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Review

Digital Transformation in the Chemical Industry: The Potential of Augmented Reality and Digital Twin

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Abstract: In the era of Industry 4.0 and industrial digitization, augmented reality (AR) is a powerful technology with the potential to revolutionize numerous sectors. However, despite a proliferation of supporting tools and hardware and demonstrated benefits in effectiveness, intuitiveness, and ease of use, the practical implementation of AR within the chemical industries remains surprisingly limited. This indicates a potential shortfall in research and development initiatives aimed at fully exploiting the capabilities of AR for industrial applications. This manuscript presents a comprehensive review of the existing landscape of AR within the industry, aiming to shed light on this intriguing paradox. After providing an extensive overview of the current state of AR in industry, we propose a schematic guideline as a systematic approach for introducing AR into industrial operations. The objective of this guide is to bridge the gap between AR's evident potential and its actual application, fostering a broader adoption of this innovative technology in the industrial sector. Our work offers valuable insights and a practical roadmap for stakeholders aiming to leverage the transformative power of AR in industrial activities.

Keywords: chemical industry; augmented reality; digital twin; framework

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1. Introduction

The acceleration of industrial digitization is increasingly evident, with a range of technologies synergizing to enable comprehensive end-to-end engineering integration across all phases of the product lifecycle [1]. One such innovative technology that has emerged as a central component of this digital revolution is augmented reality (AR) [2]. AR is a technology that superimposes digital information (e.g., sound, images, text) in the real-world environment to enhance the user's experience by creating opportunities for interaction and engagement with the physical world. Its role as a critical enabler in the evolution of Industry 4.0 and the broader sphere of industrial digitization has been considerably reinforced by the rapid proliferation of supporting tools and hardware, making it more accessible and user-friendly than ever before [3,4].

Augmented reality has been subject to extensive research and scrutiny, yielding promising results [5]. A plethora of studies substantiate its substantial benefits, such as considerable reductions in task execution time and the occurrence of errors. They affirm its effectiveness, intuitiveness, and simplicity of use, making AR an enticing prospect for myriad applications [6,7]. AR is characterized by the superposition of virtual elements in a natural environment with visualization devices [8]. In AR, the natural environment is not suppressed; on the contrary, the natural environment plays a dominant role, as it is the synthetic information that integrates with the physical world [9].

Additionally, AR exhibits versatile applicability across a wide array of knowledge domains. From medicine and entertainment to education, it is proving transformative in various aspects of modern life. Beyond these, however, its potential is also being explored and leveraged across many industrial sectors. In particular, manufacturing, construction, energy, metallurgy, and machinery are areas where AR's capabilities can be exploited to realize significant process enhancements, showcasing its potential to revolutionize industries' operations.

AR is a promising tool in various industries in the digital transformation era, offering opportunities to reshape workflows, improve efficiencies, and foster innovation. As the technological landscape evolves, AR's role in shaping industry's future looks set to become increasingly pivotal.

Even though the potential and transformative effects of augmented reality have been widely demonstrated, its application within the chemical industrial sphere remains somewhat limited. This observation suggests a possible deficiency in the focus of research and development efforts toward exploring and applying AR tools tailored to facilitate industrial operations. This discrepancy between potential and practical usage is an intriguing facet of the AR landscape and one that warrants a more extensive investigation.

While virtual reality (VR) and mixed reality (MR) offer compelling advantages for specific training scenarios, particularly for creating immersive simulations of hazardous situations, AR retains several unique strengths that make it an essential tool in high-risk industrial environments. Its ability to provide real-time information overlays, maintain situational awareness, and integrate seamlessly into existing workflows makes AR a practical and effective solution. Ultimately, the choice between AR, VR, and MR should be based on specific use cases, operational requirements, and safety considerations rather than a blanket assumption that one technology is universally superior. Each technology can be valuable in improving safety, training, and operational efficiency in the chemical industry and beyond.

While both AR and MR have their strengths, the unique challenges of hazardous environments in the chemical industry may favor using MR for specific applications. MR's ability to create immersive, interactive simulations while allowing users to remain aware of their physical surroundings offers a compelling solution for training and operational tasks. In contrast, AR, while valuable for providing real-time information and guidance, may have limitations regarding interactivity and adaptability in challenging conditions. Organizations should, therefore, consider their specific needs, operational environment, and security requirements when choosing between these technologies. Each technology can play a complementary role, and in some cases, a hybrid approach may be the most effective solution to the complex challenges faced by the chemical industry.

This work provides a comprehensive review of this topic, offering a wider perspective on the state of AR within the industrial context. Our objective is to provide a broader understanding of the current landscape, addressing the gap between the evident potential and the actual implementation of AR technology in industry.

After establishing the panoramic overview of the field, we further intend to propose a schematic guideline that outlines a systematic approach for introducing AR into industrial activities. Our goal with this guide is to make implementing AR more straightforward and clear, ultimately encouraging its broader adoption in industry. By doing so, we aim to bridge the gap between the potential of AR and its actual application, facilitating a more effective and widespread utilization of this groundbreaking technology in the industrial sector.

Thus, this comprehensive review aims to:

- Analyze the current state of augmented reality in industrial sectors.
- Investigate the adoption and implementation of augmented reality in the chemical industry.

- Identify the areas of major emphasis in augmented reality industrial applications in the chemical industry.
- Present a conceptual framework for augmented reality application in conjunction with digital twin technology.
- Provide a comprehensive overview of augmented reality and digital twin technology industrial applications.

Thus, this comprehensive review provides an in-depth analysis of the current state, adoption, and key applications of augmented reality in industrial sectors—particularly the chemical industry—while presenting a conceptual framework for integrating augmented reality with digital twin technology.

2. Methodology

Within a landscape characterized by a notable surge in academic publications and segmented research streams, bibliometrics presents a robust methodology, facilitating a systematic, transparent, and replicable review process. Its relevance has magnified in an era of exponential information growth, nuanced conceptual advancements, and burgeoning data. Hence, structured analysis employing a wide spectrum of information becomes an influential instrument, yielding substantial contributions to scientific cartography.

Bibliometric analysis is a cornerstone in unveiling temporal patterns, evolving research themes, and shifts within disciplinary confines, simultaneously spotlighting distinguished researchers and academic institutions. This technique offers a panoramic view of current research, delivering evidence-based insights that shape professional practice and bolster expert judgment. Adopting bibliometrics enables a more expansive and precise comprehension of the scholarly terrain, thereby fostering data-driven decisions and unveiling gaps in existing knowledge. Specifically, bibliometric analysis is based on the exploratory analysis of one or more databases of articles, and after defining a theme to be analyzed, the steps can be divided as follows [2]:

1. Selection of one or more databases to be searched;
2. Definition of keywords;
3. Search in the database for various combinations;
4. Compilation of metadata and export to Bibitex;
5. Evaluation of citations;
6. Thematic analysis;
7. Graphical analysis.

These steps can be performed iteratively with the others until the theme analysis is exhausted. This work used bibliometric analysis to filter and analyze the AR and DT literature related to chemical engineering.

In the context of our methodology, bibliometric analysis integrates several components to map and interpret the academic landscape systematically. It establishes a metadatabase, starting with bibliographic data collection, allowing for citation analysis to gauge individual publications' influence. Co-citation and co-authorship analyses build on this by revealing thematic clusters, foundational studies, and collaboration networks, thus illustrating both intellectual and social structures within the field. Keyword analysis then identifies key themes and emerging topics, while data visualization synthesizes these findings into clear, interpretable patterns.

The main components of bibliometric analysis typically include the following:

1. Bibliographic Data Collection: The first step in a bibliometric analysis is gathering the bibliographic data. This involves identifying and extracting metadata from relevant academic sources.
2. Citation Analysis: Citation analysis explores a publication's impact and influence by evaluating its citations' frequency and patterns in other works.

3. Co-citation Analysis: This component examines how frequently two works are cited together, which can identify core papers in a field or reveal relationships between different works.
4. Co-authorship Analysis: This part of the analysis examines collaboration between researchers, institutions, or countries, offering insights into the social structure of research fields.
5. Keyword Analysis: This step helps identify prominent themes and trends in a field over time, aiding in the discovery of emerging topics and the evolution of existing ones.
6. Visualization of Bibliometric Data: The final component is the visualization of the derived bibliometric data, which aids in interpreting the relationships, trends, and patterns identified in the analysis.

By incorporating bibliometric analysis into our methodology, we enable a rigorous and objective assessment of the academic field under study. This provides valuable insights to guide future research, inform policy and decision making, and contribute to our understanding of scientific knowledge production and dissemination dynamics.

The outline of the proposed research is visually represented in Figure 1. The first phase encompassed planning, where the objectives and research questions were defined, along with the search strategies and the databases to be consulted. The English language was defined within the Web of Science database, with searches without a definition of time. After this stage, the research began with identifying primary studies and extracting and synthesizing the results found in the sample. In Section 3, the development of the bibliometrics after the sample analysis will be presented.

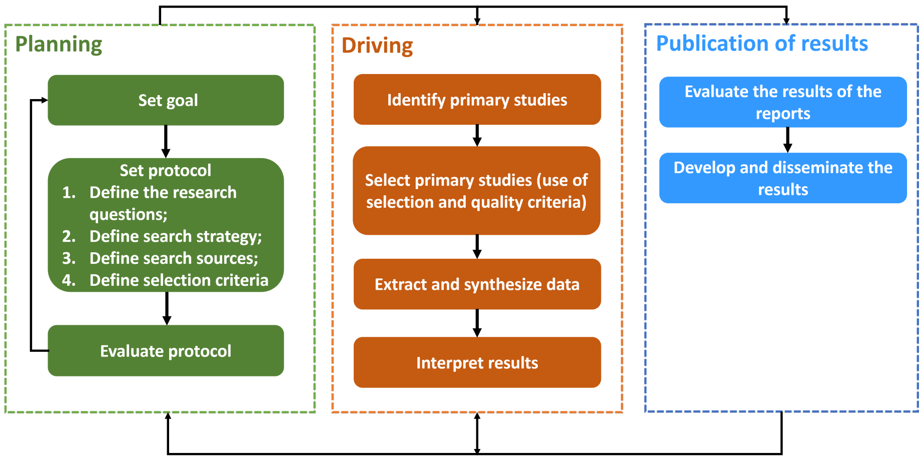

Figure 1. Methodological procedures.

