Navigating the fourth industrial revolution: a systematic review of technology adoption model trends

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Abstract

Purpose – Several disciplines and thousands of studies have used, developed and supported technology adoption theories to guide industry and support innovation. However, within the past decade, a paradigm shift referred to as the fourth industrial revolution (4IR) has resulted in new considerations affecting how models are used to guide emerging technology integration into business strategy. The purpose of this study is to determine which technology adoption model, or models are primarily used when assessing smart technologies in the 4IR construct. It is not to investigate the rigour of existing models or their theoretical underpinnings, as this has been proven.

Design/methodology/approach – To achieve this, a systematic literature review based on the preferred reporting items for systematic reviews and meta-analysis methodology is used. From 3,007 publications, 125 papers between 2015 and 2021 were deemed relevant for thematic analysis.

Findings – From the literature, five perspectives were extracted. As with other information and communication technology studies, the analysis confirms that the technology acceptance model remains the predominantly used model. However, 105 of the 125 models extended their theoretical underpinnings, indicating a lack of maturity. Furthermore, the countries of study and authors' expertise are predominantly clustered in the European and Asian regions, despite the study noting expansion into 16 different subject areas, far beyond the smaller manufacturing scope of Industry 4.0.

Originality/value – This study contributes theoretically by providing a baseline to develop a generalisable 4IR model grounded on existing acceptance trends identified. Practically, these insights demonstrate the current trends for strategists and policymakers to understand technology adoption within the 4IR to direct efforts that support innovation development, an increasingly crucial factor for survival in the digital age. Future research can investigate the additional constructs that were impactful while considering the level of research they were applied to.

Keywords 4IR, Fourth industrial revolution, Industry 4.0, Information systems, Smart technologies, Technology adoption

Paper type Literature review

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1. Introduction

The fourth industrial revolution (4IR), conceptualised in 2016 (Schwab, 2017), is said to be ushering people into an ever-digitised world with its smart technologies (Kademeteme and Twinomurinzi, 2019). Subsequently, there has been significant traction in researching technologies of this paradigm to leverage its benefits, resulting in industry restructures (Dalenogare *et al.*, 2018) and enhanced system cohesiveness and advanced automation capabilities (Hajoary, 2021). However, achieving these benefits requires developments in individual skills and organisational innovation capabilities (Belletier *et al.*, 2021; Kruger and Steyn, 2020). A part of the 4IR is Industry 4.0 (I4.0), which was conceptualised in 2011 in Germany. It is considered the widespread integration of information and communication technologies (ICT) and smart technologies in manufacturing, logistics and supply chain management (Dalenogare *et al.*, 2018). At the core of this integration is the use of cyber-physical systems (CPS), which encompasses the use of smart devices such as the Internet of Things (IoT) to optimise industrial processes for customised products and shorter lead times (Schniederjans and Yalcin, 2018).

I4.0 is focused on integrating smart technologies towards value creation in a manufacturing setting (Ghobakhloo and Ching, 2019). In contrast, the 4IR is considered a larger theme that embodies transformative technologies that impact not only business and manufacturing but also structural elements of society (Kang *et al.*, 2021). Human behaviours and interaction with these smart technologies have been a focal point, leading to several instances of technology adoption assessment (Kim *et al.*, 2017; Nikou, 2019; Roy and Moorthi, 2017; Singh *et al.*, 2020). Technology adoption encompasses the acceptance or usage of emergent technology or products that have been extensively used in ICT and information systems since the early 1980s. It stems from the theoretical work that generalised the rate of technologies spread through cultures based on a set of demographics, psychological and sociological characteristics (Rogers, 2003). Other disciplines have also used technology adoption to understand, predict and explain variables influencing human behaviour at various research levels, making it a well-established field (Rad *et al.*, 2018). However, it is pertinent to acknowledge potential limitations within these models, for instance, the technology acceptance model (TAM). Despite TAM's widespread application and its robust framework for understanding user acceptance, critics argue that it might oversimplify the complexity of technology adoption processes, especially in the fast-evolving context of the 4IR (Nikou, 2019). The model's primary focus on two areas may not fully encapsulate the nuanced factors driving adoption in an era characterised by rapid technological advancements and digital transformation (Chatterjee *et al.*, 2021). Moreover, the dynamic nature of 4IR technologies necessitates a more flexible and comprehensive approach to understanding technology adoption (Sohn and Kwon, 2020). Consequently, while TAM provides a foundational understanding, its potential limitations highlight the need for more holistic models that incorporate the multifaceted and interdependent factors influencing technology adoption in the context of the 4IR.

Consequently, there appears to be a gap in the literature regarding a comprehensive overview that explains the methodological approaches and theoretical underpinnings of current trends in 4IR technology adoption (Lee *et al.*, 2014, 2015; Nikou, 2019; Perri *et al.*, 2020; Wichmann *et al.*, 2019). The subsequent question raised is:

Q1. Which technology adoption models are being used to assess smart technology usage to navigate the Fourth Industrial Revolution (4IR)?

To address this question, this study looks to identify which model, or models, have been used in assessing the adoption of technology within the 4IR paradigm using a systematic literature review (SLR) based on principles of the preferred reporting items for systematic reviews and meta-analysis (PRISMA) (Page *et al.*, 2021). Moreover, the study, guided by existing literature, concentrates on emerging technologies of the 4IR to gain a deeper understanding of what is considered relevant in this rapid-paced environment of technological innovation (Muhuri *et al.*, 2019; Yaacob and Thing, 2021). A period of seven years, ranging from 2015 to 2021, is applied to include the conceptualisation of I4.0 and the introduction of the more encompassing paradigm referred to as 4IR (Rad *et al.*, 2018). Notably, the study does not investigate the rigour of existing models or their theoretical underpinnings, as this has been proven (Chatterjee *et al.*, 2021). Instead, the study focuses on which models are being applied in this construct, due to the nature, potential benefits and expansive impacts of this paradigm. The study is aimed at researchers who need to understand technology adoption trends in the 4IR, business strategists who must drive innovation through technology adoption and academic specialists to support relevant skills development for the future of work.

In so doing, this study aims to enhance the academic understanding of technology adoption within the 4IR by systematically describing the models used in this context. Using a PRISMA-guided literature review, it offers a comprehensive analysis of the theoretical frameworks supporting technology adoption from the introduction of I4.0 to the broader 4IR. The research outlines the prevalent models, thereby equipping researchers, strategists and educators with insights to foster innovation and skill development pertinent to the 4IR's dynamic demands. Its findings are contributory in shaping future research trajectories, informing industry strategies and guiding educational content, thus enriching the discourse on technology adoption in the 4IR.

The remainder of this paper is organised as follows: firstly, the criteria and classification of research papers in terms of methodology are presented in Section 2. Then, the existing research papers on 4IR technology adoption are examined, and the results are provided in Section 3. The results are then discussed in Section 4, ending with conclusions, limitations and suggestions for future study in Section 5.

2. Methodology

The purpose of this study is to develop insights on which technology model, or models, are primarily used in assessing 4IR technology adoption and which subject areas these occur in Oztemel and Gursev (2018) and Wichmann *et al.* (2019). To address this, the study uses an SLR methodology based on the PRISMA principle to explore existing literature while ensuring non-replication and transparency (Thomas, 2021). The study also adopts Rad *et al.* (2018), where different databases and a well-defined review protocol were used to produce relevant findings. The first stage was the development of a research question.

Secondly, a search strategy per PRISMA was used to identify relevant research papers between 2015 and 2021. Due to the large extent of research disciplines and associated contexts of the 4IR, including concepts of I4.0 and extensive literature of technology adoption, the limitation of disciplines was not ideal. To develop a narrative and identify associated insights encompassing the 4IR's extensive scope, search strings, specific terms and keywords, including certain synonyms and nuances of the new industrial movement were used (Hermann *et al.*, 2015; Liao *et al.*, 2017). The keywords and phrases can be seen in Appendix 1. The searches were done on publications published in English with multiple queries executed on the title, keywords, abstract, date of publication and the type of publication. This was applied to nine databases, including EBSCOhost, Emerald Insight, ProQuest, IEEE Xplore, Google Scholar, JSTOR, SAGE, ScienceDirect and SCOPUS, for extensive and broad coverage of relevant sources.

Moreover, to align with the study's construct, purpose-built databases which integrate artificial intelligence (AI) were also used to ensure a broad scope of application. In this study, dimensions were used. Finally, cross-referencing was conducted between the relevant articles not to overlook relevant literature (Bai, 2018). The rationale behind this is that when two articles are frequently co-cited, the commonalities between them allows the identification of clusters which could enable researchers to understand the knowledge base, intellectual structures and current scientific studies (Oliveira and Martins, 2010).

The third stage was assessing and selecting articles based on exclusion and inclusion criteria for the years 2015–2021. The reason for this time frame was two-fold. Firstly, I4.0 was presented at the Hannover Fair by, yet no articles specifically noting technology adoption within this scope was found in the databases until 2015. Secondly, 2016 is when 4IR was coined (Schwab, 2017). All articles identified were first screened based on abstract, title and keywords to identify if the study focused on relevant context or provided theoretical discussion. Duplicated literature, book reviews, dissertations, thesis, textbooks, unpublished working papers and journals not subject to blind peer review were excluded. Out of 3,007 identified, across nine databases and one database tool, 2,322 fully accessible articles were available for screening by the researchers through their institution. Based on further analyses, 354 papers were deemed relevant and downloaded. This formed the baseline for articles that were further scrutinised by assessing their full text where Mendeley, a reference software manager, was used as the reference manager and storage.

The fourth stage was to review downloaded articles to ensure eligibility and quality. To do so, per PRISMA, inclusion and exclusion criteria were applied to each article, as seen in Table 1.

Furthermore, criteria based on Rad *et al.* (2018) and Wichmann *et al.* (2019) were used. These criteria were essential to ensure quality and valuable contributions to the research community. They included considering the article's diligence, reliability, research method, affiliation of the author, model assessment and application and the technology used. Each criterion was then applied, where outcomes of 0 had a perfect alignment, 1 had excellent alignment, 2 had a majority alignment. However, 3 and above were excluded. Using the

Inclusion criteria	Exclusion criteria
The study must use a reliable methodology, and the main theory is stipulated	Articles that note technology adoption about 4IR but do not note evaluation models or research methods
Publication language must be in English	Articles not written in English are excluded
The study is in a blind peer-reviewed publication	Conference papers, master dissertations, doctoral thesis, working papers and white papers were excluded
It must include concepts relating to the 4IR or I4	Articles that did not specifically include concepts of the 4IR
A technology adoption model or combination of theoretical models must be used as a theoretical foundation for the assessment of smart technologies of the 4IR	Articles that provide information about the 4IR or I4, but do not provide an assessment on their adoption
Articles must have assessed processes or impacts of technology adoption of 4IR	Where technology acceptance was considered, but no technology models were used, they were then excluded
Studies must use empirical techniques to assess the technology of the 4IR and their adoption	Articles' date ranges were not between 2015 and 2021
The research can be done on an individual, group or organisational research level	Theoretical foundations are not explicitly noted or addressed
The research must be in an accredited journal publication	Country affiliations of authors and country of study are not indicated
Articles must be accessible by the researchers	Publications will be excluded if only the abstract but full text was not available
	Duplicate papers (same paper received from different databases)

Source: Author generated

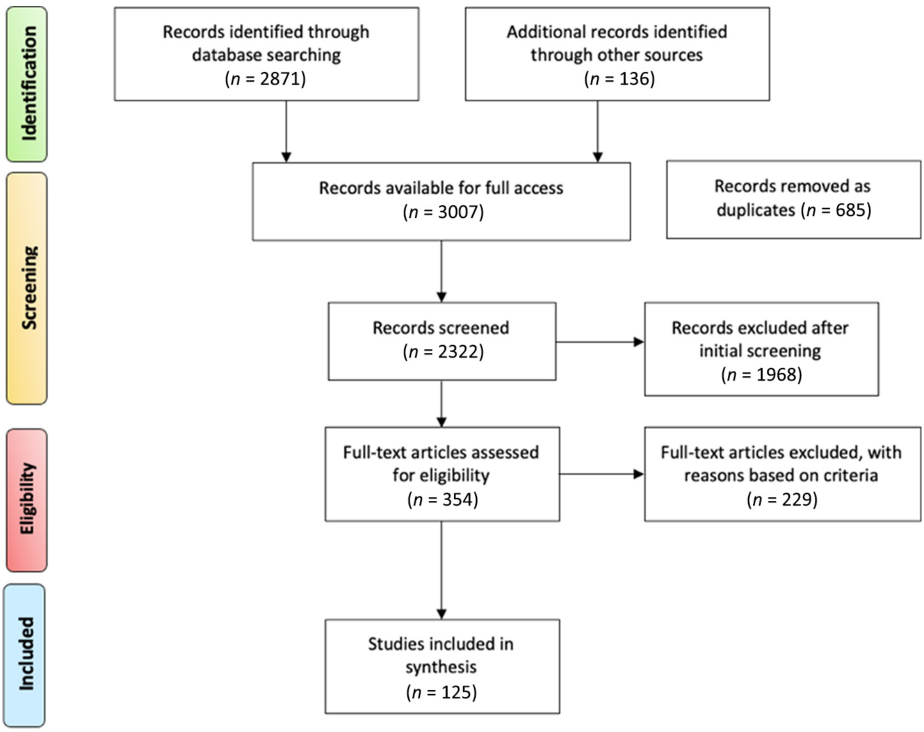
Table 1. Inclusion and exclusion criteria

thematic classification and synthesis of the 354 based on criteria, 229 papers were removed, leaving 125 articles for data extraction. This process is shown in Figure 1.

