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Scaling Up Smart City Artificial Intelligence of Things (AIoT) Initiatives

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Article

The Giant Leap for Smart Cities: Scaling up Smart City Artificial Intelligence of Things (AIoT) Initiatives

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Abstract: Despite the promise of AI and IoT, the efforts of many organizations at scaling smart city initiatives fall short. Organizations often start by exploring the potential with a proof-of-concept and a pilot project, with the process later grinding to a halt for various reasons. Pilot purgatory, in which organizations invest in small-scale implementations without them realizing substantial benefits, is given very little attention in the scientific literature relating to the question of why AI and IoT initiatives fail to scale up for smart cities. By combining extensive study of the literature and expert interviews, this research explores the underlying reasons why many smart city initiatives relying on Artificial Intelligence of Things (AIoT) fail to scale up. The findings suggest that a multitude of factors may leave organizations ill prepared for smart city AIoT solutions, and that these tend to multiply when cities lack much-needed resources and capabilities. Yet many organizations tend to overlook the fact that such initiatives require them to pay attention to all aspects of change: strategy, data, people and organization, process, and technology. Furthermore, the research reveals that some factors tend to be more influential in certain stages. Strategic factors tend to be more prominent in the earlier stages, whereas factors relating to people and the organization tend to feature later when organizations roll out solutions. The study also puts forward potential strategies that companies can employ to scale up successfully. Three main strategic themes emerge from the study: proof-of-value, rather than proof-of-concept; treating and managing data as a key asset; and commitment at all levels.

Keywords: smart city; sustainable; artificial intelligence; internet of things; artificial intelligence of things; data governance; AIoT; barriers to scale up; scaling up; strategy; data governance



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1. Introduction

The powerful convergence of AI and the Internet of Things (IoT), or Artificial Intelligence of Things, AIoT for short, is no longer on the horizon; it has already arrived. Individually, both AI and IoT are impressive technologies, to say the least. Having had a head start, for some time now IoT has allowed smart city applications to enjoy complete visibility and monitoring of urban activities and be able to remotely track and optimize their systems and assets. That was groundbreaking at that time, and still is; however, making sense of the vast amounts of data generated by sensors remains an overwhelming task for people. This is where AI can come into play. By combining AI's ability to quickly wring insights from data and the ever-growing network of connected devices and systems that generate data, smart city applications can avoid unplanned downtime, increase operating efficiency, and enable enhanced products and services. Put simply, IoT acts as a digital nervous system in which AI is the brain that drives decisions.

AI needs data, lots of it. Fortunately, IoT generates lots of it. While it may seem as if the loop is closed, many organizations struggle with the sheer volume of data and how to cleanse, engineer and analyze it to drive insights. Combining various sources of data from different and heterogeneous data sources also results in value. Generally speaking, factors such as data quality and coverage, compatibility and interoperability, external data,

information technologies and software, analytical techniques, cooperation, culture, privacy and confidentiality, and public procurement enable or constrain organizations' data-driven practices [1]. More particularly, data sharing is a condition for creating smartness in smart cities [2].

Smart cities refer to technology-supported innovations in urban spaces and city governments [3]. The smart city concept has been defined in different ways [4], with definitions varying from smart urban space to environmentally healthy smart cities [5]. Others attempt to characterize smart cities with reference to dimensions such as (1) management and organization, (2) technology, (3) policy, (4) governance, (5) people and communities, (6) economy, (7) built infrastructures, and (8) the natural environment [6]. There are six key dimensions for defining smart cities, which include a smart economy, smart mobility, a smart environment, smart people, smart living and smart governance [7]. Governments are exploring different strategies for building smart, inclusive and connected communities, from public–private partnership to the engagement of a civil society [8].

In this research, we define scaling as “the industrialization of IoT-enabled AI solutions whereby, following the proof-of-concept and the pilot experiments, these technologies are routinized into industrial practices on a large scale” [9]. Much of the business strategy literature acknowledges the role of AI and IoT and the potential they hold in terms of the development of sustainable smart cities. Despite the promise of these technologies for smart city applications, many initiatives fall short of scaling up [10]. Organizations generally start by testing the waters with a proof-of-concept and a pilot project, oftentimes grinding to a halt with no clearly defined strategy for scaling later on [11]. Figure 1 shows that after the experimentation stage, such initiatives may lead to limited or widespread adoption, or none at all.

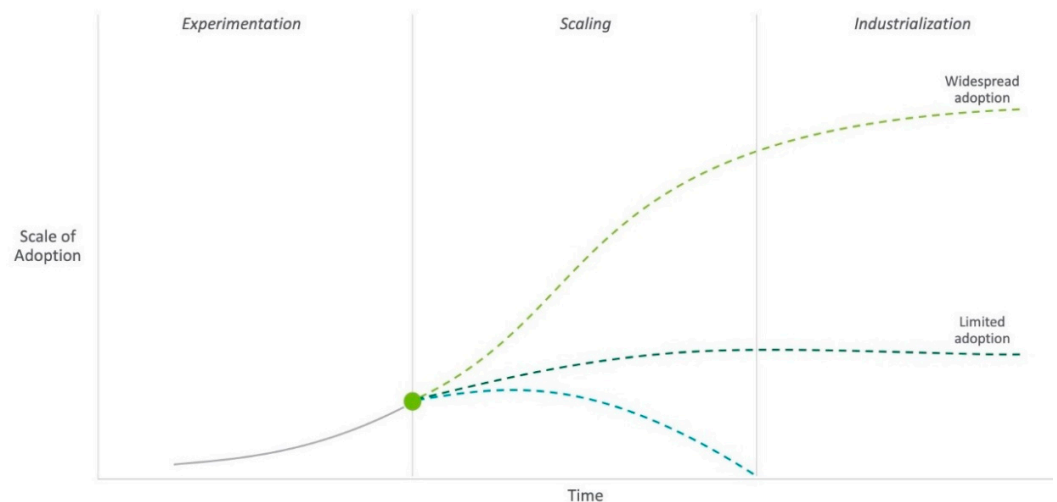


Figure 1. The conceptualization of AIoT scale-up.

This state of ambiguity, also referred to as pilot purgatory, in which organizations invest in small-scale implementations without realizing substantial bottom-line benefits, has occupied the minds of leaders and practitioners for some time. However, very little was found in the scientific literature (most of which comprised non-peer-reviewed business articles, for that matter) on the question of why most smart city applications that rely on AI or IoT, let alone AIoT, fail to scale up. As the challenges of AIoT become increasingly more relevant to smart cities, further research is needed to investigate factors that influence scaling up. This study, therefore, set out to explore which factors influence the scaling up of AIoT initiatives and what strategies can help this scale-up.