3. Augmented Reality in Industry

Regarding the first stage of data collection, after searching with the terms "augmented reality" and "industry" (string: "augmented reality" and industry), 2157 documents were obtained in the sample. It is important to note that the data presented are based on the Web of Science database and may not represent the entire universe of scientific publications. Figure 2 shows the annual number of publications on augmented reality in industry from 1998 to 2023. In 2022, there was a significant increase in the number of publications compared to 2021, with 425 registered publications. From the presented data, it is possible to observe a clear growth trend in the number of publications in recent years. The data also suggest that research on augmented reality in industry has been an area of increasing interest over the years. Since 2017, the annual number of publications has exceeded the mark of 100 publications, with a substantial increase in 2022. Interestingly, although publications on augmented reality in industry started to be registered in 1998, the annual count of publications remained relatively low until the mid-2010s. From that point on, publications significantly increased each year.

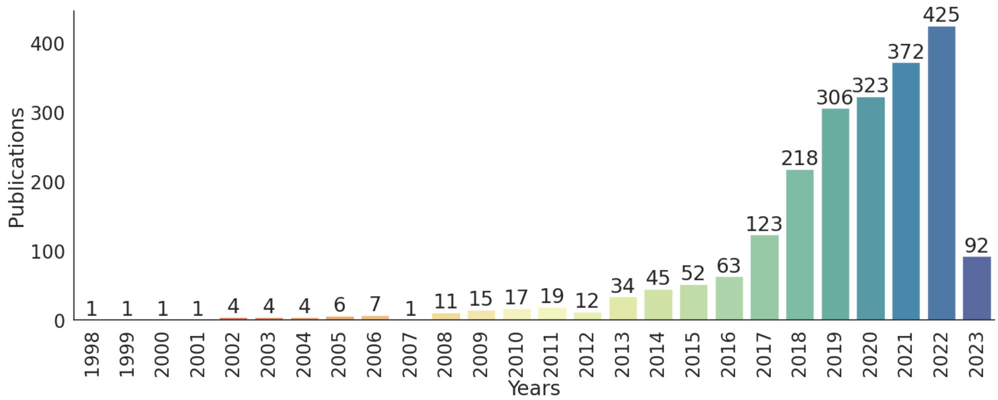

Figure 2. Publications about AR in industry over the years.

The data analysis suggests that research on augmented reality in industry is a growing research topic, with increasing interest in exploring its possibilities and applications. This trend can be explained by the increased availability of augmented reality technologies and the recognition of their potential to improve efficiency, productivity, and safety in industry. Regarding the number of publications related to augmented reality in industry in different journals and conference proceedings, the ten titles with the highest number of publications are highlighted (Figure 3). It can be observed that "Lecture Notes in Computer Science" obtained the highest number of publications with 78 papers, followed by "Applied Science Basel" with 65 articles, and "Sustainability" with 47 documents. Other journals and events with a significant number of publications include "Proceedings of SPIE" with 42 papers, "Automation in Construction" with 34 papers, and "IEEE Access" with 32 papers. In addition, it is also possible to identify other significant journals and publications related to augmented reality in industry and gaps in the literature where there are opportunities for further research.

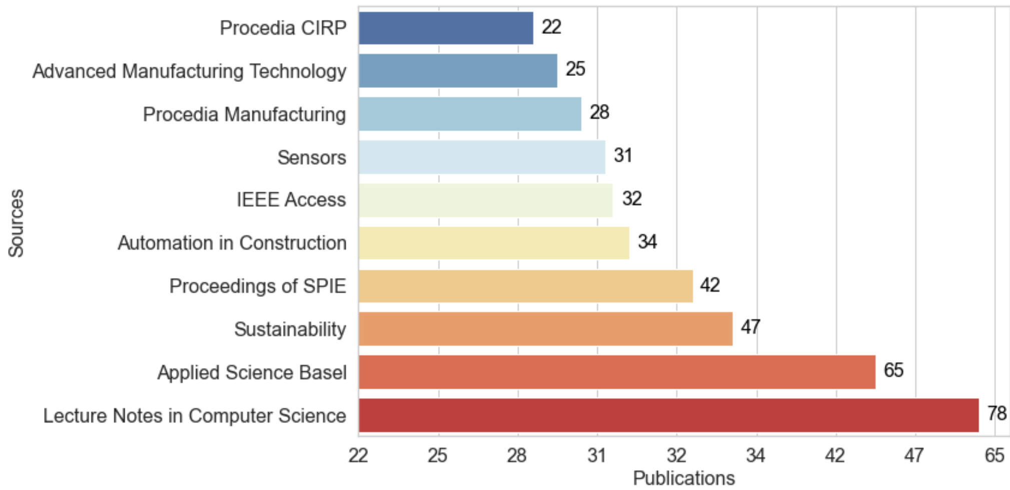

Figure 3. Journals and conference proceedings with the highest number of publications.

The graph showing the ten countries with highest quantity of publications, Figure 4, shows that the United States has the highest number of publications with 342 articles, followed by Germany with 238, China with 188, England with 176, and Italy with 173. The remaining listed countries have fewer than 120 publications each. It should be noted that the sample includes 100 countries, and the top 10 countries with the highest number of publications have been highlighted, emphasizing that this field has global interest with applications in various industrial sectors. This analysis can help identify the significant knowledge-producing countries in the field of augmented reality in industry and indicate possible areas of collaboration among researchers and institutions from different countries.

It can also be helpful for decision making in research and development investment policies in this area.

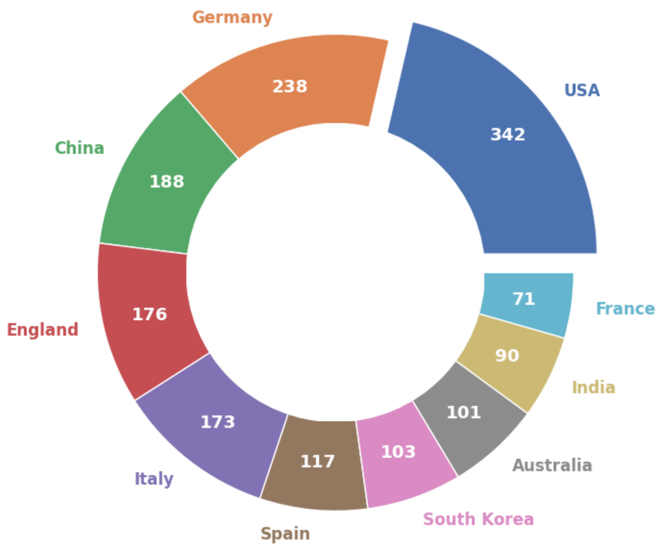

Figure 4. Countries with the highest number of publications.

An augmented reality system requires devices that enable the evaluation of the user's position (tracking) and the creation of virtual elements (which can be either geometric or non-geometric models) to integrate them into the environment through display and interaction technologies. Display and interaction technologies are part of a system that uses a set of optical, electronic, and mechanical components to generate images somewhere along the trajectory of human vision, that is, between the observer's eyes and the natural environment [6,9]. These systems comprise visualization devices that can be classified into smart glasses or head-mounted displays (HMD), all-silicon microdisplay [10], smartphones, projectors, tablets, and TVs or monitors.

According to [11], graphical elements such as images, icons, animations, and other visual resources used in augmented reality interfaces to provide information about an object or process, guide the user during a task, or provide real-time visual feedback, have certain limitations for industrial use. For instance, the occlusion of graphical elements can limit situational awareness and operator safety. Additionally, the choice of these elements can be influenced by the type of display device used. Conversely, these authors recommend using such elements to enhance efficiency and safety in industrial environments.

In this context, the data presented in Figure 5 correspond to the number of publications on AR and visualization devices (smart glasses/HMD, smartphones, projectors, tablets, and TVs) associated with the terms augmented reality and industry. In this sense, the sample revealed that the use of smart glasses/HMD and smartphones is equally frequent in augmented reality applications in industry, with 70 occurrences each. Tablets come in third place with 57 events, followed by projectors with 20, and TVs with only 8 occurrences. These results suggest that most augmented reality applications in industry are being developed for mobile devices such as smartphones, tablets, and smart glasses/HMDs. This can be explained by the fact that these devices offer greater portability and flexibility for use in different environments and situations. There is also an inference of greater availability of smart glasses and decreased costs. Moreover, it is interesting to note that the use of projectors and TVs in augmented reality applications is relatively low. This may be due to the mobility limitations of these devices and the need for a physically larger space for their use.

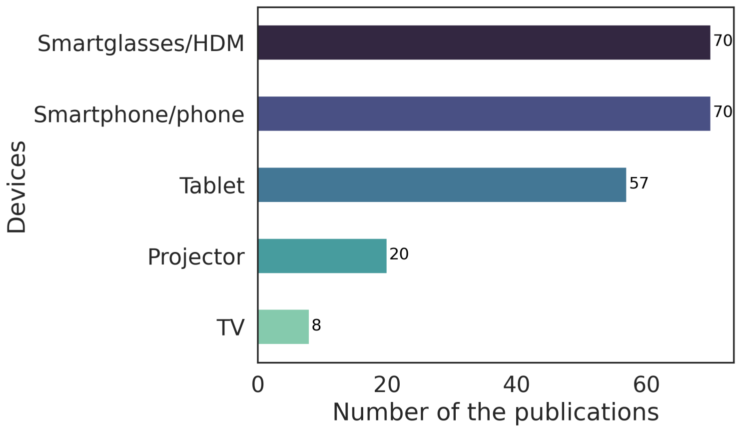

Figure 5. Most cited devices in the sample.

