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RESEARCH ARTICLE

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Leveraging technology adoption to navigate the 4IR towards a future-ready business: A systematic literature review

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Abstract

The purpose of this study was to analyze technology adoption constructs that are instrumental for organizations to effectively utilize emerging technologies, enabling them to navigate the complexities and opportunities presented by the fourth industrial revolution (4IR). To achieve this a descriptive research approach was used, guided by a systematic review of literature from 2016 to 2022. Among the 4037 studies initially identified, only 69 were deemed relevant. Meta-synthesis was then used to systematically identify, categorize, and quantify fundamental constructs inherent in the models from the relevant literature. As a result of this process, 406 constructs were identified across six thematic categories. These were subsequently integrated to develop a conceptual model that can be used to coordinate strategies to harness the potential of the 4IR towards a future-ready business. Findings show that the role of technology adoption remains pertinent in the ever-digitized world in which businesses operate and certain constructs are key to explain, support, and predict enterprise-wide adoption in the 4IR paradigm. Future studies can expand and test the model to promote digital fluency required by business constituents, noting differences across sectors.

KEYWORDS

4IR, cyber-physical systems, digital transformation, industry 4.0, smart technologies, strategy, technology adoption

1 | INTRODUCTION

Digital transformation has enabled numerous opportunities across sectors. For example, prior to the digital age, retail businesses primarily operated in brick-and-mortar stores. With the emergence of e-commerce and other digital platforms, businesses now have a global reach and can operate 24/7.[1] However, in the context of the fourth industrial revolution (4IR), emerging technologies are now able to better integrate across business units and functions, allowing organizations to generate data and use it to understand customer behaviors, preferences and buying patterns. Consequently, organizations can personalize marketing efforts, improve customer experiences and optimize operations based on more accurate forecasting. The emerging technology in question includes but is not limited to artificial intelligence (AI), Big Data analytics, machine learning, the Internet of Things (IoT), the metaverse, nanotechnology, robotics, additive manufacturing

(AM), and blockchain.[2,3] These technologies also saw utilization during the COVID-19 pandemic, addressing safety equipment shortages through AM and enhanced forecasting of concentrated areas of infection, allowing leaders to make data-driven decisions.[4,5] Despite several opportunities presented by this paradigm, the rapid expansion of emerging technologies brings with it several complexities,[6,7] consequently exerting pressure on organizations to reassess or even reinvent their business models, strategies, and systems.[8,9] Fittingly, the topic of 4IR's impact on the future of work and business sustainability has gained global interest.[10,11]

Organizations are being compelled to use emerging technologies to enhance their innovation capabilities, supporting—to a certain degree—their ability to operate competitively in an environmentally sustainable way.[12] But how have business leaders, strategists, government agencies and academics navigated such pressure to date? Scholarly inquiries[13-18] show that technology adoption models have been used and applied in different contexts to determine the application and use of new technologies.[19,20] The models explain the process by which innovation can be cultivated through the adoption of technology, a critical component for enhancing organizational competitiveness within the context of the emerging paradigm.[21] Consequently, various topical areas have seen technology adoption within the 4IR, including sustainability,[8,22-24] lean manufacturing,[10,25,26] small and medium enterprises (SMEs) and entrepreneurship,[3,27-30] production planning[10,31,32] and strategic management.[33] Notably, topical areas extend beyond specific industries, as 4IR technologies are being adopted across multiple sectors, highlighting the interdisciplinary nature of the paradigm. Yet, despite growing research across disciplines on the impact of emerging technologies, an aggregated understanding of the constructs that can explain, support, and predict adoption of technologies to navigate the 4IR remains vague,[12,34] particularly at an organizational level.[32,35-37] This gap is particularly pronounced regarding the complexity of technology adoption and the absence of standardized models or frameworks, specifically for 4IR and its associated emerging technologies. This is evident as there is continual adaptation of technology adoption models when applied on organizational level to studies conducted in the context of the 4IR. The subsequent research question raised is: *"What technology adoption model constructs support the acceptance of emerging 4IR technologies at an organizational level?"*

To address this question, the study employed a descriptive research approach using a systematic literature review (SLR). This was to identify constructs that influence the acceptance of 4IR-related "smart" emerging technologies, specifically at an organizational level. The study was limited to academic literature published between 2016 and 2022. In alignment with Moher et al.,[38] the study used the preferred reporting items for systematic reviews and meta-analyzes (PRISMA) method for the SLR to help maintain rigor and consistency in the review process, where six academic databases were used to search for relevant articles. Meta-synthesis was used to analyze the articles. This also guided the content analysis, thereby facilitating the systematic and objective identification, categorization, and quantification of key constructs across technology adoption models within the corpus. The outcome of this was to develop a conceptual model for the organization-level adoption of emerging technologies, as informed by existing literature.

This underscores the novelty of the present investigation, as the study contributes by synthesizing information into a conceptual model that shows key trends and the constructs deemed important for comprehending this novel paradigm. It also provides a guideline to enhance organizational level adoption that can be used by leaders to implement corrective measures. By illuminating how technology adoption can be supported within this emergent context, the research provides critical insights that addresses the current gap in research, extending academic literature within the rapidly evolving landscape towards future-ready business and workforce. Consequently, the objectives of this study are to (i) investigate prevalent technology adoption models and associated constructs deemed pertinent at an organizational level for the 4IR, (ii) enhance academic understanding of technology adoption within the context of the 4IR, particularly the effective utilization of emerging technologies, and (iii) develop a conceptual model that can guide policy and strategy making at various levels of an organization, enabling businesses to successfully navigate the 4IR and its associated complexities.

The article is structured as follows to address the research question to meet these objectives: First, the methodology used to identify technology adoption constructs from existing literature is presented. The findings are then presented based on six thematic categories. This is followed by the discussion, in which the conceptual model that was developed is presented. Finally, concluding remarks are provided, while noting the limitations of and acknowledgements for the study.

2 | METHODOLOGY

A descriptive research approach was selected to determine relevant technology adoption models and constructs that are deemed influential at an organizational level. This was done using a SLR. This methodology was deemed appropriate as it provides a holistic and generalizable understanding of the subject matter using reliable data from a range of sources.[39,40]

While various methodologies can be applied within SLR, this study used the PRISMA method.[38] This ensured the use of a widely applied methodology in the information systems, business, and engineering domain. Moreover, given that metadata provided limited information, such as keywords, abstracts, and the authors' names and their countries of origin, each eligible article was thoroughly examined to extract the necessary information for the study.

To this end, a meta-synthesis approach was used to guide content analysis, allowing for the systematic and objective identification, categorization, and quantification of key constructs across technology adoption models within the corpus. Based on the SLR, the first stage was the development of a research question. Using the research question, relevant articles could be identified. A search strategy was used to identify relevant research papers between 2016 and 2022 in accordance with the guidelines of Kitchenham[41] and the PRISMA method. The reason for this timeframe was that the term "4IR" had been coined in 2016.[42] It incorporates the term "Industry 4.0 (I4.0)," which is a subcategory of the 4IR. To develop a narrative and determine impactful constructs that encompass the 4IR's extensive scope, search strings and keywords, including certain synonyms and nuances of the new paradigm, were used.[43,44] Using the research question, several keywords and phrases were developed for a search string using Boolean expressions and wildcard symbols. Stop words were included to reduce the number of search strings. In addition, the domain of research was not overly focused to collect a broad range of relevant sources. The keywords applied included ["technology adoption" OR "technology adoption model" OR "technology acceptance"] AND ["4IR" OR "fourth industrial revolution" OR "industry 4.0" OR "cyber physical systems" OR "digital transformation" OR "smart technologies" OR "emerging technologies"] AND ["organization" OR "organization" OR "strategy"]. Additional criteria were also used, which were included in the shortlist at a later phase of the search process, such as adopt*, accept*, CPS*, emerging*, I4.0* and constructs*. Highly cited articles, along with seminal work in the fields of I4.0, 4IR, and organizational applications of smart technologies associated with the paradigm were then collected. This was applied to six databases, including Emerald, ProQuest, the Institute of Electrical and Electronics Engineers (IEEE), ScienceDirect, Scopus and Dimensions. The latter is a purpose-built database that makes use of AI to ensure a broad scope of coverage. Finally, cross-referencing was conducted to identify frequently co-cited papers. This was done to identify commonalities between papers. This made it possible for clusters to be formed that would enable researchers to understand the knowledge base, intellectual structures, and current scientific studies.[45]

The second stage entailed the screening of articles based on exclusion and inclusion criteria. This criterion applied is summarized in Table 1. The articles' abstracts, titles and keywords, and accessibility were first screened to determine whether the study focused on the relevant context or provided a theoretical discussion. Of the 4037 publications identified across six databases and through cross referencing, 3688 were accessible for screening by the researchers through their institution. Of these, 3224 were excluded, with 464 downloaded for a full review. This formed the baseline for articles that

TABLE 1 Inclusion and exclusion criteria used to select relevant documents per SLR

Inclusion criteria	Exclusion criteria
The study uses empirical methodology applied to a 4IR construct.	The article is a conference paper, master's dissertation, doctoral thesis, working paper or White Paper.
The publication language is in English.	The articles are not written in English.
The study is in a blind peer-reviewed publication.	The articles do not use empirical research methods.
It includes concepts relating to the 4IR or associated smart technologies.	The article does not specifically include concepts of the 4IR.
A technology adoption model or combination of models is used as a theoretical foundation for the assessment of smart technologies of the 4IR.	Articles provide information about the 4IR or I4.0, but do not provide an assessment of their adoption.
Articles consider the processes, critical success factors or impacts of the 4IR.	The articles' date ranges are not between 2016 and 2022.
Studies use empirical techniques to assess 4IR technologies and their adoption.	The research is only done on an individual or group research level.
The research is in an accredited journal publication.	The authors' country affiliations and their countries of study are not indicated.
The full text of the article is accessible by the researchers.	There are duplicate papers (the same paper is received from different databases).