This paper is structured as follows. In the next section, the research methods are outlined. Section 3 sets out the findings from the literature and the empirical evidence from the study. In Section 4, the study formulates critical strategies for overcoming those barriers, which are of both theoretical and practical value to scholars and practitioners in the

field. Lastly, Section 5 concludes by highlighting the theoretical and practical implications, contributions, and limitations of the study, and suggests a direction for future research.

2. Research Approach

Our research approach consisted of a combination of a literature review and expert interviews. The literature review was conducted to identify factors that influence scaling up outside the field of smart cities, as there was no work available in smart cities. Next, interviews were conducted based on the factors found in the literature.

In the literature on smart cities, it is evident that AIoT scaling up has received scant attention and no strategies exist for successfully extending the initial small-scale efforts in smart cities. Therefore, we reviewed the antecedent scientific literature on technology adoption, readiness, and implementation to identify factors that influence the scaling up of AIoT. From the literature, a set of influential factors previously linked to the barriers to adoption and scale-up were listed and clustered around main themes. Although the antecedent literature offers vital insights into the barriers to adopting and implementing technologies, the existing peer-reviewed literature has yet to explain the scaling issues experienced in AIoT projects.

The study benefitted from the practitioners' and researchers' views on the subject, gleaned from conducting expert interviews. Eleven experts from different smart city areas, e.g., transportation, energy, and industry, were selected primarily on their experience with AIoT implementation over a long period, and their availability (see Table 1). Interviews were conducted from April to May 2020 via online communication tools, due to the circumstances imposed by the global pandemic.

Table 1. Expert interview participants (CoE: Center of Excellence; A&C: Analytics & Cognitive).

Expert	Company	Location	Unit	Role/Function	Mode of Communication
1	Deloitte	NL	IoT CoE	Global Lead	Online Interview
2	Deloitte	NL	IoT CoE	Senior Manager (IoT/Industry 4.0)	Online Interview
3	Deloitte	NL	IoT CoE	Manager (IoT & Digital Innovation)	Online Interview
4	Deloitte	NL	IoT CoE	Senior Consultant (IoT Specialist)	Online Interview
5	Deloitte	NL	A&C	Director	Online Interview
6	Public	NL	Risk Management & AI	Head of Department	Online Interview
7	Deloitte	NL	A&C	Manager (AI Specialist Lead)	Online Interview
8	Deloitte	US	Center for Integrated Research	Managing Director	Online Interview
9	Deloitte	US	Center for Integrated Research	Senior Manager	Online Interview
10	Deloitte	US	Industrial IoT/Digital Transformation	Senior Manager	Online Interview
11	Industry	NL	Leadership	Founder	Online Interview

The expert interviews not only contributed to the refinement of the research focus and ex-ante propositions, but also helped in the formulation of a theory from this empirical research. While we avoided making significant changes in much of the content and the structure of the expert interviews, as the study revealed new insights, we often took the opportunity to discuss them with the experts and incorporate new perspectives into the research iteratively.

Expert interviews can be a vital source of information for studying contemporary phenomena, especially during the exploratory stages of research, as some experts in the field may have first-hand experience of technically sophisticated subjects for which the literature fails to provide sufficient evidence [12]. In effect, this can help the researcher identify the most relevant knowledge regarding the subject of interest in a much more time-efficient manner. This certainly does not mean that this method does not have any shortcomings, however. The very thing that enables the researcher to acquire distilled

knowledge relatively effortlessly may skew the research in the direction of the experiences or the opinions of an expert, leading to biased research. To avoid such biases without having to miss out on expert insights, this study used triangulation at two levels: one being the triangulation of perspectives by conducting interviews with multiple experts from different backgrounds and the other being the triangulation of the sources of information from the literature review and expert interviews.

3. Reviewing Factors that Influence AIoT Scale-Up

As the challenges of AIoT become increasingly more relevant for smart cities, research is needed into factors that influence scaling up. The high pace of development of technologies may have resulted in a generation of managers who lack a basic understanding of the newest technologies, eventually leading to unrealistic expectations or unincentivized business use cases [13–15]. While the importance of a solid AI strategy that aligns with the long-term business goals is highlighted in the literature [16,17], many organizations seem to fail to create one due to the incorrect prioritization of the competing investment opportunities [18–20]. Moreover, due to its data-driven nature, AI demands a data-driven leadership approach, and challenges the traditional management paradigms that are based on experience and expertise [21]. As has already been the case for many organizations, whilst keeping human judgement in place for now, organizations increasingly rely on AI in their decision-making processes [21–25].

Most executives tend to have a rather narrow perspective on AI as a technological panacea that offers organizations turn-key solutions; however, the reality could not be further from this illusion [16,18]. Some scholars acknowledge that organizations must acquire the technological capabilities and talents with AI skills while arguing that it is equally, if not more, important to align organizations' culture, structure, and strategies with AI implementation [16,18]. At the organizational level, Brock and von Wangenheim assert that cultural transitions are also required, from the siloed team to cross-disciplinary teams, and from rigid and risk-averse to agile and adaptable organizational structures [16]. Other commonly experienced organizational barriers to AI adoption include, but are not limited to, low leadership commitment to AI initiatives, the difficulty of attracting, retaining, and training AI talent, low employee acceptance of AI, cultural resistance to change, and technology partners or the lack of these [13,16,26–28].

Though largely unforeseen, most organizations are paralyzed by the availability of large amounts of data having various qualities when they have limited data analytics capabilities, which includes people with data skills and expertise, and IT infrastructure suitable for AI [13,15,29]. Structured high-quality data and competent data analytics capabilities combined, however, do not seem to guarantee success in AI, however. As seen in some of the most recent cases in Amazon's recruitment algorithms [30] or Apple's financial services [31], algorithms may reinforce the underlying biases in the training data [21]. Notably, the "black-box" nature of the technology seems to raise additional barriers in those industries that are mandated to provide transparency and interpretability in their services and products, such as insurance, banking, education, and health, further explaining the necessity of AI [13,21,23,32].

Adopting AI to enhance business operations eventually means the integration of new technologies with the existing enterprise systems or the development of new ones [13]. The barriers to AI adoption are argued to be higher for organizations that are less "digital" [15,16]. As some scholars argue [13,14,32], with the growing data security and privacy concerns in much of the developed world and stricter regulations on data practices, e.g., GDPR, the barriers to AI adoption and implementation may become much more significant, not only for those lacking digital capabilities but most probably also for the digital pioneers. That said, in the manner of any other emerging technology that reshapes business operations, AI, too, comes with uncertainties about the capabilities and the maturity of the technology, leading some executives to delay adoption [27].

Much of the discussion about the barriers to AI adoption and scale-up seems to hold for smart city IoT-enabled AI initiatives too. Some of the challenges highlighted in the literature are, but are certainly not limited to, a lack of comprehensive strategy [33,34], limited skilled talent pool as well as the attracting of one, training and retaining talent [33,35–37], lack of standardization [37–40], lack of financial resources [37,41,42], data security and cyber risks [37–41,43–45], integration with other technologies and legacy systems [33,35,38,40,44,46], siloed organizational structure and lack of cooperation among departments [33,42], organizational resistance to change [33,35,42,47], and lack of organizational support [33,35].

