Discovering IoT Implications in Business and Management: A Computational Thematic Analysis

Abstract

IoT as a disruptive technology is contributing toward ground-breaking experiences in contemporary enterprises and in our daily life. Rapidly changing business environment and phenomenally evolving technology enhancement necessitate a robust understanding of IoT implications from business and management perspective. The current study benefits from an explanatory sequential mixed-method approach to represent and interpret the inductive topical framework of IoT literature in business and management with emphasis on business model. Bayesian statistical topic model called latent Dirichlet allocation is employed to conduct a comprehensive analysis of 347 related scholarly articles to reveal the topical composition of related research. Further, we followed a thematic analysis for interpreting the extracted topics and gaining in-depth qualitative insights. Theoretical implications with emphasizing on research agenda for future study avenues and managerial implications based on influential themes are provided.

Keywords: Internet of Things; Topic modelling; Business model; Thematic analysis; Business and management; Future research

1. Introduction

Internet of Things (IoT) has flourished over the last decade as a new wave of digital transformation, which enables real-time sensing, collecting and sharing data. The unique features of IoT like ubiquity have enabled the possibility of developing advanced applications across many domains. The momentum IoT has generated makes it an ideal frontier for driving technological innovation (Siow et al., 2018), garnering significant attention from both practitioners and scholars. IoT is perceived as a disruptive innovation given its potentiality to truly reshape our world (Manyika et al., 2013). Pervasive applications of IoT are dramatically transforming many aspects of societies and economies such as healthcare (Pang et al., 2015; Tuan et al., 2019), transportation (Davidsson et al., 2016), logistic (Hopkins & Hawking, 2018), manufacturing (Birkel et al., 2019; Hasselblatt et al., 2018), and tourism (Byun et al., 2017; Gretzel et al., 2015). It is estimated that the IoT market size will reach $1.2 Trillion worldwide by 2022 (IDC, 2018). However, IoT's extensive publicity and promising future do not guarantee its widespread success, since many concerns and potential issues of gaining actual value of IoT are not yet fully known (Nicolescu et al. 2018). IoT mass adoption and actualizing its values depend not only on technological advances but more on understanding its business and managerial needs and challenges. Porter and Heppelmann (2014) maintain that we need to identify the dynamics of IoT technologies from business and management perspective to survive and gain competitive advantage during the technological transformations.

The diffusion trend of IoT leads to a call for studies to advance our understanding of research on managerial and entrepreneurial opportunities of this disruptive innovation (Clarysse et al., 2019). Despite exponentially expanding opportunities arising from IoT and ever-growing attention it attracts among scholars, practitioners, and the general public, a critical literature review indicates the lack of systematic and rigorous study on the business and management perspective of this technology. Mostly, the extant literature has taken a narrow view to discuss specific aspects of IoT business and management such as generating value from IoT data (Hajiheydari et al., 2019), concentrating on IoT applications in servitization (Rymaszewska et al., 2017), or providing a descriptive business model for IoT (Dijkman et al., 2015). This gap highlights the need for an integrative study that considers the current body of knowledge to connect the disciplinary perspective and insight around IoT studies with business and management identity.

There are several grounds that signify examining IoT from the business and management lens is both timely and essential. First, the ever-increasing growth of investment, the predicted market size (IDC, 2018), and the continuous introduction of pervasive applications (Forbes, 2019) necessitate understanding of IoT business implications. Further, calls continue for the 'Managerial and Entrepreneurial Opportunities and Challenges of IoT', principally based on the role of this disruptive technology in generating new venture opportunities, shifting the nature of competition, and eroding the traditional business models (Clarysse et al., 2019). Finally, due to growing expansion of IoT applications and related publications, researchers suggest quantitatively examining the related literature (Lu et al., 2018), to explore the hidden thematic structure of IoT research (Yoon et al., 2018), and IoT issues associated with managerial and organizational areas and theories (Mishra et al., 2016).

Previous studies have mainly focused on '*general IoT research domain*'. By applying either quantitative or qualitative methods, researchers attempted to examine the generic IoT knowledge field and objectively or subjectively analyse the literature. Co-word analysis (Kim & Kang, 2018; Yan et al., 2015), co-citation analysis (Ng et al., 2018), bibliometrics (Mishra et al., 2016), and scientometrics approaches (Erfanmanesh & Abrizah, 2018) are some of quantitative methods have been used to explore IoT research domain. On the other stream, qualitative and mainly literature review approaches have been followed to examine the IoT study domain (e.g., Atzori et al., 2010; Li et al., 2015; Siow et al., 2018; Lu et al., 2018). It thus appears that scholarly attempt with direct focus on uncovering the intellectual structure of IoT literature from the business and management perspective is largely disregarded. This study contributes to advancing the current discourse on IoT in particular considering business and management issues more holistically, by integrating, representing and synthesizing current knowledge through an innovative methodological approach.

The main goal of this systematic and rigorous research is to map and link the knowledge landscape of IoT in business and management domains. To this aim, the present study seeks to: (i) extract the inductive topical framework to portray the IoT research field in business and management, and more specifically for the highly focal domain of 'business model'; (ii) analyse and explain the main business and management latent themes and sub-themes in the research field of IoT; and (iii) highlight the trend of business and management studies in the IoT field to detect novelty and emergence. To address these objectives, we analysed the corpus of IoT research in the business and management disciplines applying an explanatory sequential mixed-method approach. This study thereby provides three key contributions. First, it drives and presents phenomenon-based constructs and grounded conceptual relationships in the IoT literature on business and management. Second, we explore and discuss the related latent subjects of these constructs and their relationships, with special attention to the business model theme. Finally, we provide theoretical contribution by proposing research agenda for future study avenues in this context, based on the identified thematic map.

2. Research Method

As quantitative and qualitative methodological approaches both have certain weaknesses (Gioia et al., 2013), researchers have called for new methods to examine organizational phenomena (Taras et al., 2009). Some propose combining them to take the advantages of both methods, addressing their limitations, and overcoming the trade-off between performing large-scale quantitative analytics and gaining in-depth qualitative insights (Creswell & Clark, 2011, p. 17; Schmiedel et al., 2018). Thereby, we use a novel algorithm-assisted inductive approach as a mixed-method study wherein: (a) topic modelling as a computational method uncovers the topical composition of IoT research in the business and management fields and (b) thematic analysis as a qualitative method enables us to thoroughly analyse and interpret the extracted topics. Recently, the interest for synergistically joining the strengths of computational modelling and the capabilities of qualitative methods for obtaining robust and interpretable results has increased among researchers (e.g. Eickhoff & Wieneke, 2018; He et al., 2020; Rai, 2016; Tidhar & Eisenhardt, 2020). In our novel mixed-methods design, we followed "explanatory sequential mixed-method" procedure proposed by Creswell and Clark (2011), because of the need for further understanding of quantitative results in detail through a follow up qualitative thematic analysis. As shown in Figure 1, we conducted this study in four stages, the details of which are discussed in the following sections.

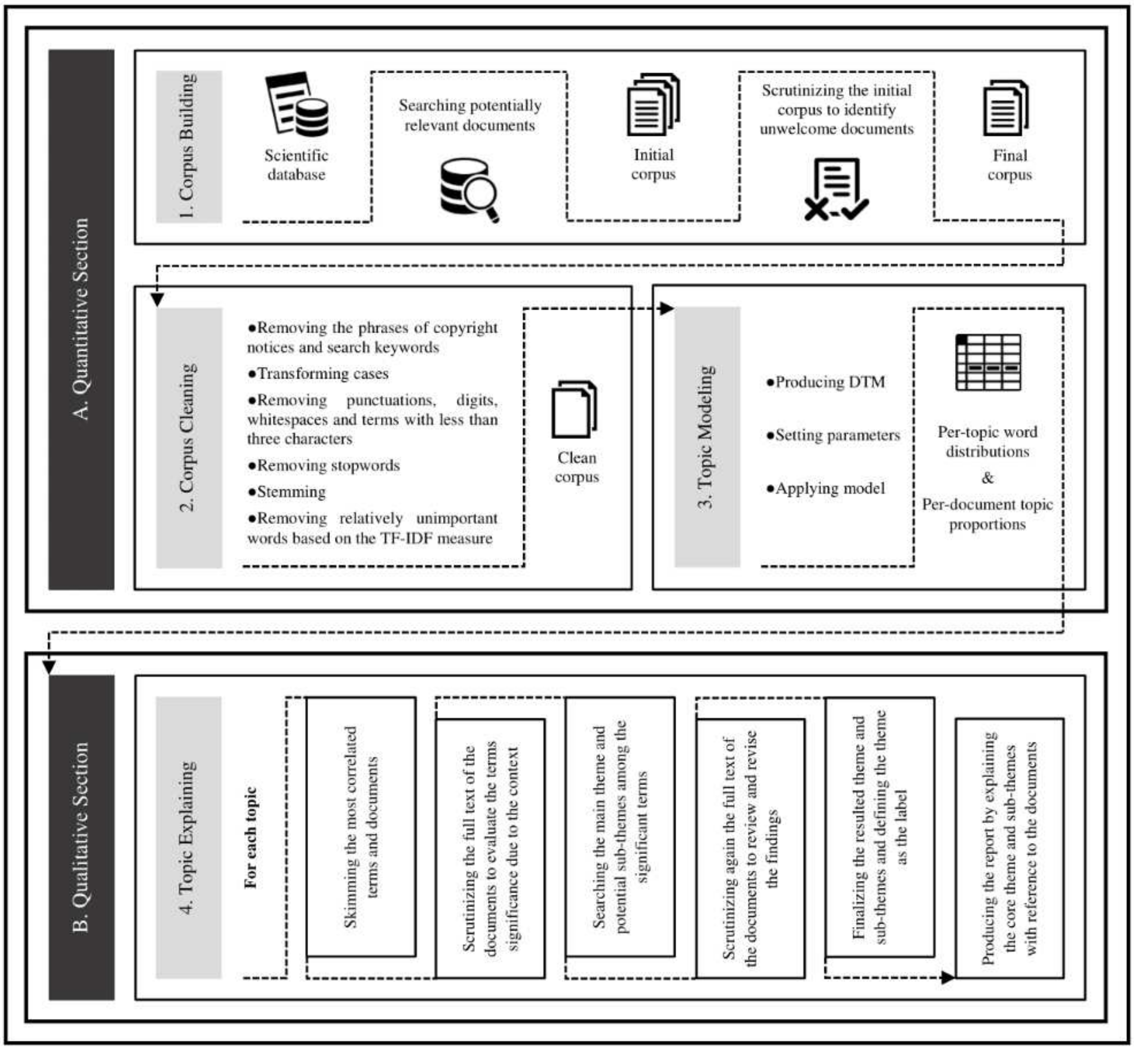


Figure 1. Main phases and their respective key steps in the research process

2.1. Corpus Building

We began our study by searching within Thomson Reuters' Web of Science (WoS) core collection to identify the corpus of IoT research in the business and management fields. On 5 May 2019, we retrieved all English papers containing either "Internet of Things" or "IoT" term in the title, abstract, or keywords and also were indexed in the business or management WoS subject categories. To include only validated and verified knowledge, we removed document types other than journal papers. The search process resulted in 412 research papers as the initial dataset. However, a closer look at these results revealed that there were some papers without desired relevance to the research issue, due to the logic of WoS in assigning a journal's documents to predefined subject categories (WoS, 2019). To eliminate irrelevant documents, first, each of the authors independently scrutinized the title, abstract, and keywords of the resulted records. Then, they reviewed the full text in cases of doubt and discussed together in cases of disagreement to reach a consensus and ensure the validity of the research corpus. Eventually, 347 journal articles dated from 2010 to 2019 were retained as the ultimate dataset. Since the abstract of a research article is the best possible distillation of its main points, we used this textual attribute of the final papers to build the intended corpus.

