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Review

Analysis of Enterprise Internet of Things Maturity Models: A Review

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Abstract: Maturity models are valuable tools when assessing the readiness and progress of technology incorporation in organizations, providing information for decision-making, resource allocation, and competitive advantage. The Internet of Things is a technology paradigm of global importance, especially for organizations, as it supports productivity improvements, real-time analysis, and customer satisfaction. Therefore, adopting and implementing this technology in enterprises brings several challenges, such as technological, organizational, security, and maturity issues. However, secondary studies that systematically compile the existing literature on these specific mechanisms for the enterprise domain are still being determined. This article aims to address this knowledge gap by conducting a review to deepen and synthesize the existing knowledge. This research followed established methodologies and protocols to synthesize and analyze the state of the art in the area; 489 documents were retrieved from seven bibliographic databases, and, applying inclusion and exclusion criteria, 36 primary studies were selected. The results indicate that the typical structures of maturity models incorporate technological, organizational, human, performance, and security dimensions through graded levels that denote the sophistication of the Internet of Things. Measurement techniques and metrics vary from model to model. There are few empirical validations or standardized improvement frameworks. The main conclusion is that there is a diversity of models, dimensions, indicators, and methods and a need for more comprehensive, adaptable, and user-friendly tools to help companies assess their Internet of Things maturity and inform future development strategies.

Keywords: maturity models; Internet of Things; companies; technology management

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1. Introduction

The Internet of Things (IoT) is a technological paradigm involving the interconnection of physical objects equipped with sensors, computational capabilities, and software, enabling them to communicate and exchange data with other devices and systems over the Internet or networks [1,2]. IoT has emerged as a globally important technology with significant societal impact in multiple domains [3]. At the societal level, IoT can improve the quality of life by creating smart homes, intelligent transportation systems, and innovative methods of managing health, safety, and security [4,5]. In the context of businesses or organizations, IoT facilitates improvements in various aspects, such as asset utilization, reliability, productivity, production analysis, identification of market trends, and supply chain management [6]. This technology also enables companies to increase efficiency, speed up processes, reduce errors, avoid theft, and implement complex and flexible organizational systems [7]. This translates into added value for the organization by providing additional services based on the company's personalized customer service.

Along these lines, technological maturity refers to the level of advancement or progression that a given technology or innovation has reached in a specific context, sector, or organization [8]. The IoT, due to its importance for companies and its potential advantages, requires periodic evaluations of its technological maturity in organizations [9] because they yield critical data on the degree of adaptation and deployment of technology [10], facilitating the improvement of decision-making processes, the efficient allocation of resources, the optimization of technological functionalities [11], and the proactive management of risks [12] and competitive advantages. It also plays a crucial role in fostering innovation and driving digital metamorphosis [13]. By assessing their technological maturity, organizations are better equipped to make well-informed decisions about future investments in IoT and other technologies [9].

Considering the above and IoT's benefits to organizations, several challenges have emerged regarding adopting and implementing this technology in enterprises. In this regard, there are challenges in different areas of the enterprise, such as technological challenges involving the integration of IoT with other technologies [14]. Also, organizational challenges include employees needing more skills or knowledge and top management commitment [15]. There are also challenges related to the immaturity of industry standards [16] and security challenges, which have to do with privacy concerns and protection mechanisms [17]. Fundamentally, challenges are associated with determining IoT technological maturity within the organizational context, such as the rapid pace of technological advancement that complicates the ability of companies to keep up with and accurately assess their current technological situation [18]. Another challenge is the continuous need for companies to adapt and evolve their solutions to remain competitive [13]. Challenges related to specific mechanisms are related to the need for comprehensive, adaptable, and easy-to-use tools that help companies assess their IoT technology maturity and inform their future development strategies [13,19].

Several mechanisms have been developed, given the importance of assessing IoT technological maturity in enterprises. Among them are technology appropriation indices [20], scorecards [13], and maturity models [21,22], the latter being the primary mechanism for this task and the most reported in the existing literature [18]. However, there is a gap in this domain because, although there are studies that compile the existing literature on maturity models for enterprise IoT, they lack a systematic characterization of internal measurement processes. Furthermore, they do not indicate how maturity models support practical post-measurement improvement within organizations. This deficiency hinders effective benchmarking and implementation of improvement strategies, leading to a lack of systematic understanding of the field and an incomplete consideration of the domain, leading to redundancies, lack of standardization, and superficial solutions [23,24]. Therefore, a comprehensive synthesis methodically relating to empirical evidence in this field is needed. In this sense, a knowledge gap has been generated that could affect the development of maturity models that estimate the readiness of IoT technologies and their effective deployment in enterprise environments, so this study aims to address it.

The main objective of this review is to deepen and synthesize the existing knowledge on maturity models specific to the enterprise IoT domain. It covers aspects such as their inner workings, dimensions considered, model validation methods, and future work, providing an in-depth view of the state of the art in this area and offering insights for future research and practical implementations.

The structure of this paper is organized systematically and logically. Section 2 provides an overview of existing studies that align with the current research. Section 3 details the methodology employed in this review. Section 4 delineates this study's implementation. Section 5 presents this study's findings and addresses the research questions. Section 6 discusses potential threats to this study's validity and critically evaluates these threats. This paper concludes with section seven, summarizing the research and suggesting areas for future exploration.

2. Related Works

In this section, a detailed analysis of secondary studies like the present research is performed, considering both analogous aspects and divergent elements. As noted above, few reviews compile existing information on maturity models for enterprise IoT due to their novelty and continuous ad hoc developments in this field. One example is the research by Benotmane et al. [25], where, based on a literature review, they seek to develop a holistic maturity model for enterprise IoT. The main results identify several challenges and limitations of current maturity models for IoT, such as the lack of specific assessment approaches for this technology and the diversity and heterogeneity of environments. The literature review is a preliminary step to building a new maturity model, so the main objective of the research is not to characterize the domain. Another perspective review is [19], which explores maturity models for the Industrial Internet of Things in the context of Industry 4.0. The results of this review indicate that while the concept of maturity and maturity models has gained considerable attention in recent years, they are still in a relatively early stage. Furthermore, they highlight that existing maturity models are often based on user opinion surveys, which hinders an objective assessment of technological progress and the knowledge stack.

Another secondary study is the proposal by Parab and Deshmukh [26], where they review the literature on maturity models for Small and Medium Enterprises (SMEs), focusing on adopting and implementing IoT in their manufacturing processes. The authors acknowledge that IoT is a crucial catalyst for the fourth industrial revolution but note that SMEs encounter numerous obstacles and barriers to fully exploiting its potential, stating that there is a need for more comprehensive and appropriate mechanisms to assess SME readiness and maturity for the technology. Their review identifies and analyzes eight maturity models regarding dimensions, maturity levels, and gaps. The results indicate that none of these mechanisms meet all the criteria for accuracy, clarity, and objectivity. They also note that most models do not consider readiness, operational performance, and organizational and environmental factors, highlighting that these mechanisms lack generalization and empirical validation with data.

Another review in the domain is [27], which identifies maturity models for IoT and their applicability to SMEs in the manufacturing sector, leading to the identification and analysis of 24 relevant studies. The authors present a comparative analysis of IoT management regarding its dimensions, levels, and objectives. The authors indicate that most mobility management applications are designed for the manufacturing industry, but only a few are specifically tailored for SMEs. Numerous maturity models exist with dimensions covering manufacturing capabilities, technology maturity, and organizational readiness, and most models define progressive maturity levels from an initial stage to an advanced stage. They also identify shared objectives, such as improved performance, quality, efficiency, and innovation. The authors stress the need for further research and development of maturity models specifically designed for SMEs, considering their unique characteristics, needs, and challenges.

In this line, other relevant papers are the proposals of Pino et al. [28,29]. These papers correspond to a systematic review and a systematic literature mapping; both focused on the general domain of mechanisms to measure IoT technological maturity in organizations. These two papers explore and deepen the domain using a methodology like the one proposed in the present research. However, their approach is more comprehensive than a single type of mechanism, such as maturity models, representing a gap in the existing knowledge that this study seeks to address.

In this context, previous research indicates that, although secondary analyses have been conducted in the domain of maturity models for enterprise IoT, they focus on specific areas or contexts or superficial aspects of the domain. This highlights the need for greater specificity and depth in constructing these measurement mechanisms. In addition, several studies perform a non-systematic search (naïve searches) to characterize maturity models, which implies a lack of specificity in the protocols used [22,30]. Therefore, this research aims to characterize the literature in detail, focusing on the inner workings of maturity models, the dimensions considered, and possible future work derived from these mechanisms.

3. Review Planning

Review is a form of secondary research that employs a rigorous and reproducible methodology to identify, select, and aggregate all existing evidence within a particular field or topic. Research questions guide this process and involve accepted methodologies to obtain the answers. The approach is formalized and systematic to minimize research biases [24,31].

The review on the domain of maturity models for enterprise IoT employed two guiding methodologies for this research (Figure 1). First, Petersen et al. proposal [32], widely accepted within the engineering domain, was used. In addition, specific guidelines from the PRISMA protocol [33] were used to screen the studies. This research was executed in five main stages, namely, (1) definition of the research questions, (2) search for studies in databases, (3) review of identified papers based on inclusion and exclusion criteria, (4) classification of papers (primary studies), and (5) data extraction and answering the research questions posed. Finally, each stage of the research process produced results that served as inputs for the subsequent stages, ensuring a systematic and rigorous approach to this study.