Following the review of the existing scientific and gray literature and preliminary expert interviews, the study identified a set of factors that are likely to affect AIoT scale-up, as shown in Table 2. Although the list may seem exhaustive, it is undoubtedly not determinate. The set of factors provide a theoretical basis for further investigation using interviews (see Table 2).

Table 2. Overview of factors affecting scale-up in the literature.

Factor	Source
Comprehensive AI/Industry 4.0 strategy	[16–18,29,33,41,42,48–50]
Perceived business benefits	[33,42,47,50,51]
Top management support	[16–18,34,41,42,47]
Business models/use cases suitable for AI/I4.0	[18,34,40,47,48,50,52]
Technology knowledge	[13,16,17,34,41,42,46,49,53]
Technology partners/vendors	[16,33,34,37,42]
Organizational culture	[16–18,29,33,34,41,47,48,50,54]
Organizational agility	[16,41,46]
Organizational structure	[18,33,35,38,41,48]
Firm network orientation	[33,35,37,41,42]
User support/resistance	[13,15–18,33,47,54]
Skilled staff and expertise	[16–18,27,33–38,41,42,44,46–48,50–52,54–56]
Organizational resources	[16,29,34,41,42,47,50,56,57]
Organizational size	[41]
Technology sponsors/champions	[17,29,41,53]
Alignment between departments	[29,34,42,46,47,50]
Competing investment opportunities	[18]
Data quality & availability	[15–18,21,23,29,34,41,50,51,57,58]
Data governance	[16,17,27,52,56]
Data security and privacy	[16,27,33,34,37,38,40–42,45,47,58,59]
Data analytics capabilities	[15,16,18,29,33,38,40,41,44,46,57,59]
ICT capabilities & infrastructure	[29,33–35,37,38,40–42,44,52,55]
Integration with other systems	[13,16,33,35,36,38,40–42,44,45,47,57,59]
Interpretability of outcomes	[13,14,21,23,50,51,58]
Standardization	[33,37,40,42,44,45,47,55]
Technology characteristics	[13,27,33,40,42,45,46,59]

4. Results

In this section, by triangulating the findings from the literature review and the expert interviews, we discuss the factors that impact organizations' AIoT initiatives and the stages at which the respective factors are more influential.

4.1.1. Upscaling Strategies

Formulating a comprehensive roadmap that aligns with smart city strategies and goals is critical for upscaling AIoT solutions. The interviewees also suggest that initiatives that do not align with strategies tend to end up consisting of ineffective efforts that are scattered and isolated across the organization, which eventually leads companies to halt their efforts altogether or switch their focus elsewhere. Indeed, one expert refers to “the complexity of the choice architecture,” which is in agreement with Lichtenthaler’s proposition [18], where the availability of alternative investment options may cause companies to freeze, and may deter them from expanding their small-scale initiatives.

Our study emphasizes the role of effective strategic partnerships in smart city efforts, especially in assisting in areas that are beyond organizations’ core competencies. This finding corroborates the findings of a great deal of the extant literature [16,33,34,37,42]. Contrary to previous studies that underlined the role of firm network orientation, this study did not find adequate evidence to support the relevancy of this factor for the AIoT scale-up, as none of the participants from the expert interviews reported it. This factor may be less relevant in the case of AIoT scale-up since AIoT initiatives are more likely to apply the existing technologies to transform the current business processes and operations, rather than innovating novel technologies, which arguably rely more on knowledge sharing.

4.1.2. Data Governance and Management

This study finds that robust data governance and practices, or the lack thereof, immensely impact smart cities’ ability to scale their IoT-enabled AI initiatives. In the same vein, as several studies have shown in the past [15–18,21,23,29,34,41,50,51,57,58], this study underpins the significance of the availability of large chunks of quality data for AI solutions. Large volumes of highly diverse data, which these systems collect, transform, organize, and analyze for AIoT, and require strong data management and operating models, yet many of these seem to fall behind in that regard.

The more digitally invested the organization is, the more likely it is to have invested in technologies and frameworks that AIoT can build on, such as cloud technologies and big data. Consistent with the previous body of literature [15,16,18,29,33,38,40,41,44,46,57,59], this study supports the idea that organizations can leverage their existing data analytics capabilities to scale their initiatives. This study also confirms the fact that cybersecurity is a crucial aspect for companies to address while industrializing their prototypes or pilots [16,27,33,34,37,38,40–42,45,47,58,59].

4.1.3. People and Organization

Digital transformation is not only about technology but also about people and organizations. This study finds that raising the understanding of the technology and promoting its organizational buy-in must happen at all levels within smart cities, including boardrooms, factory floors, and anything in between. This finding broadly supports the work of other studies in this area [13,15–18,33,34,41,42,47,54]. In line with the earlier work [16–18,29,33,34,41,47,48,50,54], this research found that instilling a culture that cultivates innovation and allows precise alignment between departments seems to be a problematic yet necessary step to take. As this study and previous work in the field suggests [17,29,41,53], this generally calls for technology sponsors that can take ownership of the technology and communicate the right messages across various levels within the organization.

Our findings support the view that investing in human capital and upskilling the existing workforce pay off. As the previous work suggests, the lack of this investment raises the barriers for initiatives [16–18,27,33–38,41,44,46–48,50–52,54,56,60]. Moreover, the research confirms the earlier findings that the siloed organizational structure hinders cross-departmental collaboration, blocking many initiatives from scaling, or even starting at all [18,33,35,41,48,57].

In contrast to earlier findings [16,34,38,41,42,47,50,56,57], the expert interviews did not conclude that firm size and resources affect companies' scaling efforts. Once firm size and available resources allow smart cities to decide to adopt technologies and launch initiatives to do so, these factors are less likely to affect the later stages. Some experts argued that the smaller the firm, the more agile and nimble it is, and therefore more adept at scaling such initiatives; however, the relevancy of firm size in the scale-up remained limited.

4.1.4. Process

As also suggested by the previous body of literature [33,42,47,50,51], the research supports the idea that promising smart city benefits, for example, efficiency increase, product and service improvement and cost reduction, seem to drive companies to invest in these technologies in the first place. Nonetheless, such outcomes are likely if there are suitable business use cases with realistic targets and deadlines. This finding also corroborates the earlier results from the literature [18,34,40,47,48,50,52]. Prior to this research, very little, if anything, was found in the literature regarding the role of operating models to provide a backbone structure to develop and integrate AI-based models continuously. Another important finding was that solid operating models for AI and other data-driven solutions alike are likely to help smart cities. One expert in the research reported that the closer the solution is to the core, the higher the barriers are. Core functions are more difficult to change. No matter how intuitive that may sound, a note of caution is due here since this finding was only mentioned by one expert.