2.2. Corpus Cleaning

To perform the pre-processing, first, we removed the phrases of copyright notices, such as '(C) 2019 Elsevier B.V. All rights reserved.' which normally appears at the end of abstracts. We also dropped the core keywords (i.e., "Internet of Things" and IoT) and stopwords by using NLTK (Loper & Bird, 2002) to avoid jeopardizing the cohesion of results. All characters were transformed into the lower-case; the corpus was stripped from the punctuations, digits, whitespaces, and terms with less than three characters. Finally, we used the Term Frequency-Inverse Document Frequency (TF-IDF) measure, as one of the best term weighting approaches (Salton & Buckley, 1988), to value the stemmed words in the corpus and identify relatively insignificant ones to be removed (Weiss et al., 2015, p. 25). As suggested by Jiang et al. (2016), we calculated the TF-IDF score for each word over all documents in the corpus (Equation 1) and then, following the recommendations of best practices for text pre-processing (e.g., Antons & Breidbach, 2018), we removed the terms with scores less than the median of all TF-IDF values. The corpus, thus, was stripped from the less relevant words without enough discriminatory power to characterize the text. In Equation 1, f_{ij} is the frequency of the i^{th} term in the j^{th} document, F_j is the number of terms in the j^{th} document, N is the total number of documents, and n_i is the number of documents that contain the i^{th} term. Except the first two steps, we used Python 3.6.0 to clean the corpus.

$$\text{TF-IDF}_i = \sum_{j=1}^{N}\left(TF_{ij}\right) * \left(IDF_i\right) = \sum_{j=1}^{N}\left(\frac{f_{ij}}{F_j}\right) * \left(log\,\frac{N}{n_i}\right) \qquad \text{Equation 1}$$

2.2. Topic Modelling

Lately, computerized text analyses have introduced as a viable quantitative techniques (Pandey & Pandey, 2019), which can provide new insights to the management and organizational research. Topic modelling, with some remarkable algorithmic and practical benefits, is one of such analyses that is well-used to divulge phenomenon-based constructs and grounded conceptual relationships in corpora. Topic models are a set of statistical algorithms that analyse the words of a textual collection to generate a representation of the latent topics discussed therein and thus organize and summarize the collection (Blei, 2012). Through the topic modelling, researchers seek to render the corpus (i.e., 'juxtaposing data and concept' and

‘categorizing data’) to inductively extract theoretical artefacts as multidimensional constructs (Charmaz, 2014; Hannigan et al., 2019) and inductively study the phenomenon based on large empirical samples (Tonidandel et al., 2018).
In this study for topic modelling, we used Latent Dirichlet Allocation (LDA) developed by Blei et al. (2003), and now is the most common topic modelling method (Jelodar et al., 2019). The LDA is a generative probabilistic model conceptualizes corpus as made up of a limited number of salient topics, each of which is a probability distribution over a fixed vocabulary of words (Blei et al., 2003). It technically assumes each document has a distribution over the topics and for each word in the document, a topic is chosen from the topics distribution (Blei, 2012). By building a joint probability distribution over both the observed data and hidden variables (Equation 2), the LDA model computes the conditional probability distribution of the latent topic structure variables (Equation 3) (Blei, 2012). We estimated the model using Gibbs sampling (Griffiths & Steyvers, 2004) as a common Markov chain Monte Carlo algorithm. In Equations 2,3; β_k represents a topic that is a distribution over the vocabulary (the per-topic word distribution), θ_d represent the topic proportions for the d^{th} document, in which $\theta_{d,k}$ is the topic proportion for the k^{th} topic in document d (the per-document topic proportion), z_d represent the topic assignments for the d^{th} document, in which $z_{d,n}$ is the topic assignment for the n^{th} word in document d (the per-word topic assignment), w_d represent the observed words for the d^{th} document, in which $w_{d,n}$ is the n^{th} observed word in document d, K represents the number of topics, D represents the number of documents in the corpus, and N is the number of words in the vocabulary (Blei, 2012).

$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D,1:N}, w_{1:D,1:N}) = \prod_{k=1}^{K} p(\beta_k) \prod_{d=1}^{D} p(\theta_d) \left(\prod_{n=1}^{N} p(z_{d,n}|\theta_d) p(w_{d,n}|\beta_{1:K}, z_{d,n})\right) \quad \text{Equation 2}$$
$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D,1:N} | w_{1:D,1:N}) = p(\beta_{1:K}, \theta_{1:D}, z_{1:D,1:N}, w_{1:D,1:N}) / p(w_{1:D,1:N}) \quad \text{Equation 3}$$

To run LDA, first, we used the CountVectorizer class provided by the highly popular scikit-learn library (Pedregosa et al., 2011) to convert the corpus into a Document-Term Matrix (DTM) as the model’s input. An element in the DTM represent a term frequency in the corresponding document. Then, we used lda package[1], developed based on the collapsed Gibbs sampling, to implement the LDA model. The results show per-topic word distributions and per-document topic proportions, which represents the topic structure of the corpus. In addition, we used pyLDAvis package (Karpovich et al., 2017), to visualize the topic map and find the inter-topic distances based on the Multi-Dimensional Scaling (MDS) (Cox & Cox, 2000). In order to tune the LDA model parameters, as there is no widely accepted method, we used four different data-driven approach suggested by Griffiths and Steyvers (2004); Cao et al. (2009); Arun et al. (2010); and Deveaud et al. (2014) (please see Appendix A for details of the analysis). The results of this analysis showed that 10 topics best illustrate the latent structure of IoT business and management related research. Furthermore, we applied cross-validation method with 10-fold to check the sensitivity of parameters. The analysis indicated that results of LDA with 10 topics were acceptable in terms of perplexity and log-likelihood (please see Appendix A).

2.4. Topic Explaining

After uncovering the topical structure hidden in a corpus, scholars propose various quantitative and qualitative methods for finding semantic meaning and interpretations in inferred topics (e.g., Marchetti and Puranam, 2020; Schmiedel et al., 2018). For instance, Chang et al. (2009)

[1] http://pythonhosted.org/lda/

suggest two quantitative measures to evaluate the latent space of topic models, that is *word intrusion* to assess whether a topic has human-identifiable semantic coherence, and *topic intrusion* to assess whether the association between a document and a topic makes sense. In another study, Sievert and Shirley (2014) introduced the *relevance* metric that enables flexibly ranking terms according to their usefulness for interpreting topics. Reviewing the extant literature for qualitatively analysing and interpreting topic modelling results indicates that the most common approach is building a list of words with the deepest linkage to each topic and using these words for labelling and interpreting the topics. However, the recent work in this area suggests more intuitive methods. For instance, Marchetti and Puranam (2020) proposed 'prototypical-text based interpretation (PTBI)' methodology for enhancing replicability and interpretability of topic modelling results. The central tenet of this approach is to show some selected prototypical texts associated with each topic to the readers, thereby they can interpret the topics by themselves. While this approach improves the transparency and replicability of topic modelling results, Marchetti and Puranam (2020) stress that PTBI is viable when documents do not refer to multiple topics simultaneously and the average length of them in the corpus is relatively low —for avoid fatigue in the readers.

As the documents in the corpus of this study are comparatively long (around 208 words) and mainly related to multiple themes, to firmly analyse and interpret the extracted topics in rich detail, we applied the thematic analysis (TA) to systematically identify, organize and describe patterns in our dataset (Braun & Clarke, 2006). In this method, a theme refers to some important concepts concerning the research questions that reflects some level of a patterned meaning within the set of data (Braun & Clarke, 2006). The main reasons for using the TA are its accessibility and flexibility that may overcome the methodological challenges (e.g., vagueness, mystique, and complexity) of other methods in recognizing what a topic has been exactly written about (Braun & Clarke, 2012). We used TA method for detailed textual analysis to identify, describe, and report topics found through topic modelling. Following the TA steps suggested by Braun and Clarke (2006) , we first skimmed the most correlated terms and documents for familiarizing ourselves with the data in each identified topic[2]. Second, we took into account each term in a topic as an initial generated code. Therefore, we examined the full text of the documents to evaluate the significance level of the codes in the topic's context. We, thus, identified the most meaningful and relevant terms in each topic, and ignored the irrelevant ones. Third, we searched the main theme and potential sub-themes among the retained terms in each topic. Forth, we reviewed the full and coded data as well as themes to revise the findings of the previous step. In the fifth step, the resulted theme and sub-themes were finalized for each topic. We then assigned names to the themes and defined them as labels of the corresponding topic based on the words and documents that were highly associated with each topic (Schmiedel et al., 2018). Finally, we precisely explained each topic based on the core theme and sub-themes regarding the documents to produce the topic modelling report. Table 1 summarizes the activates, sample of inputs and outputs in each phase of our TA process. To ensure the validity of the TA results, the steps 1 to 5 were conducted by each author independently, and the findings were cross-checked to solve conflicts and reach consensus. In addition, the applying TA as a systematic method and closely following its steps assist us to improve the reliability of our findings.

[2] In this step, the most correlated terms and documents were identified based on a cutoff number of terms in the per-topic word distributions and a threshold weight of topics in the per-document topic proportions.

Furthermore, in order to robustly discover the latent structure of IoT business model, we repeated topic modelling for it as our dominant theme. In doing so, we reran LDA procedure to the most relevant, correlated documents to this topic, and quantitatively extracted the sub-topics to reveal the intellectual structure of IoT enabled business model as a topic with high attraction.