After the quality assessment, 125 articles published between 2015 and 2021 were accepted and coded. The full text of the article bibliographic data and additional parameters not included in metadata were extracted to an Excel file (2021 version 16.54). Using this allowed the categories of the core model or theory used, study context, methodology, level of analysis, smart technology, adoption assessment level and purpose of the study to be assessed. The model extensions were then sub-categorised. Additionally, publication date, country of author, author affiliations, country of study, country of publication, open access (OA) status, database and citation count were synthesised to aggregate evidence from the studies identified. This facilitated evaluating and interpreting available research regarding the phenomenon of model adoption for the assessment of smart technologies of the 4IR. The distribution across databases from initial findings to initial screening and after screening can be seen in Appendix 2. ProQuest and Emerald Insight had the most relevant literature for this study, with 411 and 531 initially identified, respectively. However, JSTOR and SAGE, after scrutiny, produced none despite initial findings of 273 and 165, respectively.

3. Findings

The identification of adoption models used in 4IR technology is based on an analysis of 125 studies. To extract the data, all article's full-text items were downloaded for the identification of



Source: Adapted from Page *et al.* (2021) generated through PowerPoint

Figure 1. PRISMA screening flow diagram

key categories and sub-category development. Storage and management of the articles were curated with Mendeley (2022, 2.64). An R-tool (2021, Build 382) with Bibliometrix libraries was used to confirm findings, such as cross-references and duplication removal based on article metadata. However, not all critical criteria for this study could be attained from this; as such, the researchers assessed the full texts to extract and store the data from articles for analysis in Excel. Tableau Desktop (2021.4) was then used to visualise five perspectives, namely:

(1) publication attributes that includes the year of publication, access rights, database and citation count;
(2) geographical attributes such as the country where the study was conducted, country of the main author and their affiliations;
(3) methodology used that includes the research level and sample size;
(4) subject area of the study and technologies they apply to and finally the; and
(5) technology adoption model, or models adopted.

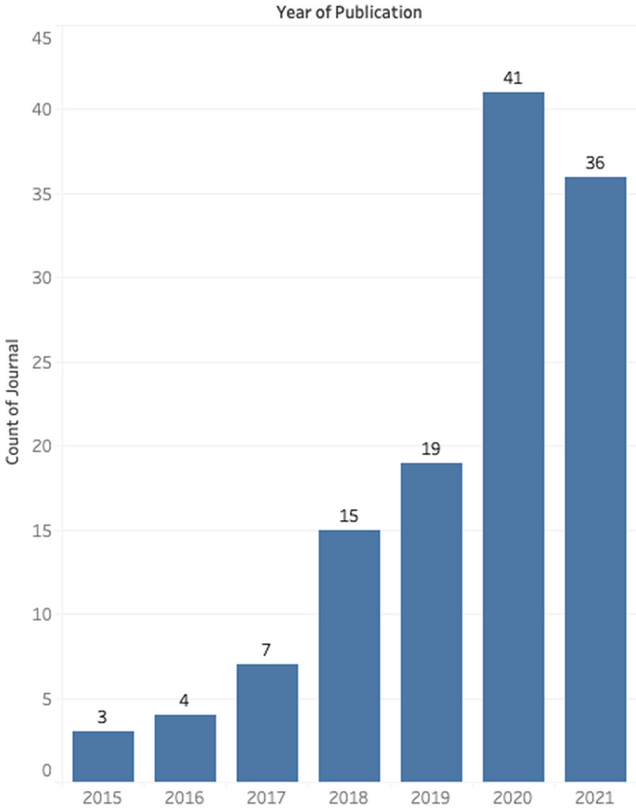
The details of this review are described in the following sections.

3.1 Publication attributes

Apart from 2021, with 36 papers, the publication dates increased steadily from 3 in 2015 to 41 in 2020. A reason for this is the high proliferation of digital technologies and the release notes for smart technology integration within the 4IR construct, which has seen the expansive increase in emerging technologies and effects on human behaviour (Ghobakhloo and Ching, 2019). Moreover, although the concept of I4.0 was coined in 2011, more comprehensive literature, endorsed by the German Government in 2013, that described recommendations for I4.0 implementation was released in 2016 (Federal Ministry of Education and Research, 2016), leading to more awareness and research (Jayashree *et al.*, 2021). Another reason for this could be the traction of leveraging such technologies across other disciplines such as Fintech (Singh *et al.*, 2020) and health care (Sharma and Joshi, 2021). However, 2021 saw a decline from 2020 with a count of 36, raising questions about applying technology adoption models maturity in the 4IR paradigm. The distribution per publications over this period can be seen in Figure 2.

As scholarship progresses, several OA journals and hybrid configurations have expanded. They are considered in this study because they are said to support the rapid dissemination of recent updates in various disciplines. This is relevant as it relates to the rapid nature of the 4IR paradigm. The distribution of OA and non-OA publications is shown in Figure 3. Where OA journals accounted for 36.80% of the papers identified. The remaining 63.20% were accessible by the researchers. However, they were behind paywalls in some form or another. The ProQuest database had the most OA articles with a count of 34, followed by SCOPUS with a count of 5. Cross-referenced articles were predominantly non-OA, with Emerald having none in this study. This could account for the distribution over the years in terms of publication, as OA allows for faster turnaround times. Moreover, the highly cited articles' maturation can attest to understanding in the field. However, Jayashree *et al.* (2021) note that time constraints and further limitations due to the pandemic are additional factors.

Citations present a challenge in this field, as it takes time to cite, considering the terms not being available for less than a decade. However, this was still included in the study to note trends in respective fields on smart technologies adoption and areas of significance. Furthermore, it demonstrated rigidity that this is a viable area of research. The average citations per publication count were 43.98. Cross-referenced articles were the most cited by count, with 2,946 as they are the knowledge base used within this studies context. Although



Source: Author generated through Tableau

Figure 2.
Distribution of research papers by year of publication count

having no OA in this study, Emerald Insights had the second-highest citation count at 921. From a yearly distribution perspective, it appears that after the initial coining of I4.0, 2015 saw significant interest as citation counts for the period were 1,587. There was then a rapid decline in 2016 and 2017; however, the 4IR was being investigated during this period, with citations rapidly climbing to 1,215 in 2018. Finally, 2021 saw the lowest citations at 134. This could be seen as a lack of confidence in repetitive use of the same model established in the 1980s. The citation count per year is shown in Figure 4.

Continuing with citations to isolate relevance saw *Computers in Behaviour*, *Telematics and Informatics* and *the International Journal of Human-Computer Interaction* as top-cited journals with a sum citation count of 597, 591 and 525, respectively. A crucial trend in this is the analysis of skills required for the digital world needed learning areas such as digital literacy (Abdullah and Ward, 2016; van Laar *et al.*, 2017). Moreover, it includes the analysis of production that relates to I4.0 (Klumpp *et al.*, 2019), institution levels of technology adoption (Kang *et al.*, 2021) and trust in interacting with smart technologies (Choi and Ji, 2015). This demonstrates that smart technologies and the rapid nature of their impacts have psychological impacts, which is a point of academic interest (Nikou, 2019; Park and Kim, 2014; Sohn and Kwon, 2020).

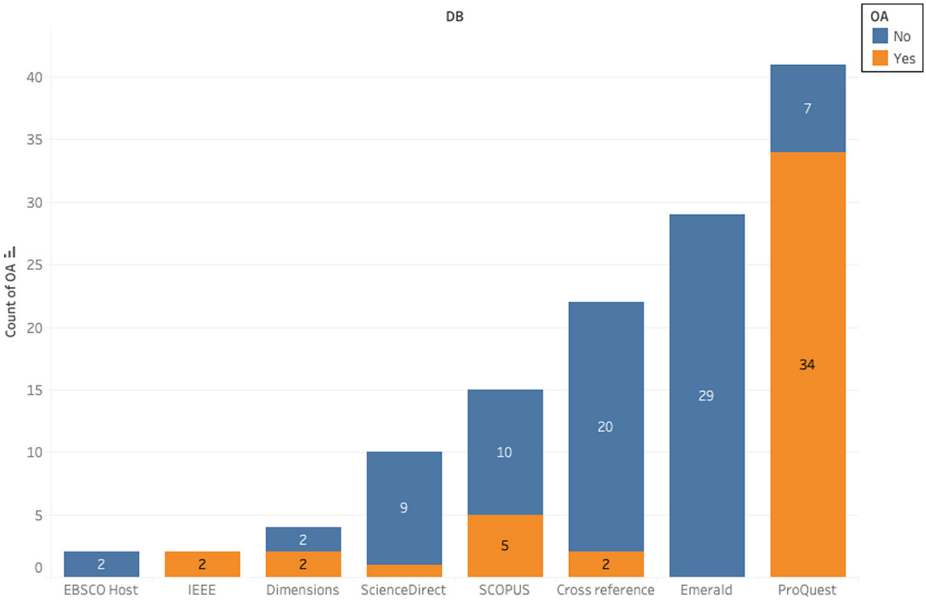


Figure 3.
Access distribution per publication count

Source: Author generated through Tableau

From a study count perspective, the *International Journal of Environmental Research and Public Health* and *the Journal of Open Innovation*: *Technology, Market and Complexity* were highest at a count of six and five, respectively, both of which are fully OA journals. An additional measure extracted was the sample size of the actual studies assessed, to identify the model's level of application. In this sense, the former journal also had the largest sample size sum of 1,955, demonstrating a sizeable empirical assessment area. The journal itself had articles strongly associated with leadership and skills required for the paradigm (Molino *et al.*, 2021), consumer adoption levels of technologies such as blockchain (Lin *et al.*, 2021) and autonomous vehicle adoption (Yuen *et al.*, 2020). In addition, the latter considered skills development, changing business models (Oke and Fernandes, 2020) and supply chain management (Kabir *et al.*, 2021). The *International Journal of Bank Marketing* was third in publication count and sample size. The remainder of citation counts per journal, the number of publications counts and sample size sum of the top ten journals are shown in Table 2.

3.2 Geographical attributes

As part of the data extraction, to understand where the technology models are being applied, who is applying them, and where the information is being processed, the country of study, main author and publication were extracted. Within this assessment, the sample size of the publication was also noted, to determine the level of maturity and application.

In terms of the study's countries, an analysis of per publication count is shown in Figure 5. As seen in the figure, many studies are conducted in Europe and Asian regions, with few in Africa and South America, which are predominantly developing regions. However, India, considered to be a developing world country, was the highest area of study with a count of 18. A reason for this is that developing countries are looking to update systems on government

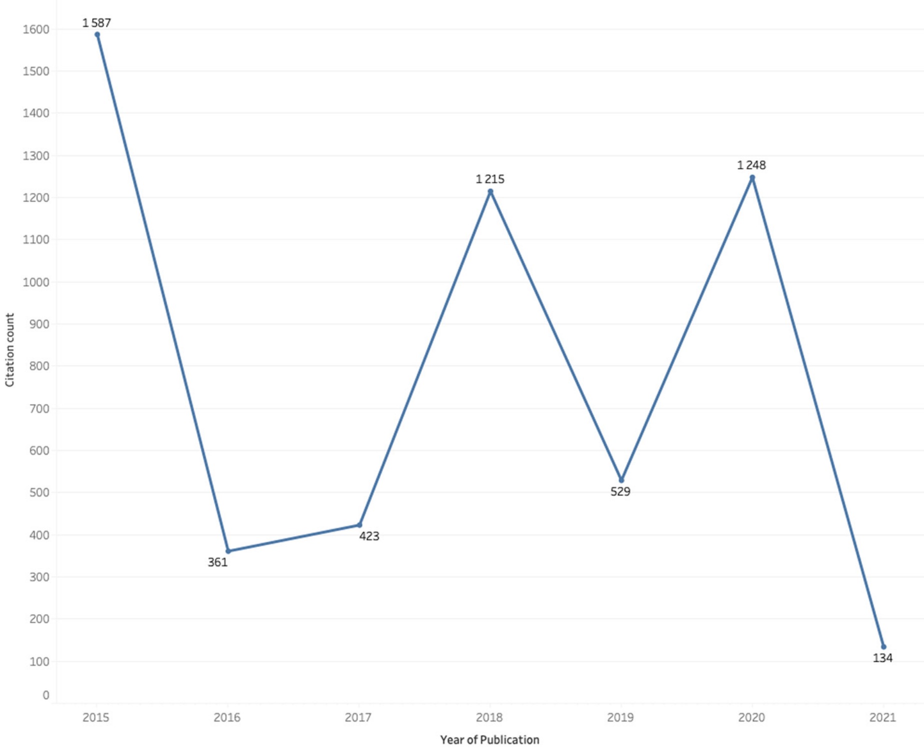


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Figure 4.
Citation count per publication per year

and organisational levels, developing ICT infrastructure to support smart technologies to exploit the opportunities (Mohammed *et al.*, 2016). A core principle of this is leadership and skills development studies, where new business models need to be formed for emerging countries to understand the barriers and address lower maturity levels (Ghobakhloo and Ching, 2019). The second highest is global studies at 13. Global studies were when three regions or more were assessed, or the studies specified a global context. The top performers from here can all be considered developed nations such as technology-centric arenas, the USA and Malaysia having a count of nine each. South Korea had eight studies conducted in the region. Taiwan and Italy had six studies in their respective country, with China at five. These technologically advanced nations have seen several studies diffuse the implementation and continuous usage of smart technologies (Jayashree *et al.*, 2021). Germany only had three studies, but this could be attributable to the region reaching maturity in terms of I4.0.

