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Article

Systems Approach for the Adoption of New Technologies in Enterprises

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Abstract: There is a great challenge in the business sector to adopt new technologies that boost companies to break into Industry 4.0, especially to obtain the capacity to adopt and develop complex systems based on: artificial intelligence, Big Data, Data Mining, and Cyber Physical Systems. However, efforts tend to be more of an empirical process, rather than a prior analysis, that allows companies to identify the complexity of the situation and trigger a viable implementation. For this reason, this research carried out a systematic review to identify and analyze, from the Systems Science approach, the proposed and most used models to face these organizational problems. In total, 42 of the 3800 documents were filtered for discussion using a systems approach. In addition, one of the models was tested by interviews with Mexican managers to understand how it promotes the abstraction of complexity necessary for a viable system change. The findings at the end of the work were to determine the lack of systemic properties in the current proposals, especially in the efforts to adopt artificial intelligence and the need to have a suitable model for the context of technology.

Keywords: TOE framework; viable technology adoption; artificial intelligence; systems

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1. Introduction

The Fourth Industrial Revolution (4IR), also called Industry 4.0, consists of the use of new technologies in companies and governmental or nongovernmental organizations that promote intelligent systems [1], the Internet of Things (IoT), Cyber Physical Systems (CPS), Big Data and artificial intelligence (AI) [2–4].

It is important to note that Industry 4.0 is not just a digital transformation, since this phenomenon belongs to the Third Industrial Revolution (3IR) with automation through the use of Information and Communication Technologies [5]. Instead, the 4IR is characterized by system intelligence; that is, [6,7] humans and processes supported by the presence of computer systems using the mentioned technologies, AI, Big Data, IoT, and CPS [8–11].

The process of adopting these new technologies has been growing in the last five years [12,13], and most of them have been executed optimally in companies with the economic, scientific, and technological capacities to make use of them, for example, Amazon, Facebook, Microsoft, Uber, important start-ups, known as 'unicorns', as well as banks such as BBVA [14,15]. All of these companies have something in common: they were born as Digital Native Companies (DNCs) [16] or have enough of a budget; that is, companies whose core business is based or founded on technologies related to Industry 4.0.

Although there are great technical computational developments and applications of Industry 4.0 [17] from the computer science (CS) approach, efforts to adopt these new technologies from the management approach for companies are minor, especially for companies outside of the technological context. Using keywords in databases to do a search can help to visualize the big difference between technical applications and changing the way an organization is set up to use new technologies, such as AI, e.g., by the following two words: “AI Adoption Framework” and “AI Applications”; SCOPUS shows a rate of 1 article for the first word to 120 articles for the second, and the Web of Science shows 1 article for the first word to 150 for the second.

This highlights a great problem for companies, because the barriers to AI adoption (AIA) are more complex than the developments of computer science (CS), since the adoption of the managerial approach is not limited by facts, but by different factors such as (1) not changing the structures of organizations toward more flexible management [18,19], (2) not understanding the implication of the process from an internal and external contextual analysis before executing any strategy [20,21], (3) financial difficulties or investment funding [22], and (4) lack of technical skills or consultancies in new technologies [23].

Today, management science has sought solutions to these barriers using models created since the mid-1950s to understand the adoption of new technologies and features that require an adopter system [24]. For example, the Technology-Organization-Environment Model (TOE) [25–27], the Technology Acceptance Model (TAM) [28–30], and the Diffusion of Innovation Model (DOI) [31], among others [32]. These models usually have variations in their way of evaluating, depending on the system analysis [33–36], and they focus on different elements inside and/or outside the organization.

During the 3IR adoption processes, the models played an important role due to their diagnostic benefits and the measurement of variables in an organization that provided important information at the managerial level for decision making prior to the execution of any adoption strategies [37], and, now, the models are being used for the same purpose: to understand and adopt Industry 4.0 technologies.

However, the old techniques are not suitable for the temporal context; as was mentioned, the new technology adoption activities are more complex now than they were in 1950. Furthermore, even though the state of the art revealed that TAM, TOE, or DOI are presented as optimal tools to define the needs of companies and promote new strategies and business models, the current models could result in false strategies or wrong decisions if they do not promote an intrinsic abstraction of complexity and viability by themselves.

On this path, there is a science approach for creating suitable business models, which explains how these incorrect strategy designs can occur easily if old management tools are used [38,39]; thereby, some researchers [40] propose to overcome this problem using the benefits of Systems Science (SS) to obtain the desired suitability.

SS looks for the whole and holistic properties in a system, since there are structures, organisms, phenomena, entities, objects, etc., with very similar principles that can be transferred from one system to another and behave similarly. This is based on theories of some system thinkers such as Bettalanffy and Wilber [41,42]; additionally, Weiner, von Foerster, and Beer stated that the main characteristic of systems is that they are controlled through cybernetics to improve their viability [43–45].

Therefore, the aims of the research are to identify the most used models to promote the adoption of new technologies, especially AI, by a systematic literature review (SLR), to carry out a critical SS analysis of the state of the art, and test one of the most used models (the TOE model). The intention is to understand and justify the shortcomings of a model without the system properties necessary to abstract complexity, design viable strategies, and provide the cyclical evolution in enterprises to achieve homeostasis in their Industry 4.0 context.

To achieve its goals, the present work is divided into three parts. The first part is an analysis of the SLR under the SS approach to find the benefits of the temporal context and weaknesses in models to push companies into Industry 4.0. The second section is a test of one of the more commonly used models (TOE) to ensure the need to adopt new technologies like AI and how their benefits can be mixed into SS. Finally, the results are revealed, laying the groundwork for future work to develop a viable model for implementing AI and related techniques.

2. Research Methods

The Figure 1 illustrates the Research Methodology (RM) that was followed throughout the work, divided into two primary stages: the first stage includes two reviews of the literature and a system critic, and the second stage includes tests and results with one of the most commonly used models.

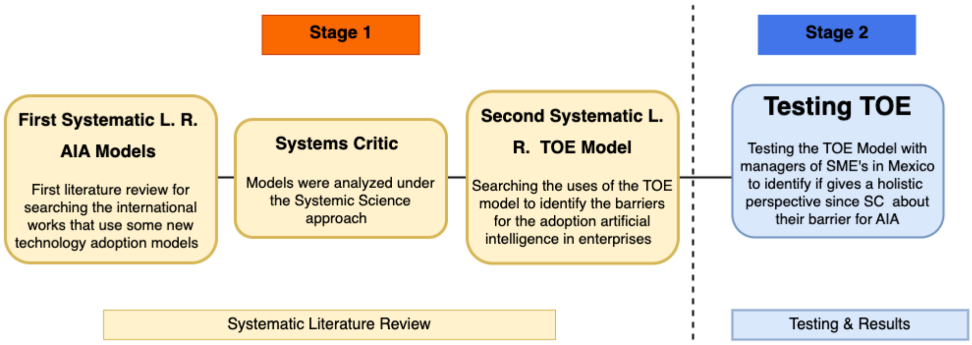

Figure 1. Research Methodology.

The systematic literature review (SLR) [46–48] was used to obtain information in the first stage, because it allows the use of specific questions, ensures that research-related papers are not omitted, identifies gaps in current knowledge, summarizes knowledge, and provides a solid scientific foundation for a new line of research [49,50].

The following steps address an SLR [51]:

1. Select the data set.
2. Clearly articulate objects and questions to be addressed.
3. Inclusion and exclusion criteria (key words, publication date, approach, etc.).
4. Analysis of data extracted from included research.
5. Presentation and synthesis of the findings extracted.
6. Transparent reporting of the method.

According to the RM, the SLR on AIA Models attempts to address the following questions:

- Which AI adoption frameworks are most widely used?
- What are the main characteristics of AI adoption frameworks?

Following the RM (Figure 1), a system critic was addressed between the first and second SLRs to identify the model that embodies a greater sense of holism during the evaluation of organizational readiness. The purpose of this intermediary critique was to determine which model would perform best in the tests. Since the analysis indicates that the TOE model is linked to better system behavior, SLR two was structured around it.

The second SLR attempts to answer the following research question:

- How is the TOE framework used?

The implementation of TOE should be known because it is one of the most commonly used models for assessing contextual complexity in an organization, and testing it demanded an extensive awareness of its application.

The second stage puts the TOE model to the test by interviewing Mexican company executives. This second procedure is not a validation or variable identification, but rather a test to see how the framework assists managers in discovering variability and recognizing the complexity of the internal/external context in the company. The final part of this section shows the interview results, emphasizing the lack of system elements in the models and proposing model integration with SC to stimulate the creation of feasible model designs.

3. Stage One: Systematic Review of the Literature

3.1. Artificial Intelligence Adoption Models

While the first systematic review of the literature (1SLR) was in progress, some article titles were reviewed, revealing that there was still more research related to engineering, algorithms, computer science, and government, among other fields. As shown in Table 1, although the keywords used were directly associated with those areas, only a range of 10% to 35.5% of the articles had a primary focus on management and business analysis.

Table 1. Databases analysis.

Web of Science			Scopus		
AIA & Business	AIA & Framework	AIA & Management	AIA & Business	AIA & Framework	AIA & Management
849 articles	735 articles	1257 articles	469 articles	647 articles	823 articles
35.5 %	31.64%	24.6 %	14.6%	10.7%	10.5%

For this reason, it was decided to limit the database search to research branches specifically related to management and business. Figure 2 explains how (1SLR) started in two scientific information databases: Web of Science and Scopus. Following the established criteria, 132 articles were identified in the first branch.