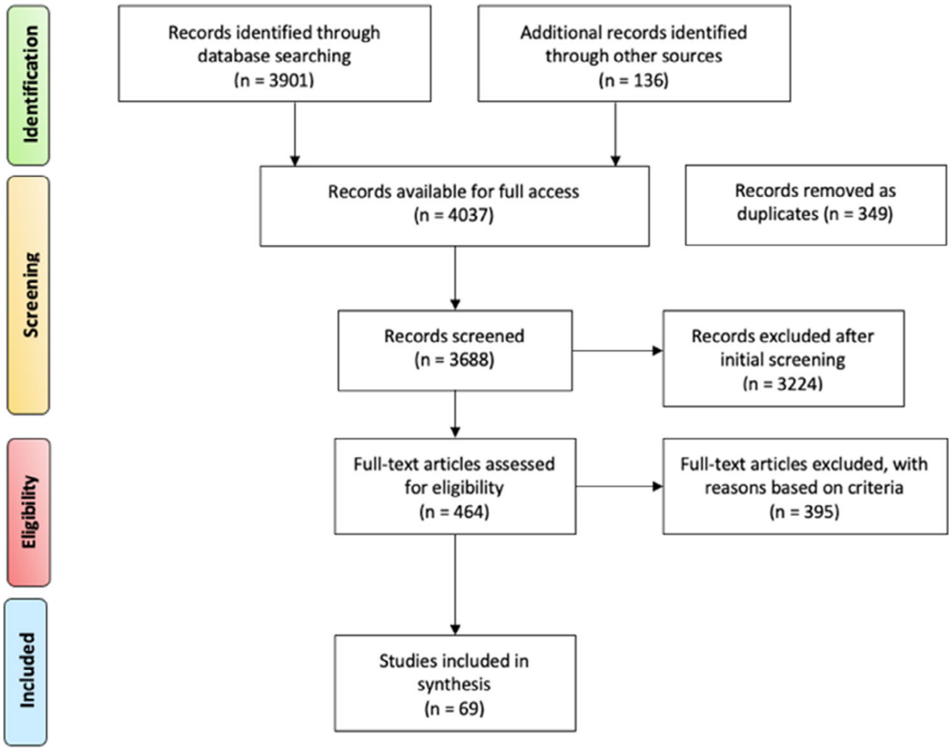

FIGURE 1 PRISMA flow diagram applied to this study. *Source*: Adapted from Moher et al.[38]

were further scrutinized by assessing their full texts. Mendeley (2022 version 2.69.0) was used as the reference manager and storage software.

To complete the identification of relevant articles within the 464 that had already been screened, eligibility took place. Criterion was applied to each article in its entirety, where the researchers noted each article's alignment and relevance to the research question, with a focus on the technology adopted, the impact, 4IR contextual relevance, constructs and the level of assessment. Outcomes of 0 had a perfect alignment, 1 had an excellent alignment, and 2 had majority alignment. However, outcomes of 3 and above were excluded. Using the thematic classification and synthesis, 395 papers were removed, leaving 69 articles for data extraction. This process, guided by PRISMA is shown in Figure 1.

Meta-synthesis was used to guide content analysis of the narrowed corpus and to develop a conceptual model. The first stage entailed reviewing the corpus's performance and trends related to technology adoption models. These findings were then synthesized and interpreted. This involved assessing them analytically and presenting them visually using tableau as a data analytics tool. This provided the foundation for the content analysis. The researchers' codification and categorization of constructs resulted in a comprehensive overview of six themes related to technology adoption at an organizational level. The frequency of each construct within the literature was analyzed, as well as the co-occurrence of constructs, revealing patterns and relationships between them. The analysis provided insights into the most influential constructs in the context of the organizational adoption of emerging technologies. A conceptual model was formulated based on the findings of the content analysis, which represented the relationships between key constructs in technology adoption models visually.

3 | FINDINGS

After quality assessment, 69 articles published over 7 years between 2016 and 2022 were accepted from the databases as follows: two from Dimensions, 21 from Emerald, 10 from ProQuest, one from IEEE, 12 from ScienceDirect, and 19 from SCOPUS. Four articles originated from cross-referencing. Of the 69 articles, 65 were empirical studies comprising 55 survey studies, five interview-based studies, three case studies, one Delphi technique study, and one experimental field study. The remaining four were literature studies. The full texts of the articles, bibliographic data and additional parameters not included in the metadata were manually extracted from each article and coded to a Microsoft Excel file (2021 version 16.54). This included the number of citations, methodology used and open access (OA) status to aggregate evidence from the studies identified. This facilitated the evaluation and interpretation of available research regarding the phenomenon of technology adoption models to assess emerging 4IR technologies at an organizational level. The sample sizes within each study were extracted to add to the meta-synthesis of the size and overarching impact of each study in the field in which it was conducted. From this data, six thematic themes were identified. These themes included regional aspects, distribution by date, primary technology adoption models used, subject areas identified, emerging 4IR technologies adopted, and a comparison of the subject area and with the technology adopted. The primary research output—a conceptual model—was then synthesized from these findings.

3.1 | Regional attributes

Countrywide frequency per publisher's location saw the United Kingdom (UK) lead with 34 articles. Thirty two of these were subscription-based and two were open-access articles. This was followed by the United States (USA) with seven subscription-based and three open-access articles. Switzerland had the most open-access articles at nine, and only one subscription-based article. The Netherlands had only one open-access article and seven subscription-based articles. See Appendix A for an overview of the access distribution per publication in terms of country of study, country of publication and author's affiliation. Overall, open-access publications accounted for 30.4% (21) of the articles, as opposed to 69.6% (48) subscription-based articles for this study. Open-access publications reduce access barriers to readers, often leading to a wider reader demographic and citation count. Despite this, the most-cited articles were subscription-based articles with 1950 citations; open-access articles accounted for 213 citations, as can be seen in Appendix B.

The geographic locations where the research was executed was meticulously evaluated, focusing on the actual concentration of the investigation within the study's area of interest, rather than only the geographic distribution of publishers. India emerged as the focal point of such studies, with a count of 11 conducted in the area. This was closely trailed by global studies accounting for 10, which were characterized by their holistic approach and integration of multiple countries. Subsequently, Malaysia contributed seven studies, the UK five and South Africa four. As depicted in Figure 2, it can be observed that the execution of studies was not confined to a particular region, demonstrating a diverse distribution within the corpus.

Despite India being the leading country in terms of studies conducted per publication, it is important to consider the sample size of each study. By examining the sample sizes in detail, one can gain a better understanding of the overall

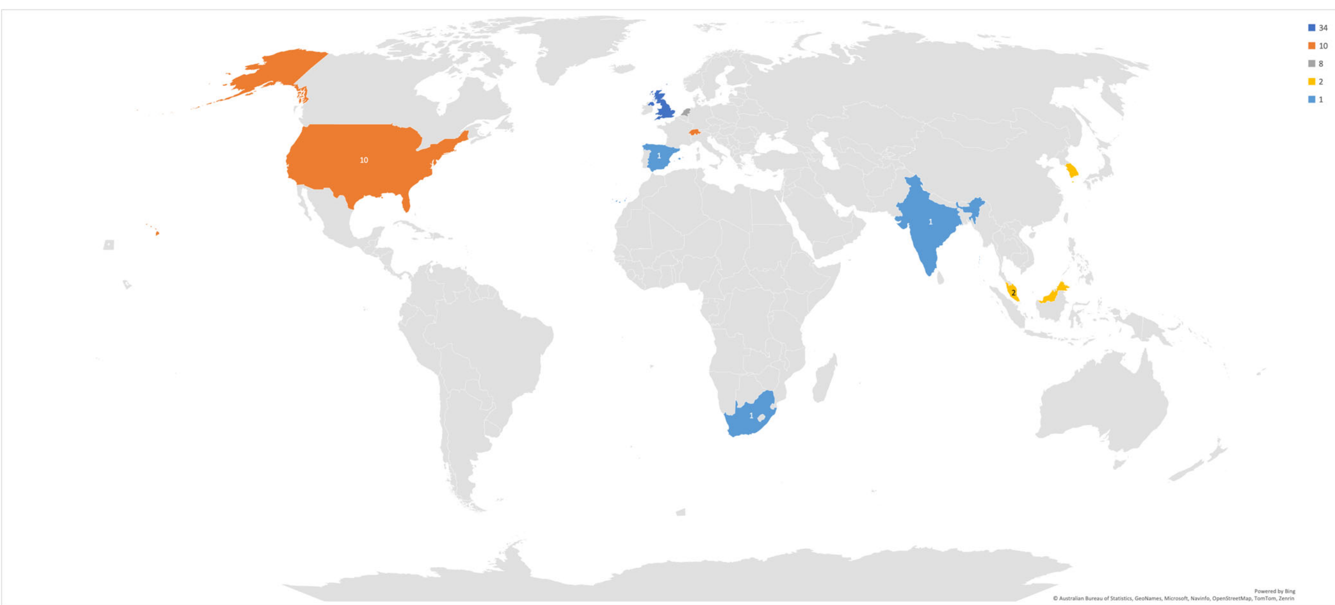

FIGURE 2 Country of study distribution per publication count. *Source*: Tableau

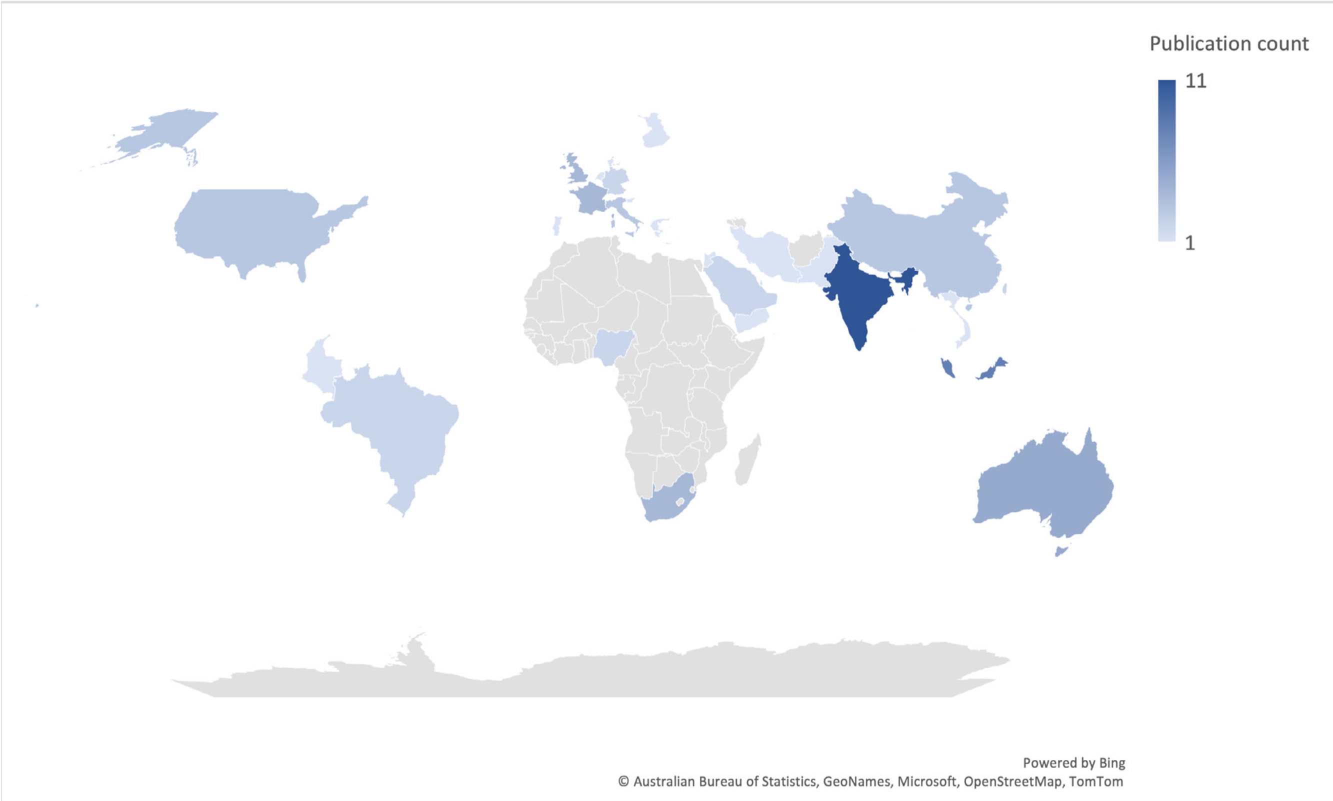

FIGURE 3 Country of authors' affiliation per publication count. *Source*: Tableau