Considering the publications involving AR in industry, [12] revealed that some of the challenges associated with AR implementation in the sector are low adoption rates, safety and operability challenges, and usability and interface issues. However, despite these challenges, augmented reality technology emerges as one of the nine enabling technologies that will drive the transformation supported by the Industry 4.0 initiative and is regarded as a critical technology for the development of intelligent manufacturing. The use of augmented reality in industry can bring various benefits, such as improving worker efficiency and productivity, reducing errors and rework, enhancing workplace safety, reducing training time for new employees, improving equipment maintenance and repair, and increasing customer satisfaction, among others [11].

3.1. AR in Industrial Sectors

Based on the data presented in Figure 6, a discernible distribution of publication count across various industrial sectors can be observed in the bibliometric analysis of augmented reality. The manufacturing sector emerges as the frontrunner with the most publications, amounting to 510 articles. Subsequently, the construction sector exhibits a substantial presence with 324 publications, followed by the energy sector with 93 publications. In contrast, the metallurgy and machinery sectors demonstrate relatively fewer publications, with 14 and 35 articles, respectively. These findings signify a greater emphasis on exploring and investigating augmented reality applications within the manufacturing and construction sectors, closely followed by the energy sector.

The significant presence of publications in the manufacturing sector can be attributed to the need to enhance efficiency, productivity, and safety in the production line. AR can assist in assembly, maintenance, and operator training by providing real-time information and instructions [13]. AR has been explored in the construction sector to improve planning, accuracy, and efficiency in construction, as well as project visualization, error detection, and communication facilitation among designers [14]. Furthermore, building operation and maintenance applications are also growing in this sector [15]. On the other hand, in the energy sector, AR can be applied to visualize real-time energy quality parameters and appliance energy consumption and aid in inspection, maintenance, and equipment monitoring, thereby enhancing energy efficiency and worker safety [16].

However, it is essential to highlight that the metallurgy and machinery sectors, although they have fewer publications, can also benefit from using augmented reality regarding process optimization, preventive maintenance, and increased productivity. This data analysis suggests that augmented reality is being explored and implemented across different industry sectors, with a greater focus on manufacturing, construction, and energy. This trend reflects the recognition of the potential of this technology to improve processes and outcomes in these areas. In addition, it indicates opportunities for further research and development in the metallurgy and machinery sectors.

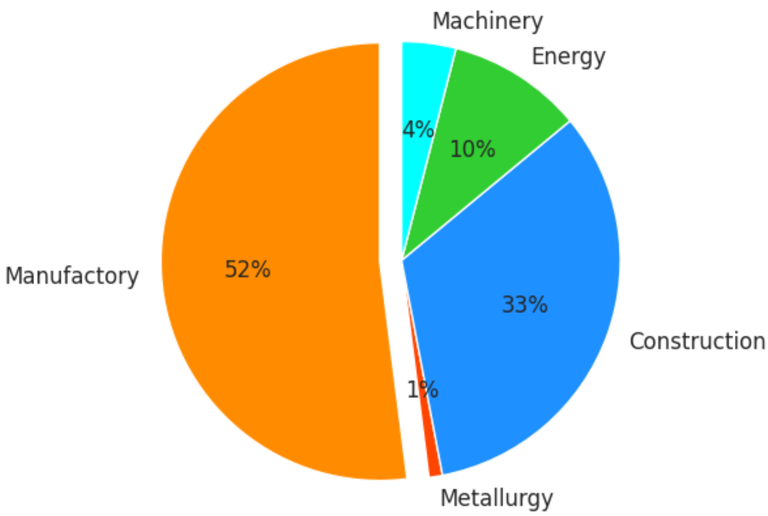

Figure 6. Augmented reality in industrial sectors.

The dominance of manufacturing in Figure 6 can be further understood and confirmed by considering the diverse applications and benefits of AR in this sector. AR has been leveraged for process monitoring and control, real-time evaluation of plant layouts, machinery and plant maintenance, facility construction, and enhancing industrial safety. These applications address manufacturing needs, such as efficiency, safety, and cost effectiveness, making AR a tool for optimizing complex processes [17].

Moreover, the potential of mobile technologies to revolutionize AR applications in manufacturing highlights the sector's readiness for innovation and its capacity to adapt to cutting-edge solutions [18]. However, despite these advancements, AR applications in manufacturing are still in an exploratory stage, with full-scale implementations of industrial AR (IAR) solutions being limited to a few cases [19].

This exploratory nature and limited deployment suggest significant further scientific investigation and development opportunities. Research could focus on bridging the gap between pilot studies and full-scale industrial integration and exploring scalable strategies for AR adoption in manufacturing environments.

3.2. AR in the Secondary Industry

Based on the data presented in Figure 7 regarding augmented reality bibliometrics in industry, a distribution of the number of publications across various manufacturing industry sectors can be observed. The automotive sector has the most publications, amounting to 41 articles. Subsequently, the textile sector demonstrates a comparatively lower number with only 5 publications, followed by the food, chemical, and pharmaceutical sectors, which have 10, 4, and 3 publications, respectively. These results prove that the application of augmented reality has been most explored and researched in the automotive sector, followed by sectors such as textile, food, chemical, and pharmaceutical. In the automotive industry, augmented reality can be applied in many areas, such as vehicle design, manufacturing, maintenance, and operator training. It can help visualize projects, optimize production processes, detect defects, and support decision making [20–22].

Although the textile, food, chemical, and pharmaceutical sectors have fewer publications, there are still possibilities for the application of augmented reality in these areas. For example, in the textile sector, the main aspects of Industry 4.0 identified focus on implementing technologies aimed at computerizing and automating processes, whose main objectives are to increase productivity and reduce costs. Projects to implement augmented reality and 3D simulation technologies in the textile and clothing industry are still in their infancy, usually implemented through tools to create and develop new models of processes, products, and commerce [23].

In the food sector, it can be applied in the commercial sector (boosting the positive effect on the desirability and probability of purchase) in the instruction of cooking techniques and the presentation of nutritional information [24–28]. In the pharmaceutical sector, augmented reality can improve production efficiency, provide employee training, improve workplace safety, and provide real-time information about production processes. However, implementing AR in industrial applications is challenging and requires customized solutions to meet the specific needs of the sector [29]. AR in the chemical industry will be highlighted in Section 3.3 below.

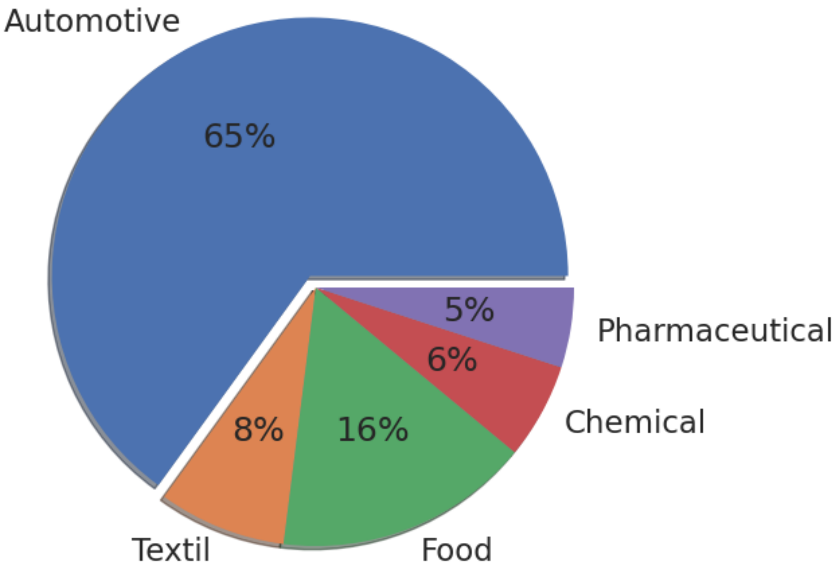

Figure 7. Augmented reality in the secondary industry.

In summary, this data analysis suggests that augmented reality has significant application potential in several manufacturing industry sectors. The automotive sector is the most explored so far, but there are still opportunities for research and development of augmented reality in the textile, food, chemical, and pharmaceutical sectors.

3.3. AR in the Chemical Industry

Based on the provided data on augmented reality bibliometrics in the chemical industry, we can observe the distribution of publications across different years. Figure 8 illustrates the number of articles published yearly in this specific field. The data indicate a fluctuating trend in publications over the years. There was publication activity in 2013, 2014, 2016, 2017, and 2018, with one article published each year. In 2020, the number increased to two publications, indicating a slight growth in research interest. In 2015 and 2019, there was a declining number of publications, with zero articles published. However, in 2021 the number increased to seven publications, showing growth in this research field. This publication activity fluctuation suggests varying research focus and engagement in augmented reality within the chemical industry. It is worth noting that the lower number of publications in specific years does not necessarily indicate a lack of interest in the topic but could be attributed to factors such as particular research projects, funding availability, or other external influences.

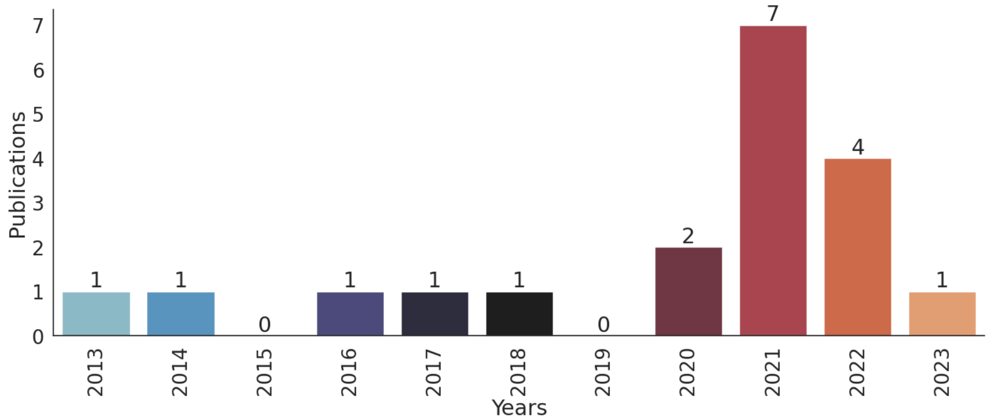

Figure 8. AR publications in the chemical industry over the years.