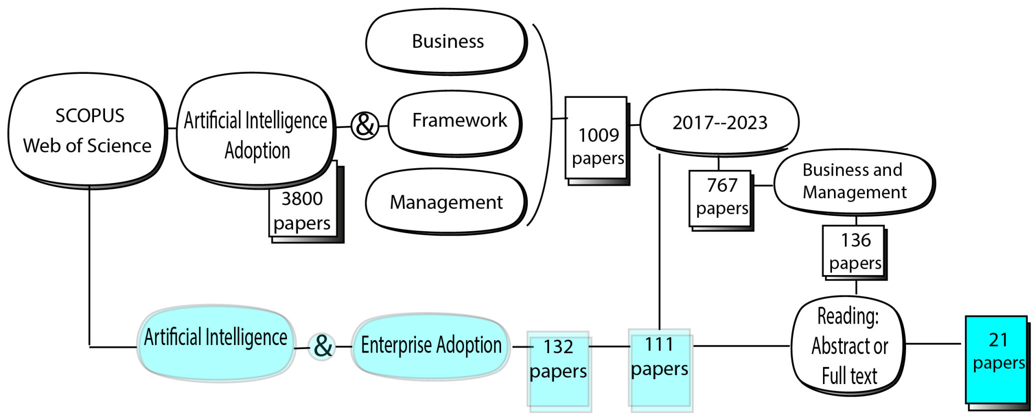

Figure 2. Systematic review process in the second branch.

A smaller second branch (depicted in cyan) was created using two keywords to connect the two approaches of the systematic review: artificial intelligence and business adoption. This was necessary because the first branch still included articles outside of the desired scope. Following the exclusion criteria, 111 articles were identified for removal. After reading the abstracts and full text, 21 were selected for in-depth analysis.

Finally, Table 2 summarizes the SLR process and describes the most relevant research to answer the first question of this phase: Which AI adoption frameworks are the most widely used?. The “Contribution” column lists the most commonly used frameworks, such as TOE and TAM, and identifies independent proposals. Additionally, as observed in the same column and in the “Classifications” column, they reveal important characteristics that address the second question: What are the main characteristics of AI adoption frameworks?

Most frameworks include business preparation (readiness) to evaluate aspects of the organization that must be considered before and during AI adoption. However, none of them provides a suitable change proposal (processes). Although conducting an analysis prior to the creation of a strategy is an important step in defining the objectives of a system, it is not the sole effort required to achieve those objectives. It is essential to clearly articulate the relevant activities that lead to successful adoption of AI.

Table 2. Systematic review analysis.

	Title	Classification	Contributions
1	Enterprise AI Canvas Integrating Artificial Intelligence into Business [52]	Readiness	Canvas applications (business models) to connect business concepts, business management, and new information technologies. Inspired by the Osterwalder Canvas [53].
2	Artificial Intelligence Adoption: AI-readiness at Firm-Level [54]	Readiness	Proposal for the adoption of AI through the Technology-Organization-Environment Model (TOE).
3	The adoption of artificial intelligence in human resource management and the role of human resources [36].	Readiness	Proposal for the Adoption of AI through the Unified Theory of Acceptance and Use of Technology (UTAUT). The origin is based on the Technology Acceptance Model (TAM).
4	Towards an artificial intelligence maturity model: from science fiction to business facts [55]	Processes	The research is based on the development of a maturation model for the integration of artificial intelligence. The authors rely on the model: Maturity Model for IT Management by Becker [56].
5	Overcoming Organizational Obstacles to Artificial Intelligence Project Adoption: Propositions for Research [15]	Readiness	It is described in a model called the Value Model, which includes organization, infrastructure, and planning.
6	Understanding AI adoption in manufacturing and production firms using an integrated TAM–TOE model [33]	Readiness	The research bases the adoption of artificial intelligence on the TOE–TAM model TOE–TAM. It combines the virtues of the TAM and TOE models and identifies the most important criteria that an organization should take into account for readiness.
7	A Framework for the Implementation of Artificial Intelligence in Business [57]	Readiness	A preparation model for companies looking to integrate new technologies is based on seven elements: employees, information management, governance, strategy, infrastructure, knowledge, information, and security. It is called the AI Enlistment Model.
8	Can we trust AI? An empirical investigation of trust requirements and guide to successful AI adoption [58]	Readiness	Based on the TAM model, added value to the model by three factors: skill, integration, and benevolence, which are involved in the perception of usefulness.
9	A Simple Tool to Start Making Decisions with the Help of AI [59]	Readiness	Use of an AI-Canva, which also inspired Ulrich Kerzel's Canva [52].
10	The Adoption of Artificial Intelligence for Financial Investment Service [60]	Readiness	Study from the perspective of the TAM model to identify criteria that will influence the decision to apply AI or not.
11	Technology acceptance model (TAM) and social media use: an empirical study on Facebook [61]	Readiness	Use of TAM to analyze why and how only the social media adoption was accepted.
12	The role of organizational culture and voluntariness in the adoption of artificial intelligence for disaster relief operations [62]	Readiness	The UTAUT model was applied to identify the readiness criteria and acceptance of artificial intelligence.
13	Adoption of Artificial Intelligence for talent acquisition in IT/ITeS organizations [63]	Readiness	Implementation of the TOE model in combination with the Task-Technology-Fit model (TTF), a model used in the recruitment of talent.
14	The adoption of artificial intelligence and robotics in the hotel industry: prospects and challenges [64]	Readiness	The foundation for understanding the adoption of AI, the TOE model was implemented.

Table 2. *Cont.*

	Title	Classification	Contributions
15	Integrated AI and Innovation Management: The Beginning of a Beautiful Friendship [65]	Readiness-Processes	One work analyzed during the systemic review makes an introduction of the need to generate holistic models that see the problem as a whole. The proposal is a model based on the Bruit and Rosemant model of developing maturation models [66].
16	Organizational Readiness to Adopt Artificial Intelligence in the Exhibition Sector in Western Europe [67].	Readiness	Use of TOE to identify readiness criteria in the use of artificial intelligence.
17	Adoption of digital technologies of smart manufacturing in SMEs [68].	Readiness	Use of TOE, adding eight conditions that can affect the adoption of new technologies.
18	An AI adoption model for SMEs: a conceptual framework [69].	Readiness	It shows a model of readiness and evaluation for artificial intelligence, bases its analysis on five important pillars, and evaluates through a questionnaire.
19	The Adoption of Artificial Intelligence in the E-Commerce Trade of the Healthcare Industry [34]	Readiness	Using TOE, however, this model adds an element that was relevant for the search. It mentions the absorption capacity of new technologies. One way to self-assess a catalyst in the process of adoption is by self-assessing.
20	Strategizing in a digital world: Overcoming cognitive barriers, reconfiguring routines and introducing new organizational forms [21]	Readiness	Proposal of an "ideal" model of three essential characteristics in a organization with the intention of AIA: cognition, routines, and structure. As a whole, the company has a greater capacity to achieve its goals. In addition, it presents a taxonomy of transformation types with the intention of giving a greater perspective on the requirements for the adopting system.
21	A conceptual framework for the cognitive enterprise: pillars, maturity, and value drivers [18]	Readiness-Processes	It proposes four fundamental pillars within an organization: technology, data, processes, and capabilities. In the conceptual model, it presents three states and proposes them as a state of maturation.

3.2. System Critic

After acquiring this information, an analysis of the Systems Science (SS) approach was performed to determine the viability and cybernetic properties. Subsequently, substantial effort was dedicated to identifying their weaknesses.

In this context, viability refers to maintaining the identity of the organization through a regulatory process that encompasses it entirely. This process involves learning, adaptation, and evolution, all of which contribute to the organization's survival. Viability depends on achieving an appropriate balance between the autonomy of subsystems and their integration within the system, as well as the balance between stability and adaptation [70,71]. In addition, intrinsically, it was also analyzed under Ashby's law of required variety [72].

With these premises, the following discussion is created under the system approach. First, we compare the models outside the TOE and TAM applications, and later, we compare these two models.

Kerzel [52] describes how they generate a new business model using two canvas models. On the one hand, the first canvas is employed to generate value from the perspective of the system owners. On the other hand, the second canvas adopts the perspective of CC experts who translate the expected value of the owners into measurable activities and metrics through the analysis of data and information using AI and Data Science techniques.

The resulting model adds value by bridging the gap between business value and technical needs. Although it may not be explicitly presented as a system process, this approach enables the description and documentation of relevant activities to alter the state of the system. Compared to stage four of the SSM, it facilitates the creation of a strategy aimed at solving the problems faced by system owners. The canvas model has strong competitive abilities at this point, but does not have a diagnosis of the system, and does not have feedback and interconnections among their subsystems involved. However, it should be noted that while the canvas model excels in creating strategies and addressing business needs, it may lack a comprehensive system diagnosis, feedback mechanisms, and interconnections among the subsystems involved.

For its part, Yams et al. [65] also defines the stages that a company must go through to implement artificial intelligence. It provides a detailed contextual analysis that extends beyond technology, embracing the characteristics of organization, worldview, information, environment, and strategy as a distinguishing property of system thinking. Although the model emphasizes the need for feedback in the stages it proposes, it does not provide a full description of the feedback process. It is important to note that among the works examined in the SLR, this one employs a Systems approach right from the problem statement, and its aims are clearly stated. However, there is an opportunity for development in terms of its utility as a viability and management support tool.

Alsheiabni et al. [55], despite being inspired by another model that incorporates features of systems that maintain stability (homeostasis), such as inputs, outputs, structure, feedback, and goal delimitation, the description only mentions the levels that an organization must meet for a gradual adoption of AI. However, the factors of internal and external contextual analysis, the proposals for creating a strategy, and the definition of subsystems that support each level that the organization must meet are not delimited in the proposal, leaving a gap between the definition of the problem and the necessary actions.

