the absence of unified integration platforms. Moreover, the need to consider broader socio-organizational and ethical contexts in the deployment of intelligent and immersive technologies is underscored.

In summary, the article provides a structured overview of the current research landscape, identifies dominant trends and underrepresented topics, and formulates concrete recommendations for future academic and industrial research, serving as a valuable knowledge base for scholars, industry practitioners, and digital transformation project developers.

5.2. Comparison with Prior Studies

The findings of this study align with, but also extend beyond, earlier research efforts focused on the use of Artificial Intelligence (AI) and Virtual Reality (VR) in production management. Prior studies have typically adopted a monothematic perspective, concentrating either on AI or VR separately. For example, Razmak et al. (2025) examined the transformative role of AI in production and operations management, emphasizing its potential to complement or replace human labor, yet without addressing its integration with immersive technologies such as VR. Similarly, Guo et al. (2020) conducted a systematic review of VR in industrial maintenance, but the scope remained narrow and did not explore decision-support functions or real-time integration with enterprise systems.

In contrast, the present study provides a comprehensive and integrated bibliometric and SLR-based exploration of both AI and VR applications across all core production management functions, including layout design, predictive maintenance, training, risk management, and ERP/MES integration. This approach more closely reflects real-world implementation strategies within Industry 4.0 and 5.0 frameworks, where technological convergence is the norm.

In terms of geographic and disciplinary patterns, our results are consistent with prior findings by Espina-Romero et al. (2024), who observed that the majority of AI-related manufacturing research is concentrated in China, the US, and Germany. However, this study goes further by examining not only volume-based metrics, but also the thematic distribution of publications and the evolution of research intensity over time.

Furthermore, earlier works have often highlighted critical implementation challenges, such as uncertainty over the degree of human-AI collaboration (Sauer, Burggräf, 2025), or the limited maturity of VR tools in real-world production settings (Lei et al., 2023; Silva et al., 2020). This study confirms such challenges but extends the analysis by proposing specific integration models, identifying key disciplinary gaps, and offering a taxonomy of underrepresented research areas, including SME adoption and interoperability.

Finally, while prior studies like Lalić et al. (2020) recognized the potential of VR in employee training, they lacked robust empirical indicators or decision-making frameworks. Our study addresses this by advocating for structured effectiveness metrics (e.g., ROI, OEE, learning curves), positioning itself as a practical reference point for future academic research and industrial deployment strategies.

In summary, this article complements existing literature but distinguishes itself through its integrated technological scope, systemic industrial framing, and focus on both bibliometric rigor and managerial relevance.

5.3. Limitations and Methodological Considerations

Despite the comprehensive nature of the conducted study, several limitations must be acknowledged in relation to the methodology and scope of the systematic literature review (SLR) and bibliometric analysis. These limitations impact the generalizability of findings and indicate directions for methodological refinement in future research.

First, the review is based exclusively on publications indexed in the Scopus database, which, although recognized for its broad coverage in engineering and management disciplines, may omit relevant studies published in local or non-English-language journals. Additionally, the inclusion criteria favored peer-reviewed journal articles and conference proceedings, excluding grey literature and industry reports that could offer valuable insights into real-world implementations of AI and VR in production environments.

Second, the search strategy-while developed with precision-was based on specific keyword combinations (e.g., “artificial intelligence”, “virtual reality”, “production”, “MES”, “ERP”), which may have led to the omission of studies using alternative terminologies or focusing on adjacent technologies (e.g., XR, AR, machine vision). As such, the findings reflect a focused yet inherently filtered snapshot of the broader research landscape.

Third, although the bibliometric analysis enabled objective mapping of publication trends, author affiliations, and subject categories, it was limited by the structure of metadata available in Scopus. For instance, nuances related to the type of AI or VR implementation, context of use (e.g., training vs. maintenance), or organizational scale (e.g., SME vs. large enterprise) could not be fully captured in the quantitative layer.