By considering authors' countries of association, the study aimed to demonstrate who knows about adopting technology. The results align with the country of study, where the highest was India, with Malaysia and South Korea in the top three. This is also true when factoring in the sample size sum of the studies, noting that a predominate number of users were factored into their studies in the respective regions. The remainder, though, indicates strong knowledge areas with global leaders in manufacturing and technology, as shown in Table 3. The top institutions for this study were the University of New South Wales, with a

S. no.	Journal	Citation	Journal	Publication count	Journal	Sample size sum
1	*Computers in Human Behaviour*	*597*	*International Journal of Environmental Research and Public Health*	*6*	*International Journal of Environmental Research and Public Health*	*1,955*
2	*Telematics and Informatics*	*591*	*Journal of Open Innovation: Technology, Market, and Complexity*	*5*	*Mathematics*	*1,805*
3	*International Journal of Human-Computer Interaction*	*525*	*International Journal of Bank Marketing*	*4*	*International Journal of Bank Marketing*	*1,776*
4	*International Journal of Production Research*	*405*	*Applied sciences*	*4*	*Energies*	*1,698*
5	*International Journal of Bank Marketing*	*191*	*Telematics and Informatics*	*3*	*Sustainability*	*1,203*
6	*Computers in Industry*	*190*	*Technology in Society*	*3*	*Journal of Open Innovation: Technology, Market and Complexity*	*1,063*
7	*Journal of Open Innovation: Technology, Market and Complexity*	*186*	*Technological Forecasting and Social Change*	*3*	*Telematics and Informatics*	*909*
8	*Industrial Management and Data Systems*	*184*	*International Journal of Production Research*	*3*	*Information Technology and People*	*898*
9	*International Journal of Social Robotics*	*155*	*IEEE Access*	*3*	*Applied Sciences*	*809*
10	*International Journal of Fashion Design, Technology and Education*	*137*	*Energies*	*3*	*Journal of Research in Interactive Marketing*	*803*

Source: Author generated

Table 2. Sum citation count per journal and sample size sum per top ten journal

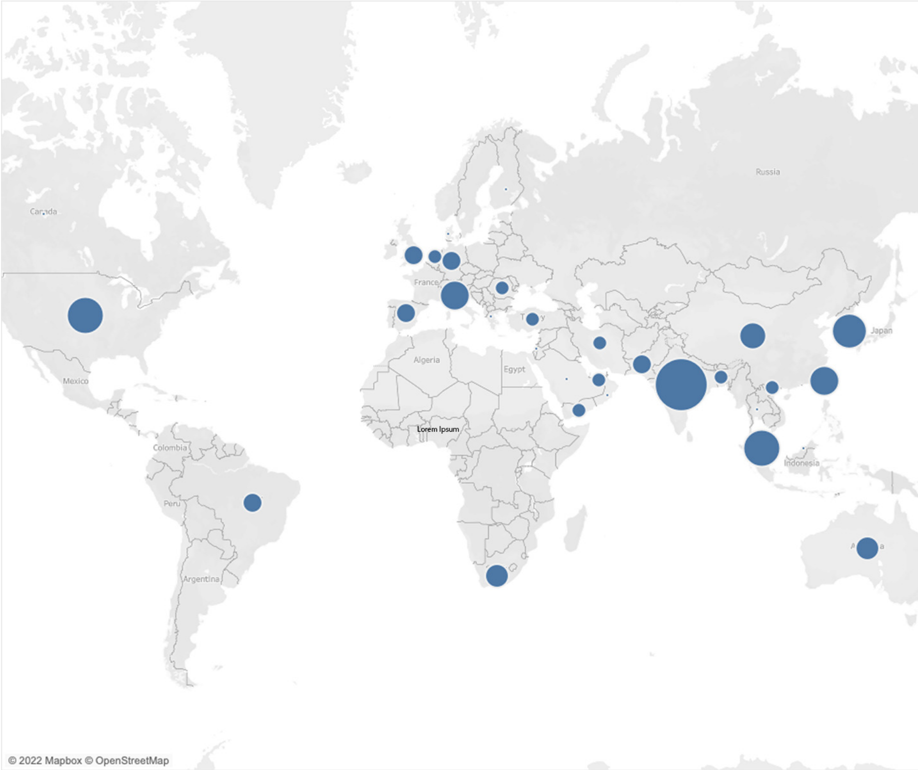
count of four based in Australia. The remaining institutions lie predominantly in the European and Asian regions, demonstrating a focused knowledge area.

In terms of country of publication, the UK, at a count of 59 was the leader, accounting for 47.20% of all papers. On the other hand, Switzerland, the USA and The Netherlands had 31, 12 and 8, respectively. This demonstrates that developed regions hold the predominant knowledge that is considered reliable and reputable. However, some instances of developing nations can be noted, where the country of publication distribution is shown in Appendix 3.

3.3 Distribution by methodology and research level

Most adoption stages assessed were early-stage adoption at a count of 95. This supports the technology phases by Sahin and Rogers (2006), where the new emerging technologies require early stages to demonstrate value. In total, 26 of the studies had an early majority, primarily smart technologies of 4IR at a count of ten and IoT at six. The type of studies used to assess these were 110 empirical studies, with mixed studies and literature studies having eight and seven, respectively. Table 4 notes the differing methodologies used but includes the count where mixed methods were deployed. This shows that the publications assessed had scientific rigour and empirical applications.

In addition to methodology, ICT and information systems technology adoption studies are grouped into individual, group or organisational levels. Individual level of adoption is the most well-known and often used level of analysis to predict technology adoption. However, with



Source: Author generated through Tableau

Figure 5. Countries where studies were conducted per publication count

S. no.	Country of author	Publication count	Country of study per sample size	Sample size	Author affiliation per publication count	Publication count
1	India	18	India	*5,546*	University of New South Wales	*4*
2	Malaysia	*11*	South Korea	*3,383*	Universiti Teknologi Malaysia	*3*
3	South Korea	*9*	USA	*3,060*	University of Turin	*2*
4	Australia	*9*	Global	*2,727*	University of Huddersfield	*2*
5	China	*8*	China	*2,424*	University of Cambridge	*2*
6	USA	*6*	Malaysia	*2,040*	University of Calabria	*2*
7	Taiwan	*6*	Taiwan	*1,609*	Universiti Teknologi MARA	*2*
8	Italy	*6*	Italy	*1,430*	Robert Gordon University	*2*
9	UK	*4*	Spain	*1,139*	National Institute of Industrial Engineering	*2*
10	Germany	*4*	United Arab Emirates	*996*	Nanjing University	*2*

Source: Author generated

Table 3. Country of main author per publication count, country of study per sample size sum and author affiliation per publication count

smart technologies and other ICT advancements, the latter two are seeing a shift in focus. Notably, though is the little scholarly attention given to studies done on group level (Rad *et al.*, 2018). Based on the review of this study, findings show that, 64.80%, or 81 out of the 126 studies, were done on an individual research level. The attention paid to individual levels can be attributed to the applicability of most common information theories to invest in smart technologies that look to what and how consumers would adopt smart technologies and that of employees in larger organisations (Van Den Berg and Van Der Lingen, 2019). With a count of 44, organisational levels were fewer, yet no group-level studies were noted.

3.4 Subject areas and technologies assessed

To understand what technologies are being assessed and in what context, the subject area of each study was extracted. A total of 16 subject areas were identified based on literature, further demonstrating the expanse of 4IR integration and study. The study's publications per subject are noted in Appendix 4. To determine the level of application, the subject area sample of application was extracted from the identified publications and noted as sample size sum. The citation count of each publication was also extracted to note the level of academic interest by calculating the citation sum as seen in Table 5.

Table 4. Methodology used per publication count

Methodology	Count
Survey	97
Literature study	12
Interview	11
Case study	4
Experiment	3
The decision-making trial and evaluation laboratory (DEMATEL)	2
TISM	1

Source: Author generated

Table 5. Subject area to the publications sample size, citation sum and publication count

S. no.	Subject area	Sample size sum	Subject area	Citation sum	Subject area	Publication count
1	Finance	*5,486*	Computer Science	*1,171*	Finance	*16*
2	Supply chain management	*3,756*	Transportation	*808*	Computer Science	*16*
3	Information systems	*3,468*	Information systems	*690*	Supply chain management	*14*
4	Computer Science	*3,357*	Supply chain management	*588*	Engineering	*14*
5	Engineering	*2,986*	Education	*440*	Business administration	*13*
6	Education	*2,717*	Marketing	*370*	Education	*11*
7	Business administration	*2,629*	Finance	*308*	Information systems	*10*
8	Transportation	*1,923*	Engineering	*293*	Manufacturing	*6*
9	Manufacturing	*1,437*	Business administration	*267*	Transportation	*5*
10	Service industry	*1,417*	Manufacturing	*244*	Health care	*4*
11	Marketing	*1,322*	Health care	*161*	Construction	*4*
12	Construction	*1,251*	Agriculture	*54*	Marketing	*3*
13	Public administration	*894*	Construction	*35*	Agriculture	*3*
14	Health care	*766*	Psychology	*33*	Service industry	*2*
15	Agriculture	*718*	Service industry	*22*	Public administration	*2*
16	Psychology	*598*	Public administration	*13*	Psychology	*2*

Source: Author generated

Based on the sample sizes of applications within the 125 publications assessed, finance was the leading subject area, with a sample size area of application of 5486. This dominance demonstrates a large drive to understand the varying technologies potential and how users are adopting to optimise the industry. Topics range from combining smart technologies of 4IR for financial payment systems (Ahmad *et al.*, 2021; Anshari *et al.*, 2021), to integrating with IoT devices (Chawla and Joshi, 2019; Hussain *et al.*, 2019), usage of AI for security and engagement (Huang *et al.*, 2021; Zhong *et al.*, 2021) and blockchain for financing (Kabir *et al.*, 2021) and cryptocurrency (Arias-Oliva *et al.*, 2021). Moreover, finance is also first in terms of publication count at 16. This level of popularity can also be attributed to internet banking using IoT devices and wireless payment options that have stimulated innovative solutions for improved user adoption. This has resulted in the financial services industry being majorly disrupted, driving the need for ubiquitous innovations when compared to traditional banking. For example, there have been over 12,000 start-ups between 2010 and 2015, with associated global investment exceeding US$50bn (Singh *et al.*, 2020). However, although this subject area is the leader in two aspects, it is only seventh in terms of citation sum at 308. This could be attributable to their publication date, which is most at a count of seven in 2021 and four in 2020 as shown in Appendix 7.

As support to these are information systems' role and application in various areas, seeing it is third in terms of sample size and citation count, demonstrating a large area of interest and academic confidence. This, despite a lower publication count of ten. Computer science was the highest cited subject at 1,171 and tied with the greatest number of publications. The reason for this is the significant interest in the technologies themselves (Kao *et al.*, 2019; Lee and Shin, 2019; McNamara and Sepasgozar, 2020), and how human-computer interactions affect their ultimate adoption, including that of the 4IR (Abdullah and Ward, 2016; Rafique *et al.*, 2020; Sohn and Kwon, 2020). Although specifically applied, part of this is transportation, as most of these studies are related to autonomous vehicles and their adoption.