use and assessment of the studies within their respective regions. The leader in this regard was Malaysia, with a total sample size of 1761. This could be attributed to Malaysia's major technological trends and drive towards industrialization in various sectors, as noted by Salimon et al.[30] India was placed second with a total sample size of 1650. It has also seen several efforts in supporting large-scale organizations to develop and leverage 4IR-associated technologies, in accordance with Mitra et al.[46] Researchers in this country have also channeled their efforts towards supporting SMEs.[47] Globally, the sample size was 1394. China took third place with a sample size of 795, which could be attributed to the region's efforts to promote automated robotics in new fields, as well as optimizing existing manufacturing.[25] South Africa, a developing region, was in fifth place with a total sample size of 752. The region is considering advancing economic challenges within the 4IR and leveraging these technologies to alleviate unemployment challenges, despite lacking key infrastructure and basic information and communication technology (ICT) skills.[48]

Overall, there appears to be a strong mix of where the studies were conducted based on the publication count and sample sizes of the studies, showing that several regions are channeling their efforts to leveraging these technologies on an organizational level. For a detailed distribution per study region, see Appendix C.

Continuing with the regional categories, the main authors' countries of affiliation follow similar trends, with a concentration in Asia. The details are contained in Appendix D. The distribution of the main authors can be seen in Figure 3. Factoring in the countries' affiliated authors by the sample sizes of the studies resulted in Malaysia taking first place (1555), followed by India (1547), and Australia (960). Using citation count as a metric gave Malaysian authors the most citations (322), followed by the UK (220), and Brazil (204). In terms of the main author's institution, the Universiti Teknologi Malaysia was ranked highest with a publication count of five. The Xiamen University Malaysia, University of New South Wales, University of Johannesburg, University of Cambridge, and the National Institute of Industrial Engineering were involved in at least two of the studies when the affiliation of the main authors was considered. However, the Xiamen University Malaysia had the most citations at 265, followed by the University of Cambridge with 190 citations. This is important to note as academic institutions are often strongly affiliated with research and development (R&D) institutions, including 4IR R&D. The leaders and associated information can be seen in Appendix E.

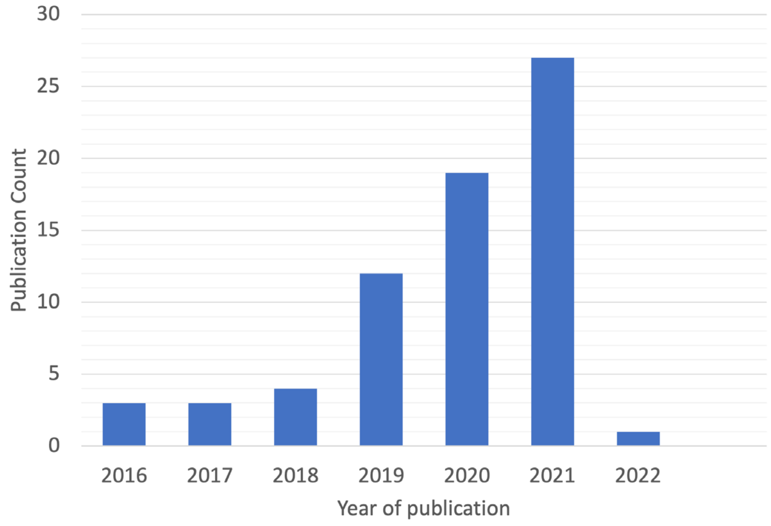

FIGURE 4 Distribution of articles by year of publication. *Source*: Tableau

3.2 | Distribution by date

Publications were staggered in 2016. This could be attributed to the origins of the publications and time required to apply and conceptualize the overall impacts of emerging technologies. The distribution per publication can be seen in Figure 4. Despite recent growth in this area from 12 in 2019 to 27 in 2021, there is great potential for more research, especially when considering the low numbers identified for 2022.

3.3 | Primary technology adoption models used

The primary underlying technology adoption model was noted for each study. In this regard, the technology-organization-environment (TOE) model, with a publication count of 32, was the most predominant. This was followed by the technology acceptance model (TAM) (25), the unified theory of acceptance and use of technology (UTUAT) model (6) and the diffusion of innovation (DOI) model (5). However, 66 of the 69 studies amended their models to a certain extent, subsequently affecting the core constructs used. This was likely due to the need to address the rapid nature of the paradigm under review. When considering this, mixed models were also assessed and incorporated, resulting in 120 models being integrated within the 69 studies. The most-used model remained the TOE, with a total count of 41 across the publications. Second was the TAM at a count of 31. This was followed by the UTAUT and DOI models, with counts of 16 and 13, respectively. These are briefly covered to provide context. Various other models also featured. However, low usage resulted in minimal constructs stemming from those models. Consequently, they were not covered.

The TOE framework was founded by Tornatzky and Fleischer[17] and it was designed for an enterprise level of analysis.[49] The framework proposes generic innovation adoption factors within the dimensions of technology, organization, and the environment, with sub-factors within each. The technological dimension describes the relevance of new technologies.[30] The organizational factors focus more on the enterprise's resources, which enable adoption, such as experience, relative advantage, and capabilities.[50] The third dimension, environmental factors, considers the context within which the organization operates. In the ever-digitalized world, this is changing, as key focus areas are changing.[10] However, due to the unstable nature of the environment, there have been several extensions to the model to ensure that it considers underlying impacts and constructs that are meaningful in effectively utilizing technologies through adoption.[35] As a result of the extensive modifications, it remains the most applied, even in the 4IR context.[10]

The TAM, which was founded by Davis,[14] has seen several versions applied to different technologies over the years and is widely accepted in information systems literature. It considers the relationship among variables such as perceived usefulness (PU), perceived ease of use (PEoU), and behavioral intention (BI). Within the 4IR, it has been applied to several studies. A reason for this is that it examines the end-user acceptance of technologies and systems based on certain characteristics, where organizations need to consider individual levels of accepting smart technologies to expedite their adoption.[51]

Several models exist to explain technology adoption in achieving the benefits they bring. A model that incorporated several of these was the UTAUT model of Venkatesh et al.,[18] which conducted empirical studies to synthesize behavioral intentions. This model facilitates various other models, such as a combined TAM-theory of planned behavior (TPB),[52] the model of PC utilization (MPCU),[53] the motivational model (MM)[54] and the social cognitive theory (SCT).[53] It also includes core constructs from the theory of reasoned action (TRA)[55] and the TPB.[52]

Rogers[16] proposed the following interplaying factors of innovation, which are synonymous with those of the TOE framework[56]: relative advantage, compatibility, complexity, trialability, and observability. Notwithstanding, he proposed that attributes of innovation can predict the rate of adoption of innovations, where the rate of adoption is *"the relative speed with which an innovation is adopted by a member of a social system"*.[16] This is strongly associated with technology, as the two are synonymous with cause-effect relations. For these studies, the technology itself was often hardware or software, where it has proven to be helpful for comparing degrees of adoption, which aids in understanding overall levels of maturity.[57]

3.4 | Subject areas identified

Another contextual factor assessed was subject area. For this study, 16 subject areas were identified. When considering the sample size of each study, the most predominant subject area was manufacturing, with a sample size of 2142. This can be attributed to the optimization organizations are looking to achieve within I4.0, which is a subcategory of the 4IR, as noted by Yaacob and Thing.[58] The premise, though, is the utilization of smart technologies to expand operational efficiencies, in several instances automation.[25] This was followed by business administration and supply chain management (SCM), which had a count of 1979 and 1908, respectively. Business administration aligns to this study, demonstrating organizations' drive to engage with 4IR technologies and guide strategy transformation and business model reinvention.[59] The purpose of such research is to create and capture new forms of value through innovation.[60] Part of such a strategy is organizations' SCM operations to deliver value. Education was fourth, with a sample size of 1359, as organizational learning and the effects of the 4IR on education were considered at an organizational level.[32] At a citation level, manufacturing and business administration were the leaders with 579 and 307 citations, respectively. Finance, though, saw much interest, with the third-highest number of citations (181), despite a publication count of only four. This could be attributed to the large movements in banking and finance, which are being affected by the digital technology referred to as blockchain.[2,3] The details of subject area distribution can be seen in Appendix F.

The core model used in each subject area was based on the number of publications, as can be seen in Figure 5. In this sense, the leading subject area was business administration, followed by manufacturing and SCM. Business administration had a mix between the four primary models identified, with TOE being the most applied model in seven publications, while the TAM came second with its application in four publications. Manufacturing only applied the TOE model and TAM in eight and five publications, respectively. SCM applied a mix of models. However, the TOE model was the most used. Construction, agriculture, transportation, and pharmaceuticals only used the TOE model for organizational assessment. However, finance, which predominantly looked at blockchain, used the TAM, despite it influencing the organizational level within the studies' parameters. As such, there was a mixed model adoption across subject areas. However, the TOE model was preferred in several areas.