Fourth, the qualitative synthesis of dominant application areas (e.g., layout planning, predictive maintenance, training) was conducted based on titles, abstracts, and keywords, without full-text analysis of each article. This approach, while ensuring feasibility and replicability, may have introduced interpretation bias or overlooked nuanced insights embedded in case-study sections.

Finally, the study did not apply advanced scientometric techniques such as co-citation or keyword co-occurrence networks, which could further enhance the understanding of thematic convergence and research clustering. The integration of such techniques is recommended for future work aiming to deepen the structural understanding of the field.

In summary, while the present study provides a solid empirical and conceptual foundation for understanding the state of research on AI and VR in production management, its methodological scope is bounded. Future studies should consider multi-source databases, triangulation with industry data, full-text content analysis, and more sophisticated bibliometric tools to achieve greater depth and breadth.

5.4. Future Research Directions

Building upon the identified gaps and thematic concentrations, several promising directions for future research can be delineated to advance the theoretical understanding and practical implementation of Artificial Intelligence (AI) and Virtual Reality (VR) in production management.

First, further studies should explore integrated frameworks combining AI and VR within unified decision-making environments. Despite numerous publications addressing these technologies separately, only a limited number of contributions examine their joint application in real-time operational contexts, such as dynamic rescheduling or real-world training adaptation. Developing holistic models that leverage both data-driven intelligence and immersive visualization could significantly enhance adaptability and responsiveness in smart manufacturing.

Second, there is a pressing need for empirical research based on real industrial data. A vast majority of studies are conceptual or based on simulated environments, often lacking robust validation. Future work should prioritize industry-academic collaborations to access operational datasets and validate the effectiveness of AI/VR systems in live production settings, particularly regarding system reliability, employee adaptation, and return on investment (ROI).

Third, the literature review revealed a lack of standardized performance metrics for evaluating the success of immersive technologies and intelligent algorithms. Future research should propose and test unified evaluation frameworks-especially those linking key performance indicators (KPIs) with production outcomes, training effectiveness, and safety improvements. Comparative studies across sectors and enterprise sizes would also support generalizability.

Fourth, research should delve into contextual factors affecting implementation success, such as organizational culture, workforce readiness, technological maturity, and sector-specific regulations. These factors are often overlooked but critically influence the adoption curve and scale of deployment, particularly in small and medium-sized enterprises (SMEs).

Fifth, emerging technologies such as Extended Reality (XR), Digital Twins, and Edge-AI warrant more focused investigation, especially in relation to energy efficiency, predictive maintenance, and human–machine interface optimization. Their synergy with existing MES and ERP platforms also remains underexplored and offers fertile ground for interdisciplinary research.

Finally, comparative cross-national and cross-industry analyses could illuminate how regional policy frameworks, economic incentives, and infrastructure readiness impact the adoption of AI and VR. Such studies would help tailor implementation strategies and inform national or regional roadmaps for smart manufacturing.

5.5. Practical and Theoretical Implications

The findings of this study yield several important implications for both academic research and industrial practice in the field of production management enhanced by Artificial Intelligence (AI) and Virtual Reality (VR).

From a theoretical perspective, the conducted bibliometric analysis contributes to the systematization of the research landscape, highlighting dominant themes, neglected topics, and institutional concentrations. The integration of AI and VR technologies into production environments emerges as a multidisciplinary domain, spanning engineering, computer science, and management. This indicates the need to refine existing theoretical models that explain technology adoption in manufacturing, moving beyond linear or isolated approaches toward frameworks that capture technological convergence, organizational dynamics, and human-centered design.

Furthermore, the analysis underlines the fragmentation of current research between technological development and organizational application. This gap suggests a demand for new conceptual models that incorporate socio-technical factors, digital capabilities, and operational maturity as key enablers of successful AI/VR deployment. Such models would benefit from being empirically tested across different industrial contexts.

From a practical standpoint, the results provide actionable insights for production managers, technology developers, and policymakers. In particular, the identification of key application areas-such as layout design, predictive maintenance, and immersive training-can guide resource allocation and strategic planning for digital transformation initiatives. The study also exposes persistent implementation barriers, such as system interoperability, lack of performance evaluation standards, and limited access to real operational data. Addressing these constraints will be essential for scaling up deployments in diverse industrial sectors.