I4.0 noted that manufacturers have a strategic priority to develop a fully integrated and collaborative ecosystem (Ghobakhloo and Ching, 2019). As a result, supply chain management was second in terms of sample-sized assessed and third in publication count. However, there appears to be an evolution from I4, where manufacturing publications on adoption were concentrated around 2018 and 2019 per Appendix 7 yet supply chain management was the most predominant subject in 2021. When factoring manufacturing as part of I4, it accounts for 20 of the publications and 832 citations. This can be attributed to CPS developments and ever digitised capabilities to automate functional areas (Chatterjee *et al.*, 2021). At the core of this is the integration of such smart technologies into systems and the human behaviours to achieve this. Huge investments have also been channelled into this region for automation capabilities and enhanced connectivity within the 21st century (Kamble *et al.*, 2019).

Finally, engineering that addresses technical aspects had a large sample size sum. This was followed by education with a sample of 2,712 and a citation sum of 440. This supports the mention in other studies that stakeholders are driving upskilling for the future of work by adopting such advancing technologies (van Laar *et al.*, 2017).

Within the subjects were various smart technologies assessed. As a result, ten primary technologies were identified for the study. The most proliferous was IoT, disrupting aspects in I4.0 such as workplaces transform with CPS and automation and supporting infrastructure and other digital technologies of the 4IR to create effective work environments and optimise efficiencies (Ammirato *et al.*, 2019). This technology accounted for 36 studies. The sample size sum was 10,863, with the most citations sum at 1,686. However, with additional levels of connectivity and intelligence of IoT, security and privacy concerns have also been noted that affect technology adoption (AlHogail, 2018).

For this study, where more than one smart technology was used or integrated, it was logged as smart technologies of the 4IR. In total, 32 of the studies applied various technologies. The sample size sum within this scope was 8,245 and the citation sum of 1,600, demonstrating their relevance and assessment in understanding their adoption. Assessment levels were equally split, demonstrating an interest in business model development and strategies for optimising efficiencies (Ghobakhloo and Ching, 2019; Kinkel *et al.*, 2021) but also understanding the adoption of individuals to ensure uptake of products (Abu Salim *et al.*, 2021) or employee upskilling (Skoumpopoulou *et al.*, 2018).

Several digital layer technologies then feature. First of which was AI that accounted for 12 publications and 208 citations. The majority of which occurred at an individual level of analysis. This can be attributed to advancements in computing capabilities, where natural language processing, voice recognition and machine learning drive intelligent products and autonomous decisions used by consumers. Secondly, blockchain, a digital layer technology of the 4IR is a decentralised and encrypted ledger with extensive usages, as the transactions are incorruptible (Karamchandani *et al.*, 2020). It is the fourth most featured technology with a publication count of 14 and a sample size sum of 3,986. The technology has seen distribution between organisational and individual assessment levels at six and eight, respectively, with applications in the supply chain that strongly relate to I4 (Kamble *et al.*, 2019; Wong *et al.*, 2020). The remaining technologies' distribution can be seen in Table 6.

In terms of publications, IoT, smart technologies and AI and were major technologies assessed on an individual level. Organisational research levels looked predominantly to smart technologies, then cloud computing and IoT, respectively, as seen in Appendix 5. This indicates that the technology adoption for individual understanding focuses on physical devices (Lu, 2021; Yang *et al.*, 2016) and digital systems that users need to adopt (Roy and Moorthi, 2017). Organisational areas, however, are considering leveraging technology for business models to address consumer needs (Dube *et al.*, 2020; Hossain *et al.*, 2017), but also the usage of such items for internal efficiencies (Vaittinen *et al.*, 2018), both of which requires advancing skills (Čater *et al.*, 2021).

3.5 Technology adoption model usage

Several theoretical models on technology adoption have been introduced to address the acceptance, or rejection, of information systems and technologies that they encompass (Dewi *et al.*, 2018; Lai, 2017; Nikou, 2019; Rad *et al.*, 2018). This study focused on assessing models'

Table 6.
Technology used of the publications and their sample size sum, citation sum, publication count and level of analysis count

Technologies used in study	Sample	Citation	Publication	Level of analysis Individual	Level of analysis Organisational
IoT	10,863	1,686	36	30	6
Smart technologies of 4IR	8,245	1,600	32	16	16
Artificial intelligence	4,129	208	12	10	2
Blockchain	3,986	584	14	8	6
Autonomous vehicles	2,709	768	7	7	0
Cloud computing	1,882	168	8	1	7
Spatial computing	940	215	5	4	1
Robotics	757	170	4	4	0
Big data	718	63	4	0	4
Additive manufacturing	496	35	3	1	2

Source: Author generated

usage within the 4IR construct. Based on the 125 reviewed articles, 14 models from existing theory formed the primary basis of the studies. When extracting the principles of the studies, two distinguishments were made. Firstly, the core model used for the study theoretical underpinnings was noted. If the model was not used in isolation and subsequently extended with others, the additional models' details were captured. The extensive model names and the list is noted in Appendix 6, where 34 models or theories were identified. The distribution and founder of the most used models are presented in Table 7. Out of the 125 papers, model extension occurred in 84%, or 105 models, while the remaining 16% or 20 were not. Linkages between models were mainly with TAM and unified theory of acceptance and use of technology (UTAUT), at a count of 23. Second to this was TAM and theory of planned behaviour (TPB) at 15. Several instances also saw TAM and diffusion of innovation theory (DOI) linked at a count of 14. Finally, TAM and technology-organisation-environment framework (TOE) were eight. In certain instances, up to five models were included in a single study (Van Den Berg and Van Der Lingen, 2019; Schniederjans and Yalcin, 2018).

Of the 125 assessed, TAM had the highest usage rate in terms of core model with a count of 55, or 44% of the studies. However, when including the extended models, a total of 75 instances of TAM were counted across the 125 articles assessed, accounting for 60% of theories used by one or more studies, thus making it the dominant theory included for this review. This finding agrees with studies that considered ICT (Rad *et al.*, 2018), although none yet in terms of smart technologies of 4IR. The popularity can be attributed to its established use in understanding existing ICT studies due to its simplicity and general applicability to new technology adoption issues, such as those presented by the 4IR. However, the amendment level raises a counterargument as most of the adoption within this model was amended.

Next to TAM was UTAUT, appearing 27 times as a core model, and used in 40 models when extended, thus placing it in second place. The TOE framework at a core model count of 17 is due to its applicability and relevance when assessing readiness for smart technology adoption and strategies to understanding changing consumer expectations and employee readiness. When including extensions, TOE had a count of 23. The remaining top eight models are expanded on in the following sections.

3.5.1 Technology acceptance model. The TAM model, founded by Davis (1985), has seen several iterations. The model describes the nature of beliefs, attitudes and intentions of human behaviour that has been extensively verified (AlHogail, 2018). Many reviews of TAM have noted that modified or expanded versions exist, as they offer theoretical and practical insights.

	Theoretical foundation of studies assessed	Main author and citation	Core model count	Extended model count
1	Technology acceptance model (TAM)	Davis (1985)	55	75
2	Unified theory of acceptance and use of technology (UTAUT)	Venkatesh *et al.* (2003)	27	40
3	Technology-organisation-environment framework (TOE framework)	Tornatzky and Fleischer (1990)	17	23
4	Diffusion of innovation (DOI)	Rogers (1963)	7	18
5	Information systems success model		4	4
6	Theory of planned behaviour (TPB)	Ajzen (1991)	4	21
7	Theory of reasoned action (TRA)	Fishbein and Ajzen (1975)	2	10
8	Technology readiness index (TRI)	Fishbein and Ajzen (1975)	1	4

Source: Author generated

Table 7. Top eight model distribution per count in publication

A further result of these modifications is that TAM has numerous advantages, such as predicting diverse users' acceptance in individual and organisational contexts. A reason for this is that it examines the end-user acceptance of information systems based on the characteristics of such systems. This has resulted in its predominant use in this study as well, including manufacturing (Chatterjee *et al.*, 2021), retail (Kim *et al.*, 2017), finance (Singh *et al.*, 2020) and skills development (Molino *et al.*, 2021; Skoumpopoulou *et al.*, 2018). Core of which is the human-computer interactions as supported by findings in terms of journal publications in Table 2. These have advanced further iterations with additional constructs used. For this study these formed part of the umbrella of TAM. In the 4IR context, the TAM exhibits limitations due to its foundational focus on perceived ease of use and usefulness, which may not encapsulate the complex and dynamic nature of 4IR technology adoption (Kang *et al.*, 2021). TAM's static framework and lack of consideration for broader contextual factors such as socio-technical systems and organisational culture limit its applicability in the rapidly evolving 4IR landscape. Consequently, despite its extensive use and modifications, TAM has seen extensive adaptation or supplementation to adequately address the multifaceted aspects of technology adoption in the 4IR era (Molino *et al.*, 2021; Skoumpopoulou *et al.*, 2018).

3.5.2 Unified theory of acceptance and use of technology. Venkatesh *et al.* (2003) did extensive research to develop a UTAUT that conducted empirical studies to synthesise behavioural intentions. Using these, UTAUT uses behavioural intentions to predict technology use behaviour. Studies have argued that UTAUT was designed for adoption at the individual level. However, there are studies that have shown its usefulness at an organisational level (Oliveira and Martins, 2010; Williams *et al.*, 2009). This is because the model facilitates various other models, including the theory of reasoned action (TRA) (Sheppard *et al.*, 1988); TAM; TPB (Taylor and Todd, 1995); a combined TAM-TPB (Taylor and Todd, 1995); Model of PC utilisation (Thompson *et al.*, 1991); the motivational model (Vallerand, 1997); social cognitive theory (Thompson *et al.*, 1991) and DOI (Rogers, 2003). However, with some limitations from the 2003 study, further extensions to UTAUT2 include a consumer context. Since its publication, it has been used in various studies within the 4IR (Ghazali *et al.*, 2020), with expansion from individual to usage cases at an organisational level (Wamba and Queiroz, 2020).

3.5.3 Technology-organisation-environment framework. Tornatzky and Fleischer (1990) developed the TOE to describe the innovation process within the frame of the organisation. Three core characteristics are assessed: organisation, environment and the technology context. The organisational level includes communication processes between employees, resources and descriptive characteristics such as size, structure, level of centralisation and management support. The environment pertains to the organisation's context, such as the market, regulatory limitations and market elements. Finally, the technology context refers to the technology available to be adopted, albeit internal or external. The TOE framework is useful for researchers to assess organisations readiness, even in the 4IR context (Van Den Berg and Van Der Lingen, 2019) that also supports the TAM (Ghobakhloo and Ching, 2019).

3.5.4 Theory of planned behaviour. The TPB notes that intention to act is based on attitude towards the action, which was modelled from psychological processes that mediate behaviour towards observed relationships. The constructs include attitude, perceived behavioural control and subjective norm. Ajzen (1991) theory claimed that control is a major cause intention to behave in a certain way or adopt a technology. Perceived control is a proxy that reflects the ease or difficulty of such behaviour.

3.5.5 Innovation diffusion theory. Also referred to so as innovation diffusion theory (IDT), DOI, focuses on characteristics that impact innovation, including observability, triability, complexity, relative advantage and compatibility (Rogers, 2003). The theory summarised individual levels of innovation adoption, which were set out in five phases.

Oliveira and Martins (2010) have noted several instances of the organisational level of assessment with this model, highlighting its application in business as noted by Vaittinen *et al.* (2018).

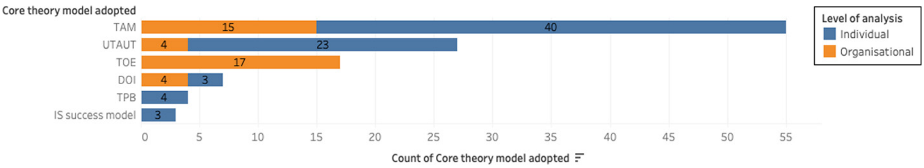
3.5.6 Theory of reasoned action. The TRA is a social psychology theory that assumes people are relatively rational. As such, it believes people systematically process information available to them. Furthermore, individuals' beliefs are seen as consequences of a particular behaviour, resulting in its usage across variable disciplines to evaluate the outcomes of their actions and attitudes (Fishbein and Ajzen, 1975).

3.5.7 Technology readiness index. The technology readiness index is an extension of the TAM in that it focuses on individuals focus on adopting technology and their readiness to do so. In addition, it focuses on workplace environments and enthusiasm for employees to adopt such technologies for technology use (Parasuraman, 2000).

3.5.8 Information systems success model. DeLone and McLean (2003) information systems success model offers an instrument that considers interdependent and multi-dimensional constructs to assess the success of information systems. In this model, information quality constructs assess semantic success, while quality refers to the systems technical success. Additionally, delivering and planning and use and user satisfaction constructs assess the overall system's effectiveness.