3.5 | Emerging technologies effectively adopted in the 4IR context

The emerging technologies that organizations have adopted in navigating the digital transformation were also assessed. When considering the sample size of the studies assessed, the predominant technology was a combination of smart technologies of the 4IR at a sample size of 5052. As part of organizational movement, especially from within an information systems perspective, the second-largest technology adopted was cloud computing at a sample size of 2426. A reason for this is its enablement to not only integrate hardware and capture data for business intelligence, but also to replace legacy systems and methods to optimize operations and deliver services in the ever-digitized environment in which businesses operate.[61,62] Another digital technology, blockchain, saw the third-largest sample size of 2149. In terms of the number of

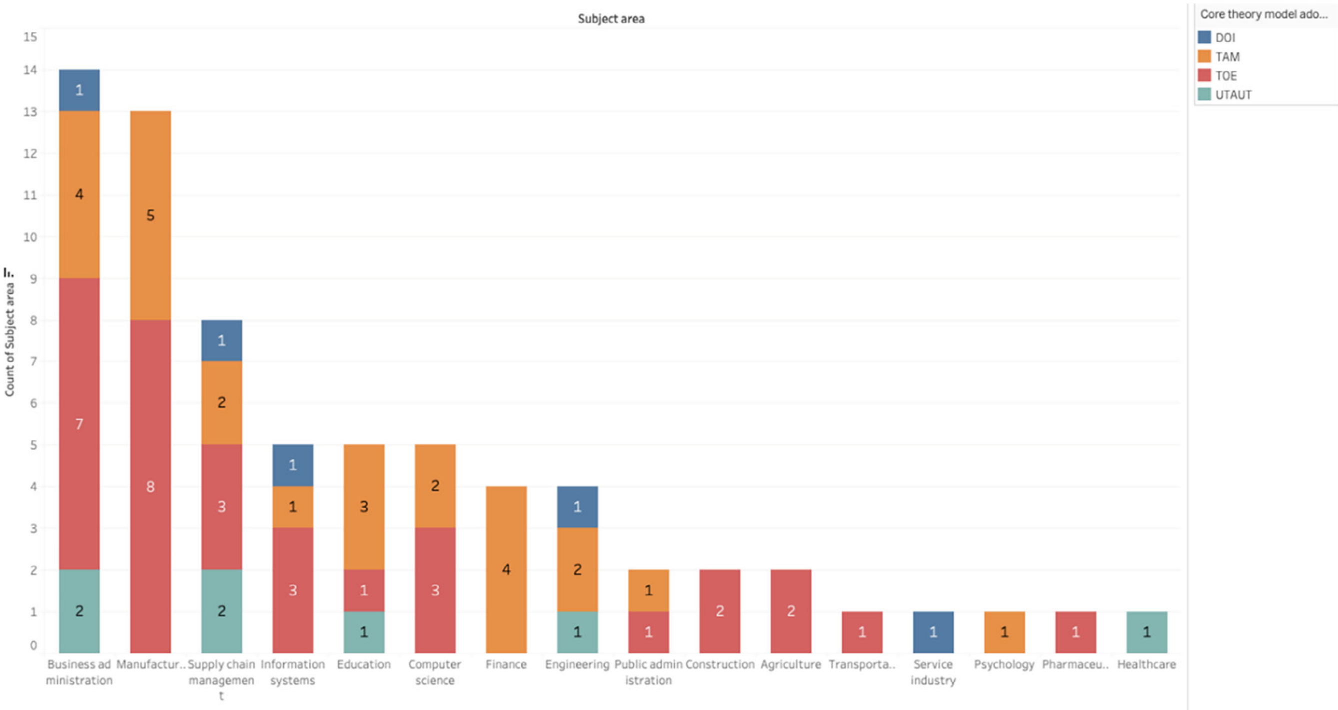

FIGURE 5 Model count to subject area. *Source*: Tableau

citations, the prevalent interest was in smart technologies, followed by blockchain with 416 citations and cloud computing with 249 citations. These details are reviewed in Appendix G.

In terms of the number of publications, smart technologies accounted for 40.6% (28) of the studies assessed. Of these, the TOE was the highest applied core model at 18, followed by TAM at five. As with sample size, cloud computing was second in terms of publication count, with five publications using the TOE model, but seven using the TAM. This could be attributed to the needs of the users being assessed and the replacement of existing systems.[10] In third position was blockchain, with the TOE model counting for five publications, yet four publications made use of the UTAUT model. This could be due to the impact of its application on organizations. However, since it is complex, it has seen predominant use considering several constructs from existing models. IoT, which is primarily hardware focused, saw the application of the TAM with a publication count of seven applied to understand its users and the impacts it has on an individual level. The models applied and associated technologies based on publication count can be seen in Figure 6.

3.6 | Comparison of subject area and technology adopted

Technologies adopted were compared in relation to subject areas based on publication count. This was to note whether there were any specific organizational concentrations to subject areas, and the technologies that are considered in this paradigm. As with Figure 6, the subject distribution remained the same, but the technology adopted was incorporated in the comparison, as can be seen in Figure 7. Business administration had a focus on 4IR smart technologies, but also an equal distribution between blockchain, a digital technology, and IoT, which is more hardware focused. Manufacturing also incorporated smart technologies with an array of distribution. SCM focused on blockchain technologies since several studies looked to optimize existing systems or address redundancies in lead times.[63]

3.7 | Constructs identified that influence 4IR technology adoption

Using meta-synthesis, influential constructs of each model were extracted from the articles. As mentioned, models were modified within the research studies to address the changing dynamics of the environment in which businesses operate.

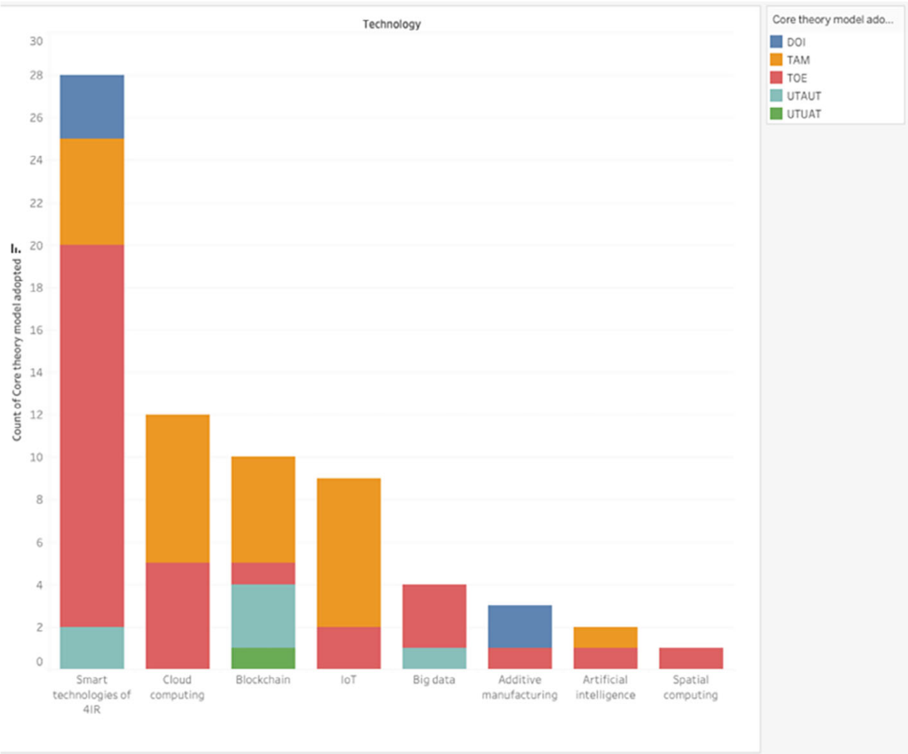

FIGURE 6 Model application to technology per publication count. *Source*: Tableau

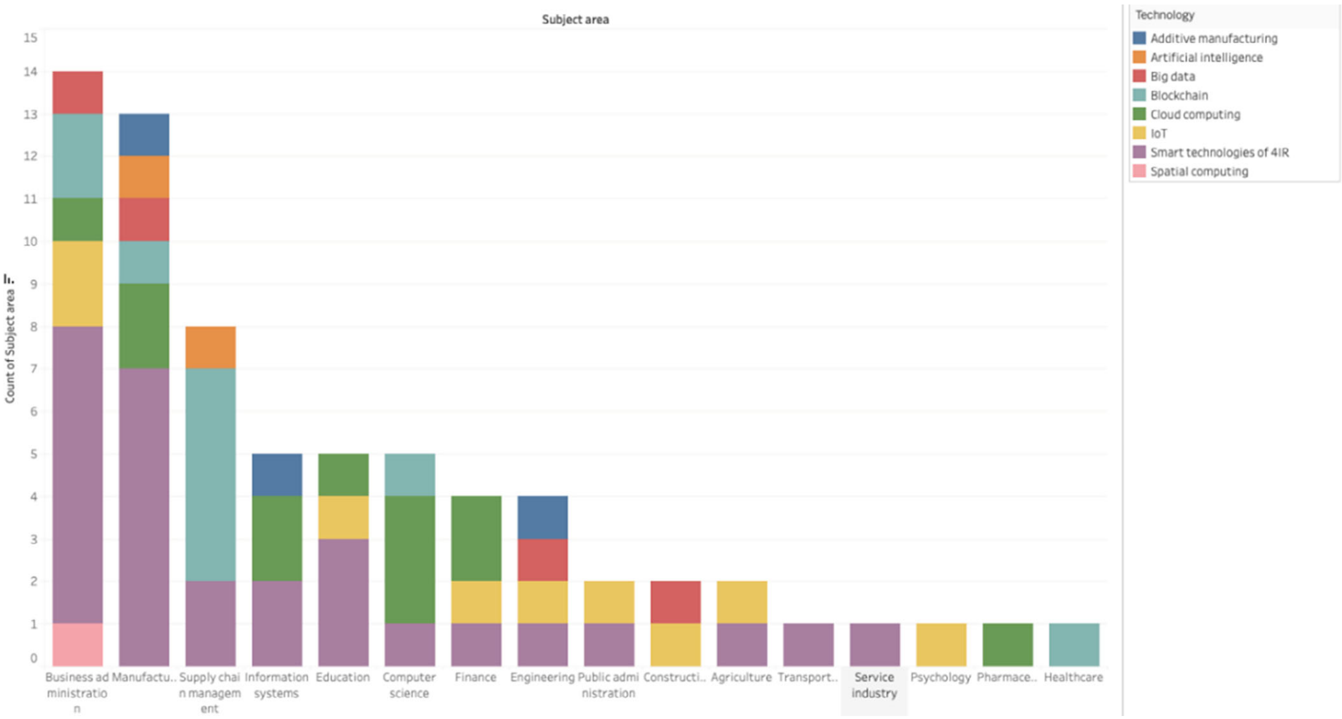

FIGURE 7 Technology concentration per subject area. *Source*: Tableau

However, certain researchers referred to certain factors differently, despite sharing commonalities in their description. For example, the adoption of digital technologies such as cloud computing or blockchain have differences in government policies, compliance and regulations. In other words, there regulatory environment. As such, this was combined into regulations and policy (RP). Consequently, similar areas were combined as far as possible to ensure that the dimensions and associated models were correctly captured. Moreover, as the TOE was the predominant model, the dimensions of technology, organization and the environment were also assigned.[10,30] Technologies' impacts on individuals were classified under technology dimensions, whereas internal resources and impacts such as staff competence were logged as organizational dimensions.[32] The intricate synthesis of influential constructed is presented in Table 2, showing an organized view of the 406 influential constructs extracted from the 69 studies. Where four or more constructs were identified, they were tabulated, including the number of times they appeared (count), name, and description of what the construct entails. Based on the papers assessed, hypothesis was developed within the context of the 4IR. Finally, the associated model and dimension of application is presented in Table 2.