Table 1. Highlights of our TA process

Phases of Thematic Analysis	Summary of activities	Example of inputs	Example of outputs
Phase 1: Familiarizing yourself with your data	Identifying valid sources Collecting and skimming documents Building the corpus Cleaning the corpus	WoS core collection Dataset containing 347 journal papers	Prepared corpus
Phase 2: Generating initial codes	Debriefing peers Sensitivity analysis and selecting number of topics Running the LDA Extracting the codes (terms) distributions for each topic Selecting the most relevant and meaningful codes based on documents	Document term matrix Results of sensitivity of analysis (Appendix A) Term distributions Topic distributions	Finalized list of most probable terms in each topic (Table 3)
Phase 3: Searching for themes	Coding and collating the data in the corpus Reviewing coded data to identify themes Diagramming to make sense of themes in the corpus Inductively (data driven) identifying potential themes and subthemes Exploring relationships between themes Triangulating researchers to cross-check	Initial coded data Potential themes and subthemes Global view of topics	List of candidate themes and subthemes Collated data relevant to each theme
Phase 4: Reviewing themes	Reviewing entire corpus and coded data Testing for referential adequacy by returning to collated data Triangulating researchers to cross-check	Set of themes and subthemes	Refined list of themes and subthemes
Phase 5: Defining and naming themes	Clearly defining and specifying themes and subthemes Documenting the focus, scope, and purpose of themes and subthemes Identifying the story that each theme tells Triangulating researchers to cross-check	Global and collated data Reviewed and discussed data related to the themes and subthemes	Named and defined themes and subthemes Deep analytics of each theme and subthemes (T1-T10)
Phase 6: Producing the report	Describing process of topic modeling and analysis of topics Thick descriptions of context Report on reasons for theoretical, methodological, and analytical choices throughout the entire study Provide a compelling story about data based on the analysis.	Fully established themes and subthemes Detailed analysis of themes	Final analysis Topic distribution over time (Figure 3, 4) Report about interesting data within and across themes (Figure 5,6)

3. Results

Figure 2 presents the global view of the topic model on IoT business and management research area. This view visualizes the output of topic modelling, wherein circles represent topics in a two-dimensional plane. Areas of the circles are proportional to the relative prevalence of the topics in the corpus. The centres of circles are estimated by calculating the distance between topics and further projected onto a two dimensions space by using multidimensional scaling to reflect the inter-topic distances (Chuang et al., 2012; Sievert & Shirley, 2014). This visualization seeks to depict answers to two questions: (a) 'How prevalent is each topic?', and (b) 'How do topics relate to each other?' (Sievert & Shirley, 2014, p. 63). As shown in Figure 2, topics 10, 8, 2 are the most extensive research areas in 10-topic model fitted with 20, 15, 14 percent of the corpus, respectively. Further, it is clear from the global view that T10 has high overlap of research topics with T8 and T3. In contrast, T2, T4 and T5 are complete exclusive topics that have distinct term distributions.

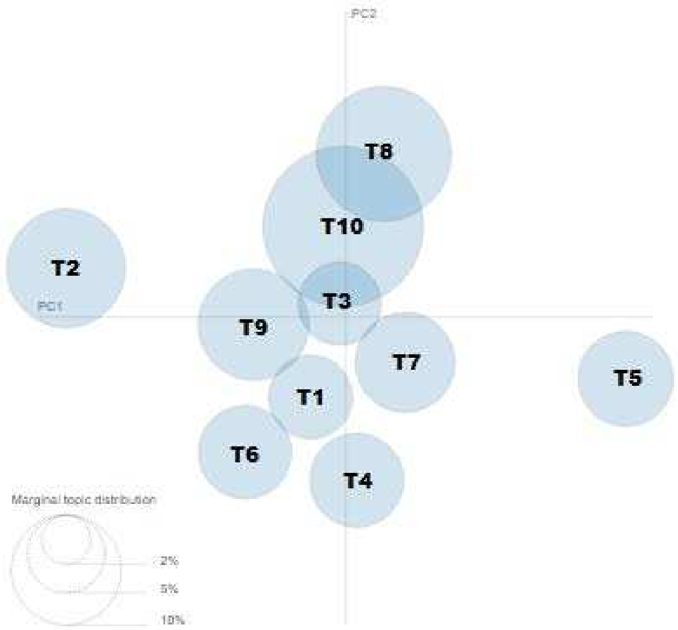


Figure 2. Global view of the IoT business and management research domain

Table 2. Number of articles and citations in each topic

ID	No. of articles	% of articles	No. of citations	% of citations	Dominant research theme
T1	18	5	70	2	Customer Experience
T2	50	14	665	21	IoT as an Emerging Technology
T3	22	6	447	14	IoT in Supply Chain
T4	25	7	213	7	Smart Living
T5	20	6	83	3	IoT and Servitization
T6	28	8	129	4	IoT in Product Management
T7	29	8	257	8	IoT Optimization
T8	53	15	594	19	Smart Manufacturing
T9	30	9	169	5	IoT and Big Data
T10	72	21	525	17	IoT-enabled Business Model
Total	347	100	3152	100	

The articles in the corpus were classified according to the subsequent probability of their belonging to each topic. Table 2 shows that the topic with the most articles is T10: *IoT-enabled Business Model* (72 articles), the second topic is T8: *Smart Manufacturing* (53 articles), and the third most prevalent topic discusses T2: *IoT as an Emerging Technology* (50 articles). In total, these three topics comprise 50% of the articles in the corpus. As shown in Table 2 from the total of 3152 references, T2: *IoT as an Emerging Technology*, T8: *Smart Manufacturing*, and T10: *IoT-enabled Business Model* together contain 57% of citations, indicating that these topics are in the focal point of researchers' attention.

Table 3 presents the 10 identified topics after labelling based on the dominant research theme within each topic. In addition, we introduced the three important journals with high impact factors and a list of the top three papers correlated with each topic.

Table 3. Identified topics in the IoT business and management research domain

Label	Most probable terms	Top journals	Most correlated articles
T1. Customer Experience	consum, use, technolog, smart, perceiv, experi, object, model, risk, adopt	Journal of the Academy of Marketing Science Technological Forecasting and Social Change Journal of Product Innovation Management	Novak and Hoffman (2019) Shin et al. (2018) Mani and Chouk (2018)
T2. IoT as an Emerging Technology	technolog, industri, new, emerg, manufactur, futur, digit, challeng, potenti, chang	MIS Quarterly Annals of Operations Research Production and Operations Management	Monteiro and Parmiggiani (2019) de Sousa Jabbour et al. (2018) Kumar et al. (2018)
T3. IoT in Supply Chain	chain, suppli, rfid, retail, data, custom, adopt, manag, logist, inventori	International Journal of Physical Distribution & Logistics Management International Journal of Production Economics Decision Support Systems	Papert et al. (2016) Fan et al. (2015) Geerts and O'Leary (2014)
T4. Smart Living	smart, system, use, citi, healthcar, context, devic, intellig, user, commun	Technological Forecasting and Social Change Expert Systems with Applications IEEE Systems Journal	Escolar et al. (2019) Lee et al. (2017) Santos et al. (2016)
T5. IoT and Servitization	servic, model, busi, user, custom, develop, product, web, social, connect	International Journal of Production Research IEEE Systems Journal Research-Technology Management	Moghaddam and Nof (2018) Temglit et al. (2017) Heinis et al. (2018)
T6. IoT in Product Management	product, decis, logist, system, time, cost, order, strategi, life, mainten	International Journal of Production Economics European Journal of Operational Research Reliability Engineering & System Safety	Joshi and Gupta (2019) Yang et al. (2019) Li et al. (2019)
T7. IoT Optimization	network, secur, devic, sensor, algorithm, wireless, machin, node, optim, power	IEEE Systems Journal Reliability Engineering & System Safety Computers & Operations Research	Hu et al. (2014) Park (2017) Fadda et al. (2018)
T8. Smart Manufacturing	system, manufactur, product, industri, process, time, applic, manag, smart, integr	International Journal of Production Economics Journal of Manufacturing Systems International Journal of Production Research	Reaidy et al. (2015) Mourtzis and Vlachou (2018) Kusiak (2018)
T9. IoT and Big Data	data, method, collect, process, energi, big, predict, model, analyt, applic	International Journal of Computer Integrated Manufacturing Decision Support Systems Information & Management	W. Wang et al. (2018) Baecke and Bocca (2017) Townsend et al. (2018)
T10. IoT-enabled Business Model	busi, valu, innov, model, compani, industri, design, firm, strategi, resourc	Technological Forecasting and Social Change Technovation Research Policy	Metallo et al. (2018) Kiel et al. (2017a) Kim et al. (2017)

3.1. Topics Distribution over Time

After exploring the hidden topics in the corpus, we examined their distribution over time. In so doing, we followed Sun and Yin (2017) and used Equation 4 to find the temporal trend of topic structure:

$$\theta_k^{[t]} = \frac{\sum_{d=1}^{M} \theta_{dk} \times \mathbb{I}\,(t_d = t)}{\sum_{d=1}^{M} \mathbb{I}\,(t_d = t)} \qquad \text{Equation 4}$$

where $\theta^{[t]}$ represent the topic distribution at time *t* for all documents, $\theta_k^{[t]}$ is the proportion of topic *k* at time *t*, and $\mathbb{I}\ (t_d = t)$ is an indicator function where return 1 if predicate $(t_d = t)$ is true and 0 otherwise.

Figure 3 shows the proportion of all the 10 topics from 2010 to 2019, in order (i.e., T1 to T10) from the bottom to the top. As the areas dedicated to each topic in Figure 3 demonstrate, the most popular five topics are T10: *IoT-enabled Business Model*, T8: *Smart Manufacturing*, T3: *IoT in Supply Chain*, T2: *IoT as an Emerging Technology*, and T5: *IoT and Servitization*.

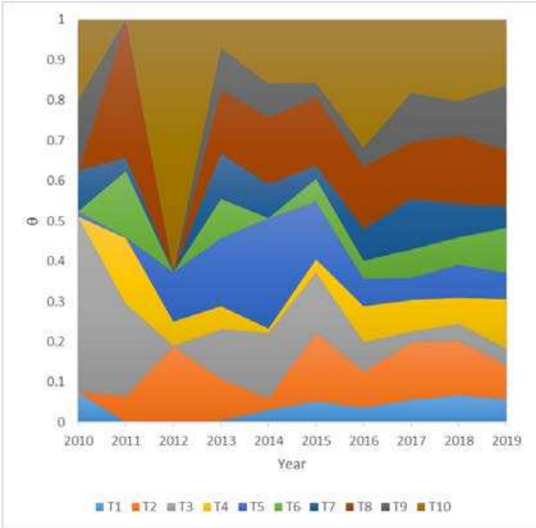
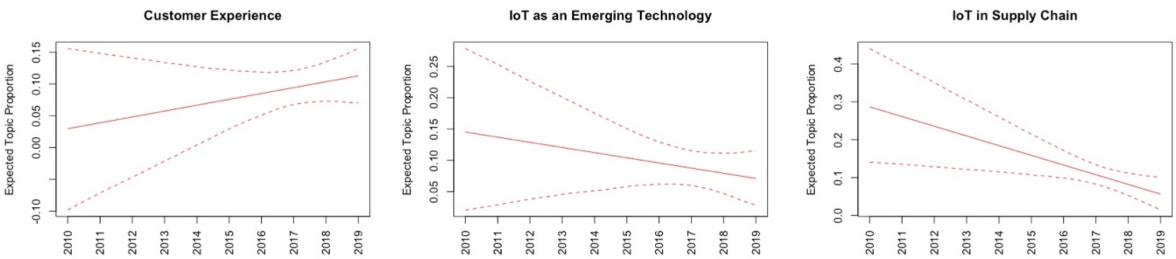


Figure 3. Topic distribution over time

Furthermore, we used the structural topic model (STM[3]) package in R to examine topics prevalence over time. Topic prevalence refers to how much of a document is associated with a topic (Roberts et al. 2019), thereby we can analyse the frequencies with which different topics appear across documents and how topics' prevalence has changed during the time. STM provides a more robust approach for analysing temporal distributions of topics since it uses regression models to predict topic prevalence by covariates (here year), rather than applying a global mean. Figure 4 presents a closer look at the temporal trends of topics. In this figure it is visible that some topics have been declining over last years, such as T2: *IoT as an Emerging Technology*, T3: *IoT in Supply Chain*, T5: *IoT and Servitization*, and T10: *IoT-enabled Business Model* (cold topics), and some of them have an upward trend, like T1: *Customer Experience*, T6: *IoT in Product Management*, T7: *IoT optimization*, T8: *Smart Manufacturing*, and T9: *IoT and Big Data*, (hot topics). Also, T4: *Smart Living* has a steady movement over time and cannot be deemed as a cold/hot topic.



