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The Internet of Things, dynamic data and information processing capabilities, and operational agility

Abstract

Whilst there are promising links between the Internet of Things (IoTs), dynamic data and information processing capabilities (DDIPCs), and operational agility, scholars have not conducted enough empirical studies that offer convincing evidence for the use of the IoTs and relevant linkages. This study therefore examines the links between such constructs and provides managerial implications for contemporary data and information driven managers who adopt evidence-based decision making for better operational outcomes. The results obtained from structural equation modelling indicate that the use of the IoTs is the key determinant for operational agility and also plays a vital role in establishing DDIPCs that further reinforce it. Additionally, DDIPCs mediate the relationship between the use of the IoTs and operational agility. By persuasively building these links based on theoretical arguments and testing them by using a unique dataset, this study contributes to the deeper understanding of the mechanisms by which the use of the IoTs and DDIPCs strengthen operational agility.

Keywords: Internet of Things; dynamic capabilities; dynamic data and information processing; operational agility; data and knowledge intensive services

1. Introduction

The Internet of Things (IoTs) has recently emerged as a key disruptive technology that not only plays a main role in daily activities, but also affects business operations and global economic systems as a whole (Atzori et al., 2010; Wortmann and Flüchter, 2015). With the use of the IoTs (i.e., the inter-networking of devices with the ability to send and receive data), business operations are becoming more agile and connected. Also, the data and information produced through the IoTs is used to generate knowledge that is ultimately employed to monitor and control business network operations. The companies that utilize the links between the IoTs and dynamic data and information processing capabilities (DIDPCs) achieve a better competitive advantage; they do so because their daily business operations become more agile as a result of these developments in their IT infrastructures (Christopher, 2000; Heisterberg and Verma, 2014; Lou et al., 2011; No et al., 2015). The significance of the IoTs and of its linkages with operational effectiveness, data, and informed decision making has been highlighted by key IT players. For instance, Microsoft believes that "the IoTs can make a difference to your business by beginning with the things in your business that matter the most. It's really the internet of your things, and it starts by building on the infrastructure you already have in place, using familiar devices and services in new ways, and incorporating the right technology to ultimately help you use data to create insights and make more informed business decisions" (Edson, 2014). As a result of this business appeal, "the IoTs, which excludes PCs, tablets and smart-phones, will grow to 26 billion units installed in 2020, representing an almost 30-fold increase from 0.9 billion in 2009, and IoTs product and service suppliers will generate incremental revenue exceeding $300 billion" (Gartner, 2013). Also, the Vodafone IoTs Barometer claims that 76% of businesses view the IoTs as critical for the future, 90% of organizations have already integrated IoTs data into their existing IT systems, and 63% of such adopters have increased their growth by at least 20% (Forbes, 2016; Vodafone, 2016).

These statistics have provided growing evidence that the use of the IoTs is demonstrably crucial in creating data and information that are associated with the capabilities of organizations, providing them with insights related to operational agility and effective decision making. The impacts of the IoTs seem to be limitless, as the connected devices provide data and information about both internal and external operations. Despite the claims and statistics presented above, the academic studies on the links between the use of the IoTs, DDIPCs, and operational agility are just emerging; the research concerning the mechanisms through which the IoTs affects operational agility is still in its infancy. More specifically, the linkages between the use of the IoTs and DIDPCs to generate knowledge suitable to improve operational agility have neither been effectively researched nor statistically estimated. Above all, the field is still devoid of clear theoretical bases (Bresciani et al., 2017; Cram and Newell, 2016; No et al., 2015; Teece, 2014a).

Given that the academic research on the use of the IoTs is just emerging, the first contribution of this study is to develop a theoretical framework by building inter-relationships between the use of the IoTs and DDIPCs, and operational agility. Conceptually, the IoTs and DDIPCs seem well linked, but answering the question of how they impact operational agility substantially contributes to closing the knowledge gap in the operational and IT domains. Secondly, operational agility itself has not been well established. In the IT literature, operational agility generally focuses on quick responses, accurate actions, and cost-efficiency pertaining to both customers and internal operations; we provide evidence that it is also linked at the macro-level. Consequently, operational agility is a second-order construct that integrates both its internal and external aspects. Finally, we test the framework and provide significant evidence by following a comprehensive statistical procedure and using a unique dataset.