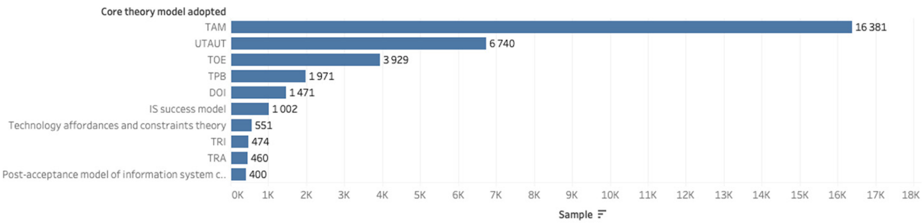
3.5.9 Research level of analysis. Of the research levels of analysis, the primary model used was TAM with a count of 15 organisational and 40 done on an individual level of analysis. UTAUT followed this with 23 counts on an individual and four on an organisational level. TOE was all organisational at a count of 17. DOI though, had a split of four and three to organisational and individual levels, respectively. Finally, IS success model had three counts on individual only, all of which can be seen in Figure 6.

3.5.10 Distribution of model usage per sample and country of study. The sample size of application was also assessed, as this demonstrates a representation of the area and scope of the areas assessed. TAM was the highest sum count (16,381), followed by UTAUT (6,740), TOE (3,929), TPB (1,971) and then DOI (1,471). The distribution can be seen in Figure 7.



Source: Author generated through Tableau

Figure 6.
Core models research-level count



Source: Author generated through Tableau

Figure 7.
Sample size per core model distribution

The model's distribution per country sees TAM applied in almost all the top ten. However, there is a continuous mix of studies, even when only considering the core model, where study application models differ as seen in Figure 8.

Finance, the most prominent study area, used UTAUT in most of its assessment as a theoretical underpinning. A further mix of models was used. Computer science saw TAM most used. A core subject area of I4, supply chain management and manufacturing, was the highest cited subject for this study to understand the adoption of new industries, but only third in model count usage. The remaining areas had a spread of models adopted, where TAM was extensively used as a core model but extended for the subject's area and level of analysis. This can be seen in Figure 9.

4. Discussion

The purpose of this study was to address a gap in the literature regarding methodological approaches and theoretical underpinnings of current trends in 4IR technology adoption. To do so, an SLR based on principles of PRISMA was used. A total of 3,007 papers were

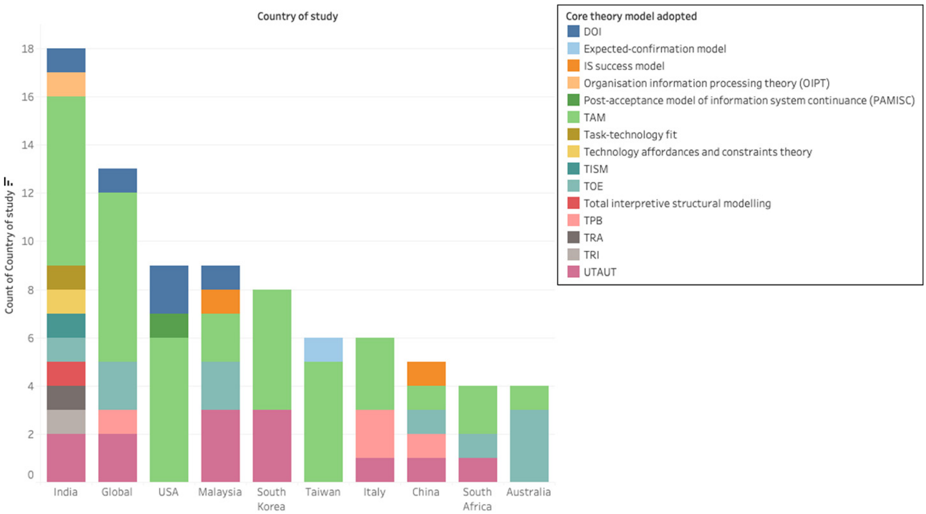


Figure 8.
Top ten model to country of study sum

Source: Author generated through Tableau

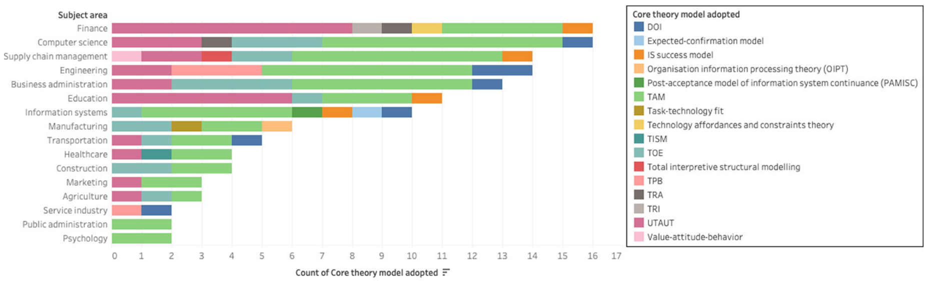


Figure 9.
Core model count to subject area

Source: Author generated through Tableau initially identified across nine databases and one database tool. Of these, 125 were selected and assessed after extensive scrutiny. The data results showed that 14 different models formed the basis of adoption assessment. The extracted data explicitly noted the foundational model of each study, but extensions of models were added, to identify the most used model, when combined as well. As a result, the overall models identified were 34, as shown in Appendix 6.

From the SLR, nuanced trends in technology adoption models within the 4IR context were identified, with the TAM being the most predominant, aligning with prior studies, confirming its foundational role in understanding technology adoption across various contexts. It appeared in 55 out of 125 papers as the core theoretical model, accounted for 55% in one or more studies. The citation count and sample size of studies using TAM were also the greatest. TAM's popularity can be ascribed to its simplicity, attributes and general applicability across individuals and organisations. Thus, it is the most dominant theory. This finding aligns with other studies such as Rad *et al.* (2018). However, our findings diverge by highlighting the extensive modifications and extensions to TAM, suggesting a nuanced understanding is required to address the 4IR's complexities. This is true when considering the extent to which models extended towards understanding adoption in this construct. Out of the 125 papers, model extension occurred in 84% or 105 models, while the remaining 16%, or 20 were not. This assertion is in line with findings that despite being the predominant model, TAM has some limitations. Alam *et al.* (2021) related to this, referring to restrictive factors present that limit predicting and explaining new solutions, noting a need to extend the TAM with context-specific constructs. Kang *et al.* (2021) further mention the need for factors beyond individuals, especially where these include social processes relating to organisational and social consequences such as those of the 4IR. Cheng (2020) supported this, noting a need for a hybrid model, especially with the complexities of the 4IR. Primary linkages from this study showed TAM and UTAUT, at a count of 23. Second to this was TAM and TPB at 15. Several instances also saw TAM and DOI linked at a count of 14. Finally, TAM and TOE were eight. Several studies then extended their theoretical models, indicating a potential mismatch between traditional models like TAM and the dynamic, multifaceted nature of 4IR technologies. This trend underscores the evolving landscape of technology adoption research, where models must adapt to encompass a broader array of factors, including rapid technological advancements, socio-technical systems and organisational culture.

From a subject area perspective, 4IR technologies show a notable thematic expansion beyond traditional manufacturing, extending into fields such as finance, health care and education, reflecting their broader transformative potential. In finance, innovations included advanced financial payment systems, AI-driven security and blockchain applications, enhancing operational efficiencies and customer engagement. Health care benefits from AI diagnostics, remote monitoring via IoT and secure data management through blockchain, were shown, improving patient outcomes and streamlining processes. In education, 4IR technologies facilitated personalised learning, smart environments and secure certification systems, preparing students for future technological demands. This diversification underscores the interdisciplinary nature of 4IR research, necessitating collaboration across subject areas to address complex challenges. And by extension, the models that underpin their adoption.

However, the concentration of studies has been in European and Asian regions, with few studies conducted in Africa and South America, which are predominantly developing regions. However, India, considered to be a developing world country, had the highest area of study. A reason for this is that developing countries are looking to update systems on government and organisational levels, developing ICT infrastructure to support 4IR technology adoption to exploit the opportunities. A core principle of this is leadership and skills development studies, where new business models need to be formed for emerging countries to understand the barriers and address lower maturity levels.

Methodologically, most adoption stages assessed were early-stage adoption. One reason for this could be that this stage is crucial for showcasing the potential value and benefits of 4IR technology through pilot projects, small-scale implementations and proof-of-concept studies. This approach also allows for effective risk management by identifying potential issues and refining strategies before committing to full-scale deployment. Additionally, early-stage adoption facilitates the collection of valuable feedback from initial users and stakeholders, which is critical for identifying strengths and weaknesses and making necessary adjustments to improve the technology. Furthermore, it enables sensible resource allocation by providing a clear understanding of the technology's value, justifying further investments and securing necessary funding. Finally, early-stage adoption contributes to building a comprehensive knowledge base that can be shared across industries, guiding other organisations in their adoption efforts and helping to develop best practices, standards and frameworks for more efficient technology integration. Consequently, future studies could look to ecosystems to support early-stage development to enhance 4IR technology adoption.

The study identified ten primary smart technologies, with the IoT being the most prominent as its integration into CPS enables automation, significantly enhancing business efficiencies. However, the increased connectivity of IoT raises security and privacy concerns, affecting its adoption. This could be due to the complexity of securing interconnected devices and the evolving nature of cyber threats. Smart technologies of the 4IR, where multiple technologies were integrated, were examined extensively. These studies explored business model development, strategies for optimising efficiencies, individual adoption and employee upskilling. The focus on these areas might be driven by the need to maximise ROI and ensure that employees can effectively use new technologies.

Additionally, the study noted that although the term Industry 4.0 (I4.0) was introduced by Germany, several other regions are leveraging its technologies. For example, the South Korean Government curbed COVID-19 transmissions by blending physical technology with system control between actors by adopting new technologies stemming from the 4IR (Kang *et al.*, 2021). Not surprisingly, several of the authors and countries of study originate in this region. Furthermore, the prominence of studies is within the European and Asian regions, demonstrating the drive toward interconnection and automation (Masood and Sonntag, 2020). This has resulted in these regions taking the forefront of publications and regions of studies, making them leaders in innovation (Schniederjans and Yalcin, 2018). At the core of which is the development of relevant skills and abilities (Ammirato *et al.*, 2019) to facilitate human-machine interactions for new types of services and business model creation of the 4IR (Masood and Sonntag, 2020).

With these results, it is evident that several theories have been applied across diverse fields. Part of which is the ever-digitised world within the 4IR, but also assesses human behaviour to positively influence adoption, aligning with the primary journals identified in Table 2.

4.1 Implications: theoretical

Theoretically, this study underscores the enduring relevance of the TAM in the 4IR context, but also highlights the necessity for model evolution to address the unique challenges of this era. The frequent extension of TAM in the literature indicates a pressing need to broaden its constructs to encapsulate factors like rapid innovation cycles, interconnected ecosystems and the socio-technical dynamics of 4IR technologies. Future research should, therefore, focus on integrating additional dimensions such as system interoperability, data security and user-centric design into the traditional TAM framework. Alternatively, develop a smart TAM. Moreover, the adoption of 4IR technologies calls for a multidisciplinary approach, integrating insights from behavioural sciences, engineering and business studies to develop a more comprehensive model of technology adoption that reflects the intricacies of the digital age.

4.2 Implications: practical

From a practical standpoint, the findings clarify the pivotal role of technology adoption in driving innovation and competitiveness in the 4IR landscape. Businesses and policymakers must adopt a forward-thinking approach to harness the potential of smart technologies, emphasizing the strategic integration of these technologies into core operational processes to enhance efficiency, agility and customer engagement. The study's indication of a significant focus on early-stage adoption in the 4IR suggests that organisations should prioritise building a robust digital infrastructure and fostering a culture of continuous learning and adaptation to capitalise on emerging technologies. For developing countries, the leapfrogging potential offered by smart technologies presents a unique opportunity to accelerate economic growth and societal advancement. However, this requires a concerted effort to build local capacities in digital literacy, technology management and innovation entrepreneurship. Additionally, the evolving nature of 4IR technologies necessitates agile educational systems capable of responding to the rapid changes, potentially through modular and flexible learning programmes like micro-credentials, which can quickly equip the workforce with relevant skills.

On the policy front, the study underscores the need for a cohesive strategy that aligns technology adoption with national development goals. Governments should foster an ecosystem that encourages research and development in 4IR technologies, supports public–private partnerships and promotes an inclusive digital economy. Regulatory frameworks must be updated to address the ethical, legal and social implications of 4IR technologies, ensuring that the benefits of digital transformation are broadly shared across society.