3 http://structuraltopicmodel.com/

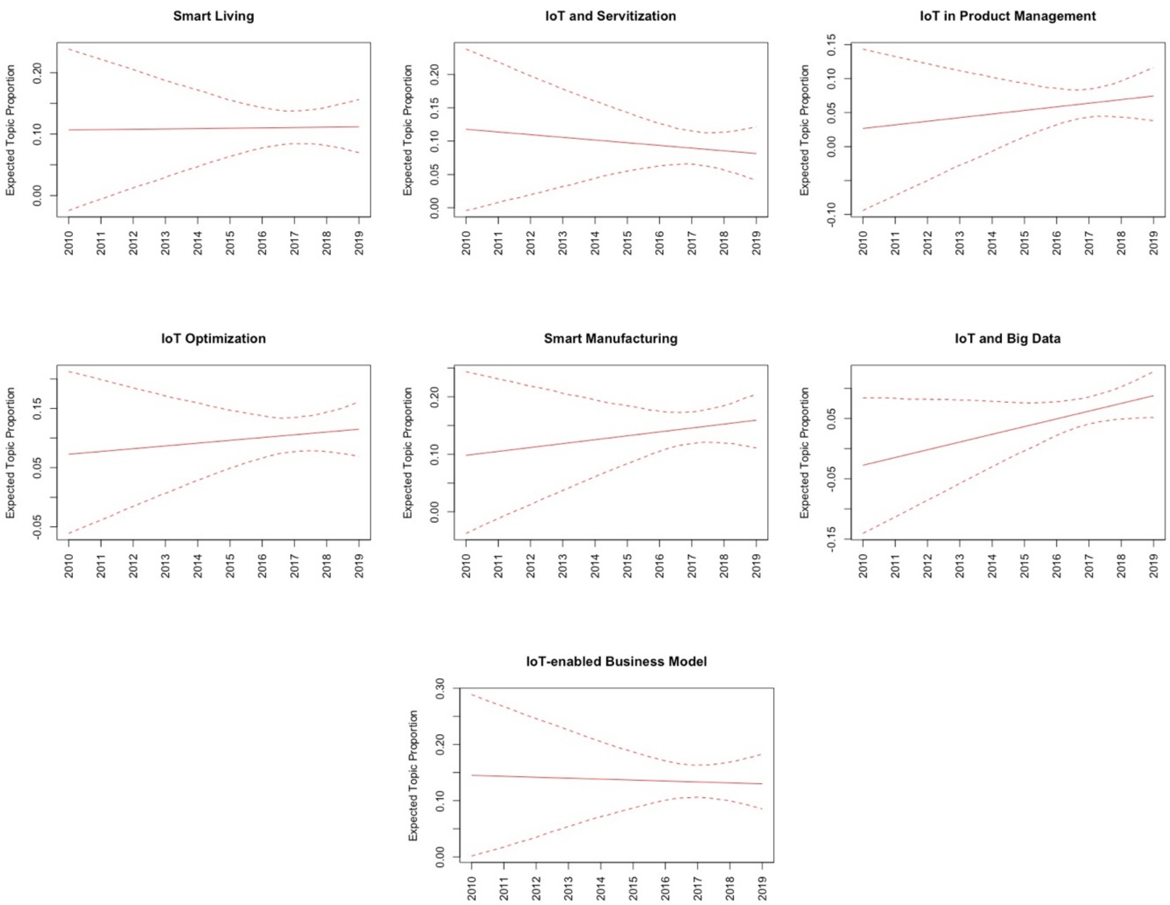


Figure 4. Prevalence of 10 topics over time

3.2. Topic Discussion

T1. Customer Experience

This theme aggregates studies that investigate different customer behaviours in relation with various IoT technologies. IoT technologies are extensively used in several areas, and inquiries about how these technologies can be adopted, used, or interacted by customers have attracted many researchers. Generally, these studies have contributed to understanding the rationale behind customer decisions that shape the lifecycle of IoT technologies, including adoption, usage, and termination. Moreover, given the unique features of IoT, particularly its smart interactivity capability, recent IoT literature have shifted their attention from objects to interactions, from technical characteristics to relational ones (Pauget & Dammak, 2019).

IoT Adoption

To investigate customers adoption of IoT, some researchers have used a specific theory or an extension of it, such as the Technology Acceptance Model (TAM) (Shin et al., 2018) or the Unified Theory of Acceptance and Use of Technology (UTAUT) (Chong et al., 2015). Others combined different theories, such as the Theory of Reasoned Action (TRA) and the Theory of Planned Behaviour (TPB) (Shin, 2017), TAM with Task-Technology Fit (TTF) (Chen, 2019), TAM with TRA and TPB (Mital et al., 2018), TAM and Innovation Diffusion Theory (IDT) (Jayashankar et al., 2018), or TAM with technology readiness perspective and organizational theory (Roy et al., 2018). In contrast, Mani and Chouk (2017) have deployed their self-developed model comprising various influential constructs.

Typically, IoT adoption studies have featured both descriptive and exploratory investigations and examined the impact of various determinants using different adoption theories and models. Three main constructs, 'attitude', 'intention', and 'behaviour' towards IoT are considered as the dependent variables. Majority of these studies have considered 'perceived ease of use' as the most influential antecedent, and the other TAM variable 'perceived usefulness' is mentioned as the other important predictor (Chen, 2019; Mital et al., 2018; Roy et al., 2018). Compatibility (Shin et al., 2018), superior functionality (Roy et al., 2018), subjective norm (Mital et al., 2018), big-5 personality traits (Chong et al., 2015), and trust (Harwood & Garry, 2017) are other reported influential factors.

Mani and Chouk (2018) studied resistance behaviour and attempted to explain why consumers are unwilling to accept new IoT services. They provided an integrative framework that combined functional, psychological, and individual barriers to explain consumers' resistance to smart services as an innovation. In a similar study, researchers found functional barriers caused by product characteristics (price, usefulness, novelty, and intrusiveness) and psychological inhibitors raised by consumer characteristics (dependence, self-efficacy, and privacy) are the main antecedents of consumer resistance to smart products (Mani & Chouk, 2017).

IoT Satisfaction and Usage

In addition to the adoption studies, the unsuccessful Google Glass case persuaded research on quality of experience, satisfaction, IoT technologies continuance and discontinuous (Canhoto & Arp, 2017; Shin, 2017; Touzani et al., 2018). Previous studies suggest various salient factors for IoT satisfaction and usage such as utilitarian, hedonic, and social values (Touzani et al., 2018), observability of activities in social media or online communities, technical infrastructure, user attitudes and goals in using IoT objects (Canhoto & Arp, 2017), coolness and affordance (Shin, 2017).

IoT Interaction

As the smart connected IoT objects are increasingly used in various contexts around us such as households, cars, offices, cities, etc, researchers have inclined toward studying their special emergent relationships with consumers. Prior work has examined three different kinds of IoT interactions including 'interaction between humans through IoT', 'human and object interaction', and 'interaction of smart objects'. As Sundar and Nass (2001) suggest, IoT distinctive capacities have provided unprecedented opportunities to improve our knowledge of relationships either between humans and objects or even between objects. Whereas, in the past, scholars merely perceived objects as passive entities that humans invest meaning in them, currently they take into account objects' active roles. In this novel view, smart objects endows with various degrees of agency, autonomy, and authority (Novak & Hoffman, 2019), and their unique capabilities in interaction with humans and with each other. IoT profoundly transforms human-machine interactions or interaction between humans and the literature is now more keen to embrace these new emergent relationships. In this manner, researchers have investigated human-object interactions in different domains, such as consumer IoT interactions (Novak & Hoffman, 2019; Roy et al., 2017; Verhoef et al., 2017), e-learning (Farhan et al., 2018), social interactions in mobile services (Qi et al., 2014), agriculture (Kitouni et al., 2018), monitoring road conditions (Laubis et al., 2019), and healthcare (Laplante et al., 2017). Given smart objects' capacities to affect and be affected, Hoffman and Novak (2017) believe traditional human-centric conceptualization is not sufficient. Thus, they raised a very important and foundational question: 'Is it time to consider expanding the boundaries of consumer behaviour from usual human-centric perspective to nonhuman-centric one?'. Similarly, Verhoef et al. (2017) introduced the POP-framework, discussing three types of connectivity: 'People-wise', 'Object-wise', and 'Physical-wise', which is not purely human-centric.

T2. IoT as an Emerging Technology

Many studies has introduced IoT as a disruptive technology with great potentiality for changing the existing industries and markets, and capability in unlocking new economic and market values (e.g. Kumar et al., 2018; Xu et al., 2018). IoT is bridging the physical and digital areas, assisting us in digitizing the physical world and turning physical attributes into digital data. IoT by providing a novel infrastructure for synthetic knowing to capture rich biographies of everything, digital materiality to add new functionalities to objects and expand capabilities of products to become smart and connected underpins a huge power for disruptive breaks in current industries and societies. Also, the new expanded automation, utilization, optimization, and personalization capabilities deriving from IoT are increasingly putting businesses under pressure to redefine how they operate (Fleishman, 2020).

Digital Knowing

Sensors expand the scope and reach of digital knowing by providing real-time rendering through seeing, hearing, tasting, smelling, and touching, they can thus increasingly mimic embodied perception. Monteiro and Parmiggiani (2019) proposed the notion of synthetic knowing to break up the dichotomy of physical versus digital and provide an integrated knowledge of both worlds. They argue that what we know as digital representations and how we know it are constituted by digitalisation. In this context, IoT has a transformational role, since sensors are currently vehicles for liquefaction (i.e., e decoupling of information from its related physical object) (Michel et al., 2008). IoT allows us to create rich repositories of current and historical data about the physical object properties, such as origin, ownership, physical specifications, and sensory context (Ng & Wakenshaw, 2017). IoT enables digital materiality of physical objects (Yoo et al., 2012) and can add new functionalities to them, like *sensibility, addressability, traceability, associability, communicability, programmability,* and *memorability* (Yoo et al., 2010).

Digitalized Industry

Industries are experiencing a revolution enabled by the employing innovative technological advancements in miniaturisation of equipment and network connectivity (Feng & Shanthikumar, 2018). Xu et al. (2018) suggest that we are at the edge of the fourth industrial revolution, wherein IoT plays a key role in this industrial revolution. IoT combines the global reach of the Internet with industrial capabilities to coordinate, manage, and control the physical world of goods, machines, infrastructures, and factories, such that can transform existing industries (Ng & Wakenshaw, 2017). Industrial companies by using IoT besides cyber-physical systems (CPS) and cloud computing would be able to employ novel solutions to develop, integrate, reconfigure, or even completely reengineer both their internal and external operations (Kim et al., 2012; Kumar et al., 2018). In addition to operations, IoT has transformed the notion of product. Integrating IoT with physical products could add two new features which radically change them: *smartness* and *connectedness* (Porter & Heppelmann, 2014). Such interconnected, intelligent, products create and collect huge amounts of data about their usage, context, recovery, and reuse (Kortuem et al., 2009). As a result, IoT opens up the opportunity of generating connected rich biographies of products and even expanding to its components and parts, which in turn enable achieving circular economy objectives (Spring & Araujo, 2017; de Sousa Jabbour et al. 2018).