4 | DISCUSSION

This study assessed influential technology adoption models and associated constructs within the context of the 4IR. Insights were developed using a SLR methodology, where the content of 69 papers published between 2016 and 2022 were reviewed in depth using meta-synthesis. The timeframe was based on the 4IR paradigm's mainstream acceptance. It was found that the paradigm has seen significant interest across sectors as the emerging technologies it brings has created new business opportunities across economies.[82] The reason: to enable coordinated efforts towards a future ready business, as the 4IR and aspects of I4.0 can increase sales, drive growth, and automate functions for cost efficiencies,[83] changing aspects of their strategies and associated business models.

To understand and address the potential of these technologies, leaders across fields of play have used technology adoption models,[60] albeit amended versions, to gain a competitive advantage. Dressler and Paunovic[59] emphasized this, noting that a more integrated approach to technology, as well as business operations, is required at a strategic level in the 4IR paradigm. Moreover, emerging technologies driving this paradigm are disruptive and smart, affecting not only the way business is conducted, but the very future of work. Laato et al.[84] mentioned that a major barrier is cultural lag, which influences overall technology acceptance across the organization, and may hamper future-of-work readiness levels. Consequently, the synthesized technology adoption constructs of this study present strong indicators for future of work readiness from an organizational perspective.

From a geographical perspective, India was found to be the leader in terms of where the study was conducted per publication count. A reason for this is the regions support of emerging technology as noted by Mitra et al.[46] Unsurprisingly, Malaysia was found to be the leader where the sample size of the applicable study was extracted as the region has seen major technology trends in terms of adoption and the drive towards industrialization in various sectors. This could be attributed to specific efforts to enhance the use of emerging technologies such as dedicated innovation hubs and resource allocation that have been shown to be effective in addressing key technology adoption constructs.[30] Notwithstanding, Asian regions are well represented in terms of the institutions of the authors' affiliations. Both these leaders and several other regions were found to be channeling their efforts to leverage emerging technologies on an organizational level. This is critical as the digital transformation has been shown to reduce geographical barriers, expanding global reach and the associated competitors of organizations in this interconnected paradigm.[85] Consequently, the study has a reasonable spread across both developed and developing regions. However, as was seen from the findings, developed regions remain strongholds in their organizational ability to effectively use and adopt emerging technologies.

The spread of technology within this paradigm was extensive, ranging from the automation of systems[25] to remotely monitoring and controlling entire infrastructure from a mobile device.[86] This shows that the emerging technology is changing the way we work by reducing barriers to access and control systems. However, organizations must consider several models and select the appropriate technology adoption theory. Prior knowledge confirms that multiple levels of analysis are required, from an organizational context to an individual level of analysis, that impact the effectiveness of adoption. A challenge here is that of the 69 studies, 66 amended their models in some form, affecting the core constructs used to address the rapid nature of the 4IR paradigm.

The next two themes that were assessed related to the subject areas identified and the 4IR technologies adopted. Business administration was the most predominant subject area, showing organizational drive to take up 4IR technologies. This requires strategy transformation and business model reinvention to create and capture new forms of value.

TABLE 2 Construct distribution usage, description, influence, associated model and dimension

Construct	Description	Hypothesis developed	Associated model/s	Dimension
Technological capabilities (TC)	Technological capabilities refer to the skills and overall technology affinity of the organization's employees.[17,30] It is strongly associated with digital transformation expertise in the 4IR.[64]		TOE, DOI, TAM	Organization
	It also refers to Rogers' consumer perceived innovativeness (CPI),[16] where it demonstrates the ease with which users take to a new technology and how quickly it will be consumed. Newness and improvements of emerging technologies such as AI, IoT and blockchain can expect individuals with higher degrees of consumer perceived innovativeness to demonstrate quicker adoption.[65]			
Count = 51	Organizational capabilities (OC), also referred to as organizational readiness, is strongly related to technological capabilities. It refers to the skills and knowledge of an organization's employees, but also to the technical infrastructure that facilitates technological integration and overall performance.[30] As such, competencies increase alongside an organization's employees, making it a complex facet.[27]	(1) Technological capabilities of organizations and their employees positively affects adoption in the 4IR.		
	To support technological capabilities, research argued that vendor support (VS) plays a critical role, where knowledge assimilated by employees with collaboration can increase their skills towards perceived usefulness.[51,66]	(2) New forms of education or micro credentials can improve perceived usefulness with vendor support.		
Relative advantage (RA)	Relative advantage refers to the degree to which an adopter, or user, perceives the benefits of a technology. This includes its features or abilities to enhance an existing system.[16]	(1) Relative advantage as a hedonic motivator positively affects technology adoption.	TAM, DOI, UTAUT	Technology
Count = 33	This also refers to hedonic motivations on both an individual and organizational level, where alternative options may prove to be better, resulting in relative advantage being a critical innovation adoption and usage factor to drive economic performance.[67]	(2) 4IR has calculated risk. However, its adoption has long-term benefits towards relative advantage.		
	Notwithstanding, previous studies have shown that relative advantage relates positively to perceived usefulness and perceived ease of use.[49] It is also related to relative value and value creation[68,69]	(3) 4IR facilitates the creation of new market segments in terms of relative advantage.		
Perceived usefulness (PU)	Perceived usefulness explains the degree to which a new technology is perceived to be better than its counterparts to improve job performance.[14] This can look to address user frustrations and employee capabilities, which is critical for business success in developing competitive advantage.[50]	(1) Perceived usefulness or benefits of technology can facilitate operational efficiencies or value creation in new ways within the 4IR.	TAM, UTUAT	Technology

(Continues)

TABLE 2 (Continued)

Construct	Description	Hypothesis developed	Associated model/s	Dimension
Count = 31	Perceived usefulness shares similarities with performance expectancy (PE) and extrinsic motivation.[18]			
Perceived ease of use (PEoU) Count = 29	Perceived ease of use is a critical adoption predictor, where difficult or sophisticated systems inhibit users' adoption.[14] Perceived ease of use is the sense of ease, or level of effort a new system or technology would have. It has strong associations with effort expectancy, control, perceived simplicity, anxiety and perceptions of control.[18]	(1) Perceived ease of use or level of effort in using or manipulating a "smart" emerging technology affects its adoption.	TAM, DOI	Technology
Facilitating conditions (FC) Count = 25	Venkatesh et al.[18] identified facilitating conditions (FC). This is defined as the level or degree to which an individual believes an organization can support the technologies' integration into existing systems or its ability to create new ones. It relates to concepts of DOI's behavioral control and C-TAM-TPB.	(1) Perceived compatibility of new technology and level of integration positively impacts its adoption, which is supported by facilitating conditions.	DOI, UTAUT	Technology
	It is also known as compatibility, which refers to the degree to which the technology or innovation fits the adopter's existing framework, including need. It also pertains to the technologies' fit within an organization.[70] In this sense, it is the compatibility of the technology within existing systems and structures.[16]	(2) More systems and levels of integration make facilitating conditions poor, negatively affecting adoption.		
Trust (TT) Count = 20	Trust demonstrates the user's affinity to believe in the safety or levels of risk associated with a technology. In the 4IR, this includes data privacy.[71] In several instances, studies refer to the security and privacy of not only user data, but also of the organization.[3] The protection of data privacy and cybersecurity policies ensures certain levels of trust.[72] This impact influences emerging technologies, as it creates more access points and data, making it a worthy note for future models and to ensure that all vulnerabilities are addressed.[73]	(1) High levels of trust support the organization or its users' technology adoption. In the 4IR, this includes data privacy and cybersecurity protection.	TOE	Technology
External environment (EE) Count = 18	The external environment is something the organization cannot necessarily control but impacts on its operations. This includes market conditions and readiness to accept smart technologies, and the impact they have on sustainable outcomes.[8] Key to this is energy usage and other impacts on the environment as natural resources diminish and populations increase.[22] It is strongly associated with competitive pressure within the market environment.	(1) Environmental impacts and sustainable outcomes support technology adoption. (2) Blurring geographical boundaries and the drive for environmentally sustainable solutions of the 4IR are expanding the external environment that organizations need to consider.	TOE	Environment

(Continues)

TABLE 2 (Continued)

Construct	Description	Hypothesis developed	Associated model/s	Dimension
Top management support (TMS) Count = 18	Top management support refers to the level of engagement, support and encouragement provided by various levels of management within an organization. This is achieved by ensuring clear communication, fairness and alignment to its vision.[19,74] It can also impact cultures, values and social norms within the organization. Top management support can permeate the regulations, policies and overall procedures needed by organizations and that impact their users.[63]	(1) Organizations with strong top management support are more likely to successfully adopt smart 4IR technologies.	TOE	Organization
Behavioral intention (BI) Count = 16	Behavioral intention refers to the user's actual intent to adopt or use technologies. Several constructs drive the achievement of users' and businesses' behavioral intention.[16,18]	(1) Behavioral intention to adopt is impacted by various factors in the 4IR.	TAM, UTAUT, DOI, TOE	Technology
Competitive pressure (CP)	Competitive pressure refers to the degree of pressure that an organization or company has from competitors within its industry. With the encroaching 4IR, the lines between industries and disciplines are blurring, giving rise to pressures from new competitors like never before.[2]	(1) Competitors who mimic actions could place pressure on organizations to adopt smart technologies.	TOE	Environment
Count = 13	Through the adoption of smart technologies and their integration into existing information systems, organizations could create new ways of outperforming their competitors and enabling penetration into new markets.[75]	(2) Industry competitors change quickly as they enter new markets.		
Complexity Count = 13	Complexity is also strongly associated with effort expectancy and perceived ease of use. It is the inverse of perceived usefulness, as tasks with a high complexity are argued to hinder adopted progression[18]	(1) Organizations are prone to adopt technologies that optimize systems and make them less complex.	TAM, UTUAT	Technology
Social influence (SI) Count =13	Social influence is synonymous with subjective norms, culture, and observability.[16] These, in turn, influence the overall perceived social status and how others can be seen in a certain context.[52] Social influence represents people and group opinions, where some are superior to others.	(1) Social influence positively affects technology adoption when there are cohesive norms and cultures that are inclined to innovation within the organization.	UTAUT	Organization
Regulations and policy (RP) Count = 12	Also associated with normative pressure, regulations and policy govern the associations, frameworks, permissions, legalities and supportive mechanisms in the region in which an organization operates. These can include economic and budgetary policies that support, or hinder, organizational growth.[76,77]	(1) Regulations and policy can drive adoption if well formulated to develop and introduce smart technologies towards sustainable development.	TOE	Environment