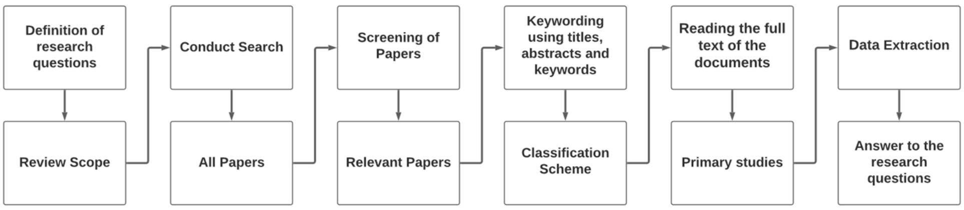

Figure 1. A methodological process was followed during this review.

To carry out this review in the specific domain, some theoretical references were adopted, such as the proposals of Parab and Deshmukh [26] and Benotmane et al. [25], which provided a framework for the domain analysis. Likewise, specific methodological guidelines proposed in the Science Mapping Workflow were followed for study collection, data collection, analysis, and visualization.

During the execution of this research, some software tools were used, such as Parsifal version 2.2 [24], a platform for planning, conducting, and reporting the literature review process, which is recognized as an excellent support for conducting this type of study. RStudio version 2022.12.0+353 [34], a programming environment for the R programming language, and Google Sheets [35] were used to create some graphs. Finally, litsearchr [36], an open-source R library, was used to identify the appropriate terms for constructing the search strategy using text mining techniques.

Finally, it is essential to note that this review follows the PRISMA protocol guidelines. In addition, the detailed protocol has been registered in the Open Science Framework repository to improve the reproducibility of this research. The protocol is available at the following link: https://n9.cl/auqb6t (accessed on 10 September 2024.).

3.1. Definition of the Research Questions

The research questions posed in this study aim to examine and deepen the internal operability of the maturity models proposed in the scientific corpus. They seek to understand the dimensions and factors considered in their construction and explore probable future research lines that may arise from these measurement tools. Table 1 shows each research question and its justification in this context, facilitating the domain information's selection, analysis, and categorization.

Table 1. Research questions posed in this review.

Questions	Sub-Questions	Motivating
How are maturity models defined in the context of enterprise IoT?	How are internal measurement processes performed within the proposed mechanisms? What do the proposed IoT maturity models consider as the main dimensions? What metrics are associated with assessing the maturity levels of the proposed maturity models in the domain?	Gain a comprehensive understanding of maturity models, their definitions, dimensions, capabilities, and associated metrics in the IoT domain.
Do the proposed maturity models support improvement after measurement in the enterprise IoT domain?	How are measurement data used to support maturity improvement in organizations?	Understand the effectiveness and application of IoT maturity models to drive organizational improvement.
How has the proposed maturity models' contribution, usefulness, value, or effectiveness been validated in the organizational IoT domain?		Explore how validation methods for the proposed maturity models have progressed over time.
What are the future work, potential improvements, or future directions derived from the proposed maturity models in the domain?		Identify trends, future work, or improvement opportunities concerning the proposed maturity models in the domain.

3.2. Construction of the Search Strategy

A systematic search chain approach was adopted to ensure a methodologically rigorous and reproducible review (Table 2). This approach involved formulating the search chain based on the PICOC criteria (Population, Intervention, Comparison, Outcome, Context), a mnemonic structure for establishing consistent search criteria [24]. This facilitates the structured organization of concepts and effectively covers the relevant topics in the domain of maturity models for IoT.

Table 2. Search strategy applied to different scientific databases.

("Internet of Things" OR "IoT") AND ("maturity model" OR "Capability maturity index" OR "maturity index" OR "maturity level" OR "technology maturity index" OR "readiness assessment" OR "self-assessment" OR "technology readiness level") AND ("Companies" OR "Corporation" OR "Enterprises" OR "Firms" OR "Businesses" OR "Organizations" OR "Ventures" OR "Entities" OR "Concerns" OR "Establishments")

The search string was applied to several recognized academic databases, such as ACM Digital Library, IEEE Xplore, ScienceDirect, Scopus, The Lens, Web of Science (WOS), and Dimensions. These databases are widely recognized for indexing high-quality research papers in the engineering context [37]. In addition, Google Scholar was used to manually select the most relevant articles in the domain. Notably, the search strategy was implemented on the titles, abstracts, and keywords of all the mentioned databases except ScienceDirect, where platform limitations require that the search string be restricted to eight terms. Finally, the search was conducted in January 2024 without temporal restrictions to cover as many relevant studies as possible.

3.3. Methodology of Selection of Primary Studies

This research adopted the guidelines of the PRISMA and Petersen protocol to conduct a review in a structured, methodological, and replicable manner. This research process, depicted in Figure 2, was executed methodically and organized, with each phase providing input for the next.

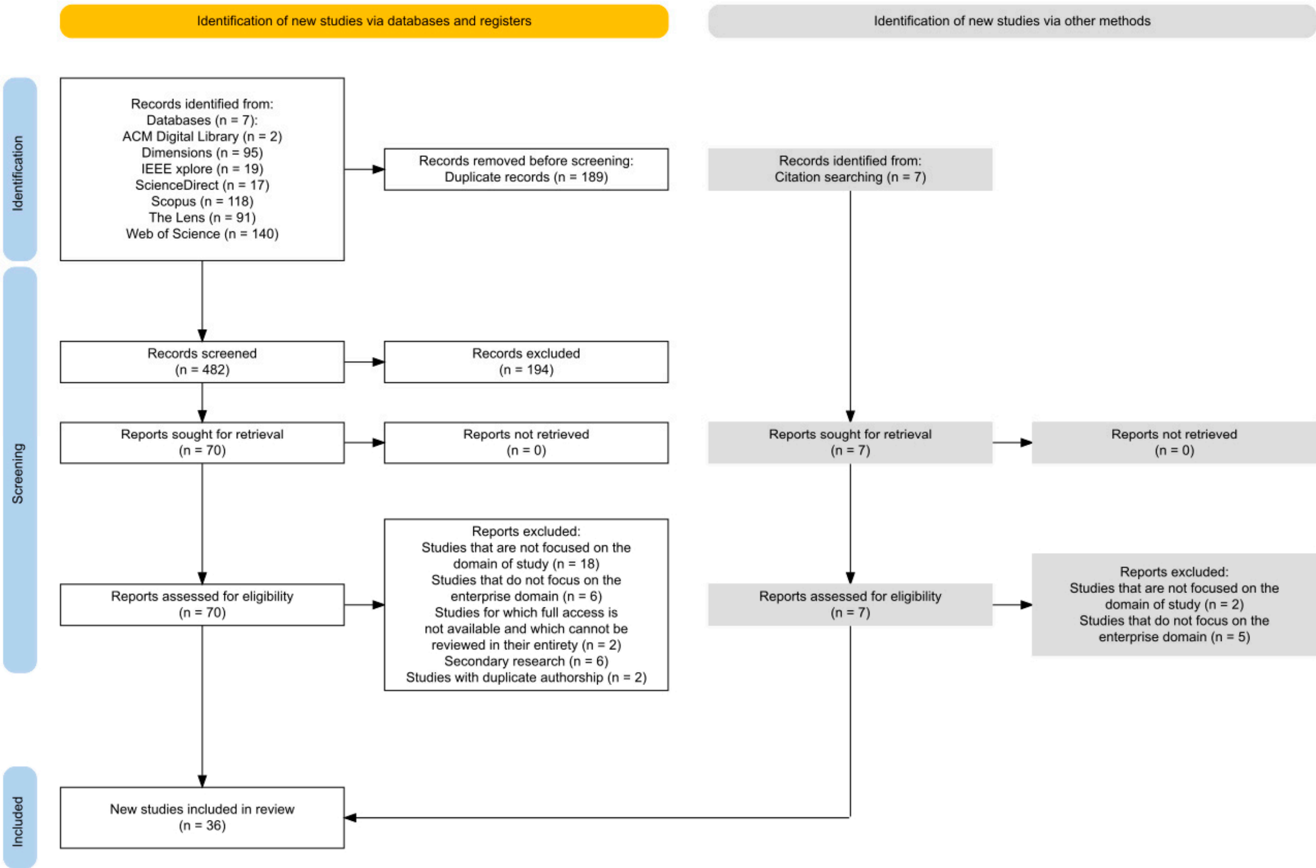

Figure 2. PRISMA diagram detailing the screening processes of the different research articles.

According to the indicated methodologies, inclusion and exclusion criteria (Table 3) were used to optimally select the primary studies on maturity models for enterprise IoT. These selected studies form the basis for answering the research questions [38]. It is crucial to note that a study is considered primary only if it meets all the specified inclusion criteria. Conversely, any study that matches at least one exclusion criterion is eliminated during the screening process.

Table 3. Inclusion and exclusion criteria were applied in the methodological process.