Digitalized Involvement

As societies move towards the era of IoT, altering static, fragmented and immobile data into dynamic, integrated, and transferrable resource generate disruption. Ng and Wakenshaw (2017) assert that IoT boost liquefaction of digitalized data which eventually improves engagement with products and also with their states, interactions, and description. Firms acquire various important benefits from IoT, particularly by engaging their customers in value co-creation processes, not only marketing but all of their internal and external operations (Agrifoglio et al., 2017). IoT facilitates a higher degree of customization and automation of on-board operations, thus can nurture customer's involvement and participation (Agrifoglio et al., 2017).

T3. IoT in Supply Chain

Supply chain is one of the most visible areas that has profoundly benefited from IoT (Atzori et al., 2010; Lu et al., 2018). Enhancing operational efficiency and effectiveness of warehousing, transportation, and logistics through the sharing of information and physical assets, besides providing revenue opportunities are the main reasons for deploying IoT in supply chains (Lee et al., 2018; Qian et al., 2017). In the recent years, supply chain managers have recognized the importance of IoT in bringing visibility to their operations. Consequently, this promoted visibility streamlines processes, reduces uncertainties, and enables data-driven decision making based on insights produced by IoT real-time collected data.

Supply Chain Visibility

The IoT automatic identification and tracking capabilities improve the visibility and traceability of individual packages to entire containers throughout the entire supply chain (Geerts & O'Leary, 2014). IoT, as an enabler of end-to-end supply chain visibility, provides access to live data of every transaction and process within the supply chain. This greater visibility contributes to managing uncertainties, product quality, security, and process control, as well as optimization in many areas, such as manufacturing, transportation, distribution, retailing, and healthcare (Fan et al., 2015; Jie et al., 2015; Papert et al., 2016; Qian et al., 2017). Papert et al. (2016) argue that IoT can provide real-time data about identity, availability, position, and status quo as the different dimensions of visibility in supply chains. In fact, IoT with identifying, locating, sensing, communicating, and data storing functionalities overpasses current technologies, such as barcodes, data loggers, and data matrix codes for visibility purpose. Today, customers also expect visible and flexible delivery services, and supply chains can use IoT to provide real-time tracking and monitoring capabilities for them (Jie et al., 2015).

IoT Adoption in Supply Chain

Digital supply chain is the result of adopting IoT in supply chains and can be defined as the exchange of strategic and operative information among members of the supply chain to enhance collaboration and coordination. Higher flexibility in the production system, effective information sharing within supply chain members, focusing on core strengths, demand forecasting on point-of-sale, development of reliable suppliers, and logistics synchronization are the main success factors for IoT adoption in digital supply chains (Korpela et al., 2017).

However, three challenges are associated with IoT adoption: ‘technological’, ‘organizational’, and ‘resource availability’ (Haddud et al., 2017). Tu (2018) identified that perceived cost, perceived benefits, and external pressure have substantial influence on IoT adoption in supply chains, while concerns about the IoT reliability, its trustworthiness, and integration with other systems might undermine IoT adoption. Additionally, Hsu and Yeh (2017) suggest that environment, organization, and security dimensions are critical aspects need to be considered for IoT adoption in the logistics industry.

T4. Smart Living

‘Smartness’ is the result of combining and integrating various IoT technologies to sense, collect, interpret, and communicate data which allow monitoring, analysing, and reacting to real-world situations. IoT is transforming humans living by the means of ubiquitous hyper-connected objects that are present at any place, any time, and can communicate with anyone and any other thing (Escolar et al., 2019). In the recent past, scholars and practitioners have introduced various applications of smart living such as smart cities (Escolar et al., 2019; Marsal-Llacuna, 2018), smart homes (Lee et al., 2017), smart grids (Whitmore et al., 2015), smart transportation (Laubis et al., 2019), smart tourism (Almobaideen et al., 2017), and smart healthcare (Da Xu et al., 2014; Dimitrov, 2016; Vesselkov et al., 2018).

Smart Environment

Smart environment refers to a “physical world that is richly and invisibly interwoven with sensors, actuators, displays, and computational elements, embedded seamlessly in the everyday objects of our lives, and connected through a continuous network” (Weiser et al., 1999, p. 694). The main purpose of a smart environment which is extensively equipped with IoT is to automatically provide various services based on users’ activities and requirements (Lee et al., 2017). To become smart, an environment, like a city uses various computing technologies to make its critical infrastructure, services, and resources more interconnected and intelligent. Put simply, a smart environment attempts to offer its inhibitors the highest possible quality services. Achieving such objective requires an intensive usage of IoT, which can sense the world by themselves and implicitly work for citizens (Escolar et al., 2019). Atzori et al. (2010) suggest that IoT brings several benefits in optimizing traditional public services, such as surveillance and maintenance of public areas, transport and parking, preservation of cultural heritage, lighting, garbage collection, and education.

IoT in Daily Life

Various IoT devices equipped with different capabilities are weaved deeply into the fabric of everyday life with the potentiality to change people experiences. For instance, IoT technologies can connect and integrate to daily life objects, such as smartphones, sport devices, personal computers, and home appliances for the applications in home entertainment, security, healthcare, and fitness (Li et al., 2015). Combination of Intelligent Personal Assistants (IPAs) with IoT can provide a perfect personal assistant with the capabilities to act, manage, and interact continuously and autonomously with the environment. It may even suggest suitable solutions to problems that arise in humans’ daily life. IoT increases IPAs knowledge by learning the behaviour of their users through direct interactions with them, and other smart objects in the users’ environment (Santos et al., 2016).

IoT in Healthcare

The main issues in the healthcare industry are collecting and transmitting patient data, tracking medical equipment, and developing hospital and laboratory information systems (Rahmani et al., 2018). IoT has capabilities to resolve these problems and enable healthcare practitioners to provide smart services, such as patient addressing, monitoring of vital signs, position and posture monitoring, and optimization of patient flow in hospitals (Da Xu et al., 2014). Dimitrov (2016) suggests that IoT is be able to transform the healthcare industry by making it *personalized*, *participatory*, *predictive*, and *preventive*, which is referred to as ‘P4 medicine’. Due to the ‘ageing boom’, elderly management is a critical concern from both social and economic perspectives. Senior care is one of the fastest-growing applications of the IoT, because of its various functionalities and capabilities, such as body sensors and connected wearables (Pauget & Dammak, 2019). The effect of wearables on the healthcare industry is remarkably different from the other digital technologies. Most of the healthcare digital innovations have taken place on supply-side like hospitals, while emerging wearable devices enable the receivers of health services to manage their wellness and diseases by themselves (Vesselkov et al., 2018).

T5. IoT and Servitization

A growing body of IoT literature argue that the emergence of IoT technologies is blurring the conventional boundaries between manufacturing firms and service providers (e.g. Velamuri et al., 2013; Raddats et al., 2019). By employing IoT technologies, businesses can shift the type of value exchanges from selling products to providing services and establish completely new relationships with their customers and partners. The creation and delivery of IoT based integrated product-service solutions (PSS) offer novel business opportunities for firms to fulfil a broader range of customers’ demands. Integrating IoT into operations and products enable firms to achieve closer and better proximity to their customers and reshape their value chains by expanding the scope of their product–service offerings (Rymaszewska et al., 2017). Turning these new opportunities aroused from IoT integrated PSS into real-world business applications and their economic benefits is an important research theme (Moghaddam & Nof, 2018).

Benefits

Servitization is the process of shifting focus from selling products to providing integrated customers solutions thorough bundling services to the core physical products in search of higher returns and additional growth opportunities (Baines et al., 2009). Opresnik and Taisch, (2015) contend that servitization can be an extremely successful differentiation strategy and sustainable competitive advantage, particularly to avoid the commodity trap and price competition and to secure market share. Connectivity, agility, and decentralization are the main requirements of modern industrial systems and ‘servitization’ is one of the approaches for addressing these challenges (Moghaddam & Nof, 2018). Motivations for servitization can be classified into three general categories of ‘competitive’, ‘economic’, and ‘demand-based’ motivations (Raddats et al., 2019). Servitization through IoT contributes in establishing new relationships with customers, increasing their loyalty and product differentiation for meeting competitive motivations (Dachs et al., 2014), increasing revenue and makes stability and profitability as economic motivations (Raddats et al., 2019), and addressing more complex customers’ requirements for demand-based reasons (Gebauer et al., 2011).

Challenges

In the servitization approach, the true potential capability of services in an IoT environment is realised when bundling services into products leads to more powerful solutions with more sophisticated functionalities. Therefore, selecting the most appropriate combination of IoT-based services to optimize the entire quality of a PPS is a complex task. The response time, price, availability, reliability , trustworthy, and also the energy level of IoT devices are important properties of service quality (Temglit et al., 2017). Furthermore, the development of smart services for PPS raises the challenge of selecting the right configuration of technology, people, organization, and information (Maglio & Spohrer, 2013).

Developing innovative models for capturing value is another crucial challenge of moving to servitization. Servitization in an advanced level offers solutions as outcome-based contracts that charges the customer for the actual performance of a product (Visnjic et al., 2017). Thus, capturing value needs new pricing models that reflect the actual delivered value by the PSS. For this purpose, pay-per-use models are among the most commonly used pricing model (Baines & Shi, 2015), but they require establishing meaningful metrics for usage, like operating time, activity type, and material processed (Heinis et al., 2018).

T6. IoT in Product Management

As noted above, IoT technologies are changing many aspects of industries and societies; product management is no exception. Traditional product life cycles are linear chains of processes, manufacturers design, build and sell products and provide after-sale services. Nowadays, by using IoT technologies, the product life cycles have accelerated and even reversed themselves. Before the era of IoT, firms had to rely on customer feedback to learn what features were working and not working about their products, but with IoT, they can obtain an unprecedented level of feedback, in real-time. Modern product management depends on smart digital infrastructures that facilitate a smooth flow of data and establishing an integrated view of the product's data throughout its lifecycle. Overall, this theme joins the studies examining how IoT improves and transforms product management.

Product Life Management

Collecting real-time data in the product life cycle is essential for realizing green and sustainable manufacturing, yet it is very challenging (Zuo et al., 2018; Yang et al., 2019). IoT technologies are used for collecting real-time and dynamic data in the product entire life cycle. Studies in cold supply chain show that IoT provides information about the location, identity, ambient, quality of cargo, and other tracking information of perishable items and their environment (Bogataj et al., 2017; Yang et al., 2019). IoT technologies give the chance of adaptive controlling of ambient conditions like temperature, lighting, and humidity, even optimizing the routes and enhance fleet efficiency to reduce the wastes and save on fuel costs (Bogataj et al., 2017). Further, embedded IoT technologies allows firms to sense, monitor, and authorize transferring products among customers, therefore, they would even be able to economically participate in collaborative consumption and sharing markets (Weber, 2017).