4.1.5. Technology

Last but certainly not least, AIoT solutions tend to involve multiple technical components and integration of systems from different areas and organizations involved in smart cities that might not have been designed to be connected in the first place. The research found that this divide becomes more visible when information technology (IT) systems and operational technology (OT) systems are required to operate together. This finding is in line with plenty of earlier studies that indicate that integration and interoperability of different systems may impede adoption [13,16,33,35,36,38,40–42,44,45,47,57,59].

Moreover, the findings from the research suggest that companies can leverage their existing ICT capabilities and infrastructure to develop, deploy, and maintain IoT-enabled AI solutions, which tend to rely on preceding technologies, such as internet connectivity and cloud infrastructure. These results are also in agreement with those of previous studies [29,33–35,37,38,40–42,44,52,55]. Some technical characteristics, e.g., scalability, reliability, and maturity, still lead some companies to hesitate. Acknowledging the presence of such concerns and their effects, as suggested by the previous literature [13,27,33,40,42,45,46,59], the study found that, with the ever-expanding capabilities these technologies currently offer for specific use cases, these factors constitute much less of a barrier currently than they may once have done.

One of the aspects in which this study diverts from the literature on AI is the importance of the interpretability of outcomes. As the earlier literature on AI has demonstrated, the black-box nature of AI solutions may inhibit their use in smart cities [13,14,21,23,50,51,58]. Despite the growing popularity of the concept of explainable AI both in academia and in the industry, this study reveals this factor to be less relevant for IoT-enabled AI initiatives. This finding can be explained by the fact that AIoT projects mostly concern smart city applications, such as predictive path planning, smart asset management, and quality assurance, which are less likely to be held to the same transparency standards as use cases such as social security or job applications.

Standardization is another aspect in which the findings from the study contradicted earlier works in the domain, primarily Industry 4.0 [33,37,40,42,44,45,47,55]. While a lack of standardization in a particular technology may pose a significant challenge, even format wars among multiple parties in some cases [61–63], the study found that it is not relevant to the scale-up of AIoT projects. Even though there are a variety of AI and IoT service

providers, they tend to share the same connectivity protocols and similar codes that can operate together with little to no friction. In the domains where some incompatible formats co-exist, say 5G technologies, this factor is more likely to affect the adoption and scale-up. However, there was simply no evidence to support the view that this is the case for IoT-enabled AI applications in smart cities.

From the interviews, five main categories of influencing factors emerged. By triangulating the findings from the literature review and the expert reviews, the study proposes a new taxonomy that classifies the factors that influence scaling up into five main categories: *strategy* (AIoT strategy, competing investment opportunities, and technology partners), *data* (data quality and availability, data governance, data security and privacy, and data analytics capabilities), *people and organization* (top management support, user support or resistance, technology sponsors and champions, skilled staff and expertise, technology knowledge, organizational culture, organizational agility, organizational structure, and alignment between departments), *process* (perceived business benefits, business models and use cases, and operating models), and *technology* (ICT capabilities and infrastructure, integration with other systems, and technology characteristics) (see Figure 2).

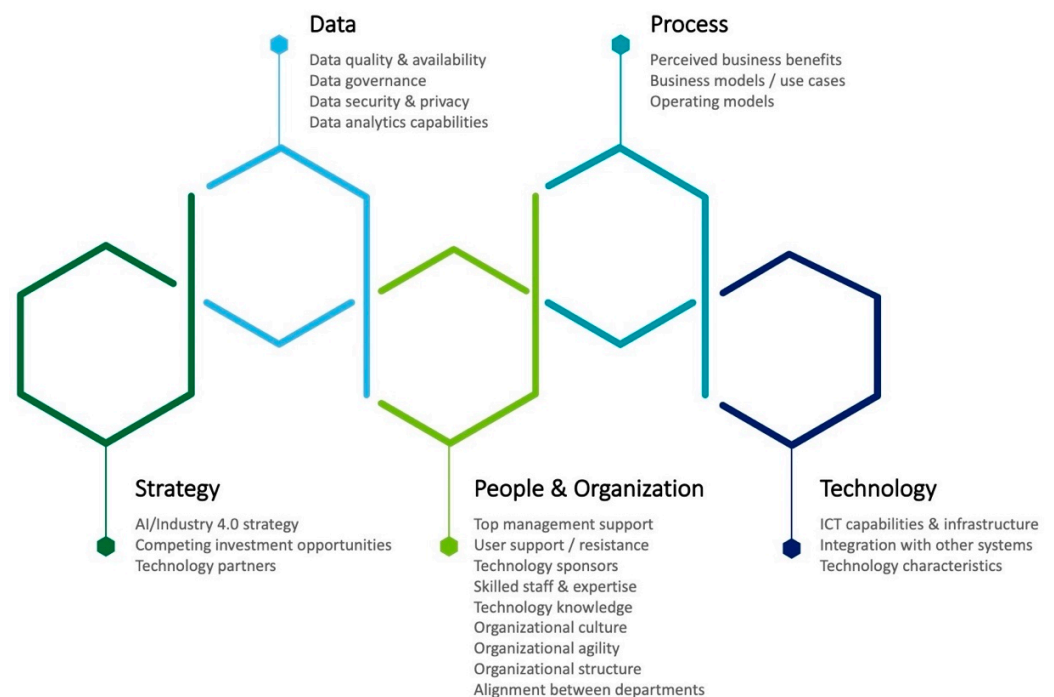


Figure 2. Overview of factors affecting the AIoT scale-up.

The proposed taxonomy provides a framework for laying out the factors affecting the scale up of AIoT initiatives, but it does not shed much light on the time dependency of such factors, nor can this be considered to be a general smart city framework. In the next section, we discuss the temporal changes in factors.

4.2. How the Influential Factors Change throughout the Scaling Process

As most interviewees pointed out, it is rather difficult to sketch out a precise timeline of events and barriers that is generalizable to all initiatives. This is simply due to the context-dependent nature of smart city projects. Each factor may manifest itself in numerous distinct ways depending on the chain of events within each setting. Nonetheless, the study discovered that some factors are more likely to play more critical roles in certain project stages, while others are less time bound (see Figure 3).



Figure 3. Mapping the factors on stages.

In accordance with the earlier body of literature [16–18,33,41,48,50,51], the findings from the study suggest that the strategic factors tend to be more prominent in the earlier stages of scale-up. As the expert interviews underscore, even before crafting their short-term and long-term business plans, smart cities are often faced with a multitude of opportunities, which seems to drive some organizations into inaction. The study also supports the notion proposed by the earlier works that organizations need to assess their potential use cases and business benefits prior to initiating projects. The research also discovered that data quality and availability are more likely to inhibit scaling efforts much earlier in the process. The lack of data quality seems to deter some smart cities from initiating the project early on in the journey.