2. Theory and hypotheses

2.1. Literature and definitions

The term *"the Internet of Things"* is used for those devices that have network connectivity and the ability to send or receive data and information to other connected objects. It is a major developmental wave—after the desktop and web-based ones—in the information and communication technology (ICT) sectors (Atzori et al., 2010; Ma, 2011). The idea is essentially based on the device-to-device connections and communication that can be effectively established using smart devices (e.g., wearable devices and Chromecast, Samsung, and Apple smartphones), their functionalities (e.g., Wi-Fi, Bluetooth), cloud computing facilities, and sensors. These devices provide accurate and real-time data and information that are used to track and trace operational resources and personnel. This enhances visibility, leading to the development of agile operations among connected business networks (Lu and Ramamurthy, 2011; Miorandi et al., 2012; Yang et al., 2013). Yang et al. (2013) provided evidence that the IoTs enhances the effectiveness of response operations in terms of the accountability of resources, specialized actions, assessment of situations, resource allocation, and multi-organizational coordination. Similarly, micro-sensors can be used to monitor patient health and smart meters can be used to monitor electricity consumption. Also, the transportation data and information linked with any connected devices are collected and processed for effective traffic management or traffic supply chain visibility and agility (Elhenawy and Rakha, 2017; Uden and He, 2017; White et al., 2005).

An organization's dynamic capabilities are viewed as its ability to promptly adopt changes and process data and information for actionable knowledge or analytics that enable the effective tackling of changes in the market (No et al., 2015; Ramírez et al., 2013; Teece, 2014a). Such capabilities help organizations to quickly turn structured and unstructured data into insights and knowledge that can be used to improve business operations. An example of such capabilities includes the complex text mining ability used to respond to consumer feedback or reviews and thus improve customer service (Kim et al., 2012; No et al., 2015). Organizations equipped with advanced electronic devices capture real-time contextual data and information that are frequently used in their daily supply chain operations. They also utilize individual speech recognition capabilities to speed up their warehouse operations. These dynamic capabilities are not only imperative for contemporary data-driven business operations, but also help to improve business network visibility and operational agility (Chou et al., 2007; Dweekat et al., 2017; Hazen et al., 2014; Reaidy et al., 2015).

In the information management literature, the term *"agility"* generally consists of three dimensions: operational, partnering, and customers. *"Operational agility"* focuses on quick responses, accurate actions, and cost-efficiency (i.e., cost economy). Importantly, it is not only related to internal processes, but also covers external operational processes. It is basically defined as the ability of organizations to swiftly react to changes and uncertainties. Secondly, *"partnering"* is the ability of organizations to leverage their network partners' knowledge and capabilities to assist in identifying problems and capturing opportunities to improve their performance. Finally, *"customer"* aspects emphasize learning from customers and acting accordingly (Huang et al., 2014; Izza et al., 2008; Sambamurthy et al., 2003). In other fields, such as supply chains and logistics (Tse et al., 2016), agility includes demand responses, customer responses, and joint planning. Huang et al. (2000) believed that agility can be used in many functions of networked enterprises, such as recovery, collaboration, partnerships, and logistics. Vickery et al. (2010) defined agility as a tool that improves responsiveness to customer needs.

In addition to its characteristics described above (quick, accurate, and cost-efficient), operational agility assists in adjusting operational changes and provides more flexibility in day-to-day operations (Langer and Alting, 2000; Pawson and Wade, 2003). It also enables the swift redesigning and building of new processes, ultimately enabling the exploitation of market opportunities that are part of external business environments (Seebach et al., 2011; Tallon and Pinsonneault, 2011). It is evident from the literature that there is no single definition of agility or operational agility, and that the latter mainly involves: 1) speed, 2) accuracy, 3) cost-efficiency, and 4) flexibility. Importantly, it encompasses both internal and external aspects in regard to the characteristics mentioned above. Correspondingly, we define operational agility as the ability of organizations to cope with demands and changes by considering the four aspects listed above both internally and externally. Thus, our definition of operational agility consists of two dimensions—internal and external operational agility—which are measured in terms of 1) speed, 2) accuracy, 3) cost-efficiency, and 4) flexibility.