(Continues)

TABLE 2 (Continued)

Construct	Description	Hypothesis developed	Associated model/s	Dimension
Cost Count = 12	Perceived financial cost refers to the cost of implementing a technology and the monetary benefits associated with it. It is also associated with relative advantage.[2] Several studies have noted that a higher level of perceived cost affects the overall adoption of a technology, especially where the investment needs to be justified to the managers. This means it has ties with top management support.[78]	(1) Perceived cost will affect adoption, including that of business as it impacts return on investment (ROI).	TOE	Technology
Triability Count = 6	Trialability refers to the level at which a technology or its associated innovativeness may be used or tested before roll-out. It has strong ties with user experience (UX).[19,79]	(1) User experience can be optimized by allowing testing.	DOI	Technology
Size Count = 5	The organization's size and economic footprint impacts its ability to quickly adopt technologies internally and produce it.[17,80] This applies to academic institutions and governments, as larger areas require more sophisticated systems and technologies than smaller regions.[28,36]	(1) Large organizations are more likely to adopt new technologies with higher levels of commitment.	TOE	Organization
Vendor support (VS) Count = 4	Vendor support is the level of collaborative support, or level of access to skills available to the organization. In the context of the 4IR, it has been noted as vital as financial support, where a lack of external agents to guide usage and the adoption of smart technologies, or the demonstration of its value, is a major hinderance to adoption.[81] Partnerships in university or other R&D areas can develop employees' skills, leadership and overall adoption by guiding technology adoption and embedding smart technologies towards value creation.[60]	(1) Vendor support directly influences employees' technological capabilities and adoption rates.	TOE	Environment

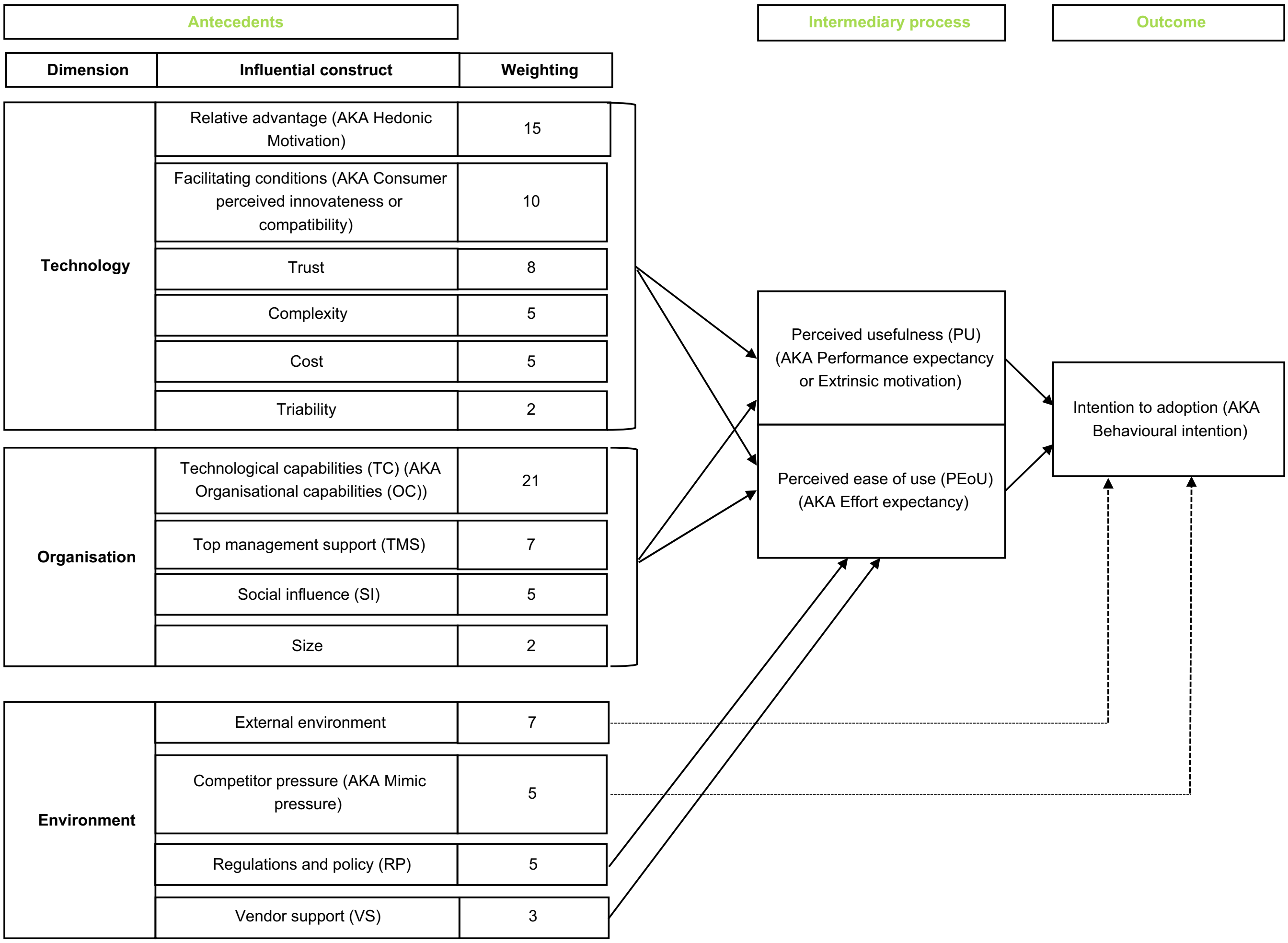

FIGURE 8 Conceptual model for emerging technology adoption at an organizational level. *Source*: Reproduced with amendments from Reference 10 page 3, with permission from Elsevier

The actual technologies assessed were widespread most likely attributable to their enablement towards integrating hardware and capturing data for business intelligence, but also replacing legacy systems and methods to optimize operations and deliver services in the ever-digitized environment in which businesses operate. The subject-to-technology mix supported this, as indicated in Figure 8. Between the subjects and technologies, there was a mixed model adoption. However, TOE remained the preferred model in several areas. Considering the purpose of the study, this demonstrates that organizations are not only assessing one aspect of the 4IR, but several impacting technologies, which are both digital and physical, to optimize existing systems or create new areas of value creation.[59,87]

The final component of the study – the primary research output – was the development of a conceptual model. Eighteen constructs were identified and articulated across four categories based on the TOE model: technology, organization, environment, and technology acceptance.[26] These were the primary constructs of organizational studies identified within the 4IR paradigm, which were weighted. The technology category describes the adoption of the technology both within the organization and externally. The constructs that influence emerging technology adoption were identified as triability (6), cost (12), trust (20), compatibility (25), and relative advantage (33). Although security in the digital age is a prevalent topic that was placed under the category of trust, the largest influential construct was found to be relative advantage. A possible explanation for this could be the recent focus on the 4IR and the value creation opportunities it brings, as well as higher costs in terms of the required R&D.[11] This reaches beyond mere usefulness. If this can be well conceptualized, new market segments can be accessed.

Organizational factors focus on the availability of resources and the proficiency of such resources to create customer value. Primary constructs identified at this level include enterprise scope, managerial beliefs, culture, mission,[35] social influences,[13,16,18] and its structure. For this study, the size of the organization (5), social influence (13), top management support (18), and technological capabilities (51) were identified as being influential. However, a lack of digital strategy negatively affects emerging technology uptake.[88] Moreover, an unclear financial plan and associated metrics to define the ROI negatively impact their uptake.[89,90] The social influence of the organization can support others' beliefs towards the awareness and possible benefits of emerging technology adoption. In this regard, leaders can influence the organization's employees. Top management support within this study supported this, as it was found to be an influential factor in creating positive beliefs, even in the 4IR. Top management can support efforts by ensuring the financial and human resources necessary for the paradigm's effective adoption.[91,92] Organizational learning has been noted to influence the decision-making abilities of leaders and managers.[32]

Notwithstanding, the technological capabilities of the organization and its employees was the most influential in this category. Within the 4IR, digital skills that ensure cross-functional synergy are vital, where innovation centres have been shown to channel and support innovation and associated skills.[60,93] Therefore, upskilling for the future of work is a critical factor to ensure organizational readiness for the 4IR.[84] Human capital is by no means a new concept. However, with this paradigm, new workforce challenges and an entrepreneurial spirit are needed.[94] A future area is the assessment of "smart" technology adoption as it presents a key area to integrate and capture the individual's role in ensuring that organizations can leverage individual adoption in an organizational context. In the context of the acceptance of smart technologies within the 4IR paradigm, the study identified key variables across three dimensions as influential.

The environmental context pertains to where the business operates, as well as impactful measures such as governmental incentives and regulations, especially where they are lacking.[81] Within the 4IR, customer demands are ever-changing, and barriers to switching are reducing. Moreover, competitors in the digital sphere are no longer limited by geographical location, where socio-cultural issues and life cycle form part of the environment. The environment in developing countries is considered to have been left behind, including within the context of the 4IR with a lack of policies or guidance.[11] This is because they struggle to adopt new technologies and fail to accelerate their adoption. This is especially true when they are complex. For this study, vendor support (4), regulations and policy (12), competitive pressure (13), and external environment (18) were identified as critical. Top management support is also critical to realize business effectiveness and mobilize business activities or create new forms of value for relative advantage. Hence, strong leadership is considered to have a moderate influence. Furthermore, the constructs have continued to receive not only scholarly interest, but also interest in terms of their real-world application, with reference made to the SDGs in this regard.