Regarding the number of publications in the chemical industry related to augmented reality, no specific journals or conference proceedings stood out, as all publications were associated with a single journal or conference. The distribution of scientific production by country reveals that Germany has the highest number of publications, totaling 18 articles. Following Germany, the United States has 12 publications, the United Kingdom has 7, and Italy and Poland have 6 publications each (Figure 9). The remaining countries, including Australia, Turkey, Belgium, China, Cyprus, the Czech Republic, and India, contributed with fewer publications, ranging from one to three article each.

It is important to note that these findings suggest Germany's prominence in terms of scientific output in augmented reality research within the chemical industry. The United States, the United Kingdom, Italy, and Poland also demonstrate substantial contributions to the field. However, the other countries mentioned have a relatively lower number of publications in this area.

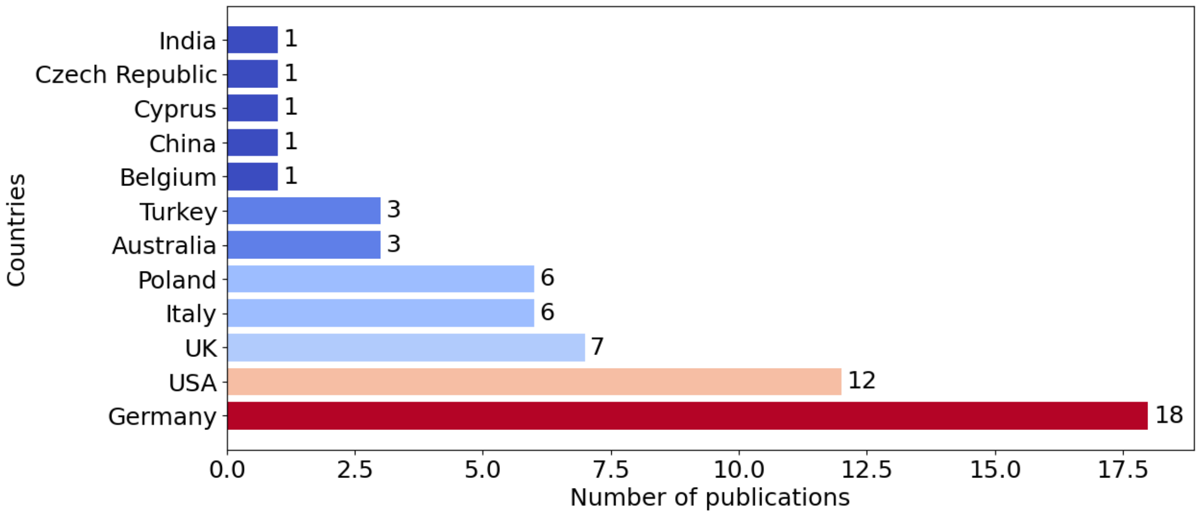

Figure 9. Countries' scientific production.

The word cloud presents the recurrence of "keywords plus", which are words or phrases that frequently appear in the articles, references, or titles in the sample, and not necessarily in the titles of the articles in the sample. Regarding the researched sample, 40 recurrent "keywords plus" were listed. The 10 principal terms can be systematically ranked by frequency to underscore the most prominent keywords within the dataset. "Generation" emerges as the most frequently occurring term, with a frequency count of four, indicating its heightened relevance. Closely following are "augmented reality" and "safety", each with a frequency of three, jointly occupying the second rank. The remaining terms—“challenges”, “cyber-physical systems”, “design”, “framework”, “knowledge”, “smart”, and “virtual reality”—each have a frequency of two, collectively constituting the third rank. This frequency-based ranking reveals that “generation”, “augmented reality”, and “safety” are the most salient terms, suggesting their critical role within the dataset (Figure 10).

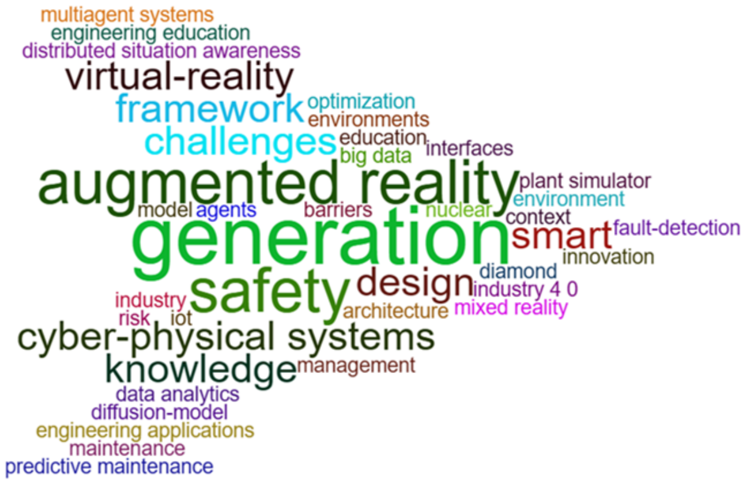

Figure 10. Most frequent words (keyword plus).

Making a qualitative analysis of the applications in the published articles, it is possible to observe the different uses intended for the chemical industry and augmented reality (Table 1) over time.

Table 1. Chemical industry applications.

Reference	Applications	Area
[30]	Corrective maintenance in chemical industries using augmented reality and digital twin.	Operation and Maintenance
[31]	Virtual reality (VR) and AR taxonomy in education.	Education
[32]	The study aims to develop effective cooperative coaching and learning systems that expedite the acquisition of fundamental construction skills.	Education
[33]	The study examines the use of AR in a practicum for training apprentices in the chemical industry.	Education
[34]	The study investigates the general approach to the concept of Industry 4.0 and levels of adoption of the basic Industry 4.0 technologies in manufacturing firms across Turkey.	Industry 4.0–Technology
[35]	To explore telescopic multi-resolution (TMR) in AR visualization, allowing for consistent approximation of interactions between microscopic and macroscopic systems through real-world measurements, interdisciplinary principles, and multi-scale visualizations.	Visualization–Technology
[36]	To identify the impact of Industry 4.0 technology on the international posting of workers considering the COVID-19 pandemic on the German chemical industry example.	Industry 4.0–Technology
[37]	Systematic literature review to identify immersive technologies applications published in the past twenty years and aimed to enhance the training and learning of operators in the process industry.	SLR for Education
[38]	To showcase how the American Fuel & Petrochemical Manufacturers (AFPM) and its members address competency training challenges and bridge the knowledge gap between generations of employees by developing a digital library of immersive learning tools, including VR and AR simulations, for broad industry use.	Education

Table 1. *Cont.*

[39]	To experimentally analyze the effectiveness of different training methods in bridging the gap between human–machine interfaces and training in the process industry, to improve reliability, cost effectiveness, environmental friendliness, and safety.	Education
[40]	Systematic literature review to assess the status of research in various domains of Industry 4.0.	SLR for Industry 4.0 Trends
[41]	To propose an approach to testing chemical, biological, radiological, nuclear (CBRN) reconnaissance hand-held products developed by additive manufacturing.	Additive Manufacturing and Immersive Technologies–Technology
[42]	To present state-of-the-art Industry 4.0 technologies and propose a strategic plan for integrating them towards achieving an autonomous smart plant for production management.	Industry 4.0–Technology
[43]	To develop a virtual sensor system for monitoring equipment aging in the chemical and process industry, providing prognostic estimates and displaying results in AR during safety walks.	Operation and Maintenance
[44–46]	To investigate the use of Bayfol® HX instant developing holographic photopolymer film in volume holographic optical elements (vHOEs) as lightweight and high-performance combiner optics for augmented reality systems.	Technology

In this sense, the studies above in the chemical and augmented reality area cover various topics, including maintenance, education, Industry 4.0, and testing, with the education domain being the most utilized. One area of focus is education, with studies exploring using AR and virtual reality (VR) technologies to enhance learning experiences and build fundamental skills in construction, apprentice training in the chemical industry, and operator training. In the process industry, these studies emphasize the potential of immersive technologies to facilitate knowledge acquisition and improve training outcomes. Another significant area of focus is Industry 4.0, with studies investigating its adoption in manufacturing companies. This includes examining levels of adoption of Industry 4.0 technologies and their effects on international labor markets, such as posting workers in the chemical industry. The objective is understanding the implications and challenges of integrating advanced technologies in industrial environments.

In the context of Industry 4.0, AR can be applied in the chemical industry to transform traditional practices by enabling more innovative, safer, and more efficient operations. This integration increases productivity and safety, which are particularly critical in the chemical sector. Therefore, some of the key applications and benefits of AR in the chemical industry within the framework of Industry 4.0 are detailed in Table 2.

Additionally, studies are exploring the use of augmented reality in maintenance operations, specifically corrective maintenance in chemical industries. Augmented reality systems and digital twin technology are utilized to improve maintenance processes by providing real-time guidance and visualization to technicians for efficient equipment inspection and repair. Furthermore, the application of immersive technologies in additive manufacturing is explored, particularly in testing portable chemical, biological, radiological, and nuclear (CBRN) recognition products. These studies focus on how augmented reality and additive manufacturing can be combined to develop and test prototypes, improving these products' design, functionality, and performance. Although the studies cover a diverse range of applications, the field of education emerges as the most used area in chemistry and augmented reality. This reflects the growing interest in leveraging these technologies for training, skills development, and knowledge transfer in educational environments.