Someh et al. [15], Najdawi [73] and, Bettoni et al. [69] provide a more comprehensive examination of the technological analysis and the process of generating a business model based on essential technological attributes, such as data, AI skills, and infrastructure. Furthermore, it specifically formulates the proposal by defining the proposals, measurements, and developing a strategic plan, ultimately resulting in the generation of value for the organization. However, it is worth noting that managers often lack a creative tool for formulating their strategies, as well as a clear indication of how to implement progressive improvements. Furthermore, they often lack a feedback process that facilitates the creation of improvement cycles. In addition, managers often face the challenge of conducting an adequate contextual analysis, which is essential for a complete diagnosis.

The latest works without TAM or TOE applications are [18,21]. These models provide an explanation of the needs of the management approach for changing mindset, work structures, and adaptability to the use of technology. However, they do not possess SS properties.

Last, the next SS critiques are made on TAM and TOE to determine which has better variability measuring and system characteristics.

TAM is a model designed by Davis in 1986 [74] and suggests two important factors, as seen in Figure 3. The *perception of usefulness* and *perception of easy use* factors influence agents who will use the new technology, including end users and workers. Their perceptions play a crucial role in whether they accept or reject the technology adopted within the system or organization [75]. The external variables can vary between age, leadership, management of new paradigms, capacities, etc., and they affect decisions of change.

The uses of TAM [76,77] illustrate the possible modifications that can be made to TAM to fully assess the characteristics of the users, according to the unique evaluation criteria desired by the management. However, TAM can become overly detailed as it primarily focuses on the organization's internal aspects and individual change. In contrast, the Systems Science (SS) approach tends to be reductionist and overlooks the holistic perspective necessary for understanding the complexities beyond the system. It also omits other elements that introduce variety to a cybernetic diagnosis.

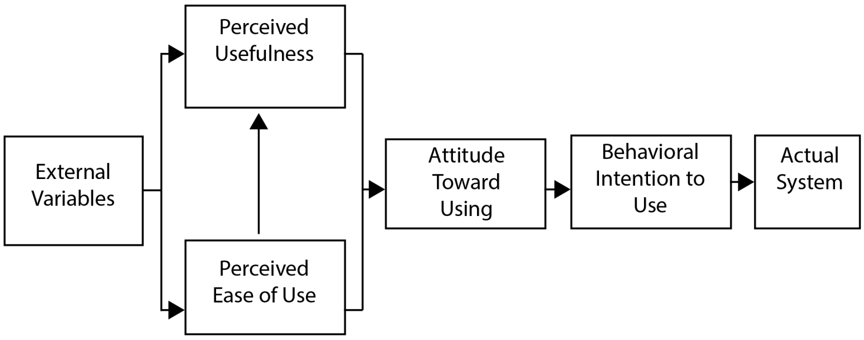

Figure 3. TAM Model. Adapted from Lai [74].

TOE (Figure 4) is a model designed in [78] to evaluate the context inside and outside a company that adopts new technologies, based on three main characteristics: technological, organization, and environment [25]. First,the technological context, the information system and equipment available, and the technological market offers. Second, the organization context evaluates the business model, structure, strategies, and the size of the company. Finally, the environment context evaluates the market, the external support in the case of requiring consultancies, government relations, and the policies that a company must follow when adopting a new technology.

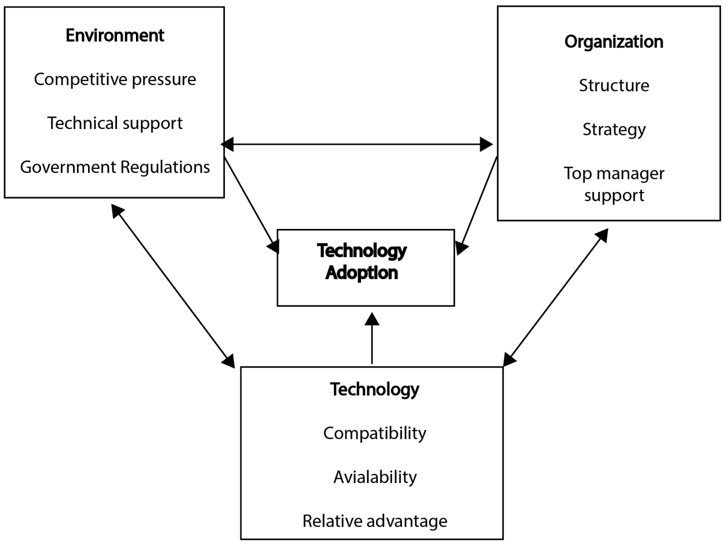

Figure 4. TOE Model. Adapted from Tornatzky et al. [78].

TOE serves as an evaluation of the company, encompassing both internal and external aspects with various criteria. It extends beyond the perspective of the person who will use AI, allowing for a more comprehensive analysis. In [79], each criterion is described in more detail in a simple manner. Compared to TAM, this model provides a complete organizational overview to directors prior to adoption. It also offers the possibility of involving stakeholders in the analysis of each element, helping to identify what is missing and what the organization already has.

Adding to earlier observations, some key elements for the creation of systemic models were compared; they were mainly taken from the system descriptions provided by Katz and Kahn [80] and Bertalanffy [41]. In terms of inputs/outputs, internal/external context, structure, transformation, process, objective feedback, and interconnection, Table 3 illustrates if TAM and TOE meet as viable models.

Table 3. Systems features.

Framework	Input/Output	Inner/Outer Context	Transformation	Structure	Process	Feedback	Aim	Connections
TAM	OK	Fail	Fail	OK	Fail	Fail	OK	Fail
TOE	OK	OK	Fail	OK	Fail	Fail	OK	OK

Even if the process is unclear, implementing TOE involves assessing input and output variables, such as technology, organization, and environment. It offers both internal and external contextual perspectives and considers the interconnections between the structure and the objective of AI adoption. However, it does not clearly illustrate the process and transformation within organizations. Additionally, it lacks feedback, which is a fundamental feature for assessing a model's viability. Therefore, although it exhibits more contextual properties than TAM, it is not perceived as a truly viable model.

For its part, TAM has fewer green values, with an analysis aimed at the person who will use the new technologies instead of the system. It lacks an external and internal vision of the variables that can influence its processes. We segment only the TOE analysis to understand how it promotes AI adoption in order to carry out the 2SLR.

3.3. Systematic Literature Review TOE Model

Once the most used models were identified and their characteristics understood, a systematic literature review (SLR) was performed on the TOE (Technological, Organizational and Environmental) framework process, as shown in Figure 5. The aim was to determine its usage and classify the primary barriers to AI adoption in organizations. After a thorough analysis of 21 articles, summarized in Table 4, we sought to answer the following question: How is the TOE framework used?

The 2SLR (second systematic literature review) reveals several key findings. First, all of the articles focus on diagnosing factors that either facilitate or hinder a company's adoption of AI. These factors are typically validated through questionnaires and interviews with experts in both technology and the specific industry of interest.

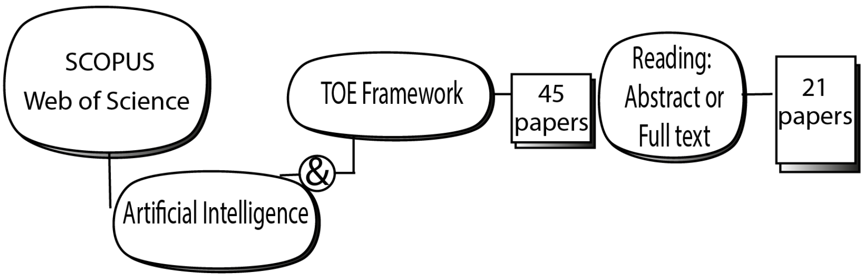

Figure 5. Systematic review process.

Secondly, most studies are conducted in first world countries with large economies and advanced technological developments. There is limited research in less developed regions, including Latin America, where this study originated.

Lastly, the articles reviewed primarily apply the TOE model to the areas of human resources, management, and marketing. This suggests potential opportunities to introduce adoption methodologies into a wider range of companies and organizations and promote systemic thinking in Latin America.

The papers discuss several factors that determine an organization's readiness to incorporate AI gradually. However, there is a noticeable repetition of these factors in all of the studies reviewed. For example, factors such as organizational culture, leadership support, strategies, employee skills, investments, infrastructure, and data quality appear repeatedly in every investigation.

Table 4. Use of TOE.

#	How Is It Used	Author	Origin	Field	Validation
1	Diagnosis	Alsheiabni et al. [55]	Australia	Unfocused (general)	Survey
2	Diagnosis	Mahroof [81]	UK	Warehouse	Empirical
3	Diagnosis	Kruse et al. [82]	Alemania	Finance	Interviews
4	Diagnosis	AlSheibani et al. [54]	Australia	General	No validation
5	Diagnosis	Seethamraju and Hecimovic [83]	Australia	Audits and Accounting	Interviews
6	Diagnosis	AlSheibani et al. [84]	Australia	General	Surveys
7	Diagnosis	Chen et al. [85]	USA	General	Surveys
8	Diagnosis	Pillai and Sivathanu [63]	India	Human Resources	Surveys
9	Diagnosis	Nam et al. [64]	Dubai	General	Surveys
10	Diagnosis	Mikalef et al. [86]	Germany	General	Surveys
11	Diagnosis	Hamm and Klesel [87]	Germany	Government	Surveys
12	Diagnosis	Schaefer et al. [88]	Germany, The Netherlands	General	Literature review
13	Diagnosis	Lee et al. [89]	Korea	Human Resources	Surveys
14	Diagnosis	Pumplun et al. [90]	Germany	Government	Interviews
15	Diagnosis	Kong et al. [34]	China	E.commerce	Survey
16	Diagnosis	Chen et al. [91]	USA	Marketing	Survey
17	Diagnosis	Chatterjee et al. [33]	India	Manufacture	Survey
18	Diagnosis	Neumann et al. [92]	Switzerland	Government	Interview
19	Diagnosis	Nam et al. [64]	USA	Hotel Industry	Interview
20	Diagnosis	Wang and Su [93]	China	Manufacture	Case study
21	Diagnosis	Sivathanu [94]	India	Manufacturing industry	Survey

Figure 6 displays the most relevant criteria factors for the model, ranked in descending order according to their importance to organizations. The selection of these relevant criteria factors is based on the work of Hamm and Klesel [87]. This information was also cross-referenced with other studies that make use of the TOE model [33,34,54,92,95].