2.2. Hypotheses

2.2.1. Use of the IoTs and operational agility

Due to its business benefits, the IoTs is regarded as one of the important digital revolutions of the modern age (Atzori et al., 2010; Del Giudice & Straub, 2011). It can act as an important storage and communication hub that links and transfers information between connected organizations and their networks (Liu et al., 2013; Uckelmann et al., 2011). Due to these characteristics, IoTs devices play a vital role in enabling modern day businesses to build better connectivity and progressive operations to improve their agility (Atzori et al., 2010; Del Giudice and Straub, 2011). The knowledge that comes through such connected devices offers agility, scalability, and reliability in the form of the timely processing of information for better decision making (Atzori et al., 2010; Del Giudice and Straub, 2011; Uckelmann et al., 2011).

The information collected through the IoTs enhances the productivity of business processes. In other words, the knowledge and analytical insights gathered through this connectivity enable business networks to make informed and evidence-based decisions, and play a vital role in building dynamic data and information processing capabilities (Grant, 1996; Teece, 2007, 2014a; Uden and He, 2017). Ultimately, such capabilities improve internal and external operational agility (Heisterberg and Verma, 2014), which has nowadays emerged as one of the key capabilities IT-oriented businesses need to survive and prosper (Braunscheidel and Suresh, 2009; Bresciani et al., 2017; Heisterberg and Verma, 2014). In a sense, the use of the IoTs is the key determinant that transforms the nature and ways of doing business, as it is noted that investing in IT infrastructure capabilities can be vital to develop organizational agility (Mathiassen and Pries-Heje, 2006; Weill et al., 2002). Through the use of the internet and digital-oriented technologies, companies are transferring vital and timely information to their international and global network partners, enabling the latter to act quickly on that information and become more agile (Lou et al., 2011). It has been suggested that the IoTs played an important role in facilitating communication, particularly the exchange of data and knowledge between entities. Such IT devices are vital for the improvement of both internal and external operational agility (Guillemin and Friess, 2009; Yang et al., 2013).

The use of the IoTs has the potential to generate both depth and breadth of knowledge, which is basically used to enhance operational agility (Atzori et al., 2010; Del Giudice and Straub, 2011; Uden and He, 2017). The research suggests that IoTs-technology has a great potential for business operations such as manufacturing, distribution, transportation, and allocation of resources (Atzori et al., 2010; Wortmann and Flüchter, 2015). It is further believed that the IoTs can revolutionize the way in which companies gather data. It can also transform business processes and the management of knowledge in ways that could play an important role in operational agility of network partners (Atzori et al., 2010; Xu et al., 2016). Due to the vital role it plays, it can be argued that the use of the IoTs is one of the key dynamic capabilities of modern businesses (Elhenawy and Rakha, 2017; Teece, 2007, 2014a; Uden and He, 2017). Researchers (e.g., Kim et al., 2012; Liu et al., 2013; Miorandi et al., 2012; Yang et al., 2013) expressed their belief that the use of such an advanced IT infrastructure enables organizations to integrate, build, and reconfigure both their internal and external operations—which can become more agile—attaining data and analytics-driven leadership in constantly shifting business environments (Akhtar et al., 2016). In fact, the use of the IoTs provides agility to all business network operations and the implementation of such advanced technology is critical for contemporary business operations to become agile (Forbes, 2016; Gubbi et al., 2013; Yang et al., 2013). The use of the IoTs essentially enhances operational agility due to the fine-grained knowledge that comes through the devices connected with the internet and the ability of companies to receive and process information in a timely fashion (Forbes, 2016; Gubbi et al., 2013; Uden and He, 2017; Yang et al., 2013). It is suggested that companies can detect the physical status of things through sensors and internet-enabled technologies, which enables not only the collection and processing of detailed data, but also immediate responses to any changes taking place in the real world, thus helping in the enhancement of operational agility (Hwang et al., 2013; Lee and Lee, 2015; Uckelmann et al., 2011). Based on these arguments, we propose the following hypothesis:

Hypothesis 1: The use of the IoTs is positively related to the enhancement of operational agility.