From the constructs, and the rapidly changing nature of the 4IR, there were several extensions to the models to ensure that they consider underlying impacts and constructs that are meaningful to effectively utilize technologies through adoption. Subsequently, this affected the core constructs used, which was likely suitable to the rapid nature of the paradigm under review. Technical capabilities played the most significant role in smart technologies within the 4IR paradigm. The future of work has seen scholarly and global interest, which supports these findings. Neglecting these factors impedes adoption. The largest nontechnical influential construct was found to be relative advantage. A possible explanation could be the recent focus on the 4IR and the value-creation opportunities it brings with it, as well as higher costs in terms of needed R&D.[11] From these insights, a conceptual model was developed, as seen in Figure 8, with Table 2 providing an overview of each construct, and a potential hypothesis for testing the model in new contexts.

The implications of these findings are that the 4IR has affected organizations' strategic and tactical focus, where the environment in which they operate is changing rapidly. This study presents key theoretical findings that can offer critical relevance for predicting the adoption of emerging technologies and ensuring their successful implementation. These findings include the following:

1. To navigate the impacts of the 4IR, there needs to be an enterprise level of innovation development using these emerging technologies. This depends largely on their ability to adopt the smart technologies of the 4IR paradigm, where the constructs presented can act as a vital guide.
2. Business models will need to be reinvented to define how value is proposed, but also how the functional dynamics of perceived usefulness and perceived ease of use, as key technology acceptance constructs, can be achieved. This will require having a strong customer focus, where systems alleviate frustrations and are able to offer new forms of value with their enabling features.
3. Vendor support and partnerships can look to support collaboration and access to positively manage R&D, as well as eliminate wasteful expenditure. Within larger ecosystems, innovation mechanisms can be key facilitators for future-of-work skills.
4. Strategically, there also needs to be a clear understanding and tracking of innovation metrics to define the ROI to ensure that the right technology adoption focus areas are leveraged.

5. Understanding the relative advantage of the technology can aid in implementing it for the right customer or market segment.
6. For future studies, there needs to be a review of the technological capabilities required of employees and leaders to use technology towards innovation as we move into an ever-changing future of work.

Based on these impacts, the study can influence policy making at various levels, such as the national, regional, and organizational level, to effectively harness the potential of these technologies and navigate the associated challenges.

Three examples can be cited:

1. National policy can be guided, where governments, as entities, can create policies that foster innovation and promote the adoption of 4IR technologies. These policies may include investments in research and development, education and skills development programs, incentives for the industry adoption of emerging technologies, and the establishment of regulatory frameworks that address concerns related to privacy, security, and the ethical implications of technology use. However, they need to account for unique challenges and opportunities within their specific geographical and socio-economic contexts to devise tailored policies that support technology adoption, workforce reskilling and regional economic development.
2. Sector-specific policy may face distinct challenges and opportunities when it comes to adopting 4IR technologies. Policymakers need to understand these nuances to identify specific factors that drive technology adoption, such as the support mechanisms identified.
3. Organizational policy can be used to regulate strategies for the adoption and integration of 4IR technologies. These may include updating organizational structures, investing in employee training and development, implementing new decision-making processes, and fostering a culture of innovation and adaptability.

5 | CONCLUSION

This study explored prevalent technology adoptions models and constructs considered vital at an organizational level, augmenting scholarly understanding of this phenomenon within the context of the 4IR. This was done across six thematic domains yielding several critical insights. Regionally, countries, are directing resources towards the integration of emerging technologies. Growth in this area has exhibited an exponential trajectory over the last few years, with potential for expansion. A review of utilized models revealed that, though the TOE model is most prevalent, modifications were made in 66 out of 69 examined articles. This illustrates the necessity for organizational agility to respond to the rapidly evolving paradigm. There is a focus on manufacturing as the predominant subject area, reflecting an emphasis on optimization efforts within this sector. Technologically, the incorporation of 4IR smart technologies appears to align with key acceptance constructs, underscoring the need for a holistic approach. Finally, the field of business administration emerged as the most salient subject in relation to technology, revealing the imperative to transform business models as organizations seek to adapt functional dynamics essential for navigating this complex paradigm. Based on a comprehensive synthesis of these themes, we identified key constructs at an organizational level which were amalgamated to create a conceptual model that equips organizations with insights needed to adapt and thrive in the dynamic landscape of the 4IR.

To this end, the study enriches existing literature on technology adoption, providing a model for organizations to bolster innovation capabilities by aggregating what is considered critical in explaining, supporting, and predicting the adoption of emerging technologies. This includes effectively adopting emerging technologies while simultaneously reinventing business models with a focus on customer value, perceived usefulness, and ease of use. The study showed that collaboration through vendor support and strategic partnerships, along with effective R&D management and a focus on ROI will be key in unlocking the full potential of 4IR technologies. The understanding of relative technological advantages, as well as an emphasis on leadership and employee capabilities, will further aid in this adoption. Within larger ecosystems, innovation mechanisms can play a pivotal role in facilitating the development of future work skills to address one of the most influential constructs: technological capability.

From a policy making perspective, the study highlights the critical need for interventions at national, regional, and organizational levels to foster innovation by promoting 4IR technology adoption. However, the complexity of adopting these technologies requires a nuanced approach that accounts for the unique challenges and opportunities within specific contexts, from geographical and socio-economic considerations to sector-specific dynamics. Overall, a coordinated and tailored strategy that aligns technological innovation, business model transformation, and supportive policies will be essential in fully harnessing the potential of the 4IR and paving the way for a future-ready workforce and organizational landscape.

Although striving for academic rigor, there are limitations to this study. First, there may be a publication bias, as only published articles were assessed, which may have led to the researchers overlooking critical articles in other formats, such as White Papers or conference proceedings that were outside the scope of the databases selected. There may also be a language bias, as only English was selected, limiting the perspectives and regional attributes of constructs and their applications. The quality of the included studies may vary, impacting the reliability of the findings. Subjectivity in the meta-synthesis may have limited objectivity, despite the efforts and processes followed. The limited search terms may have excluded relevant studies that may have used different terminologies, resulting in an incomplete synthesis of results. There was also difficulty in comparing the studies, as several used differing contexts, designs, methodologies, and survey tools. Furthermore, although the authors made an effort to exclude predatory journals from the current study, the dynamic nature of predatory publishing practices may affect the research landscape. The temporal scope of the study was a limitation, as more recent studies may have been published between the time of the data collection and the publication of this study. Finally, the broad guidelines may not adequately address the diverse and complex nature of different industrial sectors, organizational sizes, or regional contexts.

5.1 | Future research

To address these limitations and the scope of the study, future research in the field of technology adoption models and their constructs should consider addressing several critical aspects that emerged from the limitations of the current study. First, it is essential to recognize that the assessed models and their constructs may be subject to criticism due to potential oversimplification. Thus, future research should aim to develop more nuanced models that account for the complexities inherent in technology adoption processes. Second, it is crucial to empirically test the individual factors or constructs identified in different sectors to validate the model's applicability and generalizability. This would provide a stronger empirical basis for understanding the dynamics of technology adoption in various settings. Third, future research should explore the role of data privacy and cybersecurity policies in fostering trust in technology adoption processes. Investigating how these policies can contribute to the successful implementation of emerging technologies is a critical area that deserves further attention. Finally, technological competence required for employees and leaders to utilize technology for innovation as we move towards an ever-changing future of work can contribute to a comprehensive and effective approach to technology adoption in the context of the 4IR.

AUTHOR CONTRIBUTIONS

Sean Kruger: Conceptualization (equal); data curation (lead); formal analysis (lead); investigation (lead); methodology (lead); resources (equal); software (equal); validation (equal); visualization (equal); writing – original draft (lead); writing – review and editing (lead). **Adriana A. Steyn:** Conceptualization (equal); methodology (supporting); supervision (lead); writing – review and editing (supporting).

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CONFLICT OF INTEREST STATEMENT

To the knowledge of the authors, no conflicting interests are present.

PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1002/eng2.12762.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are being reviewed under the University of Pretoria's FigShare instance, and will be accessible on this platform once processed.

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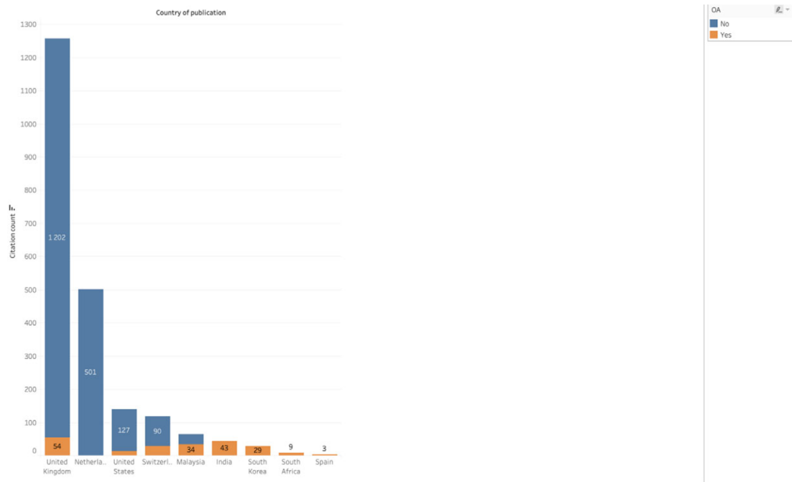
APPENDIX A. REGIONAL DISTRIBUTION OF PUBLICATION ACCESS PER PUBLICATION COUNT

Country of publication			Country of study			Country of author		
Country	**OA count**	**Non-OA count**	**Country**	**OA count**	**Non-OA count**	**Country**	**OA count**	**Non-OA count**
United Kingdom	2	32	India	4	7	India	3	8
United States	3	7	Global	1	9	Malaysia	4	4
Switzerland	9	1	Malaysia	3	4	Australia	1	4
Netherlands	1	7	United Kingdom	1	4	United Kingdom	0	4
South Korea	2	0	South Africa	1	3	South Africa	1	3
Malaysia	1	1	Pakistan	2	1	France	2	2
Spain	1	0	Italy	1	2	United States	1	2
South Africa	1	0	Brazil	0	3	Italy	1	2
India	1	0	Australia	1	2	China	1	2
			Yemen	1	1	Taiwan	1	1
			United States	0	2	Saudi Arabia	0	2
			Taiwan	1	1	Nigeria	0	2
			China	0	2	Germany	0	2
			Vietnam	1	0	Brazil	0	2
			Saudi Arabia	0	1	Yemen	0	1
			Nigeria	0	1	Vietnam	1	0
			Netherlands	1	0	Slovenia	0	1
			Kuwait	0	1	Scotland	0	1
			Jordan	1	0	Qatar	1	0
			Iran	0	1	Portugal	0	1
			Greece	1	0	Pakistan	0	1
			Germany	0	1	Netherlands	1	0
			Denmark	1	0	Jordan	1	0
			Columbia	0	1	Iran	0	1
			China	0	1	Greece	1	0
						Finland	0	1
						Denmark	1	0
						Columbia	0	1