The study corroborates the earlier findings from the literature [16–18,34,41,47] that strong leadership support and technology sponsorship maintain their vital position throughout the project. Moreover, the results suggest that the willingness of the top executives or technology champions in the organization are more likely to be what kicks off the projects. This result can be explained by the fact that such transformation projects tend to be on the rather expensive end of the spectrum, therefore demanding a generous allocation of resources to initiate, but even more to scale-up. It seems likely that top management and technology sponsors are not only the main drivers for igniting the project but also the ones fueling it throughout its course.

Another insight from the study is that AIoT projects seem to face much of the organizational and people barriers after they start to scale their solutions. Unlike proofs-of-concept and pilots, which are conducted in relatively isolated settings with limited impact on the manner of working within the organization, smart city solutions tend to experience a wide array of issues. Surprisingly, a large share of the earlier literature on AIoT attempts neither to map out the factors on the timeline nor to explain these factors. The research found that some organizational factors, such as culture, agility, structure, and alignment between different organizational entities, tend to impact slightly later in the scale-up as the project enters the territories and spheres of other organizational entities. Moreover, the results also imply that organizations need to ensure that the users are equipped with the right skills and, more importantly, are willing to adopt the solutions during the scaling phase, which is in accordance with the vast body of literature that stresses the role of human capital and training [16–18,27,33–38,41,44,47,48,50–52,54,56,60].

As far as data are concerned, the study found that as the datasets grow in diversity and volume, smart cities are more likely to experience setbacks caused by a lack of robust data governance and analytics practices, and by suboptimal operating models. It seems possible

that this digital incompetence will turn out to be more severe as it becomes more difficult for companies to manage and analyze such high-volume and diverse data streams with inefficient tools and frameworks. Similarly, our study revealed that many of the challenges concerning the integration of different systems, as well as the existing ICT infrastructure to support the solution, especially when connecting IT and OT systems, tend to arise when companies attempt to expand their pilots.

From these insights, we illustrated which factors are more influential during the scale-up (Figure 3). It is worth noting that the figure should not be taken to indicate that a factor is only significant during those specific stages. Rather, it indicates that a factor is relatively more important at that point in time and can affect the scale-up to some degree during other phases.

5. Scaling-Up Strategies

In addition to the investigation of factors and their variances across time, this research provides a set of potential strategies that companies can employ to scale up successfully. During our research, three main strategic themes have emerged: *proof-of-value over proof-of-concept, treating and managing data as a key asset, and a top-down and bottom-up approach.*

5.1. Proof-of-Value, Not Proof-of-Concept

The study found that pilots and proofs-of-concept in the domain are often technology-led implementations prompted by the hype around emerging technologies rather than value-led initiatives grounded in solid business cases. No matter how tempting the “shiny” new technology is, it is crucial to determine whether the value it might generate is higher at all than the cost of deployment and change management required to put it into production. Yet many smart cities seem to spend considerable amounts of time and resources on setting up a PoC, running it and proving—as many have before—that the concept works, without knowing whether it is a worthwhile pursuit. The study suggests turning this logic upside down by embracing an alternative approach that identifies the business value first: proof-of-value.

In line with the earlier work that stresses the vital role of selecting appropriate use cases [18,34,40,47,48,50,52], the findings pinpoint the fact that smart cities have a better chance of success if they select those use cases that can yield a measurable impact and if the technology can readily connect with existing systems and infrastructure. The term “success,” however, calls for a careful definition. The study found that some organizations initially misdefine it as successful deployment of new technology, rather than delivering meaningful business value. The research suggests that organizations focus on business value over technology, therefore linking the metrics of success with the proof-of-value, including, for example, overall equipment effectiveness, end-user statistics, and reduction in maintenance costs or machinery downtimes.

After identifying the high-value use cases and proving their feasibility, the study suggests that organizations focus on a limited set of use cases without fragmenting efforts and resources. Equally important, the end goal is—essentially—not only proving that there is value, but also delivering it. Therefore, it seems critical that smart cities adopt a scaling mindset from the start, assessing the requirements for integration and development of systems, data collection and processing, data governance, and existing technology infrastructure early on in the process. This proof-of-value approach inherently demands that smart cities pivot to piloting, where companies demonstrate the business value at the start and go right to scale.

This ultimately means that some pilots will fail due to them either not delivering meaningful value or not being able to scale. Both options seem to work in organizations’ favor, as it will in all likelihood save them from investing in projects that bring neither value nor scale. Moreover, the study found that organizational learning that occurs during a project is also of value, even if the project fails. Thus, the companies that display some

form of an agile way of thinking in this space, i.e., fail fast learn fast, are more likely to expand their solutions in the long run.

5.2. Treat and Manage Data as a Key Asset

The concept of data is not likely to go anywhere anytime soon. In line with the earlier body of literature [16–18,23,29,34,41,50,51,58], the study found that data are foundational to scaling AIoT. Yet even after years of operating with multiple streams of information, many smart cities still seem to struggle with the sheer size of data, let alone cleansing, managing, structuring, and analyzing data. While it might seem trivial, the study revealed that some smart cities have limited knowledge about the type and the depth of the data they possess, let alone who owns it. A relatively simple early action for organizations is to identify what data they have and how this relates to their company. Only then can organizations have a good understanding of what they have, and more importantly, what they need to scale.

In contrast to proofs-of-concept or pilots, smart city solutions tend to work with larger and more diverse data sets, often ingesting and integrating a variety of data sources in real-time. Hence, the need for robust data quality, data management, and data governance frameworks keeps growing [16–18,29,52]. The research recommends that organizations invest in robust data practices for collecting, storing, organizing, and maintaining such large volumes of data coming from a variety of sources, even before starting AI or IoT initiatives. Establishing solid data governance is not likely to be a one-off attempt, however. It also calls for effective operating models for the continuous generation and consumption of data when companies deploy initiatives into production.

Generating, transferring, storing, and processing such volumes of data through a network of inter-connected devices demand extra attention from organizations to ensure privacy and security. Addressing the concerns about cybersecurity as early as possible is likely to help organizations avoid unanticipated setbacks due to data privacy and security issues. In addition to securing data, the study found that many organizations involved in smart city initiatives have their data sitting in separate functional silos without clear ownership, which leads to inefficient operations and potential value not being realized. At this point, the study suggests that they clarify the data ownership throughout the organization to ensure accountable, responsible, and secure use of data to create business value as well as mitigate the potential risks.

5.3. The Importance of Commitment at All Levels

Transformations are more likely to scale up when people embrace them. The earlier works in management literature have highlighted the role of both top-down leadership commitment [16–18,34,41,42,47] and bottom-up user support [13,15–18,33,47,54] for large-scale implementations of AI and IoT projects. The study discovered that neither of these factors on its own is sufficient for building solutions at scale. As opposed to those that concentrate on only one of the two, smart cities that sustain commitment at all levels are more likely to scale up. No matter how strategically senior executives in various functions, e.g., operations, supply chain, and strategy, think to create value, those on the ground floor, be it floor managers, engineers, operators, or technicians, are the ones who can drive change and deliver value.