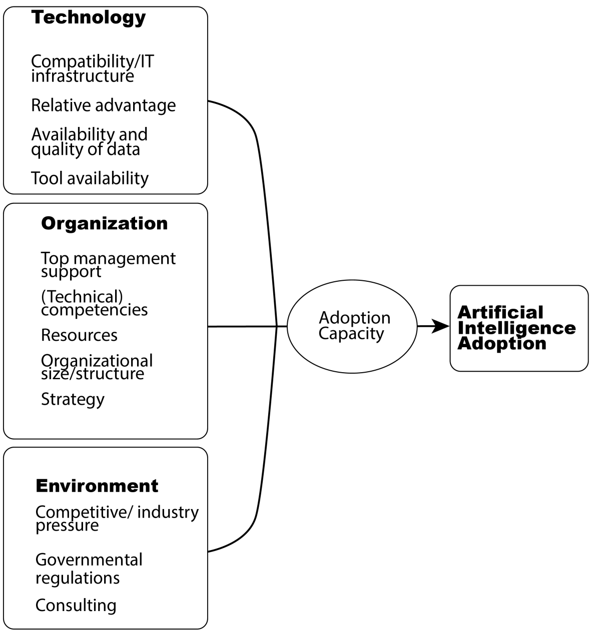

Figure 6. Proposal model TOE, adapted from Tornatzky et al. [78].

4. Stage Two: Testing and Results

In order to fully understand the TOE model under SS, a test was conducted at the end. The test questionnaire consists of four sections (Appendix A). Note that the managerial perspective is sought, not a quantitative judgment. Each result obtained during the test is to analyze TOE characteristics as a tool to provide managers with holistic views.

The first section consists of a set of open-ended questions on AI aimed at gauging how Mexican companies perceive AI. The second, third, and fourth sections, which focus on the three TOE areas of technology, organization, and environment, measure the organization's AIA capacity based on the interviewee's assessment. The questionnaire is linked to Figure 6, which contains representations of these sections. Expert opinions are rated on a scale from 1 to 6, with 1 representing complete disagreement and 6 representing complete agreement for each nuanced criterion.

An overview of the findings from the directors' interviews with Mexican enterprises is shown in the Figure 7. Alpha numbers are displayed on the x-axis; the first ones, O1–O15, represent the questions related to the questionnaire's second section, while the letter O stands for the organization's requirements. The same applies to the questions T1–T8, which stand for the technology portion, and E1–E7, which represent the environment. Furthermore, the colors at the top of the representation correspond to the five companies, labeled A to E, to help contrast their results.

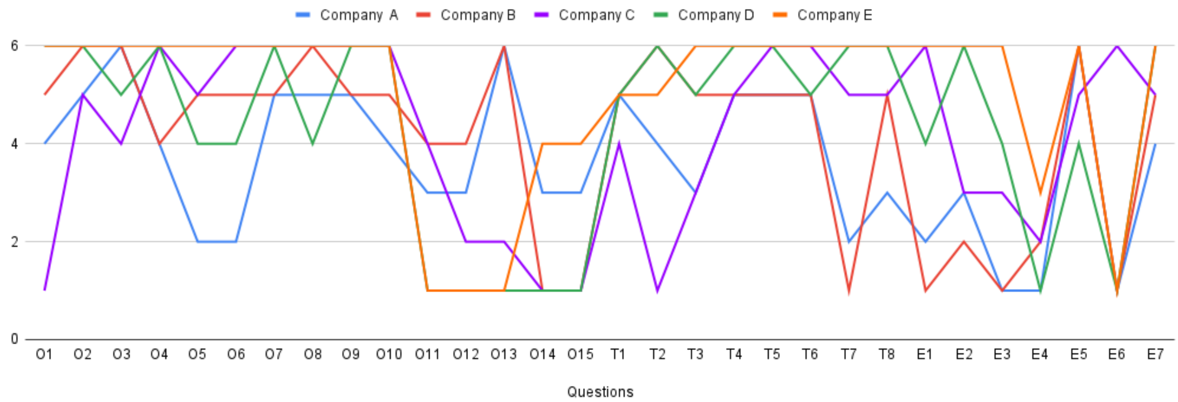

Figure 7. Test answers.

Additionally, to provide a more detailed perspective, we analyzed each of the TOE model criteria as illustrated in the following Figures 8–10. Each TOE criterion is represented by two graphs: the first expresses the precise number chosen for each company in columns, and the second is a radar graph to compare the companies. This analysis gave us insight into how these companies perceived themselves and how their perspectives on their readiness to incorporate artificial intelligence differed. For the purpose of distinguishing between each company, we use five colors: blue for the first company, red for the second, and so on until company "E" with orange color.

Figure 9 shows the most relevant criteria highlighted in technology: compatibility/availability/data quality, relative advantage, and tool ability. The initial description explores how companies perceive that they have the necessary infrastructure to adopt AI. However, this perception is contradicted by the absence of a comprehensive strategy and the obvious need for external consultation, as illustrated in the consulting graphics in Figure 10.

As we observe in the organization section (Figure 8), the evaluations of the companies vary from one another, but there is information that contributes to the overall understanding of the organization and also reveals factors that the stakeholders make apparent. First, in terms of management support, most companies show an inclination towards implementing AI to some extent. On the other hand, most also perceive that the costs and resources involved are high, yet they are willing to invest in such initiatives. Finally, the companies interviewed exhibit a distinctive gap in the area of strategies, which, if properly understood, is an essential segment for achieving the adoption objective. Without a clear goal, methodology, and strategy, accomplishing a task of this nature would be challenging. In fact, during the interview, 100% of them stated that they did not have a clear strategy.

Under the SC, the strategy (hence defined objectives) is a fundamental part, since it is the part of the system that will allow for feedback and looks for the system's homeostasis, depending on what the objective they seek and the strategy that will take them towards the system transformation.

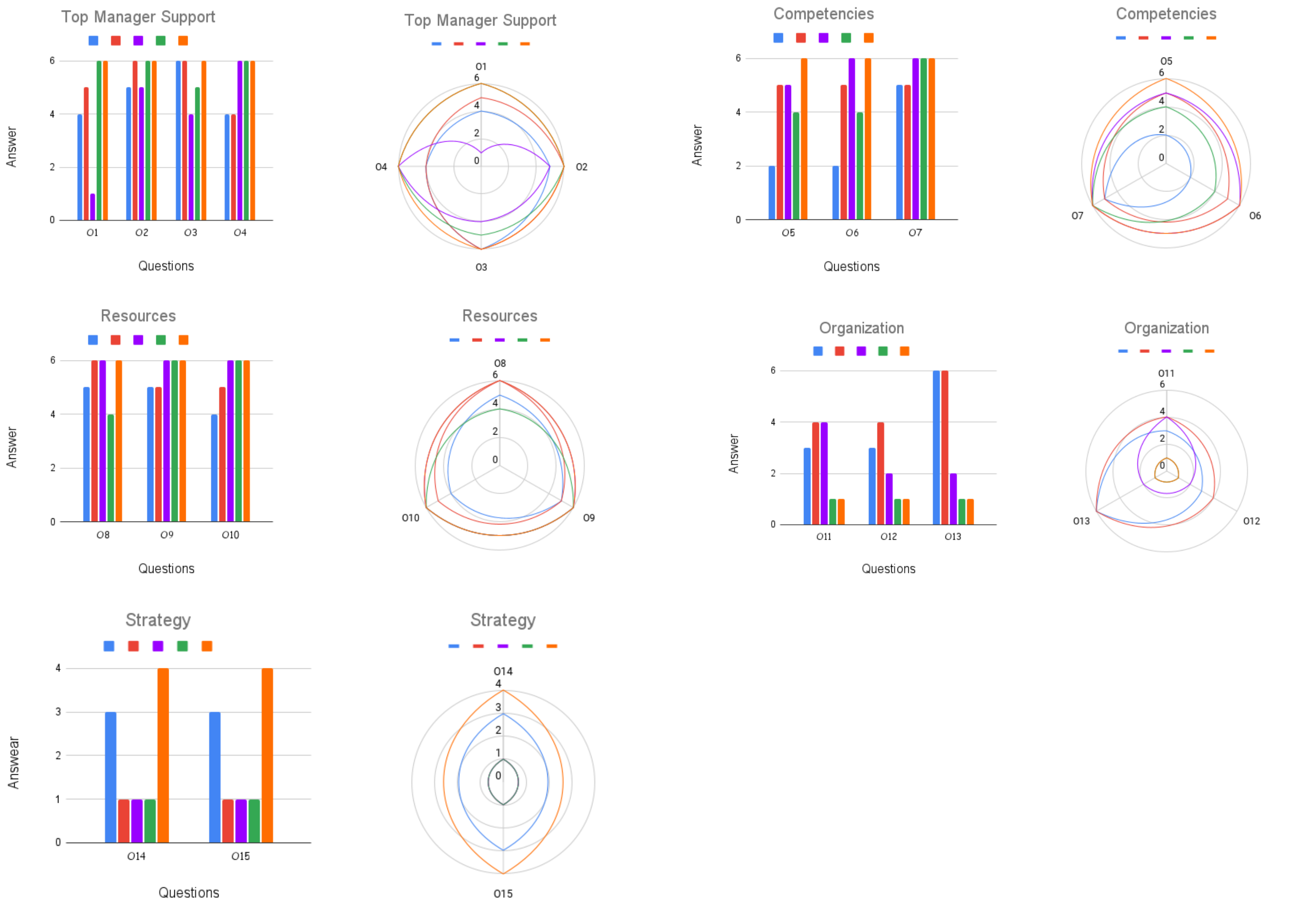

Figure 8. Organization.