This study then contributes to understanding the landscape of technology adoption within the context of the 4IR. By conducting an SLR and analysing 125 relevant papers, it has identified 14 core models, with the TAM being the most prevalent. This underscores TAM's enduring relevance, yet also highlights its limitations in the 4IR context, where extensions are often necessary to capture the complexity of new technological paradigms. The study's analysis across 16 subject areas demonstrates the widespread integration of 4IR technologies, with the IoT emerging as particularly transformative. This research not only outlines the theoretical frameworks guiding technology adoption in various sectors but also emphasises the need for models that transcend traditional constructs to address the multifaceted nature of 4IR technologies. Consequently, this study serves as an analytical resource for academics, strategists and policymakers, providing insights into technology adoption trends and fostering innovation in the digitised landscape of the 4IR.

5. Conclusion

The 4IR brings emerging technologies that enable the automation and digitalisation of processes in several spheres. Studies noted that this multi-disciplinary and multifunctional paradigm is transforming the socio and economic landscape. To address this requires an understanding of how the technologies are being adopted. However, there are many adoption theories and associated models to choose from with varying degrees of usefulness and rigour. Using a literature study based on PRISMA, this study presented insights on five perspectives into what technology adoption models are being used by various stakeholders to understand the human behaviour dynamic and subject areas of application. It was found that several models exist that have been used in the assessment of innovative technology from a 4IR perspective. Out of these models, as with other technology assessment studies, TAM was the most used. However, most cases extended their adoption model. Moreover, insights into what technologies are being used and where the studies are being conducted were shown. This study contributes theoretically as a basis for shaping future research towards developing a generalisable model in understanding smart technologies of the 4IR.

5.1 Limitations and future research

Although the paper encompasses key year ranges, 2015–2021, there are limitations. Firstly, as mentioned in previous studies, technology adoption is classified into three groups, yet this study examined the models themselves and not the varying constructs used in the different contexts. Therefore, an opportunity exists to assess these at various levels and develop relational perspectives. Secondly, the current study only considered journal articles and specifically used models. Various others exist that use constructs but do not pertain to a specific model. Future research could consider extending focus in terms of inclusion and exclusion criteria. The technologies assessed were limited to those from the findings, and as these develop, they will need to be assessed. Finally, a split between larger multinational organisations and SMEs could be performed.

References

Abdullah, F. and Ward, R. (2016), "Developing a general extended technology acceptance model for E-Learning (GETAMEL) by analysing commonly used external factors", *Computers in Human Behavior*, Vol. 56, pp. 238-256, doi: 10.1016/j.chb.2015.11.036.

Abu Salim, T., el Barachi, M., Onyia, O.P. and Mathew, S.S. (2021), "Effects of smart city service channel- and user-characteristics on user satisfaction and continuance intention", *Information Technology and People*, Vol. 34 No. 1, pp. 147-177, doi: 10.1108/ITP-06-2019-0300.

Ahmad, S., Tajul Urus, S., Nazatul, S., Syed, F. and Nazri, M. (2021), "Technology acceptance of financial technology (FinTech) for payment services among employed fresh graduates", *Asia-Pacific Management Accounting Journal*, Vol. 16 No. 2, pp. 27-58.

Ajzen, I. (1991), "The theory of planned behaviour", *Organizational Behavior and Human Decision Making Processes*, Vol. 50 No. 1991, pp. 179-211.

Alam, S.S., Susmit, S., Lin, C.Y., Masukujjaman, M. and Ho, Y.H. (2021), "Factors affecting augmented reality adoption in the retail industry", *Journal of Open Innovation: Technology, Market, and Complexity*, Vol. 7 No. 2, p. 142, doi: 10.3390/joitmc7020142.

AlHogail, A. (2018), "Improving IoT technology adoption through improving consumer trust", *Technologies*, Vol. 6 No. 3, p. 64, doi: 10.3390/technologies6030064.

Ammirato, S., Sofo, F., Felicetti, A.M. and Raso, C. (2019), "A methodology to support the adoption of IoT innovation and its application to the Italian bank branch security context", *European Journal of Innovation Management*, Vol. 22 No. 1, pp. 146-174, doi: 10.1108/EJIM-03-2018-0058.

Anshari, M., Arine, M.A., Nurhidayah, N., Aziyah, H. and Salleh, M.H.A. (2021), "Factors influencing individual in adopting eWallet", *Journal of Financial Services Marketing*, Vol. 26 No. 1, pp. 10-23, doi: 10.1057/s41264-020-00079-5.

Arias-Oliva, M., de Andrés-Sánchez, J. and Pelegrín-Borondo, J. (2021), "Fuzzy set qualitative comparative analysis of factors influencing the use of cryptocurrencies in Spanish households", *Mathematics*, Vol. 9 No. 4, p. 324, doi: 10.3390/math9040.

Bai, Y. (2018), "Has the global south become a playground for western scholars in information and communication technologies for development? Evidence from a three-journal analysis", *Scientometrics*, Vol. 116 No. 3, pp. 2139-2153, doi: 10.1007/s11192-018-2839-y.

Belletier, C., Charkhabi, M., Pires de Andrade Silva, G., Ametepe, K., Lutz, M. and Izaute, M. (2021), "Wearable cognitive assistants in a factory setting: a critical review of a promising way of enhancing cognitive performance and well-being", *Cognition, Technology and Work*, Vol. 23 No. 1, pp. 103-116, doi: 10.1007/s10111-019-00610-2.

Čater, T., Čater, B., Černe, M., Koman, M. and Redek, T. (2021), "Industry 4.0 technologies usage: motives and enablers", *Journal of Manufacturing Technology Management*, Vol. 32 No. 9, pp. 323-345, doi: 10.1108/JMTM-01-2021-0026.

Chatterjee, S., Rana, N.P., Dwivedi, Y.K. and Baabdullah, A.M. (2021), "Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model", *Technological Forecasting and Social Change*, Vol. 170, p. 120880, doi: 10.1016/j.techfore.2021.120880.

Chawla, D. and Joshi, H. (2019), "Consumer attitude and intention to adopt mobile wallet in India – an empirical study", *International Journal of Bank Marketing*, Vol. 37 No. 7, pp. 1590-1618, doi: 10.1108/IJBM-09-2018-0256.

Cheng, Y.M. (2020), "Understanding cloud ERP continuance intention and individual performance: a TTF-driven perspective", *Benchmarking: An International Journal*, Vol. 27 No. 4, pp. 1591-1614, doi: 10.1108/BIJ-05-2019-0208.

Choi, J.K. and Ji, Y.G. (2015), "Investigating the importance of trust on adopting an autonomous vehicle", *International Journal of Human-Computer Interaction*, Vol. 31 No. 10, pp. 692-702, doi: 10.1080/10447318.2015.1070549.

Dalenogare, L.S., Benitez, G.B., Ayala, N.F. and Frank, A.G. (2018), "The expected contribution of industry 4.0 technologies for industrial performance", *International Journal of Production Economics*, Vol. 204, pp. 383-394, doi: 10.1016/j.ijpe.2018.08.019.

Davis, F. (1985), "A technology acceptance model for empirically testing new end-user information systems: theory and results", Massachusetts Institute of Technology, doi: 10.1126/science.146.3652.1648.

DeLone, W.H. and McLean, E.R. (2003), "The DeLone and McLean model of information systems success: a ten-year update", *Journal of Management Information Systems*, Vol. 19 No. 4, pp. 9-30, doi: 10.1080/07421222.2003.11045748.

Dewi, M.A.A., Hidayanto, A.N., Purwandari, B., Kosandi, M. and Budi, N.F.A. (2018), "Smart city readiness model based on technology-organization-environment (TOE) framework and its effect on adoption decision", *Proceedings of the 22nd Pacific Asia Conference on Information Systems - Opportunities and Challenges for the Digitized Society: Are We Ready?, PACIS 2018*.

Dube, T., Van Eck, R. and Zuva, T. (2020), "Review of technology adoption models and theories to measure readiness and acceptable use of technology in a business organization", *Journal of Information Technology and Digital World*, Vol. 2 No. 4, pp. 207-212, doi: 10.36548/jitdw.2020.4.003.

Federal Ministry of Education and Research (2016), "Guideline industrie 4.0".

Fishbein, M. and Ajzen, I. (1975), *Belief, Attitude, Intention, and Behaviour: An Introduction to Theory and Research*, Addison-Wesley, Reading, MA.

Ghazali, A.S., Ham, J., Barakova, E. and Markopoulos, P. (2020), "Persuasive robots acceptance model (PRAM): roles of social responses within the acceptance model of persuasive robots", *International Journal of Social Robotics*, Vol. 12 No. 5, pp. 1075-1092, doi: 10.1007/s12369-019-00611-1.

Ghobakhloo, M. and Ching, N.T. (2019), "Adoption of digital technologies of smart manufacturing in SMEs", *Journal of Industrial Information Integration*, Vol. 16, p. 100107, doi: 10.1016/j.jii.2019.100107.

Hajoary, P.K. (2021), “Industry 4.0 maturity and readiness models: a systematic literature review and future framework”, *International Journal of Innovation and Technology Management*, Vol. 17 No. 7, p. 2030005, doi: 10.1142/S0219877020300050.

Hermann, M., Pentek, T. and Otto, B. (2015), “Design principles for industrie 4.0 scenarios: a literature review”, *Business Engineering Institute*, doi: 10.13140/RG.2.2.29269.22248.

Hossain, M.A., Standing, C. and Chan, C. (2017), “The development and validation of a two-staged adoption model of RFID technology in livestock businesses”, *Information Technology and People*, Vol. 30 No. 4, pp. 785-808, doi: 10.1108/ITP-06-2016-0133.

Huang, S.Y.B., Lee, C.J. and Lee, S.C. (2021), “Toward a unified theory of customer continuance model for financial technology chatbots”, *Sensors (Basel, Switzerland)*, Vol. 21 No. 17, p. 5687, doi: 10.3390/s21175687.

Hussain, M., Mollik, A.T., Johns, R. and Rahman, M.S. (2019), “M-payment adoption for bottom of pyramid segment: an empirical investigation”, *International Journal of Bank Marketing*, Vol. 37 No. 1, pp. 362-381, doi: 10.1108/IJBM-01-2018-0013.

Jayashree, S., Hassan Reza, M.N., Malarvizhi, C.A.N., Maheswari, H., Hosseini, Z. and Kasim, A. (2021), “Article the impact of technological innovation on industry 4.0 implementation and sustainability: an empirical study on Malaysian small and medium sized enterprises”, *Sustainability (Switzerland)*, Vol. 13 No. 18, p. 10115, doi: 10.3390/su131810115.

Kabir, M.R., Islam, M.A., Marniati and Herawati (2021), “Application of blockchain for supply chain financing: explaining the drivers using SEM”, *Journal of Open Innovation: Technology, Market, and Complexity*, Vol. 7 No. 3, p. 167, doi: 10.3390/joitmc7030167.

Kademeteme, E. and Twinomurinzi, H. (2019), “The ineffectiveness of technology adoption models in the 4IR era: a case of SMEs in South Africa”, 2019 Open Innovations Conference, OI 2019, IEEE, pp. 252-261, doi: 10.1109/OI.2019.8908220.

Kamble, S., Gunasekaran, A. and Arha, H. (2019), “Understanding the blockchain technology adoption in supply chains-Indian context”, *International Journal of Production Research*, Vol. 57 No. 7, pp. 2009-2033, doi: 10.1080/00207543.2018.1518610.

Kang, Y., Choi, N. and Kim, S. (2021), “Searching for new model of digital informatics for human-computer interaction: testing the institution-based technology acceptance model (ITAM)”, *International Journal of Environmental Research and Public Health*, Vol. 18 No. 11, p. 5593, doi: 10.3390/ijerph18115593.

Kao, Y.S., Nawata, K. and Huang, C.Y. (2019), “An exploration and confirmation of the factors influencing adoption of IoT-basedwearable fitness trackers”, *International Journal of Environmental Research and Public Health*, Vol. 16 No. 18, p. 3227, doi: 10.3390/ijerph16183227.

Karamchandani, A., Srivastava, S.K. and Srivastava, R.K. (2020), “Perception-based model for analyzing the impact of enterprise blockchain adoption on SCM in the Indian service industry”, *International Journal of Information Management*, Vol. 52, p. 102019, doi: 10.1016/j.ijinfomgt.2019.10.004.

Kim, H.Y., Lee, J.Y., Mun, J.M. and Johnson, K.K.P. (2017), “Consumer adoption of smart in-store technology: assessing the predictive value of attitude versus beliefs in the technology acceptance model”, *International Journal of Fashion Design, Technology and Education*, Vol. 10 No. 1, pp. 26-36, doi: 10.1080/17543266.2016.1177737.