The findings from the research corroborate the earlier propositions in the literature that technology sponsors and champions are effective in leading AIoT initiatives as well as communicating the transformation within the organization [17,29,41,53]. Executive-level technology sponsors are key drivers for smart city transformations. In addition to there being clear sponsorship from the top, strong alignment and collaboration between different business units and functions are critical [29,34,46,47,50,53]. Scaling AIoT requires multi-disciplinary teams throughout organizations, supported by the executive sponsorship that ensures alignment with C-level strategy. Therefore, the study encourages companies

to break down such silos, and form multi-disciplinary and cross-departmental teams to effectuate the transformation.

As the study shows, people are less likely to fear such digital transformations when organizations clearly show the real value of tools and address their concerns about job replacement. Therefore, so-called “automation anxiety” still exists but seems evitable. The study suggests that smart cities should establish clear communication with their workers and train them so as to ease their adaptation to the new tools and techniques. After all, smart city transformations are not only about upgrading assets or processes; they are perhaps even more about enabling change and upskilling people to adapt to new ways of working. In short, support from both sides, top-down and bottom-up, is essential.

6. Conclusions

The study not only highlights the multifaceted nature of the barriers to AIoT scale-up in smart cities, but also reveals that some factors tend to be more influential in certain stages. While strategic factors tend to be more prominent in the earlier stages, people and organizational factors tend to feature later when organizations roll out solutions. The research also confirmed the dominant role of top management and technology sponsors in igniting as well as leading the scale-up. Altogether, the study found that a multitude of factors may leave smart cities ill prepared for the challenges that the industrialization of AIoT solutions presents, which tend to multiply when companies lack much-needed resources and capabilities. Yet many organizations tend to overlook the fact that industrial transformations require them to pay attention to all aspects of change: strategy, data, people, process, and technology.

In the study, three major points emerged as potential strategies for enabling smart cities to eliminate, or at least mitigate, the barriers. These are proof-of-value, not proof-of-concept; treating and managing data as a key asset; and top-down and bottom-up support. Instead of jumping on the technology bandwagon, the study recommends that smart cities view pilots as small pieces of a bigger puzzle in their digital transformation journey. As opposed to proving the feasibility of the technology, as many have before, organizations can start by assessing the technology from the smart city perspective to identify high-value use cases and prove the real value—if there is any. To avoid unanticipated setbacks when the solution is scaled to production, the study suggests that companies adopt the scaling mindset and build their solutions for scale from the start. Inevitably, not all initiatives will scale up; often, early iterations fail. Failures, too, are part of the journey, as long as the lessons are learned. Simply put, think big, start small, scale fast—even if it means failing fast.

Data are foundational to smart city AI and IoT initiatives. The research shows that companies need to pay the utmost attention to collecting, structuring, and managing their data, even before initiating AIoT projects. Though they often go unnoticed, the study reveals that robust data governance frameworks and operating models are critical for industrializing AIoT solutions. Data are a crucial business asset, therefore the organizations should treat and manage it as such.

The study shows that the support from all levels—executive sponsorship from the top, ensuring user acceptance, and upskilling employees on the frontline—is essential for scaling up, as it probably is for most digital transformations. Yet each AIoT project brings its own set of requirements and challenges, and therefore demands a tailored approach. Smart cities must adopt a comprehensive perspective to break down all of the barriers that stand in the way of AIoT developing into fully industrialized solutions.

As one of the first attempts to thoroughly examine the convergence of AI and IoT, this research contributes to the rapidly expanding fields of AI and IoT, and offers insights into the influential factors and strategies for the scaling of these technologies. The study also provides a perspective on the contemporary barriers that are more specific to AIoT initiatives, which have not been adequately addressed in the literature. Further, the study expands the traditional organizational change frameworks and develops a new taxonomy

in this domain that can serve as the groundwork for future research. By integrating the earlier findings from the literature and the empirical evidence from this study, the study formulates critical strategies for overcoming those barriers, which are of both theoretical and practical value to scholars and practitioners in the field.

The findings from the research have limitations. Environmental factors, such as regulations, external shocks, and cultural differences, were not investigated. The interviewees in the study were disproportionately from the consulting field, which might have limited the diversity of the perspectives and have led to potential biases in the outcomes. The study also falls short in the number of academic experts that could potentially enrich the point of discussion with their theoretical perspective. Another limitation of the study is the fact that the study investigates the phenomenon in the context of large organizations. Therefore, it is unknown whether the same set of factors and barriers are present in other settings, let alone whether they change in the same manner across time. This limitation is likely to have certain implications for the applicability of the potential strategies for the initiatives of smaller organizations. Furthermore, a note of caution is due regarding the list of influential factors found in the study. As the research set out to explore a rather contemporary phenomenon, the list of factors is neither definite nor conclusive, and leaves room for the unknown.

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References

1. Choi, Y.; Gil-Garcia, J.; Burke, G.B.; Costello, J.; Werthmuller, D.; Aranay, O. Towards Data-Driven Decision-Making in Government: Identifying Opportunities and Challenges for Data Use and Analytics. In Proceedings of the 54th Hawaii International Conference on System Sciences, Kauai, HI, USA, 5–8 January 2021. [\[CrossRef\]](#)
2. Gil-Garcia, J.R.; Pardo, T.A.; De Tuya, M. Information Sharing as a Dimension of Smartness: Understanding Benefits and Challenges in Two Megacities. *Urban Aff. Rev.* **2021**, *57*, 8–34. [\[CrossRef\]](#)
3. Scholl, H.J.; AlAwadhi, S. Pooling and leveraging scarce resources: The smart eCity gov alliance. In Proceedings of the Annual Hawaii International Conference on System Sciences 2015, Kauai, HI, USA, 5–8 January 2015; pp. 2355–2365. [\[CrossRef\]](#)
4. Corbett, J.; Webster, J. Organizational sensemaking and big data frames: Opportunity, control, and data limitation. In Proceedings of the Annual Hawaii International Conference on System Sciences 2015, Kauai, HI, USA, 2015, 5–8 January; pp. 4772–4781. [\[CrossRef\]](#)
5. Schaffers, H.; Komninos, N.; Pallot, M.; Trousse, B.; Nilsson, M.; Oliveira, A. Smart cities and the future internet: Towards cooperation frameworks for open innovation. *Lect. Notes Comput. Sci. (Incl. Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinform.)* **2011**, *6656*, 431–446. [\[CrossRef\]](#)
6. Komninos, N.; Pallot, M.; Schaffers, H. Special Issue on Smart Cities and the Future Internet in Europe. *J. Knowl. Econ.* **2013**, *4*, 119–134. [\[CrossRef\]](#)