Although AR offers solutions to several technical problems in the chemical industry, there are still some specific challenges where AR could have a significant impact, including: (i) superimposing real-time instructions on equipment, providing step-by-step guidance for maintenance; (ii) monitoring multiple parameters (e.g., temperature, pressure) and visualizing the data in real-time within the actual work environment; (iii) improve safety by highlighting hazardous areas and displaying emergency procedures; (iv) provide remote troubleshooting and problem-solving guidance; (v) enable trainees to safely learn procedures in a controlled, immersive environment, improving knowledge retention and reducing risk; (vi) display compliance checklists and standardized operating procedures directly in the work environment; (vii) assist in setting up new equipment; and (viii) simplify inventory management by overlaying item details, quantities, and storage locations. Accordingly, by addressing these challenges, AR could be an enabler for improving productivity, ensuring safety and maintaining high operational standards while reducing the time and costs associated with complex processes and regulatory compliance in the chemical industry.

Table 2. Applications and benefits of augmented reality in the chemical Industry.

Application	Benefits
Remote maintenance and troubleshooting	Minimizes equipment downtime, speeds up troubleshooting, reduces the need for technician travel, and improves the accuracy of repairs.
Operator training and skills development	Provides safe, hands-on learning experiences that are critical in the chemical industry, where safety and precision are essential.
Real-time process monitoring and data visualization	Improves process control by providing instant access to critical data, helping operators make faster, more informed decisions.
Digital twin integration for predictive maintenance and optimization	Reduces maintenance costs, extends equipment life, and improves operational efficiency by predicting problems before they occur.
Security and compliance enhancements	Improves security by reducing human error and ensuring compliance with security protocols.
Quality control and inspections	Streamlines the quality inspection process, reducing human error and enabling faster identification of defects or variations in product quality.
Real-time supply chain management and inventory tracking	Improves supply chain visibility, optimizes inventory levels, and reduces the time it takes to locate critical materials.
Enhanced laboratory and R&D environments	Improves the speed and accuracy of R&D activities by allowing scientists to visualize and manipulate complex chemical reactions or product formulations.

Alternatively, we can look at the cost/benefit potential of implementing AR in the chemical industry, which depends on several factors such as initial investment, training, and the benefits of improved efficiency, safety, and accuracy. In this sense, the initial costs of implementing AR in the chemical industry are indeed high due to initial hardware investment, software development and licensing, IT infrastructure and data security, training and management, and maintenance and support. However, the long-term benefits—such as reduced downtime, improved safety and reduced risk of accidents, extended equipment life, improved compliance and quality control, faster skills development, and increased operational efficiency—often outweigh these costs, offering a potential return on investment within a few years.

However, despite its considerable potential, the implementation of AR in the chemical industry also presents several key barriers and challenges that companies must address in order to use this technology effectively. These include:

- High initial investment, not only in software and hardware but also in infrastructure upgrades, as mentioned above.
- The high complexity of chemical processes requires a large amount of data from sensors, equipment, and operating systems. In addition, exposure to hazardous environments could limit the type of AR hardware that can be used, introducing additional safety risks to using the equipment.
- Technical and operational constraints related to the importance of accuracy and reliability in chemical processes and compatibility with legacy systems and regulatory standards.

- Specific and ongoing training may be required as AR technology evolves, which could be accompanied by some resistance to change from workers.
- Cybersecurity risks could lead to significant operational risks, regulatory penalties, intellectual property theft, and privacy issues, and there will be need to address any worker concerns about surveillance and data collection.
- Hardware durability for use in harsh chemical plant environments with exposure to chemicals, high temperatures, or dust. Battery life and connectivity are also meaningful.
- Scalability can be challenging and costly, so implementing AR across multiple plant sizes with appropriate integration with legacy systems requires careful planning and resources. However, overcoming these challenges can make AR a valuable tool for improving productivity, safety, and efficiency in the chemical industry.

4. Conceptual Framework for Augmented Reality Application

Creating an augmented reality application for the chemical industry involves a well-defined process to harmonize the integration of methods, techniques, and technologies (Figure 11). The first phase consists of the detailed planning of the application. All information about the project is collected and evaluated at this stage. This includes identifying application objectives, understanding the specific demands of the chemical industry, analyzing the industrial processes involved, and defining essential requirements. Next, data collection is carried out, covering both geometric and procedural information. These data serve as the basis for creating the models implemented in the application. The quality and accuracy of the data can ensure a faithful representation of the industrial environment.

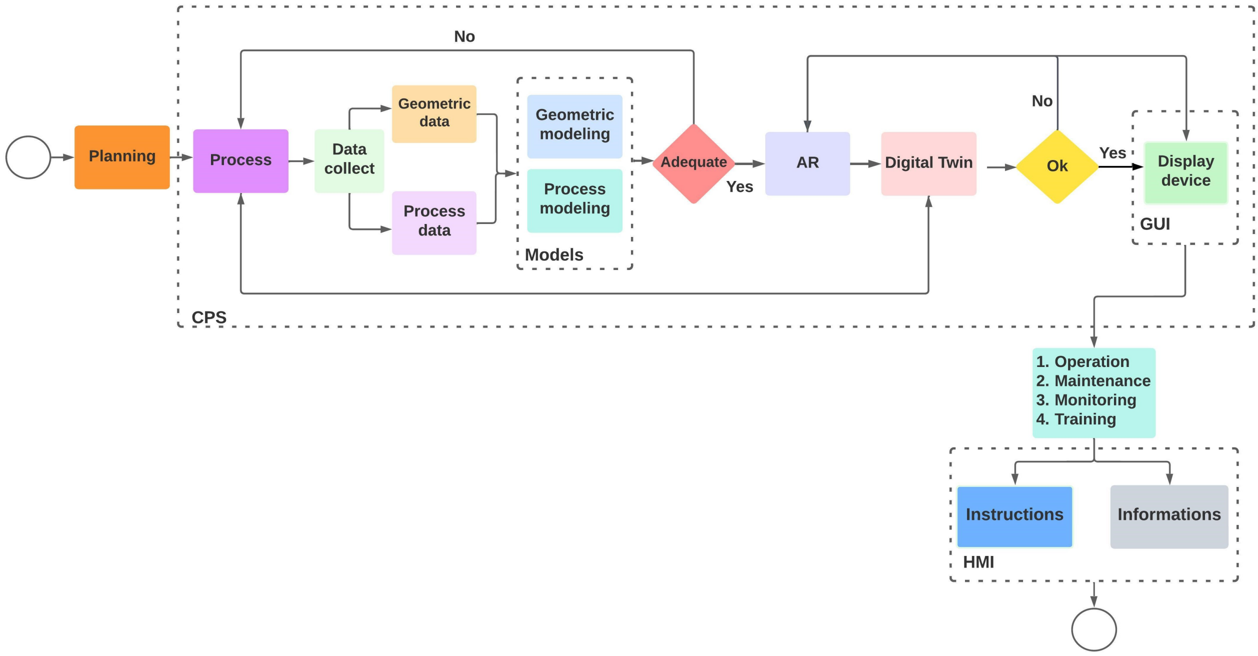

Figure 11. Conceptual framework for augmented reality application in chemical industry.

With the data in hand, models are created, which can be of different types. This step is followed by a rigorous validation process, in which the models are analyzed for accuracy and suitability. If discrepancies are identified, adjustments are made to improve the models. Once validated, the models are implemented in engines compatible with augmented reality and the digital twin. In this step, the modeling processes are united, and the type(s) of tracking will be adopted. Furthermore, the interface design is conceived with a focus on usability and user experience.

After implementation and integration, the application undergoes a detailed verification step. Simulations are conducted to ensure that the application meets established requirements and operates as expected. If flaws are identified, corrections are applied before proceeding. In the display device phase, tests will be carried out on the type and model of equipment chosen for the application (smart glasses, smartphone, projector, monitors). At the same time, the graphical interface is evaluated to ensure that the presentation of information is clear and compelling. Next, a description of each framework stage will be better detailed.

4.1. Planning

Applying augmented reality to the industrial area is a multidisciplinary task and requires a planning step. In the planning phase, it is necessary to define, prepare, organize, and structure the objective of the application. This phase is crucial as it lays the foundation for the entire development process. Some steps must be followed in this phase:

1. Defining the objective: Clearly articulate the purpose and goals of the AR application. Identify what problem or challenge the application will address in the industrial setting. It could be improving efficiency, providing real-time data visualization, supporting maintenance tasks, or enhancing worker training, among other possibilities.
2. Probing information: Conduct a comprehensive study to gather insights into the specific industrial processes, tasks, or areas to which the AR application will apply. This involves consulting with subject matter experts, stakeholders, and potential end-users to understand their needs and pain points.
3. Surveying tools and technologies: Investigate the various AR tools and technologies available in the market that align with the defined objectives. There are different AR development platforms, SDKs (software development kits), and hardware options, and choosing the right ones will impact the application's success.
4. Evaluating available resources: Assess the resources required for the AR application's development, such as personnel (developers, designers, content creators), hardware (AR devices, sensors), and software (development tools, licenses). Understanding the available resources will help determine the project scope and timelines.
5. Searching for information: Research existing AR applications in the industrial domain. Understanding what has been done before can provide valuable insights and ideas for your application. Additionally, researching best practices and user experience principles for AR can be beneficial.
6. Storyboard creation: Storyboarding involves creating a visual representation (sequence of drawings or images) of the AR application's user interface, interactions, and user experience. This aids in conceptualizing the app's flow, user journey, and overall narrative. Storyboards can be manually drawn on paper or created using digital tools, depending on the preference and expertise of the team.
7. Humanized content: AR applications often benefit from presenting data in a more humanized and easily understandable manner. Consider how the application can translate complex data into interactive and visually appealing elements that users can comprehend quickly.
8. Environment composition: Plan the design and layout of the augmented environment carefully. Consider how virtual elements interact with the real-world environment in the industrial setting. Designing an intuitive and seamless user experience is vital.
9. Scope and iterations: Define the scope of the initial release while keeping in mind that AR application development often benefits from iterative design and development. You may start with a minimum viable product (MVP) and then enhance and expand the application based on user feedback and evolving requirements.