Inclusion Criteria	Exclusion Criteria
The study should focus on IoT maturity models in enterprises.	Preliminary studies lead to further research on the same topic.
The study must be published in English.	Studies that do not directly pertain to the enterprise IoT domain.
The research must present a well-defined and structured methodology.	Secondary research such as reviews and meta-analyses.
The research must propose or present a specific solution in the enterprise context.	Studies that have not been peer-reviewed.

Applying the inclusion and exclusion criteria, this review allowed for the selection of relevant, high-quality studies that contributed to an in-depth understanding of the proposed maturity models for IoT in enterprises.

4. Execution of This Review

This research was carried out systematically and methodically, following the steps described in the previous stages. The process was divided into three distinct phases, facilitated by the Parsifal tool.

The search strategy was applied in the previously defined bibliographic databases in the first phase, obtaining 489 academic documents. Next, duplicate records were eliminated, constituting 189 studies for which a single record was left in the database. Subsequently, the remaining papers' abstracts, keywords, and titles were screened against predefined inclusion and exclusion criteria, resulting in a subset of 70 studies referred to as "primary study candidates".

The second phase consisted of a more detailed selection process. The inclusion and exclusion criteria were applied to the full text of each paper, further narrowing the selection to 36 primary studies that provide answers to the research questions posed.

The final phase consisted of data extraction, domain characterization, and answers to the research questions. The selection procedure for duplicate studies was based on their citation indexes and accessibility to the full text. Secondary research was excluded at the data extraction stage but considered for comparing the results of this research.

5. Results and Analysis

In this section, an in-depth analysis of the results is performed by applying the search strategy in various bibliographic databases to investigate the domain of maturity models for IoT in enterprises. Once this review is planned and executed, the findings obtained during this review are studied, starting with a quantitative analysis of the results to answer the research questions and clarify the knowledge gaps in the domain.

5.1. Quantitative Analysis of the Results

5.1.1. Segmentation of the Types of Studies Found in Scientific Databases

A descriptive analysis of the scientific articles retrieved from various databases is presented below. Initially, 489 studies were identified in all the databases; after applying specific inclusion and exclusion criteria, 36 primary studies were identified. The rejected studies constituted 266 studies based on the screening process, and 186 were identified as duplicates. In this line, the primary studies represent 7.36% of the total number of studies retrieved, while the rejected studies constitute 54.3%, and the duplicates represent 38% of the total. Regarding databases, Web of Science yielded the highest number of studies (140), and ACM Digital Library produced the lowest number (2). It should be noted that the Scopus and Dimensions databases provided the most significant number of primary studies, with 11 and 9, respectively, indicating their essential contribution to the domain.

Figure 3 shows that Web of Science found a significantly higher number of total studies than other scientific databases, which could be attributed to more excellent coverage of sources in this specific domain. In addition, Scopus ranks second in terms of the number of studies identified due to its role as an indexer of other scientific databases. In particular, the high proportion of duplicate studies suggests considerable overlap in indexing between the different databases in this field.

The relationship between the studies found and the primary studies indicates that despite the large number of results obtained, there may be problems related to the relevance and specificity of the studies identified. It is possible that numerous contributions to the domain are being made, but not necessarily focused on IoT, but focused on Industry 4.0, where IoT is an important technology but not a central element, as reported in the literature [39]. This may mean that the proposals are made in a general way for this industrial revolution, and the proposed mechanisms lose specificity for IoT technology, constituting future work for the domain.

Regarding the individual sources, Scopus and Dimensions have the highest number of accepted primary studies, which underlines their relevance for finding empirical evidence in the domain. Studies have already reported on this, highlighting the importance of Dimensions for engineering fields [40].

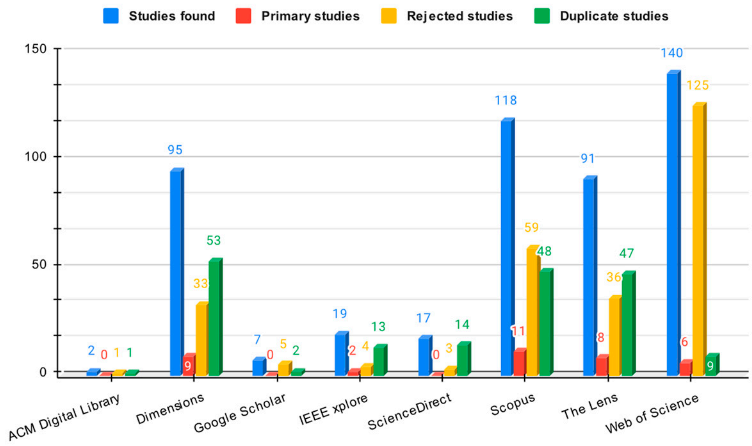

Figure 3. The distribution of studies in the domain found in the research process segmented by studies found, primary studies, rejected studies, and duplicate studies.

5.1.2. Annual Publication Frequency of Primary Publications

The evaluation of the annual frequency of publications in a specific domain is a crucial indicator for identifying upward or downward research trends, providing information on the relevance and timeliness of the domain in question for the scientific community. Figure 4 presents a graphical representation of the number of annual publications related to maturity models for IoT in enterprises, dating from 2011 to 2023, comprising 13 years of publications and with an annual average of 2.77 publications.

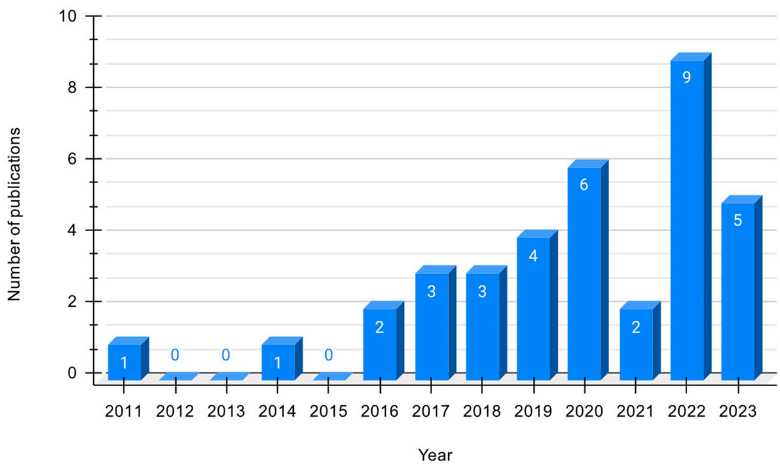

Figure 4. Annual distribution of maturity model publications in the enterprise IoT domain.

In this sense, the year with the highest number of publications was 2022, while the years with the lowest number of publications, in addition to those with zero documents, were 2011 and 2014, with only one publication. There is a general upward trend in the number of publications over time, suggesting a growing interest on the part of the research community in this area. Looking at the full-time frame, the number of publications starts low and fluctuates between 0 and 2 articles per year until 2019. After that year, the number of publications increases to three or more annually until 2023.

Empirical evidence indicates an increasing trend in the number of publications and a growing interest in maturity models within the research field. It establishes that they are consolidating as essential tools to monitor and improve IoT implementation in corporate environments. In addition, this phenomenon reflects the concern of the scientific community to know the level of development of the IoT infrastructure in organizations, identifying the current state of the organization in terms of IoT adoption, which, in turn, facilitates the improvement of its capabilities, the optimization of solutions, and the mitigation of risks associated with this technology

5.2. Answers to the Research Questions Posed

This section answers the research questions to establish state-of-the-art maturity models for enterprise IoT in depth.

5.2.1. Q1. How Are Maturity Models Defined in the Context of Enterprise IoT?

The maturity models proposed in the scientific literature have some commonalities in their structures and definitions. While some details differ, many are multi-level frameworks with dimensions and criteria for assessing an organization's IoT capabilities and progression, each tailored to the specific industry context, scope, and purpose for which they are proposed. In general, maturity models are defined as multidimensional matrix structures that combine several independent scales and derive a central value based on those dimensions [41].

Common elements in the various maturity models proposed in the literature include using levels or stages to represent an organization or system's maturity or readiness regarding IoT capabilities, processes, outcomes, or challenges in its context [42,43]. The number and names of the levels vary across maturity models but typically range from three or more levels and follow a progression from low to high maturity. For example, some models use the terms initial, repeatable, defined, managed, and optimized, while others use system monitoring, control, optimization, autonomy, and autonomy [27].

In this line, it is essential to indicate that the proposed empirical evidence uses dimensions, areas, or constructs to capture the different aspects or factors that influence or are influenced by the adoption and implementation of IoT because it allows to establish in a unified way the different aspects that converge in this technology [21,44]. In this sense, these dimensions, areas, or construct elements vary from one model to another and cover technological, organizational, human, performance, and other sector-specific aspects, generally related to technology, data, organization, culture, communication, strategy, business, performance, security, privacy, compliance, innovation, or other issues relevant to IoT technology [18,45]. The number and names of the dimensions vary between models but typically range from 3 to 11 and cover both internal and external factors. Some models, for example, use the dimensions of data, infrastructure, IoT integration into business processes, strategy, organization, and culture, while others use the dimensions of technology, organization, human resources, and performance [46]. Some models introduce additional dimensions, such as IoT capabilities, security practices, resilience, or educational objectives, further contributing to the nuanced characterization of maturity and enhancing the specificity of the models [47,48].