7. De Jong, M.; Joss, S.; Schraven, D.; Zhan, C.; Weijnen, M. Sustainable-smart-resilient-low carbon-eco-knowledge cities; Making sense of a multitude of concepts promoting sustainable urbanization. *J. Clean. Prod.* **2015**, *109*, 25–38. [CrossRef]
8. Yerden, X.; Gil-Garcia, R.; Gasco-Hernandez, M.; Burke, B. The Role of Public Libraries in Developing Smart Cities and Communities: Comparing the Perspectives of Local Governments and Public Libraries. In Proceedings of the DG.O2021: The 22nd Annual International Conference on Digital Government Research, New York, NY, USA, 9–11 June 2021; pp. 252–263. [CrossRef]
9. Kuguoglu, B.K. The Giant Leap toward AIoT at Scale: Exploring the Barriers to Scaling Artificial Intelligence of Things [TU Delft]. 2020. Available online: <https://repository.tudelft.nl/islandora/object/uuid%3A60a77dd9-3994-47af-b08e-b19c37e8c398> (accessed on 30 October 2021).
10. van Winden, W.; van den Buuse, D. Smart City Pilot Projects: Exploring the Dimensions and Conditions of Scaling Up. *J. Urban Technol.* **2017**, *24*, 51–72. [CrossRef]
11. van Winden, W.; Oskam, I.; Van Dijck, E. *Organising Smart City Projects: Lessons learned from Amsterdam Willem van Winden*; Hogeschool van Amsterdam: Amsterdam, The Netherlands, 2016.
12. Bogner, A.; Littig, B.; Menz, W. Introduction: Expert Interviews—An Introduction to a New Methodological Debate. In *Interviewing Experts*; Palgrave Macmillan: London, UK, 2009; pp. 1–13. [CrossRef]
13. Schlögl, S.; Postulka, C.; Bernsteiner, R.; Ploder, C. Artificial Intelligence Tool Penetration in Business: Adoption, Challenges and Fears. In Proceedings of the 14th International Conference, KMO 2019, Zamora, Spain, 15–18 July 2019; Volume 1, pp. 259–270. [CrossRef]
14. Kaplan, A.; Haenlein, M. Rulers of the world, unite! The challenges and opportunities of artificial intelligence. *Bus. Horiz.* **2020**, *63*, 37–50. [CrossRef]
15. Tarafdar, M.; Beath, C.M.; Ross, J.W. Enterprise Cognitive Computing Applications: Opportunities and Challenges. *IT Prof.* **2017**, *19*, 21–27. [CrossRef]
16. Brock, J.K.U.; von Wangenheim, F. Demystifying Ai: What digital transformation leaders can teach you about realistic artificial intelligence. *Calif. Manag. Rev.* **2019**, *61*, 110–134. [CrossRef]
17. Plastino, E.; Purdy, M. Game changing value from artificial intelligence: Eight strategies. *Strategy Leadersh.* **2018**, *46*, 16–22. [CrossRef]
18. Lichtenthaler, U. Beyond artificial intelligence: Why companies need to go the extra step. *J. Bus. Strategy* **2020**, *41*, 19–26. [CrossRef]
19. Davenport, T.H.; Ronanki, R. Artificial intelligence for the real world. *Harv. Bus. Rev.* **2018**, *96*, 108–116.
20. Ransbotham, S.; Khodabandeh, S.; Fehling, R.; LaFountain, B.; Kiron, D. Winning With AI. Available online: <https://sloanreview.mit.edu/projects/winning-with-ai/> (accessed on 30 October 2021).
21. Shrestha, Y.R.; Ben-Menahem, S.M.; von Krogh, G. Organizational Decision-Making Structures in the Age of Artificial Intelligence. *Calif. Manag. Rev.* **2019**, *61*, 1–18. [CrossRef]
22. Agrawal, A.; Gans, J.S.; Goldfarb, A. Exploring the impact of artificial intelligence: Prediction versus judgment. *Inf. Econ. Policy* **2019**, *47*, 1–6. [CrossRef]
23. Faraj, S.; Pachidi, S.; Sayegh, K. Working and organizing in the age of the learning algorithm. *Inf. Organ.* **2018**, *28*, 62–70. [CrossRef]
24. Jarrahi, M.H. Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Bus. Horiz.* **2018**, *61*, 577–586. [CrossRef]
25. Metcalf, L.; Askay, D.A.; Rosenberg, L.B. Keeping humans in the loop: Pooling knowledge through artificial swarm intelligence to improve business decision making. *Calif. Manag. Rev.* **2019**, *61*, 84–109. [CrossRef]
26. Lichtenthaler, U. Extremes of acceptance: Employee attitudes toward artificial intelligence. *J. Bus. Strategy* **2021**, *41*, 39–45. [CrossRef]
27. Simon, J.P. Artificial intelligence: Scope, players, markets and geography. *Digit. Policy Regul. Gov.* **2019**, *21*, 208–237. [CrossRef]
28. Kolbjørnsrud, V.; Amico, R.; Thomas, R.J. Partnering with AI: How organizations can win over skeptical managers. *Strategy Leadersh.* **2017**, *45*, 37–43. [CrossRef]
29. Davenport, T.H. From analytics to artificial intelligence. *J. Bus. Anal.* **2018**, *1*, 73–80. [CrossRef]
30. Chamorro-Premuzic, T.; Polli, F.; Dattner, B. Building Ethical AI for Talent Management. 2019. Available online: <https://hbr.org/2019/11/building-ethical-ai-for-talent-management> (accessed on 30 October 2021).
31. Nasiripour, S.; Surane, J.; Natarajan, S. Apple Card Gender-Bias Claim Shows AI Still Faces '70s Issue-Bloomberg. 2019. Available online: <https://www.bloomberg.com/news/articles/2019-11-11/apple-card-s-ai-stumble-looks-familiar-to-old-school-banks> (accessed on 30 October 2021).
32. Kaplan, A.; Haenlein, M. Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Bus. Horiz.* **2019**, *62*, 15–25. [CrossRef]
33. Schneider, P. Managerial challenges of Industry 4.0: An empirically backed research agenda for a nascent field. *Rev. Manag. Sci.* **2018**, *12*, 803–848. [CrossRef]
34. Schumacher, A.; Erol, S.; Sihni, W. A Maturity Model for Assessing Industry 4.0 Readiness and Maturity of Manufacturing Enterprises. *Procedia CIRP* **2016**, *52*, 161–166. [CrossRef]
35. Agostini, L.; Filippini, R. Organizational and managerial challenges in the path toward Industry 4.0. *Eur. J. Innov. Manag.* **2019**, *22*, 406–421. [CrossRef]
36. Karre, H.; Hammer, M.; Kleindienst, M.; Ramsauer, C. Transition towards an Industry 4.0 State of the LeanLab at Graz University of Technology. *Procedia Manuf.* **2017**, *9*, 206–213. [CrossRef]
37. Thoben, K.D.; Wiesner, S.A.; Wuest, T. "Industrie 4.0" and smart manufacturing—a review of research issues and application examples. *Int. J. Autom. Technol.* **2017**, *11*, 4–16. [CrossRef]