APPENDIX B. REGIONAL DISTRIBUTION OF PUBLICATION COUNTRY WITH OPEN ACCESS LEVEL PER CITATION COUNT



APPENDIX C. REGIONAL ATTRIBUTES OF COUNTRY OF STUDY PER SAMPLE SIZE COUNT OF THE STUDIES AND CITATION COUNT

Country	Sample size count	Country	Citation count
Malaysia	1761	Malaysia	392
India	1650	India	249
Global	1394	Brazil	237
China	795	United Kingdom	232
South Africa	752	China	190
Greece	697	Global	165
Brazil	694	Germany	109
Denmark	500	Nigeria	109
United Kingdom	486	Yemen	102
Kuwait	480	South Africa	99
Australia	425	Italy	64
Italy	408	Australia	48
Vietnam	396	Saudi Arabia	30
Yemen	354	Kuwait	28
Taiwan	338	Pakistan	25
United States	281	Vietnam	22
Netherlands	242	United States	20
Pakistan	213	Iran	17
Saudi Arabia	210	Taiwan	11
Germany	209	Jordan	7
Jordan	187	Colombia	4
Colombia	138	Greece	3
Iran	112	Denmark	0
Nigeria	6	Netherlands	0

APPENDIX D. AUTHOR AFFILIATION PER REGION PER SAMPLE SIZE OF STUDY COUNT AND CITATION COUNT

	Citation count		Sample size of study count
Malaysia	322	Malaysia	1555
United Kingdom	220	India	1547
Brazil	204	Australia	960
India	198	Germany	864
China	186	South Africa	752
Nigeria	133	Greece	697
Germany	111	France	691
South Africa	99	China	624
Yemen	97	United Kingdom	608
Scotland	90	Denmark	500
Australia	90	Italy	408
Iran	89	Vietnam	396
France	79	Portugal	375
Italy	64	Iran	360
Saudi Arabia	38	Taiwan	338
Portugal	33	Qatar	328
Vietnam	22	Brazil	319
United States	22	United States	297
Finland	20	Netherlands	242
Pakistan	15	Saudi Arabia	235
Taiwan	11	Jordan	187
Jordan	7	Colombia	138
Qatar	5	Slovenia	124
Colombia	4	Pakistan	84
Greece	3	Scotland	33
Slovenia	1	Yemen	26
Netherlands	0	Nigeria	26
Denmark	0	Finland	14

APPENDIX E. AUTHOR INSTITUTIONS' AFFILIATION PER PUBLICATION COUNT, SAMPLE SIZE OF STUDY COUNT, CITATION COUNT AND ARTICLE

Institution	Publications	References	Institution	Sample size of study count	Institution	Citation count
Universiti Teknologi Malaysia	3	8,19,95	University of West Attica	697	Xiamen University Malaysia	265
Xiamen University Malaysia	2	2,3	Karlsruhe University of Applied Sciences	655	University of Cambridge	190
University of New South Wales	2	96,97	Aarhus University	500	Universidade Federal de Santa Catarina	168
University of Johannesburg	2	12,98	Universiti Teknologi MARA	480	Shanghai Maritime University	156
University of Cambridge	2	69,99	American University of the Middle East	480	Universiti Teknologi Malaysia	116
Universiti Teknologi MARA	2	50,100	University of Johannesburg	460	University of Port-Harcourt	109
National Institute of Industrial Engineering	2	31,49	University of Finance – Marketing	396	Universität Koblenz-Landau	109
University of West Attica	1	6	Multimedia University	396	Robert Gordon University	90
University of South Australia	1	101	TBS Business School	394	University of Hormozgan	89
University of South Africa	1	102	Campus de Campolide	375	University of Johannesburg	86
University of Rhode Island	1	103	Huazhong University of Science and Technology	372	University of Bergamo	60
University of Reading	1	73	University of Hormozgan	360	National Institute of Industrial Engineering	54
University of Pretoria	1	86	Xiamen University Malaysia	351	National Institute of Industrial Engineering	49
University of Port-Harcourt	1	35	Indian Institute of Technology	340	EDHEC Business School	38
University of Milan-Bicocca	1	78	Community College of Qatar	328	Universiti Teknologi MARA	37
University of Ljubljana	1	70	School of Business IT and Logistics	318	TBS Business School	37
University of Hormozgan	1	104	University of Cambridge	293	Paulista University	36
Universiti Utara Malaysia	1	30	National Sun Yat-Sen University, Kaohsiung	242	Amity University	30

(Continues)

Institution	Publications	References	Institution	Sample size of study count	Institution	Citation count
University of Finance – Marketing	1	75	National Institute of Industrial Engineering	290	Campus de Campolide	33
University of Education	1	74	Coventry University	258	University of New South Wales	31
University of Bergamo	1	27	University of Milan-Bicocca	251	King Faisal University	30
Universität Koblenz-Landau	1	105	Avans University of Applied Sciences	242	American University of the Middle East	28
Universidade Federal de Santa Catarina	1	32	Amity University	223	Landmark University	24
Universidad de Antioquia	1	106	University of South Africa	222	University of Finance – Marketing	22
Toulouse Business School	1	107	Binghamton University	218	Indian Institute of Technology	22
Thapar Institute of Engineering and Technology	1	108	Thapar Institute of Engineering and Technology	216	Huazhong University of Science and Technology	22
TBS Business School	1	109	King Faisal University	210	Tampere University of Technology	20
Tampere University of Technology	1	57	Universität Koblenz-Landau	209	University of Reading	18
Sukkur IBA University	1	110	Al al-Bayt University	187	University of Rhode Island	17
Shanghai Maritime University	1	77	Paulista University	184	School of Business IT and Logistics	17
School of Business IT and Logistics	1	111	EDHEC Business School	181	Martin Luther Christian University	17
Sardar Patel College of Engineering	1	26	Universiti Teknologi Malaysia	180	Sukkur IBA University	15
Robert Gordon University	1	7	Universiti Utara Malaysia	174	University of South Australia	14
Politecnico di Torino	1	36	Shanghai Maritime University	165	Sardar Patel College of Engineering	13
Paulista University	1	112	Indian Institute of Management Indore	165	Coventry University	12
National Sun Yat-Sen University, Kaohsiung	1	113	Politecnico di Torino	147	University of Pretoria	9
National Institute of Industrial Engineering	1	114	Universidad de Antioquia	138	Nanjing University	8
Nanjing University	1	67	Universidade Federal de Santa Catarina	135	King Saud bin Abdulaziz University for Health Sciences	8

(Continues)

Institution	Publications	References	Institution	Sample size of study count	Institution	Citation count
Multimedia University	1	22	BML Munjal University	132	Amity School of Engineering and Technology	8
Martin Luther Christian University	1	79	University of Ljubljana	124	National Sun Yat-Sen University, Kaohsiung	7
Landmark University	1	28	Toulouse Business School	116	Al al-Bayt University	7
Laboratoire de Psychologie Sociale et Cognitive	1	115	University of New South Wales	107	Community College of Qatar	5
King Saud bin Abdulaziz University for Health Sciences	1	61	University of Education	96	University of South Africa	4
King Faisal University	1	116	Martin Luther Christian University	90	University of Education	4
Karlsruhe University of Applied Sciences	1	117	Nanjing University	87	Universidad de Antioquia	4
Indiana University of Pennsylvania	1	66	Sukkur IBA University	84	Politecnico di Torino	4
Indian Institute of Management Indore	1	46	University of Pretoria	70	Laboratoire de Psychologie Sociale et Cognitive	4
Huazhong University of Science and Technology	1	11	University of Rhode Island	63	University of West Attica	3
EDHEC Business School	1	51	University of Reading	57	Thapar Institute of Engineering and Technology	3
Coventry University	1	25	University of South Australia	55	Binghamton University	3
Community College of Qatar	1	76	Amity School of Engineering and Technology	43	Karlsruhe University of Applied Sciences	2
Campus de Campolide	1	118	Robert Gordon University	33	Indiana University of Pennsylvania	2
BML Munjal University	1	64	National Institute of Industrial Engineering	32	BML Munjal University	2
Binghamton University	1	119	King Saud bin Abdulaziz University for Health Sciences	25	University of Ljubljana	1
Avans University of Applied Sciences	1	120	Landmark University	20	Universiti Utara Malaysia	1

(Continues)

Institution	Publications	References	Institution	Sample size of study count	Institution	Citation count
Amity University	1	121	Sardar Patel College of Engineering	16	University of Milan-Bicocca	0
Amity School of Engineering and Technology	1	63	Indiana University of Pennsylvania	16	Toulouse Business School	0
American University of the Middle East	1	122	Tampere University of Technology	14	Multimedia University	0
Al al-Bayt University	1	62	University of Bergamo	10	Indian Institute of Management Indore	0
Aarhus University	1	85	University of Port-Harcourt	6	Avans University of Applied Sciences	0
Indian Institute of Management Indore	1	46	Laboratoire de Psychologie Sociale et Cognitive	0	Aarhus University	0

APPENDIX F. SUBJECT AREA TO COUNT OF CITATION, PUBLICATION AND SAMPLE SIZE OF THE STUDY AREA

Field of study	Publication count	Sample size of study count	Citation count
Agriculture	2	350	66
Business administration	14	1979	307
Computer science	5	1287	162
Construction	2	60	28
Education	5	1359	142
Engineering	4	547	33
Finance	4	1072	181
Health care	1	242	7
Information systems	5	670	72
Manufacturing	13	2142	579
Pharmaceuticals	1	372	22
Psychology	1	0	4
Public administration	2	567	36
Service industry	1	14	20
Supply chain management (SCM)	8	1908	348
Transportation	1	165	156

APPENDIX G. TECHNOLOGY USAGE PER COUNT OF PUBLICATION, CITATION COUNT AND SAMPLE SIZE STUDY COUNT

Technology	Citation count	Count of publication	Sample size of study count
Additive manufacturing	38	3	291
Artificial intelligence	24	2	995
Big Data	66	4	583
Blockchain	416	10	2149
Cloud computing	249	12	2426
IoT	166	9	1210
Smart technologies of 4IR	1138	28	5052
Spatial computing	66	1	22