A common element is using indicators, attributes, objectives, criteria, or questions to measure, assess, or evaluate the maturity level of each dimension or area. Indicators can be qualitative, quantitative, objective, or subjective and based on existing standards, frameworks, or methods [49]. The number and names of these vary between models but usually range from 5 to 62 according to the literature and reflect each maturity level's characteristics and requirements. Thus, some models use the indicators of Infrastructure, Standardization, Data Management, Data Analytics, and Strategy, while others use the indicators of Device, Network, Manager, Provider, and User [25]. In general, the levels are characterized as indicators that measure the degree of digitization, standardization, and improvement of IoT in the business context.

A notable element observed is the use of hybrid approaches in the domain, where they rely on established industry frameworks to build maturity models tailored to fit the context; examples include the Capability Maturity Model (CMM) [46], the Process Assessment Model (PAM) [50], and Bloom's taxonomy [51], which provide proven means of classifying maturity using concepts such as capability areas, knowledge domains, and competency levels. It should also be noted that although measurement and assessments provide a means of classifying maturity levels, using data to promote improvement directly is rare. In some cases, measurement data are incorporated to guide training, analyze root causes, and guide recommended actions to move from one level to another. However, assessment is often the primary goal rather than long-term progression [52], established as a possibility for improvement in the domain.

The proposed maturity models are generally adapted to specific sectors, showing great structure and dimension diversity. They typically use a combination of levels, dimensions, and indicators that reflect each model's specific context and objectives and are used to compare, diagnose, guide, or improve an organization's IoT maturity. In addition, the particularization of hybrid approaches that combine established frameworks with adaptations holds promise for maximizing the applicability of these measurement mechanisms.

Q1.1. How Are Internal Measurement Processes Performed Within the Proposed Maturity Models?

The internal measurement processes of maturity models are the methods and techniques used to assess an organization or system's current state and progress regarding its IoT maturity level, which varies depending on the maturity model's domain, purpose, and design [53]. The available literature reveals a diverse view of the internal measurement processes within the proposed maturity models. First, a common trend in several articles is the need for explicit details on these processes, where the main focus revolves around the qualitative analysis of the overall maturity levels, leaving the internal measurement processes needing to be addressed [42]. This suggests a predominant gap in the literature, where the emphasis falls more on results and assessments than on the complex methodologies employed in internal measurements. Nevertheless, some common elements among the different maturity models proposed in the scientific corpus can be identified.

In this regard, different approaches have been proposed and applied to perform internal measurement processes within maturity models in various domains and disciplines, such as digital finance [38], security and vulnerability management [54], smart objects [44], forensics [49], digital engineering, security, and IoT adoption [55]. These approaches vary in terms of methods, tools, data sources, indicators, metrics, scales, and criteria used to measure the maturity level of an organization or system. In addition, some maturity models employ more qualitative methods such as interviews, focus groups, observations, and document analysis to assess maturity [13,56]. The collected qualitative data are coded and analyzed to identify patterns related to the organization's maturity levels of IoT-related practices, processes, and technologies.

The maturity models consulted in the literature have several standard processes that establish IoT technology maturity. Starting with the data collection process, gather information from various sources, such as surveys, interviews, observations, documents, or data analysis, to assess the organization's or system's current situation regarding the maturity model [56]. Data collection methods should be reliable, valid, and consistent and cover all relevant aspects of the model. Some of the most used sources for these measurement mechanisms are the organization's employees [56], stakeholders, manufacturers, vendors, third-party reports [57], literature reviews, and expert panels [52], providing opinions, perceptions, comments, information, and empirical evidence on the current and desired state of the organization regarding IoT to the maturity model. Specifically, the most used element for data collection is questionnaires that usually consist of questions related to the maturity model's dimensions, sub-dimensions, indicators, or criteria. They ask respondents to rate their organization or system according to a predefined scale. Also, questionnaires are completed by self-assessors or consultants after analyzing practices, conducting interviews with stakeholders, and collecting data [41,52].

A second standard process in the proposed maturity models is data analysis, in which the collected data are interpreted and summarized using statistical or mathematical methods; these should be appropriate, rigorous, and transparent and provide meaningful and actionable results as inputs for subsequent phases [49]. Some of the standard methods used to perform internal measurement processes within maturity models are principal component analysis (PCA) [42], cluster analysis [58], as well as more straightforward techniques such as fuzzy assessment [59], word frequency analysis, maturity matrix, score calculation, scoring systems, capability level mapping, and benchmarking [60]. These methods can be used to reduce the dimensionality of the data, extract essential elements, divide entities into different groups, and assign them to different maturity levels, among others [25,42]. In this process, statistical methods help aggregate, summarize, visualize, and interpret the data and identify the organization's strengths and weaknesses with IoT.

The third typical process among maturity models is data visualization, which allows for the presentation of the results of data analysis in graphical or tabular form, such as radar charts [49], matrices, histograms [61], or scores, having as the main characteristic to be clear, concise, and understandable and to highlight the strengths and weaknesses of the organization on the maturity model. Some standard tools used to perform internal measurement processes within maturity models are Excel (Redmond, WA, USA) [21], RES-BPMN (Needham, MA, USA) [48], software tools [50], and digital audit tools.

The last process is related to data feedback, which involves sharing the results of data analysis and visualization with the parties involved in the organization or system, such as managers, engineers, analysts, or users. Data feedback methods should be accurate and constructive but do not suggest improvement actions or best practices to reach the desired level of maturity.

Therefore, internal measurement processes within the proposed maturity model can be performed following the common elements of data collection, data analysis, data visualization, and data feedback and adapting them to the specific characteristics and objectives of the model. In this sense, internal measurement processes are essential to assess the organization's current state and potential for improvement in the IoT domain, identify gaps, challenges, and development opportunities, and define objectives, actions, and strategies to reach a higher level of maturity or capability. Internal measurement processes can also help monitor the progress and impact of improvement initiatives and ensure alignment of the organization or system with best practices.

Q1.2. What Do the Proposed IoT Maturity Models Consider the Main Dimensions?

In the following question, to better understand the various dimensions considered in the construction and development of IoT maturity models, the following classification of these dimensions into three main categories is proposed: technological dimensions; organizational dimensions; and human dimensions. According to the reviewed scientific corpus, these categories represent significant clusters in which the different dimensions identified in the maturity models can be classified.

- **Technological dimensions**

The measurement process of the proposed maturity models for different IoT domains and applications in organizational contexts considers several technological dimensions, factors, or elements that reflect IoT solutions' level of development, integration, and sophistication [26]. It is generally considered a multidimensional assessment of complex technical components encompassing infrastructure [61], devices, networks [62], software, IoT automation [45], and soft aspects of the technology, such as practices [13], capabilities, complexity [22], and readiness. In addition, a broad set of standards, frameworks, and architectural blueprints [25] also guides these measurement processes to assess the sophistication, integration, and effectiveness of IoT transformations.

Dimensions frequently employed in maturity models include topics such as infrastructure [18], integration, interoperability [60], data quality, architecture, and security/privacy [63]. Specific technology components evaluated cover IoT devices, systems, and platforms [64]; network and communication protocols; data capture, transmission, and analysis [42]; sensors, robotics, augmented/virtual reality, and the Blockchain [65]. The capability areas are related to product knowledge, vulnerability identification, assessment, and remediation [54] and update delivery mechanisms, version tracking, and associated patches [52]. The practices aim to assess each capability's policies, processes, controls, and response mechanisms. Other factors revolve around current organizational maturity, the complexity of technology integration, prioritization based on strategic drivers, relevance to core operations/products, and overall readiness considering personnel, culture, and training [66]. The technology dimensions generally establish IoT maturity in technology issues related to its technical infrastructure, data management, application characteristics, and alignment with the organization's business processes and customer needs.

The literature consulted shows certain commonalities concerning the dimensions proposed in the domain maturity models, which can be grouped into four main categories: technology and infrastructure; data and information; process and application; and security and privacy [29].

Technology and infrastructure: these dimensions cover the availability and quality of hardware and software components that enable IoT solutions, such as devices, sensors, networks, platforms, architectures, standards, and protocols [63,67]. In general, these dimensions assess the degree of connectivity [62], interoperability [60], automation, and innovation of the technology infrastructure [57], as well as the compatibility and suitability of the technologies for the specific IoT domain and application [52]. These dimensions also consider the physical [55] and logical [48] components that enable IoT solutions' sensing, actuation, processing, and networking. The measurement process considers the type, quality, functionality, security, and reliability of devices and systems [56], as well as the degree of automation, human–machine cooperation [68], and autonomy they provide [25]. This category includes device type, priority, management, platform management, safety practices, and fine-grained elements such as water and dust protection.

Data and information: These categories cover the management analysis of data and information generated and exchanged by IoT solutions [69], such as data formats, structures, standards, quality, interoperability [47], cloud computing [65], Big data [66], business intelligence [13], and predictive analytics, among others. The measurement process evaluates the degree of data collection, storage, processing, use, value creation, and decision-making based on data and information [55]. Also, the evidence collected considers the sources, formats, structures, quality, and availability of data and information generated, collected, stored, processed, analyzed, and exchanged [13] by IoT devices, systems, platforms, and networks. Specific elements addressed in these dimensions are data quality issues [48], data quality characteristics, data quality methods, data quality measurement and assessment, data security, and enabling smart connected products.