Kinkel, S., Baumgartner, M. and Cherubini, E. (2021), “Prerequisites for the adoption of AI technologies in manufacturing – evidence from a worldwide sample of manufacturing companies”, *Technovation*, Vol. 110, p. 102375, doi: 10.1016/j.technovation.2021.102375.

Klumpp, M., Hesenius, M., Meyer, O., Ruiner, C. and Gruhn, V. (2019), “Production logistics and human-computer interaction—state-of-the-art, challenges and requirements for the future”, *The International Journal of Advanced Manufacturing Technology*, Vol. 105 No. 9, pp. 3691-3709, doi: 10.1007/s00170-019-03785-0.

Kruger, S. and Steyn, A. (2020), “A conceptual model of entrepreneurial competencies needed to utilise technologies of industry 4.0”, *The International Journal of Entrepreneurship and Innovation*, Vol. 22 No. 1, pp. 56-67, doi: 10.1177/1465750320927359.

Lai, P. (2017), "The literature review of technology adoption models and theories for the novelty technology", *Journal of Information Systems and Technology Management*, Vol. 14 No. 1, pp. 21-38, doi: 10.4301/s1807-17752017000100002.

Lee, W. and Shin, S. (2019), "An empirical study of consumer adoption of internet of things services", *International Journal of Engineering and Technology Innovation*, Vol. 9, pp. 1-11.

Lee, J., Kao, H.A. and Yang, S. (2014), "Service innovation and smart analytics for industry 4.0 and big data environment", *Procedia CIRP*, Vol. 16, pp. 3-8, doi: 10.1016/j.procir.2014.02.001.

Lee, J., Bagheri, B. and Kao, H.A. (2015), "A cyber-physical systems architecture for industry 4.0-based manufacturing systems", *Manufacturing Letters*, Vol. 3, pp. 18-23, doi: 10.1016/j.mfglet.2014.12.001.

Liao, Y., Deschamps, F., Loures, E.D.F.R. and Ramos, L.F.P. (2017), "Past, present and future of industry 4.0 - a systematic literature review and research agenda proposal", *International Journal of Production Research*, Vol. 55 No. 12, pp. 3609-3629, doi: 10.1080/00207543.2017.1308576.

Lin, X., Chang, S.C., Chou, T.H., Chen, S.C. and Ruangkanjanases, A. (2021), "Consumers' intention to adopt blockchain food traceability technology towards organic food products", *International Journal of Environmental Research and Public Health*, Vol. 18 No. 3, pp. 1-19, doi: 10.3390/ijerph18030912.

Lu, Y. (2021), "Examining user acceptance and adoption of the internet of things", *International Journal of Business Science and Applied Management*, Vol. 16 No. 3, pp. 1-17.

McNamara, A.J. and Sepasgozar, S.M.E. (2020), "Developing a theoretical framework for intelligent contract acceptance", *Construction Innovation*, Vol. 20 No. 3, pp. 421-445, doi: 10.1108/CI-07-2019-0061.

Masood, T. and Sonntag, P. (2020), "Industry 4.0: adoption challenges and benefits for SMEs", *Computers in Industry*, Vol. 121, p. 103261, doi: 10.1016/j.compind.2020.103261.

Mohammed, F., Ibrahim, O. and Ithnin, N. (2016), "Factors influencing cloud computing adoption for e-government implementation in developing countries: instrument development", *Journal of Systems and Information Technology*, Vol. 18 No. 3, pp. 297-327, doi: 10.1108/JSIT-01-2016-0001.

Molino, M., Cortese, C.G. and Ghislieri, C. (2021), "Technology acceptance and leadership 4.0: a Quali-quantitative study", *International Journal of Environmental Research and Public Health*, Vol. 18 No. 20, p. 10845, doi: 10.3390/ijerph182010845.

Muhuri, P.K., Shukla, A.K. and Abraham, A. (2019), "Industry 4.0: a bibliometric analysis and detailed overview", *Engineering Applications of Artificial Intelligence*, Vol. 78, pp. 218-235, doi: 10.1016/j.engappai.2018.11.007.

Nikou, S. (2019), "Factors driving the adoption of smart home technology: an empirical assessment", *Telematics and Informatics*, Vol. 45, p. 101283, doi: 10.1016/j.tele.2019.101283.

Oke, A. and Fernandes, F.A.P. (2020), "Innovations in teaching and learning: exploring the perceptions of the education sector on the 4th industrial revolution (4IR)", *Journal of Open Innovation: Technology, Market, and Complexity, MDPI Multidisciplinary Digital Publishing Institute*, Vol. 6 No. 2, p. 31, doi: 10.3390/JOITMC6020031.

Oliveira, T. and Martins, M.F. (2010), "Information technology adoption models at firm level: review of literature", *4th European Conference on Information Management and Evaluation, ECIME 2010*, Vol. 14 No. 1, pp. 312-322.

Oztemel, E. and Gursev, S. (2018), "Literature review of industry 4.0 and related technologies", *Journal of Intelligent Manufacturing*, Vol. 31 No. 1, pp. 1-56, doi: 10.1007/s10845-018-1433-8.

Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E. and Chou, R. (2021), "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews", *BMJ*, Vol. 372, p. n71, doi: 10.1136/bmj.n71.

Parasuraman, A. (2000), "Technology readiness index (TRI)", *Journal of Service Research*, Vol. 2 No. 4, pp. 307-320, doi: 10.1177/109467050024001.

Park, E. and Kim, K.J. (2014), "An integrated adoption model of mobile cloud services: exploration of key determinants and extension of technology acceptance model", *Telematics and Informatics*, Vol. 31 No. 3, pp. 376-385, doi: 10.1016/j.tele.2013.11.008.

Perri, C., Giglio, C. and Corvello, V. (2020), "Smart users for smart technologies: investigating the intention to adopt smart energy consumption behaviors", *Technological Forecasting and Social Change*, Vol. 155, p. 119991, doi: 10.1016/j.techfore.2020.119991.

Rad, M.S., Nilashi, M. and Dahlan, H.M. (2018), "Information technology adoption: a review of the literature and classification", *Universal Access in the Information Society*, Vol. 17 No. 2, pp. 361-390, doi: 10.1007/s10209-017-0534-z.

Rafique, H., Almagrabi, A.O., Shamim, A., Anwar, F. and Bashir, A.K. (2020), "Investigating the acceptance of mobile library applications with an extended technology acceptance model (TAM)", *Computers and Education*, Vol. 145, p. 103732, doi: 10.1016/j.compedu.2019.103732.

Rogers, E.M. (1963), *Diffusion of Innovations*, Free Press, New York, NY.

Rogers, E.M. (2003), *Diffusion of Innovations*, 5th ed., Free Press, New York, NY.

Roy, S. and Moorthi, Y.L.R. (2017), "Technology readiness, perceived ubiquity and m-commerce adoption: the moderating role of privacy", *Journal of Research in Interactive Marketing*, Vol. 11 No. 3, pp. 268-295, doi: 10.1108/JRIM-01-2016-0005.

Sahin, I. and Rogers, F. (2006), "Detailed review of rogers' diffusion of innovations theory and educational technology-related studies based on Rogers", *The Turkish Online Journal of Educational Technology*, Vol. 5 No. 2, pp. 14-23.

Schniederjans, D.G. and Yalcin, M.G. (2018), "Perception of 3D-printing: analysis of manufacturing use and adoption", *Rapid Prototyping Journal*, Vol. 24 No. 3, pp. 510-520, doi: 10.1108/RPJ-04-2017-0056.

Schwab, K. (2017), *The Fourth Industrial Revolution*, Crown Publishing, New York, NY.

Sharma, M. and Joshi, S. (2021), "Barriers to blockchain adoption in health-care industry: an Indian perspective", *Journal of Global Operations and Strategic Sourcing*, Vol. 14 No. 1, pp. 134-169, doi: 10.1108/JGOSS-06-2020-0026.

Sheppard, B.H., Hartwick, J. and Warshaw, P.R. (1988), "The theory of reasoned action: a meta-analysis of past research with recommendations for modifications and future research", *Journal of Consumer Research*, Vol. 15 No. 3, pp. 325-343, doi: 10.1086/209170.

Singh, S., Sahni, M.M. and Kovid, R.K. (2020), "What drives FinTech adoption? A multi-method evaluation using an adapted technology acceptance model", *Management Decision*, Vol. 58 No. 8, pp. 1675-1697, doi: 10.1108/MD-09-2019-1318.

Skoumpopoulou, D., Wong, A., Ng, P. and Lo, M.F. (2018), "Factors that affect the acceptance of new technologies in the workplace: a cross case analysis between two universities", *International Journal of Education and Development Using Information and Communication Technology (IJEDICT)*, Vol. 14, p. 209.

Sohn, K. and Kwon, O. (2020), "Technology acceptance theories and factors influencing artificial intelligence-based intelligent products", *Telematics and Informatics*, Vol. 47, p. 101324, doi: 10.1016/j.tele.2019.101324.

Taylor, S. and Todd, P. (1995), "Decomposition and crossover effects in the theory of planned behavior: a study of consumer adoption intentions", *International Journal of Research in Marketing*, Vol. 12 No. 2, pp. 137-155, doi: 10.1016/0167-8116(94)00019-K.

Thomas, C.G. (2021), *Research Methodology and Scientific Writing*, Thrissur, Springer Nature.

Thompson, R.L., Higgins, C.A. and Howell, J.M. (1991), "Personal computing: toward a conceptual model of utilization", *MIS Quarterly*, Vol. 15 No. 1, pp. 125-142, doi: 10.2307/249443.

Tornatzky, L.G. and Fleischer, M. (1990), *The Processes of Technological Innovation*, Lexington Books, MA.

Vaittinen, E., Martinsuo, M. and Ortt, R. (2018), "Business customers' readiness to adopt manufacturer's new services", *Journal of Service Theory and Practice*, Vol. 28 No. 1, pp. 52-78, doi: 10.1108/JSTP-03-2017-0053.

Vallerand, R.J. (1997), "Toward a hierarchial model of intrinsic and extrinsic motivation", in Zanna, M. (Ed.), *Advances in Experimental Psychology*, Academic Press, New York, NY, pp. 271-360.

Van Den Berg, J. and Van Der Lingen, E. (2019), "An empirical study of the factors affecting the adoption of mobile enterprise applications", *South African Journal of Industrial Engineering*, Vol. 30 No. 1, pp. 124-146, doi: 10.7166/30-1-1992.

van Laar, E., van Deursen, A.J.A.M., van Dijk, J.A.G.M. and de Haan, J. (2017), "The relation between 21st-century skills and digital skills: a systematic literature review", *Computers in Human Behavior*, Vol. 72, pp. 577-588, doi: 10.1016/j.chb.2017.03.010.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003), "User acceptance of information technology: toward a unified view", *MIS Quarterly*, Vol. 27 No. 3, pp. 425-478.

Wamba, S.F. and Queiroz, M.M. (2020), "Industry 4.0 and the supply chain digitalisation: a blockchain diffusion perspective", *Production Planning and Control*, Vol. 33 Nos 2/3, pp. 193-210, doi: 10.1080/09537287.2020.1810756.

Wichmann, R.L., Eisenbart, B. and Gericke, K. (2019), "The direction of industry: a literature review on industry 4.0", Proceedings of the International Conference on Engineering Design, 2019-Augus, pp. 2129-2138, doi: 10.1017/dsi.2019.219.

Williams, M.D., Dwivedi, Y.K., Lal, B. and Schwarz, A. (2009), "Contemporary trends and issues in it adoption and diffusion research", *Journal of Information Technology*, Vol. 24 No. 1, pp. 1-10, doi: 10.1057/jit.2008.30.

Wong, L.W., Tan, G.W.H., Lee, V.H., Ooi, K.B. and Sohal, A. (2020), "Unearthing the determinants of blockchain adoption in supply chain management", *International Journal of Production Research*, Vol. 58 No. 7, pp. 2100-2123, doi: 10.1080/00207543.2020.1730463.

Yaacob, M.H. and Thing, N.S. (2021), "A systematic literature review of industry 4.0: bridging between the information asymmetry and Cor-Porate governance", *Journal of Information and Knowledge Management (JIKM)*, Vol. 11, pp. 32-43.

Yang, H., Yu, J., Zo, H. and Choi, M. (2016), "User acceptance of wearable devices: an extended perspective of perceived value", *Telematics and Informatics*, Vol. 33 No. 2, pp. 256-269, doi: 10.1016/j.tele.2015.08.007.

Yuen, K.F., Huyen, D.T.K., Wang, X. and Qi, G. (2020), "Factors influencing the adoption of shared autonomous vehicles", *International Journal of Environmental Research and Public Health*, Vol. 17 No. 13, pp. 1-16, doi: 10.3390/ijerph17134868.

Zhong, Y., Oh, S. and Moon, H.C. (2021), "Service transformation under industry 4.0: investigating acceptance of facial recognition payment through an extended technology acceptance model", *Technology in Society*, Vol. 64, p. 101515, doi: 10.1016/j.techsoc.2020.101515.