It is clear that managers are aware of the data pertaining to their organization and think they have the necessary information at their disposal. However, from the perspective of experts in the field of CCs, it becomes apparent that merely knowing what information is required is insufficient. Instead, a comprehensive process of data storage, projection, and visualization, as highlighted by [96], is necessary.

Upon examining the aforementioned two graphs, it becomes evident that there is a correlation between the presence of managerial support and the perception of an organization of the comparative benefits associated with the adoption of novel technologies. These benefits include increased operational efficiency and mitigation of expenses. According to [52], the assessment of AI adoption activities is frequently centered on this particular aspect, which is of significant importance for most companies.

From this section, it is inferred that there is a perceived advantage within the organizations, and the stakeholders are aware of their interest in promoting new technologies. However, without expert support or guidance in decision-making, there is a risk that managers may develop inefficient processes.

Ultimately, the diagram presented in Figure 10 illustrates environmental criteria, and there exists a lack of legislation or standards specifically tailored to SMEs. This absence can potentially offer certain benefits, such as increased flexibility in the implementation of technological advancements. However, laws can also provide valuable information on the optimal functioning and seamless integration of technologies. In the field of SS, a notable difficulty extends beyond the scope of individual firms and belongs to the Latin American area. Specifically, this challenge revolves around the inadequacy of government initiatives aimed at facilitating the proficient use of technology within small and medium enterprises (SMEs) [97,98].

Hence, it is imperative to build a governance framework that fosters a facilitated environment for the implementation and utilization of technology in SMEs. This may help to mitigate the obstacles facing organizations and foster the widespread adoption of technology in the region.

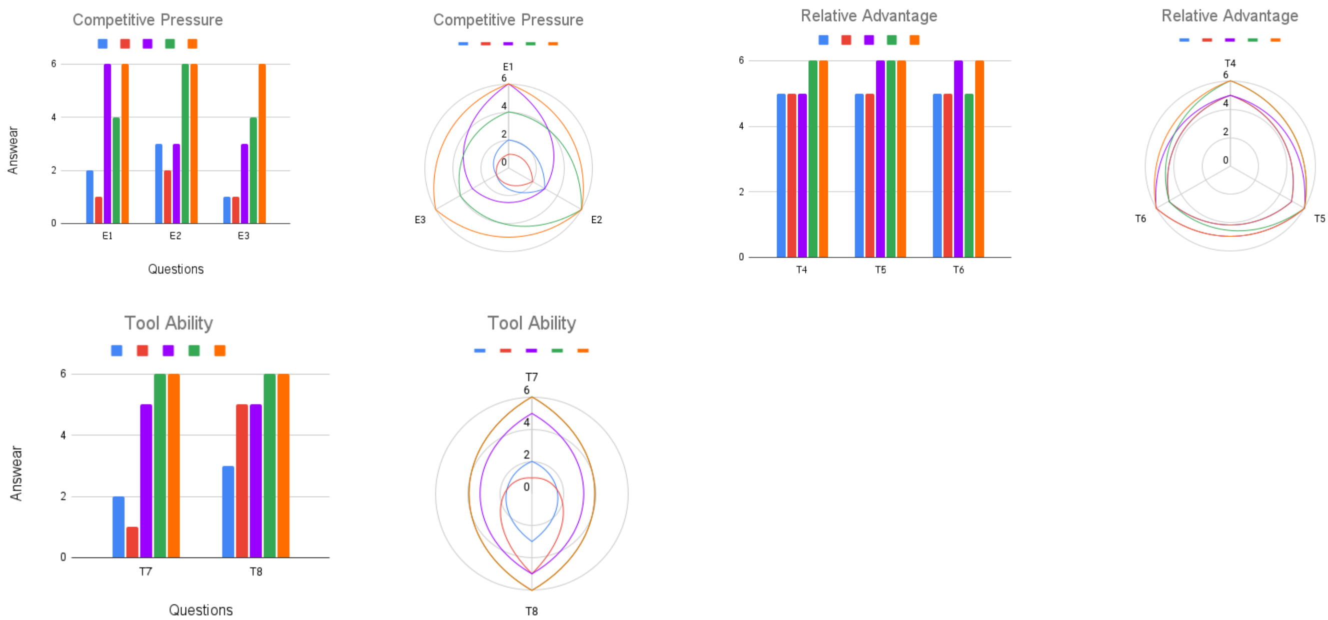

Figure 9. Technology.

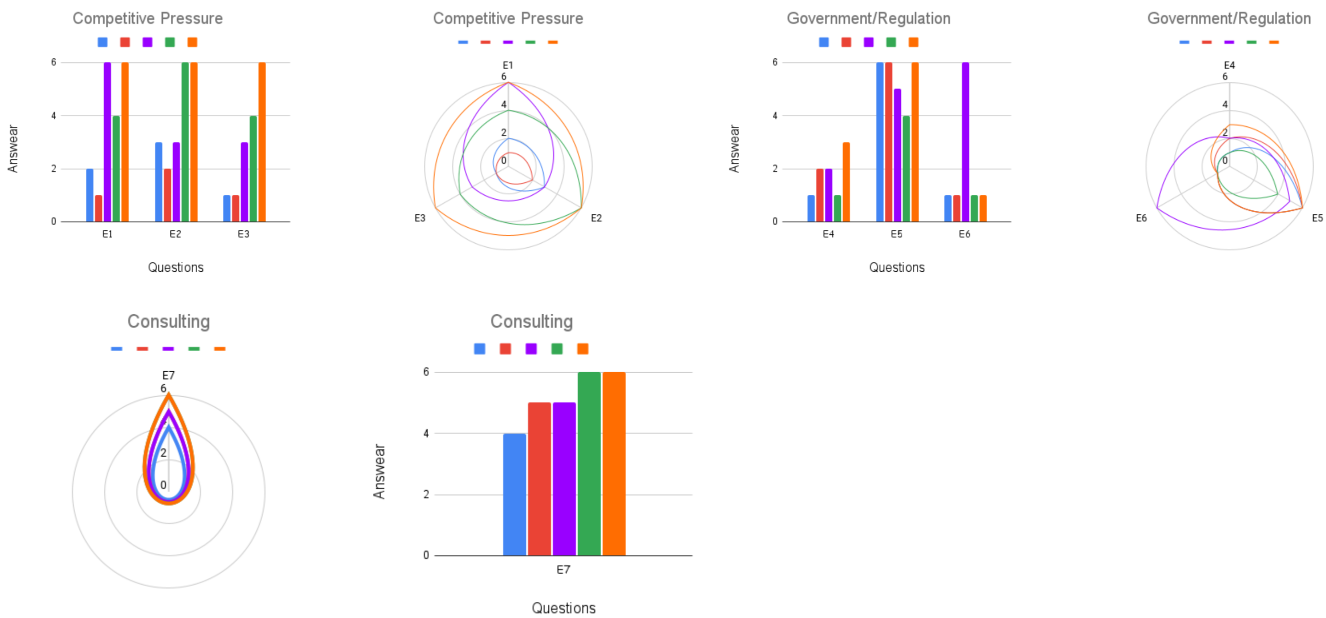

Figure 10. Environment.

In contrast, within the context of the consultation chart, participants expressed agreement on their need for guidance and support from experienced individuals in AI, as they lacked clarity regarding their specific needs. From this point of view, managers recognize that external consultation plays a key role.

5. Discussion

Below we describe some of the main ideas that were being constructed throughout the two phases of the research methodology, along with some of its limitations.

First, this study presents a comprehensive SLR aimed at identifying the models most commonly used in interventions for the adoption of AI. Additionally, it explores innovative suggestions that seek to drive changes in management paradigms. It is important to acknowledge that a majority of managers are now attempting to tackle this difficulty using models that were developed before the advent of Industry 4.0, the 3RI. Therefore, it is crucial to develop models and proposals that are suitable for the fast rate of technological advancements.

Within the context of the 1SLR, the community has consistently identified two significant characteristics in the models presented: readiness models and process models. These particular characteristics were exclusively found in a limited number of works, and the systemic paradigm was not sufficiently explored or elaborated on in terms of its applicability to the requirements of the systems in question.

Subsequently, a critical evaluation is conducted utilizing the SS methodology (Section 3.2) for each pertinent model identified in Section 3.1. This enabled the demonstration of their limited ability to effectively handle intricate technological advances, such as artificial intelligence. The most innovative approaches suggest a reconfiguration of the business model by incorporating new technology as an integral component of the organization, rather than only as a tool. However, these sources do not provide a comprehensive elucidation of the specific managerial roles required to effectively implement these novel organizational models. From a systemic point of view, these proposals persist in being implemented through classical management approaches, disregarding the fact that contemporary organizations are extremely complex and cannot be effectively governed solely through mechanistic, hierarchical methods, and rigid processes that hinder adaptability to external fluctuations.

The critic's discourse not only disregarded models based on SS concepts but also included additional factors such as usability, acceptance within the community, and frequency of utilization. This prompted our exploration of the TOE and TAM frameworks. In the end, among all of the ideas discussed, TOE stands out as the most significant premise of the inquiry.

Reviewing Section 3.3, which belongs to the 2SLR, it is evident that this particular framework is of significant importance among the academic community. Numerous studies rely exclusively on this model, as it effectively categorizes various dimensions that are essential for governmental analysis, corporate evaluations, national assessments, and specific industrial sectors. This substantiates the significance of its incorporation in the third industrial revolution, the fourth, and possibly even the fifth.