Process and application: The dimensions covered in this section encompass the design, implementation, and management of IoT solutions that support business processes and customer needs [70], such as product [59] and service [67] development, testing, deployment, implementation, governance, monitoring, and maintenance [52]. The measurement process assesses the degree of alignment, integration, and optimization of IoT solutions with business processes and customer requirements and the impact and benefits of IoT solutions on operational and functional performance [43,56]. In addition, measurement considers the effects and outcomes of the IoT technology, data, information, application, and service on the organization or system and external stakeholders [62], such as customers, partners, suppliers, regulators, and society [51]. It is important to note that these types of dimensions are less frequent in maturity models, and aspects such as the absolute value of applying this type of mechanism in the enterprise should be included.

Security and privacy: This category covers dimensions related to the protection and preservation of security and privacy of IoT solutions in organizations [18], such as confidentiality [67], integrity, availability [60], authentication, encryption, security updates, vulnerability assessment and remediation, attack tolerance and recovery, and access control [57,67]. The measurement process evaluates the degree of implementation and compliance with security and privacy measures and practices and IoT solutions' management, risk, and threat mitigation [71]. This section highlights the methods and tools that enable the identification, collection, preservation, examination, analysis, and presentation of digital evidence in IoT incidents, considering the availability, adequacy, and suitability of forensic tools and techniques, as well as the degree of compliance, policy, and standardization they provide.

It is important to note that these categorizations are only strictly followed in some maturity models but are the most considered when building this type of mechanism. Furthermore, these dimensions are not mutually exclusive. However, they are interrelated and interdependent, seeking to capture the complexity and diversity of IoT technology and its applications and provide a comprehensive and flexible framework for assessing and improving the IoT maturity level of different organizations and domains.

- **Organizational dimensions**

In maturity models, an organizational dimension refers to an entity's different aspects or areas whose maturity can be assessed, typically corresponding to different business functions or organizational capabilities [72]. The maturity measurement process for IoT adoption and implementation considers several organizational dimensions, factors, or elements that reflect the organization's strategic, managerial, operational, and technical aspects. Due to the diversity of elements within an enterprise, multiple factors and dimensions related to the organization can be categorized. These dimensions, factors, or elements can be grouped into different categories as follows:

Strategy, vision, and objectives: These dimensions assess the alignment and clarity of the organization's objectives [70] and strategies for the adoption, implementation, and exploitation of IoT in the organization [71], as well as the support and commitment of top management [52] and stakeholders. It also involves the assessment of the organization's value proposition [56], its market position, and its potential for innovation in IoT technology [59]. Examples of the elements in these categories are technology vision [63] and roadmap [22], decision-making, management support, willingness to adapt business processes, alignment, and methods [18];

Culture and organization: This category reflects the organization's values, beliefs, and norms that influence the adoption and implementation of IoT in the organization [52,55]; it also considers the organization's willingness and readiness to embrace change, innovation, and data-driven decision-making, as well as collaboration and communication between different departments and functions involved in IoT projects [46]. This category includes organizational culture and governance [73], customer integration, strategic orientation, innovation cooperation, and digital culture. It is essential to indicate that these types of dimensions are established in maturity models to a lesser extent, but there has been an apparent increase in the frequency of appearance of this type of categorization in recent years for these measurement mechanisms [59];

Process and performance: This category evaluates the impact and improvement in IoT technologies on the optimization and efficiency of organizational resources and processes and the quality and reliability of products and services [61]. It also refers to business processes and workflows impacted by or supporting IoT [45], which involves process optimization, integration, standardization, and metrics and indicators to monitor and evaluate process performance [42]. This category includes resources/processes, asset utilization, labor, quality, performance monitoring, and process documentation [22,43];

Technology and data: Dimensions used to a lesser extent and are more technical categories, where the availability and reliability of data sources and technologies used by the organization [18], both within and across domains and companies, as well as the standardization and interoperability of data and technologies, are evaluated [13]. This category includes domain knowledge, data quality, data analytics, data failures, security, risk assessment, and reference architectures [47,48];

Equipment and competencies: This category assesses the existence and competence of a dedicated, cross-functional team that manages and executes IoT projects [52] and the recruitment and development of people with digitization skills. Examples of elements in this category are the IoT team, digital competencies, experience, and training, among the most prominent [49];

Resources: This dimension covers the physical, financial, and information resources required to establish IoT technology [69] and includes aspects of resource allocation, utilization, and management, as well as information systems and technologies to support the measurement process [42];

Governance and management: This category includes the procedures and division of responsibilities for IoT adoption, implementation, and security within the organization [54], the integration of IoT into development and quality processes and parameters [58], the use of reference architectures and standard frameworks for risk assessment and compliance [25], the investment of resources and capabilities in IoT adoption and security, and the monitoring and feedback mechanisms for continuous improvement and innovation [57];

Collaboration and communication: This category includes collaboration and communication between the various departments and functions involved in IoT adoption [62], the creation of cross-functional and cross-organizational digitization networks to facilitate knowledge sharing [18] and collaboration, the coordination and alignment of IoT team roles and responsibilities, and the involvement and integration of customers and partners in the IoT ecosystem [50].

These dimensions, factors, or organizational elements are not mutually exclusive and can interact and influence each other within the measurement process of maturity models. While some models focus on technical capabilities, others take a more holistic view, incorporating organizational factors such as business processes, culture, governance, and resource management [70]. Many models assess an organization's willingness and ability to adopt new technologies or work methods. In general, several models recognize that organizational dimensions beyond technology influence maturity and capability, but only some of these aspects are considered in these mechanisms;

- **Human dimensions**

The measurement process of the proposed maturity models for IoT and associated technologies incorporates multiple dimensions, factors, or elements linked to human beings, who are IoT technology's leading actors and beneficiaries. According to the existing literature, human elements can be grouped into four categories: skills and competencies; culture and awareness; involvement and participation; and feedback and evaluation. However, the predominant maturity models focus primarily on organizational processes, practices, and technological capabilities, often disregarding an overall integration of the human elements;

Capabilities and competencies: This set of dimensions refers to the knowledge, education, training, and experience of the organization's employees, managers, and stakeholders in IoT and related technologies [43,54]. Skills and competencies can influence adoption, implementation, and innovation within this technology domain, impacting the performance and quality of IoT integration processes and outcomes. Some maturity models assess the current state and development needs in areas such as employee digital skills [25], IoT awareness and capabilities [69], role-specific qualifications, and overall workforce readiness to adopt new technologies. The assessment of human capabilities enables optimal system functionality and effective utilization of technology by the workforce [74]. Some indicators or subdimensions of this category are IT knowledge and skills, IT capabilities, IoT competencies [47], digital skills and experience [52], technical skills, interdisciplinary skills [68], management skills, professional training, innovativeness, and human–machine–environment harmony [45];

Culture and Awareness: This category refers to the acceptance, support, motivation, and openness of organizational culture [41], individual attitudes towards IoT [18], and related technologies. Culture and awareness can influence the willingness, readiness, and satisfaction of employees [45,55] and stakeholders to use and benefit from IoT solutions, as well as the alignment of the organization's vision and goals with the opportunities and challenges of this technology. The proposed measurement mechanisms generally measure vision alignment, openness to change, communication and feedback channels, and a culture of continuous improvement and innovation where favorable conditions allow for progress along the maturity continuum [46]. Some of the indicators or subdimensions of this category are culture, governance [43], improvement culture, awareness, innovative culture, ethical sense, and responsibility [55];

Involvement and participation: This category refers to the degree and quality of interaction, collaboration, and communication among an organization's employees, managers, and stakeholders regarding IoT and associated technologies [44,49]. Involvement and participation can affect the efficiency, effectiveness, and resilience of IoT processes and outcomes, value creation, and solution delivery [70]. It is accepted in the literature that collaboration and communication within different work processes are beneficial in multiple aspects and areas [75]; in the specific domain of maturity models for IoT, collaboration between internal teams and external stakeholders is understood to be essential in determining maturity, where interdisciplinary cooperation [65], knowledge sharing between departments, coordination with IoT ecosystem partners, and stakeholder cooperation are assessed [60]. Multi-stakeholder involvement and dialogue facilitate problem-solving, leading to higher technological maturity [71]. Some indicators or sub-dimensions of this category are customer communication, partner communication, collaboration, team, autonomy, stakeholder involvement and engagement, user role and opinion, and practitioner involvement;

Feedback and evaluation: This dimension refers to the methods and mechanisms used by the organization to collect, analyze, and use feedback, evaluations, reports, and suggestions from employees, managers, stakeholders, and customers regarding the performance, usability, reliability, security, and value of IoT in the organization [66,69]. The comments and feedback can help the organization assess, monitor, and improve the maturity level, performance, and quality of processes and identify and address gaps, risks, and problems with solutions achieved with this technology. Indicators or sub-dimensions include data quality and expectations [48], satisfaction with data quality, feedback, complaints, usability, user satisfaction, efficiency, usefulness, and value attributed to IoT and its influence among various organizational stakeholders [52,57]. Collectively, these elements contribute to the overall capability and quality of human involvement in various technological areas where IoT intervenes in the organization.