Appendix 1

Primary keywords	Search strings
Technology adoption	Technology adoption *OR* technology adoption model *OR* technology acceptance *OR* technology acceptance model
Technology adoption model	*AND*
Technology acceptance	4IR *OR* fourth industrial revolution *OR* Industry 4.0 *OR* cyber-physical systems *OR* I4
Technology acceptance model	*OR*
4IR	Big Five theory (BIG5)
Fourth industrial revolution	Delone and McLean is success model (ISS)
I4	Diffusion of innovations (DOI)
Industry 4.0	Expectation confirmation theory (ECT)
Cyber physical systems	Extended technology acceptance model (TAM2)
	Flow theory
	Inter-organisational relationship (IOR) theory
	Perceived value model
	Social capital theory
	Social cognitive theory (SCT)
	Social identity theory
	Task technology fit model (TTF)
	Technology acceptance model (TAM)
	Technology-organisation-environment framework (TOE framework)
	Theory of planned behaviour (TPB)
	Theory of reasoned action (TRA)
	Trust model
	Unified theory of acceptance and use of technology (UTAUT)
	Unified theory of acceptance and use of technology (UTAUT2)
	Uses and gratifications (U&G) theory

Table A1.
Keywords and search strings

Appendix 2

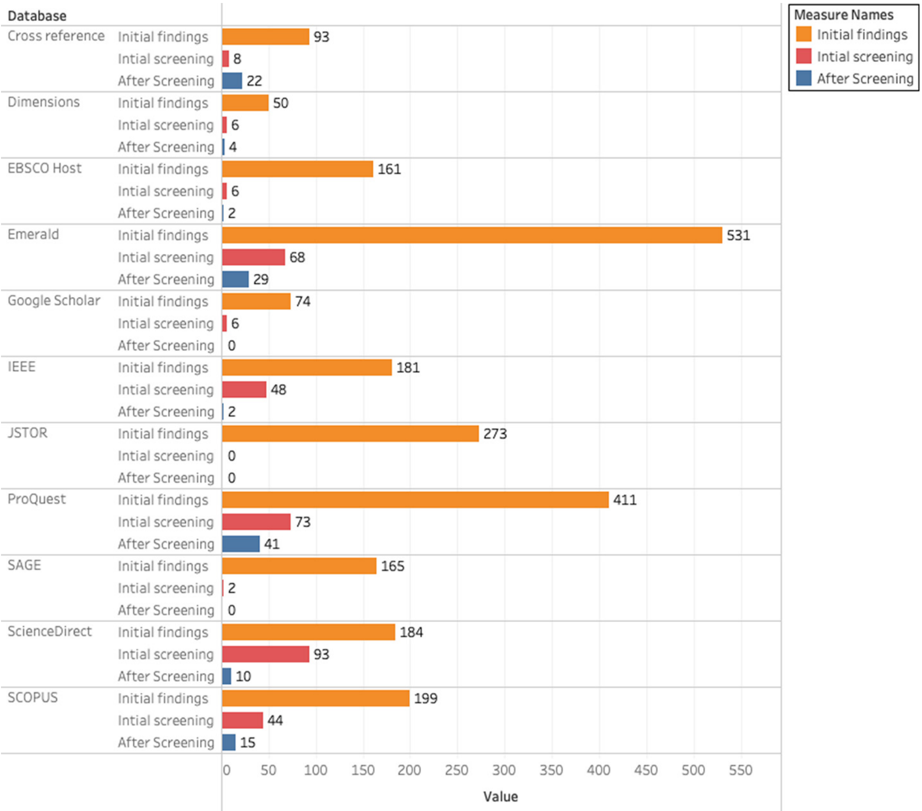


Figure A1.
Distribution of papers in databases per initial findings, initial screening and after screening

Appendix 3

Table A2. Country of publication

Country	Count
UK	59
Switzerland	31
USA	12
The Netherlands	8
Egypt	3
Germany	2
Croatia	1
India	1
Japan	1
Lithuania	1
Malaysia	1
South Africa	1
South Korea	1
Taiwan	1
West Indies	1

Appendix 4

Table A3. Subject areas of studies and references

Subject area	References of publications
Agriculture	Hossain *et al.* (2017)
Business administration	Ahmad *et al.* (2021), Alam *et al.* (2021), Ammirato *et al.* (2019), Čater *et al.* (2021), Jayashree *et al.* (2021), Lu (2021), Masood and Sonntag (2020) and Molino *et al.* (2021)
Computer Science	Abdullah and Ward (2016), Kao *et al.* (2019), Klumpp *et al.* (2019), Lee and Shin (2019), McNamara and Sepasgozar (2020), Mohammed *et al.* (2016), Rafique *et al.* (2020), Singh *et al.* (2020) and Sohn and Kwon (2020)
Construction	
Education	Oke and Fernandes (2020) and Skoumpopoulou *et al.* (2018)
Engineering	Abu Salim *et al.* (2021), Ghazali *et al.* (2020), Kademeteme and Twinomurinzi (2019), Nikou (2019), Perri *et al.* (2020), Schniederjans and Yalcin (2018) and van den Berg and van der Lingen (2019)
Finance	Ahmad *et al.* (2021), Anshari *et al.* (2021), Arias-Oliva *et al.* (2021), Chawla and Joshi (2019), Huang *et al.* (2021), Hussain *et al.* (2019), Kabir *et al.* (2021), Singh *et al.* (2020) and Zhong *et al.* (2021)
Health care	Sharma and Joshi (2021)
Information systems	AlHogail (2018), Cheng (2020), Kang *et al.* (2021), Roy and Moorthi (2017) and Yang *et al.* (2016)
Manufacturing	Ghobakhloo and Ching (2019)
Marketing	Kim *et al.* (2017)
Psychology	Belletier *et al.* (2021)
Public administration	
Service industry	Vaittinen *et al.* (2018)
Supply chain management	Chatterjee *et al.* (2021), Kamble *et al.* (2019), Karamchandani *et al.* (2020), Kinkel *et al.* (2021), Lin *et al.* (2021), Wamba and Queiroz (2020) and Wong *et al.* (2020)
Transportation	Choi and Ji (2015) and Yuen *et al.* (2020)

Appendix 5

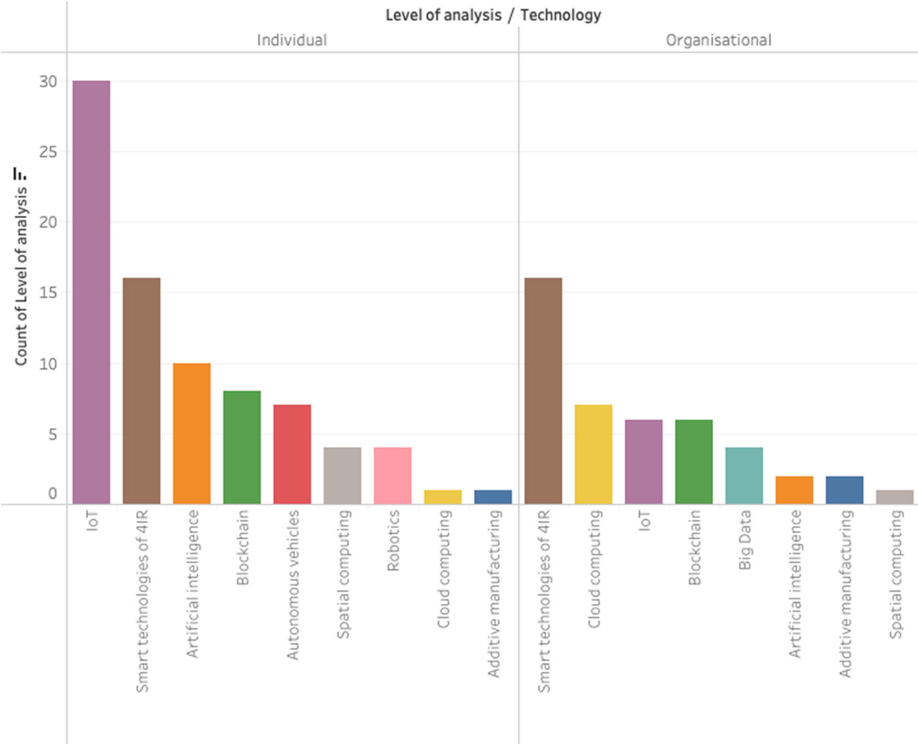


Figure A2.
Technology per publication across research-level count

Appendix 6

Model	Core model	Models used when extended
Technology acceptance model (TAM)	55	75
Unified theory of acceptance and use of technology (UTAUT)	27	40
Technology-organisation-environment framework (TOE framework)	17	23
Theory of planned behaviour (TPB)	4	21
Innovation diffusion theory (IDT) also diffusion of innovations (DOI)	7	18
Theory of reasoned action (TRA)	2	10
Information systems success model	4	4
Technology readiness index (TRI)	1	4
Post-acceptance model of information system continuance (PAMISC)	1	2
Social cognitive theory	0	2
Total interpretive structural modelling (TISM)	2	2
Worker-centric design and evaluation framework for operator 4.0	0	2
Actor network theory (ANT)	0	1
C-TAM-TPB model	0	1
Consumer co-production theory	0	1
Consumer perceived innovation (CPI)	0	1
Dynamic capabilities	0	1
Expected-confirmation model	1	1
Fit viability model	0	1
Grounded theory	0	1
Institutional theory	0	1
Job characteristics model	0	1
Open innovation theory	0	1
Organisation information processing theory (OIPT)	1	1
Resource matching theory	0	1
Resource-based view	0	1
Risky technology adoption model	0	1
Social capital theory	0	1
Task-technology fit	1	1
Technology affordances and constraints theory	1	1
Trust theory	0	1
Value-attitude-behaviour	1	1
Value-based adoption model	0	1
Total interpretive structural modelling	0	1

Table A4.
Model distribution count

Appendix 7

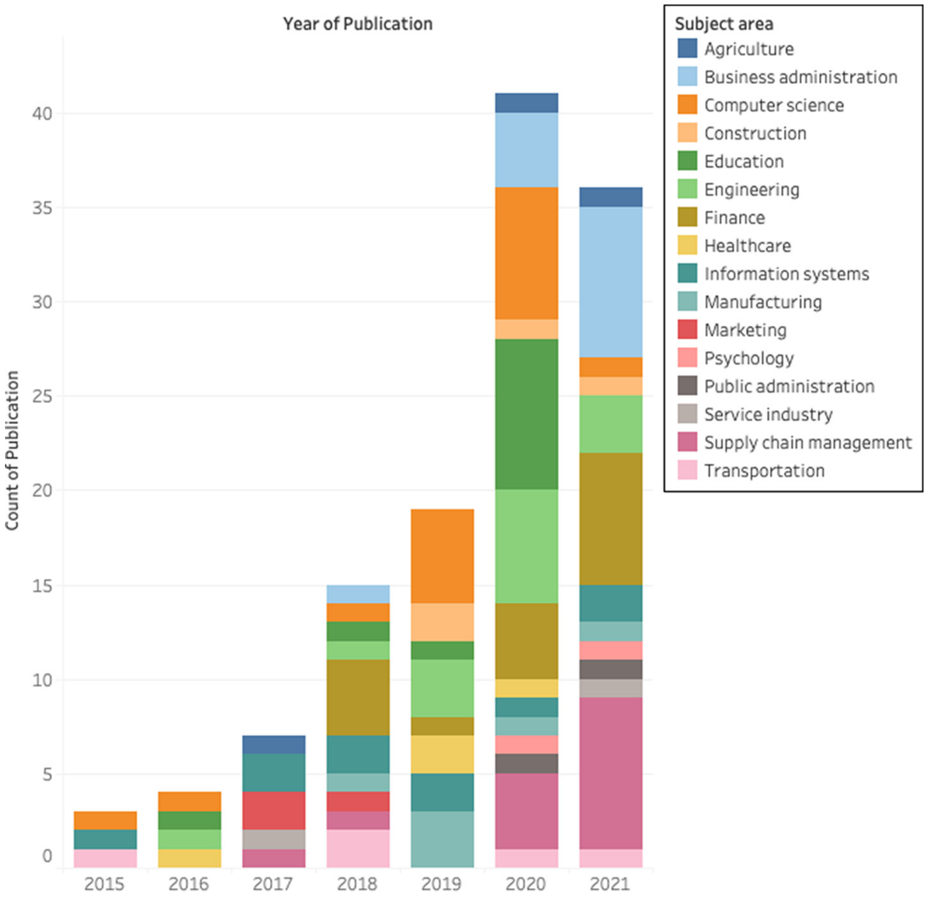


Figure A3. Subject distribution between 2015 and 2021 per publication count

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