Product End-Of-Life Management

During the last two decades, End-Of-Life (EOL) product management and reverse logistics have been hot research areas mainly due to the sustainability issues and governmental regulations (Alqahtani et al., 2019; Joshi & Gupta, 2019). The EOL product management is a difficult process and IoT plays a significant role in reducing the uncertainties and ambiguities related to the quantity, conditions, types, and remaining lives of the returned EOL products (Joshi & Gupta, 2019). Collected data from sensors embedded in products and RFID tags enables the determination of characteristics of products such as model number, warranty, customer information, sales date, critical failures, bill of materials, remaining life of the components, etc. (Joshi & Gupta, 2019; Li et al., 2019). Additionally, using embedded sensors and RFID tags in advanced manufacturing-to-order systems allows customers to define minimum quality demands and guarantees for their orders.

T7. IoT Optimization

Optimization is an important concern in developing IoT technologies and researchers point out several challenges affecting the quality and quantity of data collected, transmitted, and processed by IoT (Mukhopadhyay & Suryadevara, 2014). An important challenge in using IoT is the significant amount of resources required for flawlessly sensing, connecting, and computing data. Ensuring sensing coverage (Chen et al., 2014; Fadda et al., 2018; Gong et al., 2018), balancing the workload of sensors (Hu et al., 2014), high robustness and reliability of the sensor networks (Park, 2017), and sensor selection (Jones et al., 2018) are among the most important issues in IoT optimization.

IoT Coverage and Flexibility

Wireless technologies have some advantages, such as flexibility, mobility, and coverage over hard-to-reach locations with lower cost of installation and maintenance fitting them for harsh environments. Typically, sensing coverage is considered as a significant measure for data service quality in IoT since it indicates how well the sensors cover a specific region of interest (Chen et al., 2014). Some scholars proposed efficient and autonomous ways for determining the number and location of wireless nodes to fully cover an environment (Gong et al., 2018). Intelligently sensing and monitoring moving targets is another important application of IoT. The quality of target detection principally involves balancing between the probability of missing a target, the delay for detection, and the network lifetime. The failure or loss of connection between sensors and actuators may result in money or life loss (Hu et al., 2014). Opportunistic IoT based on social engagement model is a new suggestion for solving the problem of gathering data when the coverage of hubs and hotspots is insufficient. In this sharing model, by exchanging a reward, selected users permit access to their devices as mobile hotspots to gather data in large-scale areas, like cities, which otherwise need a huge expensive network (Fadda et al., 2018).

IoT Energy Efficiency

As IoT nodes are normally powered by batteries with limited energy, reliable and energy-efficient data transmission is a big challenge for IoT based systems (Kaur & Sood, 2015a). There is a trade-off between the amount of data collected and analysed by IoT devices and their energy consumption (Song et al., 2017). Thus, the more IoT nodes collect or process data, the more energy they consume. Further, the energy consumed in a node can be classified into the computation energy and communication energy consumption (Tian et al., 2015). Different cooperative communications are introduced to improve energy-efficient communications, reliability, overall throughput, power control, and resource allocations in IoT systems. Recently, business and technological benefits of Low-Power Wide-Area Networks have been introduced as economically enable connecting massive number of IoT objects. Many mobile operators, start-up companies, and independent users have adopted this type of network, which provides better coverage at significantly lower costs and power consumption than the existing cellular networks (Sandell & Raza, 2018).

IoT Security and Privacy

The security goals of integrity, confidentiality, authentication, encryption, detecting attacks, and nonrepudiation in a logical single step are critical for the realization of IoT applications (Selis & Marshall, 2018; Yeh, 2018; M. Zhang et al., 2015). Typical IoT devices with low computing power and limited storage are usually connected to the public networks; therefore, securely sending a message from a sensor to a host is a vital issue for successful IoT function. For detecting sophisticated attacks, IoT objects need processing a large amount of data in a short period and because of their low computational capability, they are not capable to discover an attack in real-time (Selis & Marshall, 2018). In this respect, some scholars proposed new efficient heterogeneous online/offline encryption schemes, such as signcryption (Ting et al., 2017), or attribute-based hash proof system (M. Zhang et al., 2015). In addition, IoT objects, like wearable consumer devices, have shown significant potentiality for contactless mobile payments but the traditional payment security infrastructures are not appropriate for IoT networks with limited computing resources and constrained bandwidth (Yeh, 2018).

IoT applications raise serious privacy concerns, as IoT objects not only collect personal information, but could also monitor user activities, habits, and interactions with others. Privacy is Indeed often considered as a double-edged sword (Zhou & Piramuthu, 2015). From one side, users want to dynamically restrict or disclose information to others, depending on their preferences and location (Celdrán et al., 2014); on the other hand, companies require customers' information for enhancing their products/services or providing innovations. Since complete privacy protection is extremely difficult, Zhou and Piramuthu (2015) argue that privacy issue should be seen context-aware and consumer-heterogeneous, with which users are able to dynamically restrict or reveal information to others (Celdrán et al., 2014). Privacy issues are currently understudied, especially in terms of the scalability and the complex environment characterising IoT scenarios (Sicari et al., 2015).

T8. Smart Manufacturing

In smart manufacturing as a new paradigm, manufacturing machines are largely integrated with IoT technologies to improve system efficiency, product quality, and sustainability while decreasing costs (Kusiak, 2018). In this novel paradigm, the relations of humans, objects, and systems allow self-organized, dynamic, real-time improved, and cross-company value creation networks (Yin et al., 2018), while more autonomy is rendered to production systems (Mourtzis & Vlachou, 2018). Decision-making authorities thus can be transferred and delegated from a centralized hierarchical setting to a semi-autonomous collective of equipment, machines, operators, and mobile devices (Yin et al., 2018). In addition, IoT unique capabilities enable dynamic intelligent manufacturing processes and provide integrated and self-organized operations that can predict and react to unexpected changes throughout the whole manufacturing process (Fatorachian & Kazemi, 2018). In this theme, literature considers IoT as one of the enablers of the manufacturing revolution, increasingly used to develop innovative intelligence in manufacturing and operational processes.

Planning and Decision Making

Applying IoT enables capturing the real-time status of the distributed manufacturing resources that facilitates runtime production exception identification and dynamic decision-making (Y. Zhang et al., 2015). Recent advances in IoT technologies, like ambient intelligence and RFID, empower data collection from production lines and allow the development of a new approach in manufacturing domain so-called 'bottom-up' (Reaidy et al., 2015). The conventional approach is static-based, while the bottom-up approach is autonomous and uses IoT infrastructure and multi-agent interactions to establish self-organization behaviour and connected network between manufacturing entities. IoT based agents, by communicating with each other, form self-organized systems to discover the best local solution for the resource management problems, such as order fulfilment, replenishment, and path planning issues (Reaidy et al., 2015). For two important reasons, the connection between the physical and information world changes the ways in which manufacturing processes are conceptualized and implemented: (1) enabling the interaction between IoT objects and humans to reach organizational goals; and (2) integrating different organizational levels (Neubauer et al., 2017).

Monitoring and Controlling

Manufacturing companies use different information systems to manage performance through pervasive monitoring and control; however, they struggle for capturing real-time data that reflect the current situation. IoT interconnected sensors are an effective solution for this problem (Hwang et al., 2017). They can detecting events, measuring signals, and collect real-time data from factory floors and monitor the health conditions of manufacturing equipment and operations (Wu et al., 2017). Meyer et al. (2011), in their study, indicated that by using IoT technologies, realizing decentralized monitoring and control in the manufacturing context is possible. In another study, H. Lee (2017) showed while continuously monitoring various quality aspects are very difficult in multi-sites and multi-products manufacturing, using IoT beacons in manufacturing machines and devices to measure manufacturing processes' quality factors is an appropriate solution for self-monitoring and real-time controlling.

T9. IoT and Big Data

The adoption of IoT has a worldwide and growing impact (Da Xu et al., 2014), which results in generating and collecting massive amount of data, more than ever before (Atzori et al., 2010; M. Chen et al., 2014). However, if this huge amount of data cannot be transferred to a central repository and analysed in real-time and fast, the results would not be much promising. The big data collected by IoT in the form of numbers, text, image, audio, and video, when combines with data analytics practices generates innovative opportunities for automating or supporting business decision-making. Although IoT and big data analytics evolved independently, over the recent period, more and more they have become intertwined, facilitating the emergence of edge computing. Edge computing is a new networking philosophy attempting to shift computing as close to the source of data as possible instead of relying on the cloud in order to provide fast on-demand and real-time information and knowledge.

Cognitive IoT and Streaming Analytics

IoT devices gather a vast amount of structured and unstructured data and are increasingly capable to perform analytics at the source of data generation and collection. This IoT capability leads to 'streaming analytics' as a new type of analytics in the edge computing, which continuously extracting useful information and insights from the streaming data generated from human activities, machines, or sensors. Streaming analytics has great potential for many businesses because of its real-time event analysis capability to discover patterns of interest, simultaneously with generating and collecting data. Streaming analytics is used not just for monitoring current conditions, but also for predicting future situations (Lee, 2017).

To make a smart IoT solution, after mining and analysing the collected data, the extracted information have to be utilized in cognitive decision-making (Wu et al., 2014). The cognitive IoT can be effectively used in various contexts. For instance, the ubiquity of the sensing capability of IoT objects enables the continuous monitoring of employees' actions, which makes regular performance evaluation possible (Kaur & Sood, 2015b). Recently, deep learning has received much interest as an advanced artificial intelligence to analyse IoT sensory big data. Deep learning techniques by extracting knowledge from collected data, play a critical role in predicting analytics, gaining new insights, enhancing operational efficiency, supporting making decisions, and reducing errors (J. Wang et al., 2018). Combining real-time events with historical data allows the development of predictive and prescriptive analytics, to solve problems and propose solutions in real-time. However, a key challenge in IoT big data realm is how to manage and process data to prepare it for mining and analysis to gain new insights (Cuomo et al., 2017).

IoT Big Data Applications

Massive amount of data generated via IoT provides new possibilities for further improvement of reliability and efficiency of business operations. Businesses can use IoT big data analytics for improving product quality, system productivity, sustainability, and reducing costs (J. Wang et al., 2018). For instance, real-time manufacturing data can be collected and by embedding and using IoT, bottleneck detection and prediction in shop-floor can be realized (Huang et al., 2019). Due to increasing energy prices, new environmental legislation and concerns over energy scarcity, industries extensively use IoT to access and analyse real-time and multi-source energy consumption data (W. Wang et al., 2018). In marketing, an increasing amount of IoT objects with pervasive networks supports the collection of detailed data about customers' behaviour. In insurance domain, Baecke and Bocca (2017) proposed combining and analysing telematics data with traditional customer-specific, car-specific, and past claims to analyse the risk elements. In dynamic operational fields like underground coal mines, Wu et al. (2019) suggest that fast analysis of big data collected by IoT would assist in identifying major issues that affect equipment and operation. Also, since frequent monitoring to be aware of exact operational status is inefficient and costly, new managerial event-driven and periodical monitoring empowered by IoT technologies and big data analytics could provide essential descriptive and predictive insights for better operation management (Townsend et al., 2018).

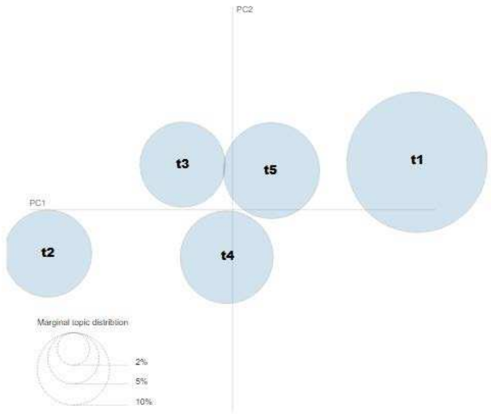
T10. IoT-enabled Business Model

The great 'anything, anytime, and anywhere' IoT gold rush has begun, and it is significantly influencing industries. A large number of firms are working on how to exploit new revenue opportunities arising due to the IoT and actualize its innovative capacities in the creation and delivery of new business values.