Importantly, in specific domains such as organizational education for IoT technology use, the models incorporate Bloom's taxonomy to assess levels of competence in line with the hierarchical framework of learning outcomes [47]. This highlights the importance of understanding and adapting to the cognitive processes involved in learning and applying technological topics.

Finally, maturity models provide a framework for systematically assessing the human elements interrelated to the maturity measurement process, considering elements such as developing expertise through learning, creating an enabling organizational environment, enabling open communication and teamwork, and ultimately delivering user-centric systems that add value. As enterprises digitally transform, holistically addressing these socio-technical dynamics is imperative. This leads to the challenge of addressing the complexity and interconnectedness of human involvement in various technological domains, highlighting the need for comprehensive and adaptive maturity models, and recognizing the gap between the potential and actual use of IoT technology in your environment.

Q1.3. What Metrics Are Associated with Assessing the Maturity Levels of the Proposed Maturity Models in the Domain?

Assessing the maturity levels of the proposed models requires using metrics adapted to the attributes and objectives to track the expected evolution of specific dimensions or aspects covered by the proposed mechanism. It is crucial to note that according to the literature, metrics can be classified into three distinct types: quantitative; qualitative; and mixed, where each type has its own set of advantages and limitations [26]. Consequently, there is no universally accepted set of metrics, but common approaches use maturity scores assigned from quantitative aggregates or qualitative assessments of organizational capabilities and maturity level descriptors defined within the models themselves to assess progress [51,67,71]. The specific choice of metrics and calculations is tailored to the focus, dimensions, and intended uses of each proposed maturity model, ensuring a complete and accurate assessment of the IoT maturity level in the organization.

Quantitative metrics are numerical values that measure the performance, efficiency, quality, or effectiveness of IoT technologies, processes, or systems, typically calculated from responses to a questionnaire, data analysis results, or a mathematical formula application. Quantitative metrics help to provide an objective and comparable assessment of maturity levels but may not capture the complexity and diversity of the entire IoT domain [76,77], such as stakeholder opinions. Some of the most representative examples of quantitative metrics are scores, percentages, frequencies, means, standard deviations, ranks, ANOVA, and Chi-square.

On the other hand, qualitative metrics are descriptive measures that assess the characteristics, attributes, or capabilities of IoT technologies, processes, or systems, often derived from the definitions and characteristics of each maturity level, the comparison of the current and desired state of the organization, or the identification of gaps and opportunities for improvement [78]. Qualitative metrics help provide a comprehensive and detailed assessment of maturity levels but may not be easily quantifiable and standardizable [48], often delineated by descriptive characteristics or assessment criteria that denote what an organization can do at each level; in general, these types of metrics are used to a lesser extent in the proposed maturity models for the IoT domain. Qualitative metrics include descriptions, criteria, characteristics, and profiles [51,63].

Mixed metrics are a combination of quantitative and qualitative metrics that aim to provide a balanced and holistic assessment of maturity levels, often obtained by integrating or mapping quantitative and qualitative metrics or using a hybrid method to assess maturity levels [22,67]. Mixed metrics may require more effort and resources to implement and validate. In general, scores typically range from 1 to 5, 0 to 4, and 0 to 100, or use labels and then discretize these into numbers received by the model [18]. Examples of mixed metrics are scores and descriptions, percentages and criteria, frequencies, and indicators.

In general, the metrics that are associated with assessing the maturity levels of the maturity models encountered vary depending on the purpose and method of the model, where the literature indicates that the most common types of metrics are quantitative and, to a lesser extent, qualitative and mixed metrics that seek to ensure a detailed and nuanced understanding of IoT organizational maturity. Metrics and methods are also influenced by existing frameworks or standards that influence the proposed mechanisms, such as Capability Maturity Model Integration (CMMI) [67], Control Objectives for Information and Related Technology (COBIT) [46], and the International Organization for Standardization (ISO) [63].

Considering the above, future research should consider the suitability and feasibility of metrics for IoT and maturity models, using a combination of quantitative and qualitative methods to achieve a more reliable and complete assessment of the technology's current state against a benchmark.

5.2.2. Q2. Do the Proposed MATURITY Models Support Post-Measurement Improvement in the IoT Domain in Enterprises?

In reviewing the existing scientific literature on proposed maturity models in the IoT domain, it is difficult to determine whether these models effectively support post-measurement improvement, as there is no consensus or explicit articulation of the answer to this question. In particular, most articles emphasize the role of the maturity model in assessment rather than addressing its ability to facilitate post-measurement improvement [61]. These mechanisms focus primarily on identifying organizational strengths and weaknesses. Some models provide clear guidance for moving from one maturity level to another, while others only define each level's expected outcomes or capabilities; others include specific processes or phases for identifying improvement potential, implementing actions, and reassessing the maturity level [71,73]. In general, maturity level improvement processes are based on identifying the positives and negatives of the current maturity state and suggesting possible actions and steps to address gaps and challenges, providing a common language and shared vision for the organization and stakeholders to communicate and collaborate in the improvement process [18]. However, the models must provide a comprehensive and detailed framework to drive maturity improvement after measurement.

Now, some proposed maturity models offer specific internal mechanisms that support improvement after measurement, the most common way being to provide a benchmark that allows the company to compare its results and progress with those of other organizations or with the expected results, learning from the experiences and success stories of other organizations [70]. This is the case of Liu and Pan [43], who propose a maturity model that analyzes the tasks and requirements of the development of Chinese manufacturing companies based on the conditions of the Asian country, allowing them to compare the results among the organizations that apply the model. Another clear example is the proposal of Klisenko and Serral Asensio [18], which allows for the evaluation of the organization, compares its results and progress with those of other companies at the same or higher maturity level, and learns from their best practices and experiences. Generally, benchmarks [50] are inherent to any maturity model and are established as one of the main advantages of this type of mechanism in the domain. This type of maturity support does not explicitly rely on improvement after measurement and is positioned more as an analysis or assessment tool.

Some maturity models for IoT provide feedback and recommendations to the organization based on assessing or measuring the maturity level. Feedback is based on assessing or diagnosing the organization's current state and identifying gaps and improvement opportunities [41]. Recommendations are suggestions or proposals to improve or enhance the performance and effectiveness of the organization based on best practices or lessons learned from the literature or case studies. This is the case of Philipp [65], whose proposal offers strategic recommendations to improve maturity by defining the characteristics and strategies of each port classification and the range of scores corresponding to each maturity level.

Along these lines, another way to improve maturity measurement in the models reported in the literature is when the mechanisms present a roadmap or direction that guides the organization to plan and implement improvement actions and initiatives based on the gap analysis and prioritization of improvement areas, also describing the characteristics and requirements of each maturity level, as well as the steps and actions needed to reach the next level [60]. The papers found that the only study that reports an explicit roadmap for advancing maturity is [61], which supports improvement by providing a structured and stepwise approach to integrating metrological principles and methods into IoT sensor networks. The maturity model also provides a framework for assessing sensor network metrology's current and desired states and identifying gaps and actions needed to improve this section.

Likewise, another maturity model explicitly outlines a continuous improvement process, where the mechanism provides a continuous improvement process that allows the organization to monitor and evaluate the progress and results of improvement actions and initiatives and adjust strategies and actions accordingly. This process involves collecting and using data and feedback, the regular and frequent use of the maturity model for a self-assessment or external audit, and the iterative and incremental improvement cycle aligned with the organization's objectives and strategies. In this sense, the proposal by Kim et al. [63] supports post-measurement maturity improvement by providing a roadmap for the organization to identify the strengths and weaknesses of its current processes, prioritize areas for improvement, set goals and objectives for the desired maturity level, implement actions and changes for improvement, monitor and control improvement progress and performance, and evaluate and validate the results and benefits of the improvement.

In this sense, the proposed maturity models that support maturity improvement after measurement allow for identifying several drawbacks, such as the lack of empirical validation [46] or practical application of improvement suggestions, the lack of specific guidelines or methods on how to improve the maturity level, giving an ambiguous improvement process [63], and the lack of customization or adaptation of the models to the specific context and needs of the organization [66].

At a general level, the information gathered in this review allows for the conclusion that the proposed maturity models do not explicitly support the improvement of maturity after measurement, positioning themselves more as analysis tools that provide a snapshot of the current state of maturity than as improvement elements to achieve higher maturity levels except in specific cases. In this sense, driving organizational maturity improvement seems to be an area that deserves further research for this type of mechanism in the IoT domain, so in future work, providing a clear and comprehensive framework that helps the organization to understand its current situation, compare it with best practices or benchmarks, identify strengths and weaknesses, and set objectives and goals for improvement seems to be a significant contribution to this domain.

Q2.1. How Are Measurement Data Used to Support Maturity Improvement in Organizations?

The data obtained from these mechanisms is one aspect of the post-establishment improvement processes of IoT technology maturity in organizations, as it provides information on the status and progress of the organization or process being assessed with the technology. However, based on the review conducted, this aspect is often not adequately addressed or discussed in most of the maturity models proposed in the literature.