38. Fatorachian, H.; Kazemi, H. A critical investigation of Industry 4.0 in manufacturing: Theoretical operationalisation framework. *Prod. Plan. Control* **2018**, *29*, 633–644. [[CrossRef](#)]
39. Wan, J.; Tang, S.; Shu, Z.; Li, D.; Wang, S.; Imran, M.; Vasilakos, A.V. Software-Defined Industrial Internet of Things in the Context of Industry 4.0. *IEEE Sens. J.* **2016**, *16*, 7373–7380. [[CrossRef](#)]
40. Xu, L.D.; Xu, E.L.; Li, L. Industry 4.0: State of the art and future trends. *Int. J. Prod. Res.* **2018**, *56*, 2941–2962. [[CrossRef](#)]
41. Ghobakhloo, M. The future of manufacturing industry: A strategic roadmap toward Industry 4.0. *J. Manuf. Technol. Manag.* **2018**, *29*, 910–936. [[CrossRef](#)]
42. Orzes, G.; Rauch, E.; Bednar, S.; Poklemba, R. Industry 4.0 Implementation Barriers in Small and Medium Sized Enterprises: A Focus Group Study. In Proceedings of the 2018 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM) 2018, Bangkok, Thailand, 16–19 December 2018; pp. 1348–1352. [[CrossRef](#)]
43. Botta, A.; De Donato, W.; Persico, V.; Pescapé, A. Integration of Cloud computing and Internet of Things: A survey. *Future Gener. Comput. Syst.* **2016**, *56*, 684–700. [[CrossRef](#)]
44. Zhou, K.; Liu, T.; Zhou, L. Industry 4.0: Towards future industrial opportunities and challenges. In Proceedings of the 12th International Conference on Fuzzy Systems and Knowledge Discovery, FSKD 2015, Zhangjiajie, China, 2015, 15–17 August; pp. 2147–2152. [[CrossRef](#)]
45. Sadeghi, A.-R.; Wachsmann, C.; Waidner, M. Security and privacy challenges in industrial internet of things. In Proceedings of the 52nd Annual Design Automation Conference on—DAC’15, San Francisco, CA, USA, 7–11 June 2015; pp. 1–6. [[CrossRef](#)]
46. Samaranyake, P.; Ramanathan, K.; Laosirihongthong, T. Implementing industry 4.0—A technological readiness perspective. In Proceedings of the IEEE International Conference on Industrial Engineering and Engineering Management 2018, Singapore, 10–13 December 2017; pp. 529–533. [[CrossRef](#)]
47. Horváth, D.; Szabó, R. Driving forces and barriers of Industry 4.0: Do multinational and small and medium-sized companies have equal opportunities? *Technol. Forecast. Soc. Chang.* **2019**, *146*, 119–132. [[CrossRef](#)]
48. Agarwal, N.; Brem, A. Strategic business transformation through technology convergence: Implications from General Electric’s industrial internet initiative. *Int. J. Technol. Manag.* **2015**, *67*, 196–214. [[CrossRef](#)]
49. Magistretti, S.; Dell’Era, C.; Messeni Petruzzelli, A. How intelligent is Watson? Enabling digital transformation through artificial intelligence. *Bus. Horiz.* **2019**, *62*, 819–829. [[CrossRef](#)]
50. Dwivedi, Y.K.; Hughes, L.; Ismagilova, E.; Aarts, G.; Coombs, C.; Crick, T.; Duan, Y.; Dwivedi, R.; Edwards, J.; Eirug, A.; et al. Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *Int. J. Inf. Manag.* **2019**, *57*, 101994. [[CrossRef](#)]
51. Lee, I.; Shin, Y.J. Machine learning for enterprises: Applications, algorithm selection, and challenges. *Bus. Horiz.* **2020**, *63*, 157–170. [[CrossRef](#)]
52. Metelskaia, I.; Ignatyeva, O.; Deneff, S.; Samsonowa, T. A business model template for ai solutions. In Proceedings of the 2018 International Conference on Intelligent Science and Technology, London, UK, 30 June–2 July 2018; pp. 35–41. [[CrossRef](#)]
53. Duan, Y.; Edwards, J.S.; Dwivedi, Y.K. Artificial intelligence for decision making in the era of Big Data—Evolution, challenges and research agenda. *Int. J. Inf. Manag.* **2019**, *48*, 63–71. [[CrossRef](#)]
54. Lee, J.; Suh, T.; Roy, D.; Baucus, M. Emerging technology and business model innovation: The case of artificial intelligence. *J. Open Innov. Technol. Mark. Complex.* **2019**, *5*, 44. [[CrossRef](#)]
55. Hofmann, E.; Rüscher, M. Industry 4.0 and the current status as well as future prospects on logistics. *Comput. Ind.* **2017**, *89*, 23–34. [[CrossRef](#)]
56. Canhoto, A.I.; Clear, F. Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential. *Bus. Horiz.* **2020**, *63*, 183–193. [[CrossRef](#)]
57. Farahani, B.; Barzegari, M.; Shams Aliee, F.; Shaik, K.A. Towards collaborative intelligent IoT eHealth: From device to fog, and cloud. *Microprocess. Microsyst.* **2020**, *72*, 102938. [[CrossRef](#)]
58. Wang, W.; Siau, K. Artificial intelligence, machine learning, automation, robotics, future of work and future of humanity: A review and research agenda. *J. Database Manag.* **2019**, *30*, 61–79. [[CrossRef](#)]
59. Gubbi, J.; Buyya, R.; Marusic, S.; Palaniswami, M. Internet of Things (IoT): A vision, architectural elements, and future directions. *Future Gener. Comput. Syst.* **2013**, *29*, 1645–1660. [[CrossRef](#)]
60. Hoffman, R. Using Artificial Intelligence to Set Information Free. In *MIT Sloan Review*; The MIT Press: Cambridge, MA, USA, 2019; p. 58. [[CrossRef](#)]
61. Suarez, F.F. Battles for technological dominance: An integrative framework. *Res. Policy* **2004**, *33*, 271–286. [[CrossRef](#)]
62. Shapiro, C.; Varian, H.R. The art of standards wars. *Calif. Manag. Rev.* **1999**, *41*, 8–32. [[CrossRef](#)]
63. Farrell, J.; Saloner, G. Standardization, Compatibility, and Innovation. *RAND J. Econ.* **1985**, *16*, 70. [[CrossRef](#)]