4.2. Data Collection, Geometric and Process Data

After completing the planning phase, the subsequent step involves data acquisition, wherein information pertaining to the object to be implemented, be it a single component or an entire system, is collected. This data acquisition process encompasses both geometric and non-geometric data. Geometric data, fundamental for generating 3D geometric models, are acquired through various techniques, either in isolation or integrated together. Among the technologies utilized for geometric data acquisition, 3D scanning, particularly 3D laser scanning, is a prominent method in engineering applications.

The 3D laser scanning technique involves emitting pulsed or phased laser beams, primarily in the visible or near-infrared spectrum, and rapidly rotating or oscillating mirrors within the scanner to gather data from the object. The resulting dataset, known as a "scan" or dot coverage, provides detailed information about the physical contours and dimensions of the scanned object. The appeal of 3D laser scanning lies in its ability to rapidly and accurately capture object measurements, making it highly favored in engineering contexts [47].

Collecting process data for constructing a digital twin is crucial in the chemical industry. This practice involves the systematic acquisition and recording of relevant information throughout all stages of production, from the synthesis of chemical substances to storage and distribution processes, to create a precise and real-time virtual representation of the entire production process. Data collection plays a crucial role in building the "digital twin" in augmented reality, and it is carried out through various sources, such as sensors, monitoring systems, and historical records. The quality and quantity of this information are essential to ensure the accuracy and reliability of the virtual representation. These data provide the foundation for creating a detailed and precise replica of the physical object or system, allowing real-time simulations and analysis.

To achieve this, data related to production scheduling, such as timelines, task sequencing, and resource allocation, are collected. Additionally, information regarding production capacity and equipment availability is recorded. Operational data from machinery and equipment, such as speed, temperature, pressure, and production levels, is monitored to monitor the performance of chemical processes. IoT sensors in the facilities allow real-time data collection, providing a detailed view of the operations. Another essential aspect is collecting information about the sequence of steps in the production process, including execution times and interdependencies between activities. These data are essential for understanding workflow and identifying potential bottlenecks or optimization opportunities in the production chain.

In addition to the data mentioned above, various other types of information are collected in the chemical industry for the construction of the augmented reality digital twin:

- Chemical composition: detailed data on each product's chemical formula and composition, including component proportions and purity specifications.
- Chemical reaction parameters: data related to temperatures, pressures, reaction speeds, and other specific parameters that affect the outcome of chemical reactions.
- Quality control: information about quality tests conducted during production ensures that products meet standards and specifications.
- Raw material consumption: data on the quantity of raw materials used in each production stage and the material stock level.
- Emissions and environmental control: information about energy consumption, gas emissions, waste treatment, and other practices related to environmental control.
- Equipment condition monitoring: data on the health and integrity of equipment, such as piping systems, tanks, and reactors, to prevent failures and ensure safety.
- Safety and occupational health: information about safety measures adopted during production to protect workers and prevent accidents.
- Logistics and distribution: data on the transportation, storage, and distribution of chemical products, including supply chain information.
- Process data analysis: information collected from data analysis and statistics to identify trends, patterns, or optimization opportunities.

The data collected during all these stages is fundamental to creating an augmented reality digital twin of the chemical production process. This virtual representation enables the simulation, analysis, and optimization of operations. It is possible to identify patterns, predict issues, improve operational efficiency, and perform predictive maintenance to maximize efficiency and quality in chemical production through data analysis.

4.3. Modeling

This section describes the main types of models used in engineering. This field uses models for various purposes, including design, construction, optimization, control, industrial operation, and maintenance. In this sense, each model type has a different structure that aims to show specific aspects of the modeled system. Figure 12 shows a schematic tree diagram that classifies the models according to some characteristics. The first classification is based on the model type. According to this logic, Figure 12 shows that the models can be physical, mathematical, or geometric. The following topics describe each of the model types. In general, physical models are built as prototypes, mockups or pilot plants to visualize the system in a physically manipulable approach. Mathematical models, in turn, are widely used in engineering for design, simulation, optimization and control of industrial processes. Within engineering, the distinction between the applications of models is more diffuse since, in many applications, the model's characteristics, whether data-driven or phenomenological, are irrelevant. As an example, [48,49] shows that data-driven models can have very high performance for applications where, by default, engineering uses phenomenological models.

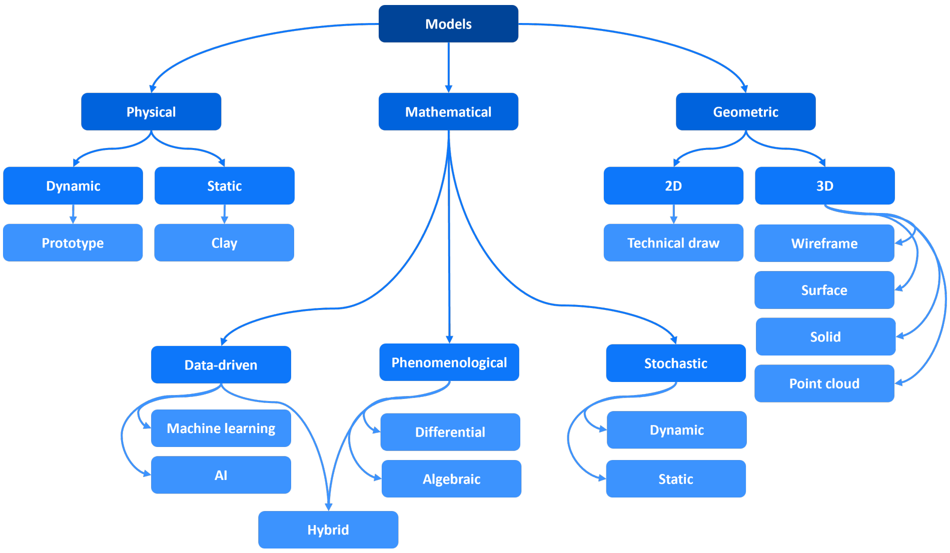

Figure 12. Model classification tree.

4.3.1. Physical Models

Physical models are used when a real-scale or reduced-scale physical representation of a given system is required. These physical models can be static when they are, for example, the clay models widely used in the automotive industry [50,51] and models in architecture. On the other hand, physical models can be dynamic when endowed with operating characteristics similar to the original system. In this set are included prototypes. Specifically in the oil and gas industry, industrial processes are commonly built on a laboratory scale, then on a reduced scale, and finally on an industrial scale. This sequence is known as scale-up [52–54].

It is considered, however, that physical models can be constructed in line with mathematical or geometric models. In this sense, with the emergence of 3D printing, prototypes and full-scale models of equipment or parts have become standard tools to aid in designing, planning, and operating industrial systems. In industry, 3D prototyping and additive manufacturing in operation sites helps in the execution of maintenance and assembly activities. As a consequence, the cost of operation and maintenance is reduced through the use of these tools [55–57].

4.3.2. Mathematical Models

Mathematical models, in turn, are essential tools in industrial plants' design and operation stages. These models can be divided into data-driven models, deterministic models based on fundamental laws of chemistry and physics, and stochastic models based on probability laws. This classification is not unique and will produce different combinations depending on the objective of the categorization.

Data-driven models have gained prominence in recent years due to the versatility of training, application, and use [49,54,58,59]. Data-driven models can be divided between machine learning and artificial intelligence. In both cases, the applications are varied. On the one hand, artificial intelligence seeks to build models and algorithms that mimic human behavior in decision making. On the other hand, machine learning is a branch in which the objective is to make a machine learn to reproduce a behavior observed in the data or encouraged by the reward functions.

In turn, phenomenological mathematical models are constructed based on fundamental laws [60–62]. The main characteristic of these models is that they have a theoretical basis and an excellent capacity for extrapolation. These models can be built based on differential or algebraic equations in the different possible applications. In the first case, the models obtained may be dynamic or not and dependent on spatial or temporal coordinates. In the second case, the models will not depend on differential terms of time or space but may explicitly depend on time or exogenous inputs. In both cases, the models can be used for applications that have or do not have an explicit dependence on time. Data-oriented and phenomenological models can be used to operate, control, and monitor production in industrial systems. However, some differences make the use distinct. On the one hand, data-driven models have a higher computational construction cost than models based on fundamental laws. On the other hand, phenomenological models are more challenging to build for complex systems and, in some specific cases, have a computational cost considerably higher than a data-oriented model.

Data-driven models are of great importance in building digital twins for process systems. That importance derives precisely from the computational cost involved in solving phenomenological models. In some applications, the numerical solution of a complex phenomenological model may have a running time close to the actual operating time of the system. This long processing time makes implementing a phenomenological digital twin difficult. On the other hand, using a data-oriented surrogate model allows several scenarios to be tested with less computational time. Additionally, when a digital twin is used for production planning and optimization, the optimization algorithms perform numerous objective function queries and solves each model during the problem solving. If the model used is based on fundamental laws, the computational cost of these applications can become prohibitive. On the other hand, using data-oriented models makes solving these problems feasible in parallel with the real process [63].

Another set of possible models is based on probability analysis. These models are known as stochastic. The main feature of these models is that they do not provide the same answer for the same input set, so the model prediction is obtained based on the probability of occurrence of concurrent events. Commonly, these models are used more frequently to represent financial or human systems. However, in industry, these models provide essential information in dealing with the reliability and probability of failure of instruments, equipment, and human beings in a factory site and the design and representation of queue management systems.

4.3.3. Geometric Modeling

In turn, geometric models are used for representations in two or three dimensions to provide critical information for industrial systems' design, construction, operation, and control. Specifically, in the case of technical drawing for the process industry, the diagrams are built based on the ISA 5.1 standard [64], which defines all the elements and lines that can and should be used so that there is a standardized understanding of the symbology.