Table 4. Identified topics in the IoT-enabled business model research domain

Label	Most probable terms	Inter-topic distance map
t1. IoT Business Model Configuration	valu, industri, servic, new, data, develop, process, product, technolog, design	
t2. IoT Business Model Typology	adopt, valu, success, offer, sector, gener, innov, specif, use, logic	
t3. Strategic Venture Development	ventur, resourc, opportun, valu, growth, firm, oper, entrepreneuri, smart, allianc	
t4. IoT Business Model Innovation	innov, technolog, market, strategi, manag, firm, relationship, industri, knowledg, develop	

t5. IoT Ecosystem Business Model	busi, model, network, ecosystem, differ, chang, actor, valu, structur, connect



The fact that many academic and practice research have recognized IoT as a key enabler of business models and as it is the most prevalent topic in our IoT corpus, we were encouraged to render the latent structure of this topic. Thus, we repeated the LDA process for IoT-enabled business model corpus to explore the most important sub-themes in this topic (Table 4). Sub-themes of the IoT-enabled business model topic was again labelled based on examining the associated key terms and documents in each topic.

t1. IoT Business Model Configuration

Several scholars have examined the whole, or some important ***building blocks*** of IoT business models by mapping to the Osterwalder et al.'s (2005) business model ontology (e.g. Arnold et al., 2016; Dijkman et al., 2015; Kiel et al., 2017a; Metallo et al., 2018). Abbate et al. (2019), in a comparative study of IoT companies, contend that in offering ‘customized products and services’ only *key resources* are core elements and *key activities* and *partners* stand as complementary factors. In a study about how active companies in the IoT industry configure the essential components of their business models, Metallo et al. (2018) found that *value proposition* and *key activities* are the salient elements, and the main differences in business models are rooted in *key activities* and *key resources*. By using IoT, companies are seeking to change their business model *value* and trying to offer novel or enhanced products, services, or even PSS. Higher efficiency, improved performance, getting the job done, and more convenience are among the values companies propose to their customers (Dijkman et al., 2015).

Offering complex IoT-based products and services requires a close relationship and consultation with customers. Co-creation and self-service are the two distinct *customer relationship* styles enabled by IoT (Dijkman et al., 2015). Having a close relationship with customers requires robust *channels*. Complementing direct traditional channels with inherited communication in products through IoT helps companies to have continuous and stable relationships with their customers (Kiel et al., 2017a; Momeni & Martinsuo, 2018). While IoT capabilities support addressing new markets and *customer segments*, Kiel et al. (2017a) argue that some companies prefer or are only proficient to offer IoT-enabled values to their current customers. The various combinations of hardware and software components in IoT require special value-added *activities*. Simulating, product and process design, platform and software development (Metallo et al., 2018), acquisition, mining, and analysing data (Rymaszewska et al., 2017; Turunen et al., 2018) along with common standardised and modularised functions are significant *key activities* in IoT business model. To perform crucial activities, human resource roles are changed from operators to sophisticated controllers and problem solvers, thus, new skills and qualifications in IT, CPS, and data analytical know-how are required (Arnold et al., 2016). Sensors, software components, and relevant IT systems, such as cloud technologies are other *key resources* in IoT business models (Rymaszewska et al., 2017).

Key partnership is another building block, which is considered more important and complex than in conventional business models (Dijkman et al., 2015; Kiel et al., 2017a). Collaborating with software and app developers, hardware partners, and data analysis companies through a secure, robust, and consistent platform-based network is a prerequisite in IoT business models. Besides these key partnerships shaped on the IoT-inherent horizontal connectivity (Arnold et al., 2016), customers are considered as a strategic partner in developing, engineering, and designing the products and services (Abbate et al., 2019). Considering the value capture dimension, IoT enables novel *revenue streams*, such as pay-by-usage models, dynamic pricing, performance-based payment, and licensing models (Arnold et al., 2016). Finally, the technology-driven character of IoT necessities new *cost structure* related to IT facilities, software, and platforms (Arnold et al., 2016).

t2. IoT Business Model Typology

Suppatvech et al. (2019) identified four archetypes of IoT-enabled business models according to their main value propositions. In the 'add-on business model', companies use IoT to provide additional utilities or personalised services to the existing physical products or services. 'Sharing business model' is close to renting, in which ownership of the physical good is not transferred and the customers pay only for using or accessing it. 'Usage-based business model' adopts pay-per-use and subscription revenue models, and deploys IoT to measure the actual usage and needs. In a B2B context, the 'solution-oriented business model' refers to business models that utilize IoT in enabling the provision of availability and optimization/consulting solutions to business customers.

IoT mobile apps provide machine-to-machine connectivity, allow sharing of data services, and facilitate ubiquitous computing across various devices. Guo et al. (2017) propose four possible business models for such apps including 'novelty', 'efficiency', 'lock-in', and 'complementarity' that if properly selected by developers assist them to satisfy their customers and retain IoT value. Therefore, businesses have different options for defining IoT-enabled business models based on their target market and value configuration.

t3. Strategic Venture Development

It has been argued that IoT brings advantages for organisational adaptation, innovation, and success in a dynamic world, especially for companies with large amounts of data and connectivity (e.g. Guo et al., 2016; Yu et al., 2016). Although IoT pervasive connectivity provides various opportunities for entrepreneurs, it lacks successful reference business models (Guo et al., 2016), particularly, for new ventures. One of the main challenges in IoT venturing is how different organizational resources should be utilized, combined, or transformed to achieve success or growth. Two venturing principles, 'effectuation' and 'causation', guide entrepreneurs' decision-making in 'resource bundling'. Resource bundling helps entrepreneurs creatively combine IoT resources, such as smart objects with traditional resources to create extraordinary venturing growth (Guo et al., 2016). Based on a dynamic capability perspective, IoT capability can be defined as the ability to align IoT resources, knowledge, and skills with organizations' strategic directions and innovations. With IoT capability as a competitive advantage, organizations can make strategic decisions effectively and efficiently, exploit business opportunities, counter to environmental threats, and sustain their competitiveness (Yu et al., 2016).

Furthermore, IoT capability provides entrepreneurship opportunities by (1) bridging vertical markets; (2) enabling the growth and rising of new market segments and applications; and (3) optimising business processes (Miorandi et al., 2012). However, using IoT alone is not sufficient for fully actualising the benefits. Akhtar et al. (2018) argued that companies should link IoT capabilities with productive data and information processing competences to enhance agility and achieve a better competitive advantage. Balancing exploration and exploitation is an important concern for many businesses. Ambidexterity is not easily achievable, especially in complex contexts, such as integrating IoT into big and multinational organizations. Today, companies are looking for the exploitation of business opportunities that come from the application of IoT technologies to new markets. Nevertheless, they also try to explore new profitable business models to commercialise and to profit from different products and services presented by IoT capabilities (Bresciani et al., 2018).

t4. IoT Business Model Innovation

Several researchers and futurists posit that smart IoT objects are reshaping industries and the nature of competition, thus companies need new business models. Business model innovation as an umbrella term outlines companies' attempts to find new business logic or new ways to create and capture values (Casadesus-Masanell & Zhu, 2013). At the core of business model innovation is the transformations triggered by new technological means (Cortimiglia et al., 2016). IoT as an emerging technology has driven new opportunities for designing and redesigning business models (Rymaszewska et al., 2017). Yu et al. (2016) demonstrated that IoT capability could enhance product innovation. However, IoT capability alone is not enough and IoT strategic alliance with external entities is also required for both product and process innovation.

Finally, there are different pathways to actualize business model innovation, such as developing and commercialising customer-centric novel business models based on innovative servitization and individualization (Kiel et al., 2017b) and offering to retrofit to customers (Amshoff et al., 2015) to equip and prepare customers for IoT implementation. IoT-based servitization (Turunen et al., 2018) and IIoT-driven innovation (Kiel et al., 2017b) exemplify generating higher value and reaching competitive advantage through combining data from many sources, providing platforms that facilitate combinatory innovation, as well as reducing time-to-market and increasing flexibility (Moeuf et al., 2018).

t5. IoT Ecosystem Business Model

There is a rising trend among IoT scholars (Leminen et al., 2018; Papert & Pflaum, 2017; Rong et al., 2015; Westerlund et al., 2014) to examine the expansion of business model boundaries from an individual company to an ecosystem perspective. In today's networked economy, firms are often members of complex business ecosystems and having direct experience with the IoT contributes to their partnerships. The core of an IoT ecosystem is bridging the physical world of things with the digital world of software, Internet, and standards (Kim et al., 2017; Mazhelis et al., 2012). Westerlund et al. (2014) identified four key areas of value in IoT business model ecosystems including 'drivers', 'nodes', 'exchanges', and 'extraction dynamics'. Value nodes are members, activities, and systems that are linked together in an ecosystem, while value drivers are the motivations of members to extract and exchange value in the ecosystem.

IoT is a novel infrastructure for collaborative value creation; however, it is strategically important to examine the ecosystem contextual issues, such as interdependencies, interactions, and partnerships in designing IoT business models. Leminen et al. (2018) propose four types of IoT ecosystem business models based on the nature of service and the type of ecosystem: ‘value chain efficiency model’, ‘industry collaboration model’, ‘horizontal market model’, and ‘platform model’. Burkitt (2014) further argues that there are three different strategic roles in these ecosystem business models: ‘enablers’ who develop and implement the core technologies underpinning the ecosystems, ‘engagers’ who plan, implement, integrate, and deliver IoT services to customers, and ‘enhancers’ who devise value-added services on the top of the services provided by engagers.

In another study, Papert and Pflaum (2017) examined the role of solution integrator as a central role in the IoT ecosystem. They assert that the main duty of solution integrator is to produce a complete IoT platform involving hardware, applications, and connectivity. In addition, this role maintains and orchestrates network formation and coordinates and integrates knowledge across the diverse actors of the heterogeneous network (Prince et al., 2014). Finally, Rong et al. (2015) highlight that IoT-based business ecosystems are much more complex networks than ordinary ones. To understand how IoT-based business ecosystem works, they proposed a 6C framework: ‘context’, ‘construct’, ‘configuration’, ‘cooperation’, ‘capability’, and ‘change’.

4. Conclusion and Implications

4.1. Theoretical Implication and Future Research

Our findings contribute to the literature on business and management of IoT in three ways. First, the findings of this study uncover and present a thematic map of IoT research streams in business and management domains. This study is a response to a call by Lu et al. (2018) that highlight a need for a more quantitative approach to drive and present the inductive classification framework for eliciting the latent structure of IoT extant literature. To map out a broad and rich picture of the business and managerial related thematic landscape of IoT, we designed a computational thematic analysis method as a new mixed-method approach, addressing the call for methodological pluralism to study organizational phenomena (Schmiedel et al., 2018). In the current paper, we proposed a research framework to incorporate topic modelling as a computational technique into inductive thematic analysis to cover both the breadth and depth of the subject. The results of topic modelling by applying LDA method reveal 10 topics for IoT in the business and management areas. For each topic, we presented the most probable terms, top journals, most correlated articles, and its distribution over time. Then, by following a thematic analysis process, we discussed and critically analysed the latent themes.