The most significant critique of the TOE model is that it has been applied mainly only to business perception analysis conducted through manager questionnaires. However, this type of questioning can be extended to include strategies, technical requirements, infrastructure, information systems, and other components that a system and/or computer specialist can use to their advantage.

In addition, in order not to limit the work to just a literary review process, the authors proceeded to test the TOE model through interviews with companies located in the Valley of Mexico (Section 4). During the interviews, it was determined that TOE works as a holistic analysis tool for the business adoption of new technologies. However, we must not ignore the fact that the results are too subjective and that managers' perceptions are as complex as their abilities to manage the variety of their own companies.

We highlight that entrepreneurs are willing to innovate and invest in new technologies such as AI because they perceive that, over time, this will provide them with a competitive and financial advantage in the market. However, the assistance of specialists in the field is essential. Because, without the insight of Industry 4.0 and SS technologies experts, stakeholders' perception of what to do during AI adoption could easily be lost.

Lastly, we acknowledge the limitations of the test, as it was limited to a smaller number of managers than the articles discussed during the 2SLR. However, we made clear that the goal of the article was to critique and identify opportunities to merge reliable models, such as TOE and TAM with SS, to establish the foundations for a meta-model.

6. Conclusions and Future Works

The present study effectively identifies prevalent models used in interventions for the AIA through the SLRs, highlighting the importance for models that can be modified to fit the rapidly changing technological environment.

The study emphasizes the prevalence of readiness and process models within the existing literature on AIA. However, it also emphasizes that these models have limited application when it comes to modern and complex companies.

The study underscores the entrepreneurial perspective, highlighting that entrepreneurs are driven to invest in AI based on their perception of gaining a competitive edge. However, it also emphasizes the importance of seeking help from industry experts in Industry 4.0 and smart systems SS technologies to ensure the successful implementation and adoption of AI.

TOE, which emerges as the most significant premise to analyze AI adoption in both academic and practical contexts, is criticized for its primary application through manager questionnaires. To enhance its effectiveness, the study recommends expanding its application to encompass various branches of technical and systems.

Finally, this area of opportunity opens perspectives for other researchers to improve the low capacity of AIA in companies and create a truly viable tool with the necessary construct to handle the complexity that TOE allows us to see in its implementation as an evaluation tool.

One proposal is to take, during TOE evaluation, the characteristics a manager expresses and turn them into specific functions that must be fulfilled during their adoption processes. That is, create a meta-model evaluated by TOE and design viable strategies with systems principles.

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Appendix A. Questionnaire for Interviews

Part 1. Perspective

1. Do you have doubts about the interest in the research and interview process?
2. What do you mean by Artificial Intelligence?
3. Currently, how many artificial intelligence projects exist in your company?
4. What is the objective of the project?
5. What is the status of the project? Planning, In Process, Implemented
6. When will users be able to use the product?
7. Are partners/owners involved in the project?
8. Who else is involved in the project?
9. If possible, can you give me the approximate budget for the project?
10. Are other projects planned or awaiting execution?
11. Do you have an AIA strategy?

Evaluation range from 1 to 6, where 1 = completely disagree and 6 = completely agree

Table A1. Part 2. Organization.

	Top Management Support	
1	The managers and owners of the organization are interested in supporting and integrating AI in their projects	1–6
2	Innovation is promoted in your organization	1–6
3	In your organization, management is used to modifying structures and workflow during projects	1–6
4	In your organization, It would be acceptable to modify software or work tools to integrate AI into the current business model	1–6
	(Technical) Competencies	
5	The organization has personnel capable of understanding the concepts of AI to integrate into its business model	1–6
6	The organization has personnel capable of handling AI tools (software)	1-6
7	In your organization they would be willing to train their staff to modify their job profile in collaboration with AI	1–6
	Resources	
8	The application and AIA is expensive	1–6
9	Your organization would be willing to invest in training your staff	1-6
10	In your organization they would be willing to invest in infrastructure capable of being introduced into your business model	1–6
	Organization	
11	The size of your organization (staff) limits the intention to adopt AI	1–6
12	A company with more staff will have more difficulty in AIA	1–6
13	A company with fewer staff will have greater ease of AIA	1–6
	Strategy	
14	Your organization's business model contemplates the use of AI	1–6
15	They have an AI integration plan in their current work systems	1–6

Table A2. Part 3. Technology.

	Compatibility/Availability/Quality Data	
1	AI is compatible with current production or service systems	1–6
2	The organization has the infrastructure to store business model information	1–6
3	The organization knows how to obtain quality information depending on what it wants to analyze	1–6
	Relative Advantage	
4	The use of AI in my production will make my organization more efficient	1–6
5	The use of AI in my production will make my organization more competitive in the market	1–6
6	The use of AI in my production will make my organization reduce costs	1–6
	Tool Ability	
7	The organization knows of AI tools on the market that I can use in my production	1–6
8	The organization can have access to tools and knowledge of the management and integration of artificial intelligence in a simple way	1–6

Table A3. Part 4. Environment.

	Competitive Pressure	
1	Some competitors are already implementing AI in their processes	1–6
2	Technology in our industry changes rapidly	1–6
3	New products and ideas are being created from the use of AI in our industry and we are being displaced	1–6
	Government/Regulations	
4	The government encourages or provides facilities for companies to promote AIA	1–6
5	Government support is important for the use of AI in organizations	1–6
6	There are some kind of special regulations for using AI in the production sector that your organization works	1–6
	Consulting	
7	In your organization, it is important to have external consulting, support from a supplier, and/or a partner to assist in your process.	1–6

References

1. Ertel, W. *Introduction to Artificial Intelligence*; Springer International Publishing: Cham, Switzerland, 2017. [CrossRef]
2. Mahmud, H.; Islam, A.K.M.N.; Ahmed, S.I.; Smolander, K. What influences algorithmic decision-making? A systematic literature review on algorithm aversion. *Technol. Forecast. Soc. Chang.* **2022**, *175*, 121390. . [CrossRef]
3. Canbay, K.; Akman, G. Investigating changes of total quality management principles in the context of Industry 4.0: Viewpoint from an emerging economy. *Technol. Forecast. Soc. Chang.* **2023**, *189*, 122358. . [CrossRef]
4. Devezas, T.; Leitão, J.; Sarygulov, A. Introduction. In *Industry 4.0: Entrepreneurship and Structural Change in the New Digital Landscape*; Devezas, T., Leitão, J., Sarygulov, A., Eds.; Springer International Publishing: Cham, Switzerland, 2017; pp. 1–10. [CrossRef]