Different models are used during the operation of an industrial plant, including floor plans, isometric diagrams, control diagrams, and instrumentation. Additionally, each subsystem of the industrial plants has specific designs and points of interaction with the other subsystems.

Still, in the context of geometric designs, the 3D geometric model can be characterized as a set of information of an object stored in a computer. This information concerns the topology of the object, such as connections of vertices, edges, surfaces, and volumes, as well as their dimensions, contours, and tolerances, and there may also be derivations of the shape to specify materials and other properties [65]. The principal types of geometric models include wireframe, surface, solid, or point cloud models.

- Wireframe: Also known as wireframe models, these are 3D representations consisting solely of lines and edges without any surface presence. These models are useful for visualizing the basic structure of the object but do not provide detailed information about its form [66].
- Surface Models: In this type of model, in addition to lines and edges, the surfaces of the object are represented. However, these surfaces are considered “empty” or without thickness, meaning they lack volume. Surface models are commonly used in design and visualization applications.
- Solid Models: Solid models are 3D representations with volume that define the object’s complete shape, including its surfaces and interior. These models are more complex and provide detailed information about the object’s geometry, making them widely used in engineering, manufacturing, and simulations. The complete modeling calculates mechanical properties such as weight and center of gravity [67].
- Point Cloud Models: The object’s surface is represented as a collection of three-dimensional points in this model type. Each point has X, Y, and Z coordinates, and together, they form a point cloud that describes the external shape of the object. Point cloud models are useful for capturing the geometry of complex objects and for detailed analyses such as surface reconstruction and precise measurements [68].

The choice of geometric model type depends on the specific purpose of the application and the level of detail required to represent the object adequately. Each model type has its advantages and limitations, and the decision of which one to use will be based on the needs and requirements of the project.

Specifically for process industry applications, 3D models are primarily used in manufacturing sites’ design and construction stages. Despite the advanced digitization of industrial processes and the use of advanced process simulators, 3D models and the construction of digital twins for iterating and managing industrial processes lack development and boosting of applications.

Good practices during the modeling process require a cyclical approach to building, validating, and using models [69]. Regardless of the type of model used, the steps involve the proposition of the model, choice of parameters when applicable, evaluation of the prediction or representation capacity, validation, and final adjustments before use. In this sense, Figure 1 presents a closed cycle that indicates that the model can be entirely reconstructed if it does not meet the requirements. It is considered, additionally, that this reassessment can and should be carried out throughout the useful life of the model, mainly in the context of dynamic models that may undergo modifications during operation so that the model deviates from the observed behavior and, consequently, no longer represents reality.

4.4. Augmented Reality

After the geometric and process modeling, an assessment is conducted to determine whether the collected data align with the intended objectives of the application. In cases where geometric models are exported, it is essential to monitor for any potential loss of geometry, which may necessitate revisiting the previous phase. Once the geometric and process models are deemed satisfactory, the subsequent step involves implementing the model for visualizing the digital twin in augmented reality.

During this phase, the selection of the object tracking system and visualization equipment, such as the display device, is determined. The primary goal of tracking systems is to calculate the real scene's orientation based on captured images, ensuring accurate positioning of virtual objects that will be incorporated into the background [6,70]. The selection of tracking technology depends on the sort of environment, the sort of data, and the availability of required budgets. These tracking techniques can be categorized as sensor-based, vision-based, or hybrid, depending on whether they rely solely on sensors, solely on visualization, or on a combination of both methods [71]. Some of these techniques are as follows:

- Vision-based tracking—using markers—The tracking technique using markers is characterized by using cards containing a symbol inside. The markers must be previously registered in the system so that the software can recognize their pattern and connect with the virtual object. It is considered the simplest technique [72]. Some factors may interfere with marker recognition, such as (i) ambient lighting, (ii) camera orientation of the marker, and (iii) registration of markers with similar patterns [73]. A requirement of this technique is the need for a visual range for the marker to be recognized by the system [71].
- Vision-based tracking—markerless—This technique recognizes the image through "natural" markers, that is, through objects in the scene. In this technique, any part of the natural environment can be a marker. The advantage of this technique is that it does not introduce elements that are not part of the scene into the environment, such as a printed marker. However, the tracking to be developed tends to be more complex and specific [74]. In this technique, the tracking of objects in the environment can be performed with the characteristics of the points, lines, edges, and textures present in the objects.
- Sensor-based tracking—Systems using the sensor-based tracking technique may rely on acoustic, optical, mechanical, inertial, and magnetic sensors. For this, they can use the following methods: Global Positioning System (GPS), Wi-Fi, Bluetooth, ultrasonic sensors, infrared, and radio frequency identification (RFID), among others [71].

Regarding the benefits of visual tracking, one can enumerate accuracy, stability, and widespread applicability. Nevertheless, it comes with the drawback of necessitating a physical marker for marker-based tracking and being vulnerable to variations in ambient lighting conditions. Conversely, markerless tracking can be employed in diverse environments and alleviates registration interruptions by leveraging natural features. However, it entails a trade-off between real-time performance and registration accuracy. Sensor-based tracking exhibits the advantage of rapidity and simplicity in its registration algorithm, albeit occasionally incurring higher costs and restricting natural interactivity due to the need for extra facilities and calibration. The hybrid technique complements each component to achieve maximal functionality.

4.5. Digital Twin

After completing the stages of data collection, geometric model development, process model construction, and evaluating the effectiveness of representing these approaches, it is time to integrate these two tools to create a digital twin in an augmented-reality-enhanced environment. This process is conceptually illustrated in the flowchart presented in Figure 11.

As previously mentioned, the digital twin of an industrial process represents, virtually and in real time, a physical system or process in the digital environment. By collecting and integrating data from sensors and other sources, this digital model faithfully mirrors the characteristics and behaviors of the real-world object, enabling precise monitoring, simulation, and optimization of its performance. With valuable insights provided by the digital twin, decisions are made in an informed and strategic manner, while virtual tests allow the identification of potential improvements and anticipation of issues in the physical world [75–77].

The digital twin of augmented reality goes beyond a mere virtual representation of the industrial process. Its true strength lies in the continuous real-time integration with the physical system, making it a faithful and dynamic copy of the real process, instantly reflecting any change, update, or relevant event [78,79]. Through this continuous integration, the digital twin receives real-time data from sensors, equipment, and other sources, ensuring that its virtual model remains synchronized with the ever-evolving reality of the industrial process. This approach provides an accurate and up-to-date view of the system at hand [80,81]. Furthermore, the close relationship between the digital twin and the industrial process allows for applying advanced techniques such as artificial intelligence and machine learning. With the continuous flow of real-time data, the digital twin learns from the behavior of the physical system and enhances its predictions and analyses, generating even more value and insights for the operation [82,83]. The digital twin offers several advantages to the process, one of them being its ability to anticipate the performance of the product or system, identifying and predicting potential issues, which guides towards proper optimization. This approach significantly advances the accuracy and efficiency of material selection used in the product [84] and enables detailed monitoring of the evolution of dynamic parameters.

The innovative methodology based on digital twins enables this optimization by combining static analyses with dynamic executions [85]. The digital twin plays a crucial role in this process, allowing the monitoring of the design stages' history and tracking improvements over time, ensuring a highly effective iterative optimization. By refining the focus on iterative optimization, we attain a high-level design, incorporating continuous improvements in the product's conception, from its initial phase to the finest detail [86]. This approach goes beyond the limitations of traditional simulations, which often overlook crucial aspects of project success. With the assistance of digital twins, it becomes possible to thoroughly explore the complex interactions of the system, identify areas for improvement, and make informed decisions at every stage of the design process. This results in more robust, efficient products that align with market and customer expectations [87].

Integrating digital twins with augmented reality is a powerful combination that allows for a comprehensive and in-depth evaluation of the industrial process and the physical structure of equipment from various perspectives. This synergy between the technologies provides a new level of interactivity and immersion, empowering operators and engineers to explore the process's and equipment's vital details in real time. This makes decision making more informed and proactive, enabling agile problem solving and continuous improvement of industrial processes [83]. Beyond operational benefits, integrating digital twins and augmented reality opens up new possibilities in training and development. Professionals can acquire knowledge and skills in a secure virtual environment, simulating real-life situations without the associated risks of the physical world. This provides more comprehensive and efficient training, preparing them to handle diverse and challenging scenarios in the workplace. In summary, the fusion of digital twins with augmented reality enhances industry's efficiency, safety, and learning capabilities, paving the way for a new era of innovation and progress in the industrial sector.

It is crucial to emphasize that a digital twin is more than a static representation; it is a resource in constant evolution. To maintain its relevance and effectiveness over time, it must undergo a process of continuous improvement. This entails constantly updating the data and parameters in the model, incorporating real-time information from the corresponding industrial process. Through this dynamic exchange of information, the digital twin can accurately mirror the current conditions and performance of the real system. In Figure 11, this exchange of information is exemplified by the established connection between the digital twin and the actual process, supporting the concept of continuous learning and bidirectional information exchange.

4.6. Display Device

In this step, tests will be carried out with the visualization system chosen for the application. Visualization systems can be classified according to the devices used. These systems employ a combination of optical, electronic, and mechanical components to generate images somewhere along the trajectory of human vision, i.e., between the observer's eyes and the real environment where the virtual object will be inserted. Depending on the optical system used, the image of the virtual object can be generated on a plane or a more complex surface [9].

Ref. [88] classified these types of systems as follows: (i) non-immersive video-monitor-based, (ii) immersive video-monitor-based, (iii) direct optical vision optical see-through, (iv) video see-through, (v) entirely graphic video display environments, and finally (vi) entirely graphic display environments with interference from real objects (Figure 13). In the non-immersive video-monitor-based system, as the name implies, computer-generated elements are digitally superimposed through monitors, whereas in the immersive video-monitor-based system, immersive head-mounted devices are used. The direct optical vision system refers to a head-mounted device equipped with a display, where computer-generated elements can be overlaid and directly viewed in the real environment. On the other hand, in the video vision system, the real environment is viewed through a video feed, and virtual objects are superimposed.