The study additionally points to the strategic importance of integrating AI and VR with MES/ERP systems, as such integration allows for real-time synchronization, automated decision-making, and operational transparency. This highlights the necessity for collaborative platforms between IT vendors, process engineers, and plant operators to co-develop scalable solutions.

Finally, the research emphasizes the role of human capital and organizational readiness as critical success factors. Immersive training, AI-driven coaching systems, and adaptive learning environments can accelerate workforce upskilling and improve safety, efficiency, and employee engagement in smart factories.

5.6. Limitations and Future Research Directions

Despite its comprehensive scope and methodological rigor, this study presents several limitations that should be acknowledged and addressed in future research efforts.

First, the data source was limited to the Scopus database, which although widely recognized for its coverage of scientific literature may omit relevant publications indexed elsewhere (e.g., Web of Science). This may lead to a partial representation of the full research landscape, particularly in practice-oriented domains or grey literature.

Second, while the analysis aimed to exclude publications focused solely on quality management, classification ambiguities and overlapping keywords might have led to the inclusion of borderline cases or the exclusion of relevant records. Additionally, bibliometric techniques provide quantitative insights, but may overlook nuanced conceptual developments or methodological subtleties present in individual studies.

Third, the temporal scope of the data, extending to May 2025, imposes a snapshot perspective. Given the dynamic evolution of AI and VR technologies, especially in industrial settings, future developments might shift the thematic and geographic centers of research, requiring updates of the present findings.

Moreover, the lack of a detailed impact assessment framework-such as benchmarking models or maturity scales-limits the ability to evaluate the real-world effectiveness of AI/VR implementations. Future research should focus on the development of such frameworks, integrating objective indicators like ROI, OEE, KPI, or immersive training effectiveness metrics.

In light of these limitations, several future research directions emerge:

- Development and empirical validation of integrated models combining AI and VR functionalities with production management systems.
- In-depth case studies analysing implementation processes, barriers, and enablers in specific sectors (e.g., automotive, aerospace, pharmaceuticals).
- Exploration of ethical, legal, and organizational challenges related to decision automation, data governance, and human-machine interaction in smart factories.
- Investigation of the role of SMEs in the adoption of immersive and intelligent technologies, with attention to scalability, cost-effectiveness, and support ecosystems.
- Cross-comparative analyses of regional and institutional strategies for AI/VR integration in industrial policies and innovation programs.

By addressing these areas, future studies can deepen the theoretical foundation of smart production and bridge the gap between academic discourse and industrial transformation.

6. Conclusion

The integrated application of Artificial Intelligence (AI) and Virtual Reality (VR) in production management currently represents one of the key directions of industrial development in the context of Industry 4.0 and 5.0. The conducted systematic and bibliometric analysis has demonstrated that these technologies-initially perceived as experimental-are increasingly being implemented in industrial practice, ranging from production layout design and maintenance management to operational training and integration with MES/ERP systems.

The greatest intensification of research occurred after 2020, as confirmed by bibliometric data indicating a sharp increase in the number of publications, particularly in East Asian countries (China, South Korea), the United States, and selected European research centers. The dominant scientific disciplines are computer science and engineering, while the leading topics include digital twins, operational planning, failure prediction, and immersive VR training.

Despite rapid development, significant research gaps have been identified, including the absence of comprehensive integration models, limited use of empirical data, and implementation constraints stemming from organizational and technological barriers. There is also a need for more in-depth studies on the impact of AI and VR on human capital, workplace safety, and the effectiveness of operational management systems.

The knowledge gathered through this study not only allows for the identification of current research and technological trends but also enables the formulation of recommendations for future development. In particular, the analysis points to the necessity of undertaking interdisciplinary projects that integrate technological, organizational, and social components-allowing for the full exploitation of the potential of AI and VR in modern production management.

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