Second, tracing the studies in each topic shows that identified themes can be allocated to the juxtaposition of three main spaces: individual, organizational, and supra-organizational (Figure 5). To deepen our understanding of extracted topics, we focused on two key dimensions of IoT—interconnectivity and smartness—to realize how IoT could create value for its stakeholders. Focusing on three distinct but interconnected levels of analysis, we examined the affiliation of topics with these two IoT features and different beneficiaries. IoT unique capability of interconnecting physical and digital world provides great exceptional opportunities for innovative applications that were not possible before. IoT interconnectivity capacity could link human, things and software at individual, organizational, supra-organizational levels in ways that can radically transform many aspects of functions and interactions. Some examples of emerging applications of IoT in business are: making products smart and connected, facilitating sharing and collaborative economies, restructuring industries and supply chains, contributing to realizing circular economy and sustainability, and developing new business models.

At the individual level, smart connected products offer new functionality, greater performances, higher engagement, and capabilities that cut across and transcend traditional product boundaries (Porter & Heppelmann, 2014), offering new emerging relationships from consumers' interactions with them (Novak & Hoffman, 2019). At the organizational level, IoT provides a smart, connected infrastructure for modern product management, dynamic intelligent manufacturing, and differentiating businesses by moving beyond merely selling products to delivering integrated product-service solutions to their customers. At the supra-organizational level, IoT improves collaboration and coordination between members of a supply chain by bringing visibility and traceability to the entire chain, enables social environments like cities to make their critical infrastructure, services, and resources more interconnected and intelligent, and provides a novel infrastructure for collaborative value creation in the networked economy.

Finally, at the intersection of these spaces, digital knowing and big data could be positioned. IoT by its pervasive interconnectedness capability at different levels generates and collects huge amounts of data, which might be correlated to any level of its applications from individual to supra-organizational. Furthermore, this huge amount of data is processed and analysed to create rich biographies about how products are used and humans interact with them.

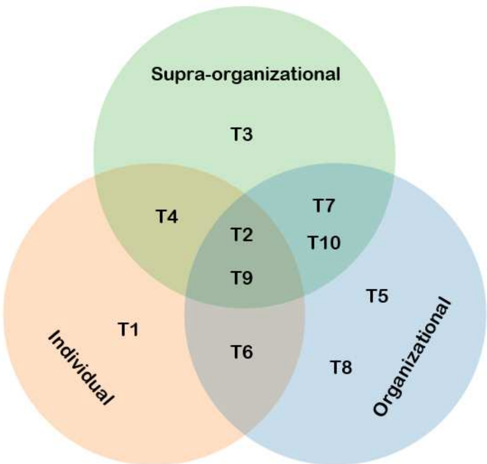


Figure 5. Venn diagram of identified themes

Further, using a thematic analysis approach we explored and discussed latent sub-themes in each topic. Figure 6 shows the knowledge structure of the IoT business and management research at a glance.

Figure 6. Mind-map of the IoT business and management research domain

Finally, drawing on the results of the mixed-method analysis, the third theoretical contribution of our study is identifying and proposing future research avenues for IoT business and management. The future research streams are discussed as follow:

IoT shapes new interactions, consumers' consumption habits, and engagement. Analysing related theoretical models and frameworks used by current studies reveals a heterogeneous set and different paradigms. Some scholars have considered pre adoptions behaviours of IoT; while the others have focused on its usage and satisfaction, mostly by testing classical theories and models. However, future research may leverage other theoretical lenses, especially in social contexts, like the theory of self-expansion and consumer culture theory and broaden their studies to consider context-specific factors, or economic and social factors, such as price, social presence, and co-presence modes. Most of the studies have examined human and IoT object relationships, but future research could explore social interactions through IoT and consider a new perspective and expand the boundaries to nonhuman-centric consumer behaviours (Hoffman & Novak, 2017). Scholars have increasingly addressed servitization, yet, there is still a paucity of well-suited theoretical and empirical models and methods, in applying IoT technologies and shaping inter-company relationships to exploit opportunities provided by PSS (Böhmann et al., 2014; Kamp & Parry, 2017). IoT facilitates inter-organizational collaborations by enabling visibility, but future research could consider IoT roles in less studied supply chain activities, such as sourcing or reverse logistics, and also offer solid and comprehensive frameworks for IoT adoption in a digital supply chain context. While many believe IoT has disruptive power and put emphasis on the scientific theory and its engineering design, analysis of its innovation dynamics has been largely overlooked. Future studies could examine the

commercialization, standardization, and diffusion of IoT technologies. Smart products, built with sensing and embedded control features is a hot topic in integrating IoT with product life cycle management. IoT impacts in shaping collaborative consumption experiences and examining consumers' active role in smart product lifecycle are worth further investigation. Most of important IoT applications involve solutions that are not merely technical, thus for studying them considering socio-technical perspective is necessary. Interoperability, compatibility, standardization and risk management in the entire lifecycle of smart products are critical areas for future research. Future research on smart manufacturing can investigate regulatory framework and end-to-end digital integration, reference architectures for crucial infrastructures for IIoT and return on investment of advanced IoT innovations in industry 4.0 initiatives. IoT holds the promise of improving humans' life which requires using tons of things, with seeing, sensing, hearing, and smelling capabilities. Social policies and legal systems in the national and international levels should consider the impacts of IoT technologies on people's life. Examining the influence of different factors on successfully deploying IoT services in human life and investigating security and privacy issues are potential research streams in this topic. Designing appropriate tools that could measure other dimensions of smart living experiences is also suggested (i.e. social, psychological, emotional, and cognitive dimensions). With the rapid expansion of IoT, many scholars have tried to explore different ways to extract useful information or knowledge from a large volume of generated data. Potential emphases for future research in IoT big data are considering temporal aspect, metadata and semantics, management, authority, integrity, and governance of IoT data.
Research on IoT emerging impacts on business models is discussed largely. Some studies have examined the IoT potential changes on main elements of established business models, and the others attempted to design novel business models based on IoT innovative products and services. Future research should discuss the benefits of different business models from a customer's point of view, as innovative business model adoption is also likely to rely on customer perspective (Suppatvech et al., 2019). Given the fact that IoT business models are still in their early stage, conducting longitudinal surveys to observe the IoT business models' evolution and their effect on long-term performance is beneficial. Finally, the strategic values of implementing and deploying IoT are less considered by scholars. Therefore, future studies could take the perspective of dynamic capabilities or resource-based view to explore how businesses can exploit the combination of IoT resources and capabilities with existing ones.

4.2. Managerial Implication

This study offers a range of insight for entrepreneurs and managers. Mangers can augment IoT into their existing services and products and make them more efficient for their customers. They should consider IoT capabilities for offering customized products or services, and the cooperation with customers through IoT networks as a differentiating competitive advantage. Additionally, inheriting automated analysis capacity in IoT technologies or processing big data sensed and collected enable managers to gain more knowledge about their customers and their operations. Managers can leverage these new insights to initiate the corrective actions, adjust business rules and optimize business processes as well as systems in real-time. To take the advantages of IoT business opportunities, changing the role of workforces from operators to problem solvers is extremely important but it requires companies to make a serious effort for educating their employees to gain new skills, abilities, and knowledge. Supply chain practitioners can also use various IoT technologies to enhance visibility and increase efficiency and effectiveness of operations. Managers can integrate IoT to create more innovative, beneficial business values for their customers. They should consider utilizing IoT as a central feature in proposing innovative PSS that support their customers' requirements. Reconfiguring business models according to IoT capabilities is another strategic concern for innovative companies.

Entrepreneurs who intends to develop IoT solutions for consumers should employ smart technologies that are compatible and interoperable with greater ease of use, superior functionality, and high usefulness. Moreover, entrepreneurs need to ensure that the IoT solutions encompass hedonic and social dimensions. In designing IoT services, both quality of service and quality of experience should be considered. Security and privacy are also significant factors for consumers, particularly where sensitive personal data is collected. Companies, thus should invest in their IoT platforms security and privacy. In designing novel business models, entrepreneurs also can incorporate IoT capabilities in configuring value map to fulfil their customer needs, to optimise their resources and partnership or to transform their revenue streams.

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Appendix A

Topic modelling sensitivity analysis

We followed Griffiths and Steyvers (2004) recommendations to run LDA on our corpus using Gibbs sampling with T ranging from 6 to 24 and 1000 iterations. The LDA packages[4] that we used for sensitivity analysis, estimates the values of alpha and beta parameters with starting score of T/50, 0.1, respectively. We calculated the metrics of four LDA models and presented the normalized results of them in the left part of Figure A-1. In two of these models, i.e. Griffiths and Steyvers (2004) and Deveaud et al. (2014) we seek maximum scores, while for the other two models, i.e. Cao et al. (2009) and Arun et al. (2010), we look for minimum scores.

Following Geva et al. (2019), we summed the scores of the four models for each number of topics to find a topic number with good aggregated score. We computed (1-score) for two models in which higher values consider better (i.e. Griffiths and Steyvers, 2004; Deveaud et al., 2014). As a result, the optimal number of topics was the one with the minimum overall score. The aggregated scores of four models are shown in the right part of Figure A-1.

Note: Series A-1: Griffiths and Steyvers (2004); Series 2: Cao et al. (2009); Series 3: Arun et al. (2010); Series 4: Deveaud et al. (2014).

Figure A-1. **Left**: results of four models, **Right**: aggregated results of sensitivity analysis

We further used 10-fold cross-validation analysis to evaluate the performance of our LDA model. In 10-fold cross-validation, the dataset is randomly partitioned into 10 equal size subsamples. Of the 10 subsamples, a single subsample is retained as the validation data for testing the model, and the remaining 9 subsamples are used as training data. We computed the perplexity of LDA models with different numbers of topics to find the optimal number. From the figure A-2, we can see 10 number of topics yields the best results, with the lowest average perplexity on the 10 different hold-out sets.

[4] topidmodels package: (https://cran.r-project.org/web/packages/topicmodels/index.html), and ldatuning package: (https://cran.r-project.org/web/packages/ldatuning/index.html)

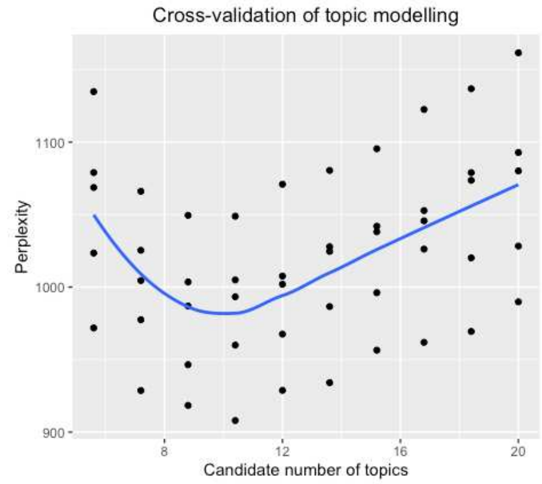

Figure A-2 Perplexity results of LDA models with different number of topics