Figure 13. Video and optical see-through types of devices.

Fully graphical display environments present the real-world environment through video and incorporate physical objects that interact with the synthetic environment, allowing users to reach or pick up objects using their hands. Alongside conventional devices, there are ongoing developments in other systems designed for specific user interactions [88]. The device type selection, alongside equipment costs, relies heavily on the intended application. For instance, smart glasses are particularly well-suited for equipment maintenance tasks, where workers must keep their hands free. However, their broader adoption is hindered primarily by the lack of knowledge in effectively integrating smart glasses into production workflows [89]. Conversely, smartphones are more commonly used in AR applications due to their affordability, user-friendliness, and widespread accessibility. The versatility and convenience offered by smartphones make them a preferred choice for AR experiences. Continued research and improvements are essential to unlock smart glasses' full potential and expand their adoption in various industries and applications.

5. Digital Twin AR in Chemical Industry

Combining digital twins with augmented reality technologies has proven extremely promising in the chemical industry, offering a range of innovative applications and significant advantages. Here are some of the diverse ways in which the integration of digital twins with augmented reality has been applied in this sector:

- Enhanced Maintenance and Repair: The creation of accurate digital twins of complex chemical equipment enables technicians to perform maintenance and repairs with overlaid real-time information. Using augmented reality devices, technicians can visualize performance data, maintenance histories, and repair instructions directly onto the equipment, facilitating problem detection, decision making, and the execution of complex tasks.

- Training and Simulation: Combining digital twins with augmented reality provides operators and technicians with advanced training opportunities. Realistic simulations of operational scenarios allow professionals to familiarize themselves with processes and procedures before encountering real-world situations, reducing errors and enhancing efficiency.
- Real-Time Process Monitoring: Digital twins can be fed with real-time data from chemical processes, and augmented reality allows these data to be intuitively and immersively visualized. This enables operators to monitor critical parameters, identify trends, detect anomalies, and take preventive measures more effectively.
- Workflow Optimization: Augmented reality can overlay contextual information onto operators' work environments. By combining this information with data from digital twins, operators can optimize workflows, minimizing the time needed to access information and make decisions.
- Design and Layout Planning: In the design and planning phase of new chemical facilities, digital twins can assist in visualizing layouts, identifying potential issues, and optimizing design. Augmented reality enables engineers and designers to visualize 3D models of projects at an accurate scale and make adjustments before physical construction.
- Remote and Shared Collaboration: Distributed teams can benefit from augmented reality to collaborate on projects, diagnose issues, and resolve maintenance problems. Overlaying information from digital twins in shared environments allows remote experts to provide real-time guidance.

While AR combined with digital twin technology offers innovative ways to improve operational efficiency and training in the chemical industry, mobile and tablet-based solutions can offer practical advantages that make them more effective in certain scenarios. Their user-friendly interfaces, flexibility for training, and enhanced collaboration capabilities position them as valuable tools, especially in the early stages of process implementation or when team collaboration is critical.

Organizations should assess the specific needs of their operations and consider how mobile solutions can complement, or even serve as an alternative to, AR, ensuring that the chosen technology is aligned with their goals for training, communication, and operational effectiveness. A hybrid approach that utilizes both mobile solutions and, where appropriate, AR technologies may also deliver the best results, combining the strengths of each to address the diverse challenges of the chemical industry.

It is important to highlight that this entire process is iterative and interdisciplinary, where experts in augmented reality and digital twins, chemical engineers, computer scientists, and user interface professionals collaborate to achieve the best results. Therefore, applying digital twin augmented reality in the chemical industry demands a well-structured and careful process integrating several technologies. The required operations span a wide range, from operation and maintenance to industrial process monitoring and training. This resource integration streamlines global management and can improve decision making, operational control, continuous learning, and other essential facets of industry.

Additionally, this proposed mix of augmented reality with digital twins allows for more realistic immersion during training and simulation in industry. In this case, during immersive training, the proportions of flows, volumes, and other physical properties can be perceived in a more user-friendly way. On the other hand, pure mathematical models, such as differential or algebraic equations, or process simulations, such as those used in process-flow simulators, require higher analytical and abstraction skills. Likewise, if an augmented reality model is adopted that is not faithful to the process issues, the analysis may be impaired. Thus, this paper argues that a joint approach should be sought since the use of augmented reality is directly aligned with the ability of new generations to learn in virtual environments and to be typically more adapted to immersive activities. Additionally, the associated use of models will allow for a more accurate physical understanding of the process.

However, despite its considerable potential, the implementation of AR in the chemical industry also presents several key barriers and challenges that companies must address to use this technology effectively. These include the following:

- High initial investment, not only in software and hardware but also in infrastructure upgrades, as mentioned above. Chemical processes are highly complex and require a large amount of data from sensors, equipment, and operating systems. In addition, exposure to hazardous environments could limit the type of AR hardware, introducing additional safety risks when using the equipment.
- Technical and operational constraints related to the importance of accuracy and reliability in chemical processes and compatibility with legacy systems and regulatory standards.
- Specific and ongoing training may be required as AR technology evolves, accompanied by some resistance to change from workers.
- Cybersecurity risks could lead to significant operational risks, regulatory penalties, and intellectual property theft; privacy issues must address worker concerns about surveillance and data collection. Hardware durability is critical in harsh chemical plant environments where workers are exposed to chemicals, high temperatures, or dust. Battery life and connectivity are also necessary.
- Scalability can be challenging and costly, so implementing AR across multiple plant sizes with appropriate integration with legacy systems requires careful planning and resources.

Some limitations can be highlighted, such as the bulkiness and discomfort of AR devices and their limited battery life, which are indeed significant barriers to the widespread adoption of AR in the chemical industry. Then, the high costs and specialized skills required for developing and maintaining AR content pose substantial challenges. Addressing these issues will require advances in AR hardware design to improve usability and battery life and investment in training and resources to support the creation of high-quality AR content. By overcoming these barriers, companies can better leverage the benefits of AR to improve safety, training, and operational efficiency.

Data security and privacy issues are also critical to the successful implementation of AR in the chemical industry, particularly given AR's reliance on real-time data from potentially sensitive sources. These concerns include risks to intellectual property, unauthorized access, and data breaches. Organizations must prioritize these aspects in their AR strategies by adopting robust encryption, secure data transmission protocols, and strict access controls. Furthermore, investing in employee training and awareness ensures adequate protection of sensitive data and maintains stakeholder trust.

From another perspective, environmental conditions and integration with legacy systems significantly impact the practical implementation of AR in the chemical industry. Addressing these limitations requires advancements in AR technology to enhance sensor performance in demanding environments and the development of strategies to integrate AR into existing systems seamlessly. As industry evolves and technology advances, overcoming these barriers could enable broader adoption of AR, ultimately enhancing operational efficiency, safety, and training within the chemical sector.

Therefore, overcoming these challenges can make AR a valuable tool for improving the chemical industry's productivity, safety, and efficiency.

Implementation Aspects

Adopting a systematic approach that considers practical, technical, and cultural aspects is essential to overcome the limitations of adopting augmented reality (AR) in the chemical industry and ensure that it is implemented effectively. Some strategies to consider follow:

1. Start with small-scale pilot projects to demonstrate the value of AR, collect feedback, and refine applications before expanding them. In the context of AR, starting with small-scale projects allows the company to validate the applicability of the technology in its specific environment without the financial and operational risks of full implementation from the beginning. In addition, by starting with a scaled-down version,

it is possible to collect genuine feedback from employees and stakeholders, identify potential improvements in the developed solutions, and adjust the functionalities to better meet the needs of the team and operational challenges.

2. Partner with AR technology providers and experts in the chemical field to create tailored solutions that address specific challenges and regulatory requirements. Collaboration with experts in the chemical industry is essential for AR solutions to be appropriate and effective. Working with experts makes it possible to develop tailored solutions that meet these specific requirements and ensures that AR implementation is aligned with industry regulations.
3. Focus on developing AR solutions that integrate seamlessly with existing digital systems and processes to minimize disruption. Integrating AR into existing digital systems and processes prevents the implementation of the technology from causing operational disruption. Like any other industrial sector, the chemical industry already has well-established processes and digital systems that manage data, operations, and production logistics. The introduction of AR should be done in a way that does not interfere with these processes but rather complements and optimizes existing operations. The transition to AR use should be smooth, with an implementation process that minimizes the impact on day-to-day operations and ensures that employees can continue their activities without interruption.
4. Implement training initiatives that emphasize the benefits of AR and ensure that employees feel confident in using the technology. One of the main barriers to adopting new technologies is employee resistance. To overcome this resistance, it is essential to implement training programs that clearly explain the benefits of AR and show employees how it can improve their daily work. Additionally, employees will feel more confident about adopting the technology by promoting an understanding of the tangible benefits of AR, such as increased safety, reduced errors, and increased efficiency.

6. Conclusions

Augmented reality, despite its transformative potential across industries, remains underutilized in the chemical sector, suggesting that efforts to exploit the potential of AR for industrial applications fully may be lacking in research and development. This study reviewed the current state of AR in various industries and proposed a structured guideline for its integration into industrial processes. Initial research aimed to identify the use of AR in industry, which uncovered 2157 documents on the Web of Science with "augmented reality" and "industry" as keywords. Data analysis revealed a growing trend in industrial AR research over recent years, highlighting top journals, country contributions, and commonly cited visualization devices. Primary and secondary sectors within industrial AR applications were examined, with a focus on chemical industry bibliometrics, analyzing publications over the last decade by country and topic, where education—especially in training, skills development, and knowledge transfer—was a dominant area. The result of this work was the formulation of a guideline for the application of augmented reality in the chemical industry, which provides a comprehensive description of each stage.

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