5. Turner, P. *Management During the First Industrial Revolution: European Pioneers—The Genesis of Modern Management*; Springer International Publishing: Cham, Switzerland, 2021; pp. 33–63. [CrossRef]
6. Osterrieder, P.; Budde, L.; Friedli, T. The smart factory as a key construct of industry 4.0: A systematic literature review. *Int. J. Prod. Econ.* **2020**, *221*, 107476. [CrossRef]
7. Nimmi, P.; Vilone, G.; Jagathyraj, V. Impact of AI technologies on organisational learning: Proposing an organisation cognition schema. *Dev. Learn. Organ. Int. J.* **2021**, *36*, 7–9. [CrossRef]
8. Klingenberg, C.O.; Borges, M.A.V.; do Vale Antunes, J.A. Industry 4.0: What makes it a revolution? A historical framework to understand the phenomenon. *Technol. Soc.* **2022**, *70*, 102009. [CrossRef]
9. Kumar, K.; Zindani, D.; Davim, J.P. *Process Planning in Era 4.0*; Springer: Singapore, 2019; pp. 19–26. [CrossRef]
10. Schiele, H.; Bos-Nehles, A.; Delke, V.; Stegmaier, P.; Torn, R.J. Interpreting the industry 4.0 future: Technology, business, society and people. *J. Bus. Strategy* **2022**, *43*, 157–167. [CrossRef]
11. Napoleone, A.; Macchi, M.; Pozzetti, A. A review on the characteristics of cyber-physical systems for the future smart factories. *J. Manuf. Syst.* **2020**, *54*, 305–335. [CrossRef]
12. Martinho-Truswell, E.; Miller, H.; Asare, I.N.; Petheram, A.; Stirling, R.; Mont, C.G.; Martínez, C. *Hacia una Estrategia de IA en México: Aprovechando la Revolución de la IA*; Oxford Insights-Gobierno de México-CMinds: CDMX, Mexico, 2018.
13. Islas-Cota, E.; Gutierrez-Garcia, J.O.; Acosta, C.O.; Rodríguez, L.F. A systematic review of intelligent assistants. *Future Gener. Comput. Syst.* **2022**, *128*, 45–62. [CrossRef]
14. Kartanaitė, I.; Krušinskas, R. Financial Efficiency of Unicorns: Regional and Sector Related Aspects. *Eng. Econ.* **2022**, *33*, 200–214. [CrossRef]
15. Someh, I.; Wixom, B.; Zutavern, A. *Overcoming Organizational Obstacles to Artificial Intelligence Value Creation: Propositions for Research*; University of Hawaii at Manoa Hamilton Library: Honolulu, HI, USA, 2020.
16. John, G.; Samadda, N.O.S.S.; Hughes, H.K. *Maturing AI in the Organization*; Infosys Knowledge Institute: Richardson, TX, USA, 2020.
17. Ahmed, I.; Jeon, G.; Piccialli, F. From Artificial Intelligence to eXplainable Artificial Intelligence in Industry 4.0: A survey on What, How, and Where. *IEEE Trans. Ind. Inform.* **2022**, *18*, 5031–5042. [CrossRef]
18. Elia, G.; Margherita, A. A conceptual framework for the cognitive enterprise: Pillars, maturity, value drivers. *Technol. Anal. Strateg. Manag.* **2021**, *34*, 377–389. . [CrossRef]
19. Füller, J.; Hutter, K.; Wahl, J.; Bilgram, V.; Tekic, Z. How AI revolutionizes innovation management—Perceptions and implementation preferences of AI-based innovators. *Technol. Forecast. Soc. Chang.* **2022**, *178*, 121598. . [CrossRef]
20. Verma, P.; Kumar, V.; Daim, T.; Sharma, N.K.; Mittal, A. Identifying and prioritizing impediments of industry 4.0 to sustainable digital manufacturing: A mixed method approach. *J. Clean. Prod.* **2022**, *356*, 131639. [CrossRef]
21. Volberda, H.W.; Khanagha, S.; Baden-Fuller, C.; Mihalache, O.R.; Birkinshaw, J. Strategizing in a digital world: Overcoming cognitive barriers, reconfiguring routines and introducing new organizational forms. *Long Range Plan.* **2021**, *54*, 102110. [CrossRef]
22. Soni, G.; Kumar, S.; Mahto, R.V.; Mangla, S.K.; Mittal, M.; Lim, W.M. A decision-making framework for Industry 4.0 technology implementation: The case of FinTech and sustainable supply chain finance for SMEs. *Technol. Forecast. Soc. Chang.* **2022**, *180*, 121686. [CrossRef]
23. Iftikhar, N.; Nordbjerg, F. Adopting Artificial Intelligence in Danish SMEs: Barriers to Become a Data Driven Company, Its Solutions and Benefits. In Proceedings of the 2nd International Conference on Innovative Intelligent Industrial Production and Logistics IN4PL, Online, 25–27 October 2021; pp. 131–136. [CrossRef]
24. Bryan, J.D.; Zuva, T. A Review on TAM and TOE Framework Progression and How These Models Integrate. *Adv. Sci. Technol. Eng. Syst. J.* **2021**, *6*, 137–145. [CrossRef]
25. Baker, J. The technology–organization–environment framework. In *Information Systems Theory: Explaining and Predicting Our Digital Society*; Springer: New York, NY, USA, 2012; Volume 1, pp. 231–245.
26. Wulandari, A.; Suryawardani, B.; Marcelino, D. Social Media Technology Adoption for Improving MSMEs Performance in Bandung: A Technology-Organization-Environment (TOE) Framework. In Proceedings of the 2020 8th International Conference on Cyber and IT Service Management (CITSM), Pangkal, Indonesia, 23–24 October 2020; pp. 1–7. [CrossRef]
27. Saedi, A. Cloud computing adoption framework: Innovation translation approach. In Proceedings of the 2016 3rd International Conference on Computer and Information Sciences (ICCOINS), Kuala Lumpur, Malaysia, 15–17 August 2016; pp. 153–157. [CrossRef]
28. Bradley, J. If We Build It They Will Come? The Technology Acceptance Model. In *Information Systems Theory: Explaining and Predicting Our Digital Society*; Dwivedi, Y.K., Wade, M.R., Schneberger, S.L., Eds.; Springer: New York, NY, USA, 2012; Volume 1, pp. 19–36. [CrossRef]
29. Inayatulloh. Technology Acceptance Model (TAM) for the Implementation of Knowledge Acquired model for SME. In Proceedings of the 2020 International Conference on Information Management and Technology (ICIMTech), Bandung, Indonesia, 13–14 August 2020; pp. 767–770. [CrossRef]
30. Sani, A.; Nawaninatyas P.; Rizal, N.; Khristiana, Y.; Udin Zailani, A.; Husain, T. E-Business Adoption Models in Organizational Contexts on The TAM Extended Model: A Preliminary Assessment. In Proceedings of the 2020 8th International Conference on Cyber and IT Service Management (CITSM), Pangkal, Indonesia, 23–24 October 2020; pp. 1–5. [CrossRef]

31. Sugarhood, P.; Wherton, J.; Procter, R.; Hinder, S.; Greenhalgh, T. Technology as system innovation: A key informant interview study of the application of the diffusion of innovation model to telecare. *Disabil. Rehabil. Assist. Technol.* **2014**, *9*, 79–87. [CrossRef]
32. Fonseka, K.; Jaharadak, D.A.A.; Raman, D.M.; Dharmaratne, D.I.R. Literature Review of Technology Adoption Models at Firm Level; Special Reference to E-Commerce Adoption. *Glob. J. Manag. Bus. Res.* **2020**, *20*, 1–9. [CrossRef]
33. Chatterjee, S.; Rana, N.P.; Dwivedi, Y.K.; Baabdullah, A.M. Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technol. Forecast. Soc. Chang.* **2021**, *170*, 120880. [CrossRef]
34. Kong, Y.; Hou, Y.; Sun, S. *The Adoption of Artificial Intelligence in the E-Commerce Trade of Healthcare Industry*; Springer: Singapore, 2021; pp. 75–88.
35. Ruiz-Real, J.L.; Uribe-Toril, J.; Torres, J.A.; Pablo, J.D. Artificial intelligence in business and economics research: Trends and future. *J. Bus. Econ. Manag.* **2020**, *22*, 98–117. [CrossRef]
36. Hmoud, B. The adoption of artificial intelligence in human resource management and the role of human resources. In *Forum Scientiae Oeconomia*; Faculty of Applied Sciences of WSB University Dąbrowa: Górnicza, Poland, 2021; Volume 9, pp. 105–118.
37. Gangwar, H.; Date, H.; Raoot, A. Review on IT adoption: Insights from recent technologies. *J. Enterp. Inf. Manag.* **2014**, *27*, 488–502. [CrossRef]
38. Pieroni, M.P.; McAloone, T.C.; Pigosso, D.C. Business model innovation for circular economy and sustainability: A review of approaches. *J. Clean. Prod.* **2019**, *215*, 198–216. . [CrossRef]
39. Bowen, F.; Aragon-Correa, J.A. Greenwashing in Corporate Environmentalism Research and Practice. *Organ. Environ.* **2014**, *27*, 107–112. [CrossRef]
40. Schlüter, L.; Kørnøv, L.; Mortensen, L.; Løkke, S.; Storrs, K.; Lyhne, I.; Nors, B. Sustainable business model innovation: Design guidelines for integrating systems thinking principles in tools for early-stage sustainability assessment. *J. Clean. Prod.* **2023**, *387*, 135776. [CrossRef]
41. Bertalanffy, L.V. *General System Theory: Foundations, Development, Applications*; G. Braziller: New York, NY, USA, 1968.
42. Wilber, K. *A Theory of Everything: An Integral Vision for Business, Politics, Science and Spirituality*; Shambhala Publications: Boulder, CO, USA, 2001.
43. Galison, P. The Ontology of the Enemy: Norbert Wiener and the Cybernetic Vision. *Crit. Inq.* **1994**, *21*, 228–266. [CrossRef]
44. von Foerster, H. Cybernetics of Cybernetics. In *Understanding Understanding*; Springer: New York, NY, USA, 2003; pp. 283–286. [CrossRef]
45. Beer, S. Cybernetics and management. *J. Symb. Log.* **1960**, *25*. .. [CrossRef]
46. Liberati, A.; Altman, D.G.; Tetzlaff, J.; Mulrow, C.; Gøtzsche, P.C.; Ioannidis, J.P.; Clarke, M.; Devereaux, P.; Kleijnen, J.; Moher, D. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: Explanation and elaboration. *J. Clin. Epidemiol.* **2009**, *62*, e1–e34. [CrossRef]
47. Gebhart, G.F.; Schmidt, R.F. (Eds.) Systematic Review. In *Encyclopedia of Pain*; Springer: Berlin/Heidelberg, Germany, 2013; pp. 3824–3824. [CrossRef]
48. Purssell, E.; McCrae, N. The Aim and Scope of a Systematic Review: A Logical Approach. In *How to Perform a Systematic Literature Review: A Guide for Healthcare Researchers, Practitioners and Students*; Springer International Publishing: Cham, Switzerland, 2020; pp. 19–30. [CrossRef]
49. Dikert, K.; Paasivaara, M.; Lassenius, C. Challenges and success factors for large-scale agile transformations: A systematic literature review. *J. Syst. Softw.* **2016**, *119*, 87–108. [CrossRef]
50. Keele, S. *Guidelines for Performing Systematic Literature Reviews in Software Engineering*; Elsevier: Amsterdam, The Netherlands, 2007.
51. Aromataris, E.; Pearson, A. The systematic review: An overview. *AJN Am. J. Nurs.* **2014**, *114*, 53–58. [CrossRef]
52. Kerzel, U. Enterprise AI Canvas Integrating artificial intelligence into business. *Appl. Artif. Intell.* **2021**, *35*, 1–12. [CrossRef]
53. Osterwalder, A.; Pigneur, Y.; Oliveira, M.A.Y.; Ferreira, J.J.P. Business Model Generation: A handbook for visionaries, game changers and challengers. *Afr. J. Bus. Manag.* **2011**, *5*, 22–30.
54. AlSheibani, S.; Cheung, Y.; Messom, C. Artificial Intelligence Adoption: AI-readiness at Firm-Level. In Proceedings of the PACIS 2018, Yokohama, Japan, 26–30 June 2018; p. 37.
55. Alsheiabni, S.; Cheung, Y.; Messom, C. Towards an artificial intelligence maturity model: From science fiction to business facts. In Proceedings of the PACIS 2019, Xi'an, China, 8–12 July 2019.
56. Becker, J.; Knackstedt, R.; Pöppelbuß, J. Developing maturity models for IT management: A procedure model and its application. *Bus. Inf. Syst. Eng.* **2009**, *1*, 213–222. [CrossRef]
57. Nortje, M.A.; Grobbelaar, S.S. A framework for the implementation of artificial intelligence in business enterprises: A readiness model. In Proceedings of the 2020 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC), Cardiff, UK, 15–17 June 2020; pp. 1–10.
58. Bedué, P.; Fritzsche, A. Can we trust AI? An empirical investigation of trust requirements and guide to successful AI adoption. *J. Enterp. Inf. Manag.* **2021**, *35*, 530–549. [CrossRef]
59. Agrawal, A.; Gans, J.; Goldfarb, A. A Simple Tool to Start Making Decisions with the Help of AI. *Harvard Business Review*, 17 April 2018.
60. Noonpakdee, W. The adoption of artificial intelligence for financial investment service. In Proceedings of the 2020 22nd International Conference on Advanced Communication Technology (ICACT), Phoenix Park, Republic of Korea, 16–19 February 2020; pp. 396–400.