In general, most of the proposed maturity models do not explicitly discuss how measurement data are used to support improvement, where they mainly focus on assessment methods, model evaluation, and maturity level definitions, which highlights a gap in knowledge about leveraging measurement data for the explicit purpose of supporting improvement. Furthermore, it is essential to indicate that implicitly, one of the ways of taking data derived from maturity measurement is the self-assessment process that is recognized as constructive dialogues to define improvement actions [70]; therefore, no framework that directly employs measurement data for maturity improvement is detailed.

Considering the above, some of the proposals in the domain explicitly state how they use data to improve the company's position concerning maturity measurement, such as the article by Kim et al. [63], who describe a maturity model for data quality management, where the collected measurement information is used to analyze the causes of problems, correct nonconformities and transform processes as part of improving data quality at subsequent maturity levels. Another example is [51], which presents a maturity model for individual competence and curriculum guidelines, where individual competence levels help to identify areas for improvement through specific training. Finally, Dube and Mohanty [46] proposes a maturity model for IoT data governance, where measurement data on current maturity levels for each control objective are used to define maturity states. Implementation teams then work to achieve those target states by applying controls. After implementation, a reassessment is performed to validate progress. The above are explicit examples of how data has been used in the domain to improve the position of IoT technology in organizations.

Along these lines, the rest of the documents either do not mention how measurement data are utilized to support improvement or merely state that measurement data are used to assign a corresponding maturity level to strategic recommendations for improvement. However, they do not detail how these recommendations are implemented, monitored, or evaluated. Some research points to this aspect as part of future work, suggesting that the proposed models should be better defined and operationalized.

In conclusion, this review highlights the need for measurement data to support improvement within the proposed maturity models. Although some articles allude to the potential application of measurement data for improvement, detailed frameworks describing the processes and methodologies involved are needed. This represents a research opportunity and underscores the need for future studies to address this critical aspect in developing and applying maturity models.

5.2.3. Q3. How Has the Proposed Maturity Models' Contribution, Utility, Value, or Effectiveness Been Validated in the Organizational IoT Domain?

The metrics or parameters that validate the contribution, usefulness, value, or effectiveness of the proposed maturity models vary depending on the domain, scope, and purpose of the models as ways to demonstrate the applicability and potential value of the proposed mechanisms. The importance of correctly validating this type of mechanism is fundamental because it allows determining the degree of contribution to the scientific corpus of the domain, its applicability in other contexts, and its replicability [79]. In this line, it is essential to indicate the existence of some standard methods and criteria used to assess the validity and reliability of the models, like other scientific fields, in validating their proposals. Among the most prominent are the following methods:

Expert opinion: This method consists of consulting experts with knowledge and experience in the IoT domain about the proposed model and obtaining their comments and suggestions on the proposal, development, and refinement of the proposal [71], usually applied through interviews, surveys, panels, and working groups to obtain qualitative feedback [58]. Expert opinion can help ensure the model's relevance, specificity, and accuracy and identify its strengths, weaknesses, and areas for improvement [80]. A derivation of this type of validation of maturity models in the domain is the collection of comments and opinions from all stakeholders (not only limited to experts), where qualitative data are collected that reflect the perceptions [47], experiences, and suggestions of those involved in or affected by the maturity model, such as practitioners, experts, researchers, customers, and organizational staff [46]. Comments and opinions can be obtained through interviews, surveys, or observations, providing information on the maturity model's relevance, importance, applicability, and usefulness [73];

Data collection and analysis: This method consists of distributing a survey or questionnaire to a sample of potential users or stakeholders of the proposed model [61] and collecting and analyzing their responses, helping to measure the perception, satisfaction, and acceptance of the model, as well as to assess the applicability, feasibility, and suitability of the model for different contexts and scenarios [57]. Following this process, statistical methods are used to determine trends that cannot be observed with the naked eye, such as correlation [43], regression [49], factor analysis [62], cluster analysis [58], or structural equation modeling [46]. Data analysis can help quantify and measure the impact and benefits of the model, as well as reveal patterns, trends, and insights from the data;

Case studies and field testing: This method involves applying the proposed model to a real-world case study or field test [56], conducting an experimental design, determining variables of interest, and observing and analyzing the results [45]. Case studies and field testing can help demonstrate the feasibility and effectiveness of the model, as well as validate and verify its assumptions, hypotheses, and predictions [59]. This form of validation is considered the most reliable according to the scientific literature because it shows in a real scenario the behavior of the proposal, allowing to provide evidence and examples of the benefits and results of the mechanism, such as improvement, enhancement, or innovation of the IoT in the organization with the proposal;

Metrics or parameters: This approach is used to demonstrate tangible improvements resulting from the application of the maturity model [68], such as increased efficiency, reduced costs, improved quality, reduced lead times, increased revenue and profitability, increased customer retention, and increased competitive advantage [60]. This type of method obtains quantitative data that allows for the comparability of the results of the proposed mechanisms. Later, correlation and regression statistical techniques can validate the relationships between maturity levels and business performance indicators [42];

Comparative methods: Used to contrast and highlight the differences and similarities between the proposed maturity model and other existing models or frameworks in the literature or practice, allowing to show the strengths, weaknesses, gaps, and opportunities of the maturity model, as well as to justify and support the novelty and originality of the proposal [18]. The comparison of the results over time and with best practices provides a contextual validation of the proposal.

In this line, it is fundamental to indicate that there are isolated forms of validation that have been presented in domain maturity models; this is the case of Dube and Mohanty [46], who uses structural validation of the design, components, and integration of the dimensions of the maturity model through surveys and empirical tests of consistency, coherence, and suitability. Reliability, generalizability, and validity measures affirm the robustness of the model construction. Likewise, another model [48] applies the evaluation of the usability of the proposed mechanism, which consists of measuring the ease of use, user satisfaction, and acceptance of the model or support tool using the System Usability Scale (SUS) [81], which can be used to quantify the usability of a tool that implements the model, allowing to indicate the feasibility and practicality of the model, as well as its ease of use and intuitiveness.

Finally, these methods and criteria can be used individually or in combination, depending on the proposal's nature and scope and the data's availability and quality. Validation and evaluation of the proposed model can help assess its contribution, usefulness, value, and effectiveness and provide guidance and recommendations for improvement and implementation. However, challenges and limitations remain, such as lack of standardization, subjectivity and bias of data sources, the difficulty of generalization and replication, and the need for more evidence and empirical data. Therefore, future research should address these issues and propose more rigorous and detailed validation methods and metrics for maturity models, employing models against measurable success indicators to substantiate their ultimate usefulness to the industry.

5.2.4. Q4. What Are the Future Work, Possible Improvements, or Directions Derived from the Proposed Maturity Models in the Domain?

Exploring future works, possible improvements, and subsequent lines of research derived from the various proposed maturity models is essential to advance in this field because they facilitate refining the executed tasks, avoid redundancies, and align with the right research direction [82]. Punctually, future work or possible improvements derived from the proposed maturity models in the domain are diverse and depend on the context, the area of application, and the specific objectives of each model, as well as the limitations, challenges, and opportunities encountered when implementing the mechanisms, but some studies have provided information on specific aspects; a broader domain overview reveals the following common perspectives of the authors:

Validation and refinement: Most of the proposed maturity models are based on theoretical foundations, the literature reviews, or expert opinions and lack empirical validation and refinement with real-world data and scenarios [18,46]. Therefore, a future direction expressed by the authors is to conduct more case studies [59], experiments [57], surveys, or interviews with different types of organizations and professionals to test and verify the applicability, effectiveness, and usefulness of the models, allowing to identify strengths, weaknesses, gaps, and opportunities for improvement [21]. In terms of validation, mention is made of increasing the size and diversity of the sample (organizations) [57], comparing across countries [37], sectors, or industries, and using empirical data, case studies, or benchmarking to improve the generalizability, applicability, and robustness of the models [59]. The above speaks to the need for further standardization in the domain, as there is no universally accepted methodology to validate proposals that speak to the youth of the field at the same time;

Scaling and integration: Maturity models are often limited in scope, coverage, and granularity [46], leaving out some essential aspects, dimensions, indicators, or criteria that could affect the maturity level or the improvement process [48]. Therefore, a recurrent future direction is to extend and integrate the models to include more factors [61], variables [21], indicators, or criteria that reflect the complexity and diversity of IoT, such as sustainability [66], ethics [49], interoperability [60], and innovation, allowing to contrast the models with other existing proposals or standards in IoT or related fields. Furthermore, other future work should explore the interrelationships [45], dependencies, and trade-offs between the different factors and the weighting, prioritization, and aggregation of the factors into a meaningful and actionable score or maturity level;

Customization and adaptation: Most of the proposed maturity models are generic and do not consider the needs and specific characteristics of different industries, sectors, regions, or contexts adopting or using IoT solutions [47,59]. Therefore, a repetitive future direction is to customize [49] and adapt [22] the models according to the particularities and contingencies of each situation, such as the type and size of the organization, industry, market conditions, and regulatory environment, allowing to provide more personalized and relevant recommendations and guidelines for the improvement and transformation of IoT maturity in enterprises. Also, an element that stands out in this section is the exploration of the relationships between model components and organizational outcomes to see the effectiveness of this type of mechanism [58];

Development and application: Many of the proposed maturity models are conceptual and descriptive and need to provide practical methods and tools to measure and improve IoT maturity [42,48]. Therefore, a future direction could be to develop and implement more concrete and user-friendly methods and tools, such as web applications [56], dashboards [50], and apps [42], that automate and facilitate the assessment and evaluation of the maturity level of an organization or an IoT project, providing more specific and actionable suggestions and strategies for IoT maturity improvement and innovation [48,61].

In general, future work derived from the proposed maturity models covers a broad spectrum of activities, including validation, refinement, customization, and application in various contexts, collectively contributing to the continuous evolution and improvement of the maturity models. In this regard, the critical areas indicated in the measurement mechanisms are validation, tool development, integration/scope extension, customization, and upgrading to new technologies. Overall, it is recognized that these initial proposals can be strengthened through the systematic accumulation of evidence and knowledge derived from implementation.

6. Discussion of Results

This study reviewed the state-of-the-art maturity models for IoT in enterprises, addressing four research questions related to these models' definitions, measurements, dimensions, and metrics. The maturity models proposed in the scientific literature usually have some commonalities in their structures and definitions, with some details that differ. In most cases, these mechanisms are multilevel frameworks with dimensions and criteria for assessing an organization's IoT capabilities and progression, each tailored to the specific industry context, domain, and purpose for which they are proposed. Although the structures of the models vary, the key elements include technological, organizational, human, performance, and security dimensions assigned to stages that denote the complexity of IoT integration and performance. In terms of definition, maturity models are defined as multidimensional matrix structures that combine several independent scales and derive a central value based on those dimensions.

Regarding publication trends, analysis indicates a growing interest in IoT maturity models, reflecting their importance as essential tools for assessing and optimizing IoT deployments in enterprises. However, primary studies remain relatively low compared to other domains and technologies [24,83]. Along these lines, the predominance of conceptual proposals rather than empirical validations highlights the need for more studies with real cases to examine the applicability of models in different contexts. Meanwhile, the extension of purely technical models to include organizational and human factors reflects a greater recognition that the success of IoT also depends on socio-technical dynamics beyond the technological infrastructure.

In particular, the measurement processes of the proposed models need more explicit detail and focus more on maturity outcomes than on the complex methodologies employed to perform this work. Although several quantitative and qualitative techniques are suggested, standardized parameters and calculations tailored to IoT capabilities still need to be made more explicit, limiting the replicability of measurement and benchmarking initiatives and suggesting the need for more rigorous, transparent, and reproducible measurement techniques. In addition, this study reveals that most maturity models focus on assessment rather than facilitating post-measurement improvement. While recommendations for transitioning between maturity levels are standard, concrete processes for formulating, implementing, and validating improvement strategies using assessment data are scarce, indicating another area requiring further research.

An unexpected finding found in this study is the extent of qualitative assessment methods employed in the proposed maturity models, in contrast to the quantitative assessment often associated with maturity frameworks, as well as the reliance on expert analysis and descriptive criteria rather than discrete metrics, suggesting that IoT sophistication involves not only technological enhancement but also managerial and cultural capabilities in organizations, which allows for rethinking how maturity is conceived in the context of rapidly advancing IoT, where constant adaptation is required and speaks to the need for multidimensionality in measurement design.

This review contributes to the IoT domain by consolidating the emerging but growing research on enterprise IoT maturity, whereby the structured synthesis of standard models, applications, measurement processes, and improvement frameworks provides a holistic perspective that previous reviews have only superficially addressed by assessing the scientific body of IoT maturity models, identifying persistent gaps and future directions for focused efforts by researchers. Also, analysis of proposed model validation methods indicates the need for standardized empirical approaches that go beyond conceptual description or solicitation of expert opinion, which would improve model reliability as model adoption expands. In addition, more consistent validation methods and empirical tests are needed to corroborate model claims and their applicability in different contexts, so demonstrating tangible organizational improvements remains an ongoing challenge for this type of mechanism.

This review provides a consolidated synthesis of existing maturity models for IoT in the enterprise domain, providing a structured analysis of internal measurement processes, an aspect superficially addressed in previous research. In addition, it highlights new avenues of research on the conceptualization of maturity in the context of IoT technology, which is constantly evolving. On a practical level, this review's analysis of standard dimensions and metrics used in IoT maturity models can help practitioners select and tailor models appropriate to their specific organizational contexts and needs. It also underscores the need for more practical and actionable guidance to foster IoT maturity within organizations. Finally, in education, this study, which analyzed the skills and competencies assessed in the maturity models, can serve as a basis for curriculum development initiatives, enabling students to acquire the knowledge and skills necessary for successful IoT implementation and continuous improvement of IoT maturity.

7. Threats to Validity

This study has conducted a review to identify and analyze the state of the art of maturity models for IoT in enterprises. However, this study has some limitations and threats to validity that need to be recognized and addressed.

Search strategy: A detailed search strategy involving multiple scientific databases, keywords, and inclusion and exclusion criteria was used to retrieve relevant studies in the domain. However, some papers not indexed in the selected databases used different terms or synonyms or were published in other sources, such as books, reports, or these, which may have been omitted. In addition, only studies published in English were considered, which may have introduced a linguistic bias and excluded relevant studies in other languages. To mitigate this threat, we also performed a hand search of references of the primary studies and the related literature to identify additional studies that might be relevant to the research questions;

Selection bias: A two-stage screening process was applied to select primary studies based on their titles, abstracts, and full texts. However, this process could be subject to selection bias due to the reviewers' subjective interpretation of the inclusion and exclusion criteria. To mitigate this threat, a rigorous protocol was followed, including using a screening tool and defining clear and objective criteria. When necessary, disagreements were resolved by discussion or consultation with a third reviewer;

Quality assessment: The quality of the primary studies was assessed using a customized quality assessment checklist based on the criteria proposed by Petersen et al. [32]. However, this assessment may have been subjective and inconsistent, as different reviewers may have different perceptions and expectations of study quality. A transparent and objective scoring system was used to address this threat; the checklist was adjusted, and inter-reviewer concordance was calculated;

Data extraction and synthesis: Data were extracted from the primary studies using a data extraction form and a narrative synthesis approach. However, this process could be affected by incomplete or inconsistent study reporting, heterogeneity of maturity models, or reviewer interpretation. Data extraction forms were collated to mitigate this threat; a common framework was used to compare maturity models, and themes were validated against the primary studies and the existing literature.

8. Conclusions and Future Work

This research planned and executed a review of maturity models for IoT in companies or organizations, allowing for the characterization, synthesis, and analysis of the existing knowledge in this domain. For the execution of this study, the methodology proposed by Petersen and the PRISMA protocol, which served as a guide for research development, were used. A total of 489 documents were identified in different databases, which were subjected to inclusion and exclusion criteria, resulting in the characterization of 36 primary studies that addressed different aspects of maturity models, such as their internal functioning, the dimensions considered, validation methods, and future work derived from these investigations.

The primary result of this research is that the maturity models proposed in the literature have some commonalities in their structures and definitions, such as the use of levels, dimensions, and indicators to represent and measure the maturity or readiness of an organization in terms of IoT capabilities, processes, or outcomes. However, there is great diversity and variability in the number, names, and descriptions of these elements, as well as in the methods and tools used for data collection, analysis, and visualization. In addition, maturity models address various aspects or factors that influence IoT adoption and implementation, encompassing technological, organizational, human, performance, and other specific dimensions, depending on each proposal's context, scope, and purpose.

The internal measurement processes of these mechanisms involve data collection, analysis, visualization, and feedback methods tailored to the purpose and design of the model, where quantitative, qualitative, and mixed metrics are used to assess maturity. While these mechanisms effectively measure IoT adoption and implementation in organizations, most do not explicitly support post-measurement improvement because some provide benchmarks, recommendations, and roadmaps. However, practical improvement frameworks are limited and need more. Different methods have been used to validate maturity models, such as case studies, surveys, comparative metrics, or expert reviews. However, more rigorous and detailed validation approaches involving multiple stakeholders are needed to provide empirical evidence of these measurement mechanisms' impact and results in organizations.

Critical areas for future refinement of IoT maturity models include additional validation, development of process support tools, expansion of scope and indicators, customization for different contexts, and updating for new IoT-related technologies. Also, some limitations and gaps in the current body of science lack empirical validation and evaluation of the proposed models, the paucity of details on measurement processes and methods, the limited consideration of human and social factors, and the limited use of data to promote improvement and progression along the maturity continuum.

Finally, future work derived from this research should focus on developing more comprehensive, holistic, and standardized models that not only address the technological aspects but also integrate the organizational, human, and social dimensions of IoT and the interrelationships and interdependencies between them. It is also crucial to conduct case studies, field tests, and experiments in various organizational environments to assess the practical applicability and effectiveness of current and future maturity models. Furthermore, it is necessary to develop and apply standardized and rigorous methodologies for constructing and validating maturity models, going beyond conceptual descriptions and expert opinions. In terms of data collection and analysis methods, it is essential to sophisticate these processes by using advanced techniques such as machine learning and natural language processing to gain a deeper understanding of organizational data. Finally, it is essential to consider incorporating new dimensions or indicators related to Industry 5.0, sustainability, social responsibility, and user experience, thus addressing emerging trends in IoT.

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