61. Rauniar, R.; Rawski, G.; Yang, J.; Johnson, B. Technology acceptance model (TAM) and social media usage: An empirical study on Facebook. *J. Enterp. Inf. Manag.* **2014**, *27*, 6–30. [CrossRef]
62. Behl, A.; Chavan, M.; Jain, K.; Sharma, I.; Pereira, V.E.; Zhang, J.Z. The role of organizational culture and voluntariness in the adoption of artificial intelligence for disaster relief operations. *Int. J. Manpow.* **2021**, *43*, 569–586. [CrossRef]
63. Pillai, R.; Sivathanu, B. Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations. *Benchmarking Int. J.* **2020**, *27*, 2599–2629. [CrossRef]
64. Nam, K.; Dutt, C.S.; Chathoth, P.; Daghfous, A.; Khan, M.S. The adoption of artificial intelligence and robotics in the hotel industry: Prospects and challenges. *Electron. Mark.* **2021**, *31*, 553–574. [CrossRef]
65. Yams, N.B.; Richardson, V.; Shubina, G.E.; Albrecht, S.; Gillblad, D. Integrated AI and Innovation Management: The Beginning of a Beautiful Friendship. *Technol. Innov. Manag. Rev.* **2020**, *10*, 5–18. [CrossRef]
66. Bruin, T.D.; Rosemann, M.; Freeze, R.; Kaulkarni, U. Understanding the Main Phases of Developing a Maturity Assessment Model. In Proceedings of the 16th Australasian Conference on Information Systems 2005, Sydney, Australia, 29 November–2 December 2005; pp. 8–19.
67. Hradecky, D.; Kennell, J.; Cai, W.; Davidson, R. Organizational readiness to adopt artificial intelligence in the exhibition sector in Western Europe. *Int. J. Inf. Manag.* **2022**, *65*, 102497. [CrossRef]
68. Ghobakhloo, M.; Ching, N.T. Adoption of digital technologies of smart manufacturing in SMEs. *J. Ind. Inf. Integr.* **2019**, *16*, 100107. [CrossRef]
69. Bettoni, A.; Matteri, D.; Montini, E.; Gładysz, B.; Carpanzano, E. An AI adoption model for SMEs: A conceptual framework. *IFAC-PapersOnLine* **2021**, *54*, 702–708. [CrossRef]
70. Beer, S.; Beer, S. *Diagnosing the System for Organizations*; Wiley: Chichester, UK, 1985.
71. Lechler, R.C.; Lehner, P.; Röösli, F.; Huemann, M. The project-oriented organisation through the lens of viable systems. *Proj. Leadersh. Soc.* **2022**, *3*, 100072. [CrossRef]
72. Ashby, W.R. *An Introduction to Cybernetics*; Chapman & Hall Ltd.: London, UK, 1961.
73. Najdawi, A. Assessing AI Readiness Across Organizations: The Case of UAE. In Proceedings of the 2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Kharagpur, India, 1–3 July 2020; pp. 1–5. [CrossRef]
74. Lai, P. The literature review of technology adoption models and theories for the novelty technology. *J. Inf. Syst. Technol. Manag.* **2017**, *14*, 21–38. . [CrossRef]
75. Petter, S.; DeLone, W.; McLean, E. Measuring information systems success: Models, dimensions, measures, and interrelationships. *Eur. J. Inf. Syst.* **2008**, *17*, 236–263. [CrossRef]
76. Hasija, A.; Esper, T. In artificial intelligence (AI) we trust: A qualitative investigation of AI technology acceptance. *J. Bus. Logist.* **2022**, *43*, 388–412. [CrossRef]
77. Lim, J.; Zhang, J. Adoption of AI-driven personalization in digital news platforms: An integrative model of technology acceptance and perceived contingency. *Technol. Soc.* **2022**, *69*, 101965. . [CrossRef]
78. Tornatzky, L.G.; Fleischer, M.; Chakrabarti, A.K. *Processes of Technological Innovation*; Lexington Books: Lexington, MA, USA, 1990.
79. Bhattacharyya, S.; Shah, Y. Emerging technologies in Indian mining industry: An exploratory empirical investigation regarding the adoption challenges. *J. Sci. Technol. Policy Manag.* **2022**, *13*, 352–375. [CrossRef]
80. Katz, D.; Kahn, R.L. *The Social Psychology of Organizations*; Wiley: New York, NY, USA, 1978; Volume 2.
81. Mahroof, K. A human-centric perspective exploring the readiness towards smart warehousing: The case of a large retail distribution warehouse. *Int. J. Inf. Manag.* **2019**, *45*, 176–190. [CrossRef]
82. Kruse, L.; Wunderlich, N.; Beck, R. Artificial intelligence for the financial services industry: What challenges organizations to succeed. In Proceedings of the 52th Hawaii International Conference on System Sciences (HICSS 2019), Maui, HI, USA, 8–11 January 2019; Volume 2019, pp. 6408–6417.
83. Seethamraju, R.; Hecimovic, A. Impact of artificial intelligence on auditing—An exploratory study. In Proceedings of the Americas Conference on Information Systems (AMCIS2020), Virtual, 15–17 August 2020.
84. AlSheibani, S.; Cheung, Y.; Messom, C. Re-thinking the competitive landscape of artificial intelligence. In Proceedings of the 53rd Hawaii International Conference on System Sciences, Maui, HI, USA, 7–10 January 2020; Volume 2020, pp. 5861–5870.
85. Chen, H.; Li, L.; Chen, Y. Explore success factors that impact artificial intelligence adoption on telecom industry in China. *J. Manag. Anal.* **2021**, *8*, 36–68. [CrossRef]
86. Mikalef, P.; Lemmer, K.; Schaefer, C.; Ylinen, M.; Fjørtoft, S.O.; Torvatn, H.Y.; Gupta, M.; Niehaves, B. Enabling AI capabilities in government agencies: A study of determinants for European municipalities. *Gov. Inf. Q.* **2021**, *39*, 101596. [CrossRef]
87. Hamm, P.; Klesel, M. Success factors for the adoption of artificial intelligence in organizations: A literature review. In Proceedings of the 27th Americas Conference on Information Systems (AMCIS), Montreal, QC, Canada, 9–13 August 2021.
88. Schaefer, C.; Lemmer, K.; Kret, K.; Ylinen, M.; Mikalef, P.; Niehaves, B. Truth or dare?—How can we influence the adoption of artificial intelligence in municipalities? In Proceedings of the Hawaii International Conference on System Sciences (HICSS), Kauai, HI, USA, 7–10 January 2020; Volume 2020, pp. 2347–2356.
89. Lee, J.; Kim, J.; Kim, Y.; Song, Y. A Study on Priorities for Utilization of AI Recruitment System. In Proceedings of the 2021 21st ACIS International Winter Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD-Winter), Ho Chi Minh City, Vietnam, 28–30 January 2021; pp. 278–279. [CrossRef]

90. Pumplun, L.; Tauchert, C.; Heidt, M. A new organizational chassis for artificial intelligence-exploring organizational readiness factors. In Proceedings of the European Conference on Information Systems (ECIS), Stockholm, Sweden, 8–14 June 2019.
91. Chen, J.; Frankwick, G.; Zhang, Z. *Adopting Artificial Intelligence to Manage a Turbulent Environment: An Abstract*; Springer: Cham, Switzerland , 2022; pp. 223–224. [CrossRef]
92. Neumann, O.; Guirguis, K.; Steiner, R. Exploring artificial intelligence adoption in public organizations: A comparative case study. *Public Manag. Rev.* **2022**, 1–27. . [CrossRef]
93. Wang, Y.; Su, X. Driving factors of digital transformation for manufacturing enterprises: A multi-case study from China. *Int. J. Technol. Manag.* **2021**, *87*, 229. [CrossRef]
94. Sivathanu, B. *Adoption of Industrial IoT (IIoT) in Auto-Component Manufacturing SMEs in India*; IGI Global: Hershey, PA, USA, 2021; pp. 719–746. [CrossRef]
95. Kinkel, S.; Baumgartner, M.; Cherubini, E. Prerequisites for the adoption of AI technologies in manufacturing—Evidence from a worldwide sample of manufacturing companies. *Technovation* **2022**, *110*, 102375. . [CrossRef]
96. Morita, P.P.; Hussain, I.Z.; Kaur, J.; Lotto, M.; Butt, Z.A. Tweeting for Health Using Real-time Mining and Artificial Intelligence-Based Analytics: Design and Development of a Big Data Ecosystem for Detecting and Analyzing Misinformation on Twitter. *J. Med. Internet Res.* **2023**, *25*, e44356. . [CrossRef] [PubMed]
97. Filgueiras, F. Designing artificial intelligence policy: Comparing design spaces in Latin America. *Lat. Am. Policy* **2023**, *14*, 5–21. [CrossRef]
98. Monje, D.; Caballero, F.S. Artificial intelligence: The blind spot of info-communication platform policy-making and regulation in Latin America. *J. Digit. Media Policy* **2023**, *14*, 149–167. [CrossRef]