2.2.2. The use of the IoTs and dynamic data and information processing capabilities

Besides making operations agile, the use of the IoTs provides large amounts of structured and unstructured data, which can enhance an organization's dynamic data and information processing capabilities for knowledge generation (Del Giudice and Straub, 2011; Gubbi et al., 2013; Malhotra, 2000, 2005). Dynamic data and information processing capabilities can be valuable resources for network partners (Teece, 2007; Zahra and George, 2002), and are also vital for the development of a competitive advantage in high volatile markets (Teece et al., 1997). Organizations need dynamic data and information processing capabilities to process the huge volume of data coming through various connected devices with diverse digital technologies (Atzori et al., 2010; Barnaghi et al., 2013; Del Giudice and Straub, 2011; Elhenawy and Rakha, 2017).

The IoTs may also impact an organization's dynamic data and information processing capabilities due to the dynamic nature of the knowledge that comes through it (Uden and He, 2017; Waller and Fawcett, 2013; Xiang et al., 2015). One of the key benefits of the IoTs is the enormous amount of data generated from devices connected to the internet. An organization's ability to process such a vast amount of data determines the overall usefulness of the IoTs. Put differently, those organizations that invest in data and information processing capabilities will be in a better position to exploit the data coming through the IoTs (Gubbi et al., 2013). In a sense, the use of the IoTs puts additional pressure on organizations to improve their internal data and information processing capabilities in order to take advantage in a timely fashion of the huge amount of data and information generated through the devices connected with the internet, and thus develop a sustainable competitive advantage. It is also suggested that the use of the IoTs requires organizations not only to equip themselves with massive data storage capabilities, but also to develop the ability to process data in a timely and speedy manner in order to make real-time decisions (Lee & Lee, 2015), thus indicating the important influence exerted by the use of the IoTs on dynamic data and information processing capabilities. In order to benefit from the use of the IoTs, many organizations are now developing dynamic data and information processing, and collaboration capabilities to share real-time information with both their customers and supply networks (Bradley et al., 2013; Lee and Lee, 2015). The development of such capabilities is vital in view of the massive amounts of heterogeneous data that are generated by the devices connected with the IoTs and that organizations need to process and store efficiently. According to a Gartner report, the current architectures of organizations' data processing centres are not suited to deal with the vast amount of heterogeneous data, a capability that may be crucial to enhance agility (Rivera and van der Meulen, 2014).

Modern organizations invest in advanced IT infrastructures (e.g., the IoTs and big data technologies) to improve their dynamic data and information processing capabilities in order to take advantage of the knowledge they provide (Gubbi et al., 2013; Malhotra, 2000; Uden and He, 2017; Wortmann and Flüchter, 2015). Such technologies then help the effective transfer of valuable insights to network partners, with the aim of improving the overall network agility (Gubbi et al., 2013; Lou et al., 2011; Uckelmann et al., 2011). Since the IoTs is connected through network-oriented systems interlinked with various smart objects that produce and consume vital information, IoTs-devices play an important role in enhancing dynamic data and information processing capabilities (Heisterberg and Verma, 2014; Miorandi et al., 2012; Weill et al., 2002).

The information that comes through such smart objects can play an important role for an organization's wide data and information processing capabilities in terms of the generation of important and timely knowledge (Atzori et al., 2010; Miorandi et al., 2012). It has also been noted that devices connected with various objects generate huge amount of data that can influence the development of dynamic data and information processing capabilities (Atzori et al., 2010; O'Leary, 2013). In order to effectively utilize and process the information obtained through the IoTs, organizations need to possess dynamic data and information processing capabilities (Saldanha et al., 2015). The possession of such capabilities is important for digitally connected organizations as they handle huge amounts of data, and their timely processing can affect the whole network (Chen and Zhang, 2014). Thus, the sensing, seizing, and transferring of opportunities and capabilities can be developed through the IoTs, and organizations can reconfigure their key processes and capabilities to handle agile operations based on the data and information processing capabilities linked with the IoTs (Kim et al., 2012; Liu et al., 2013; Miorandi et al., 2012; Uden and He, 2017; Yang et al., 2013). These IoTs-enabled capabilities need to be linked with analytical insights used to improve business operations (Xu et al., 2016). The above discussion leads us to the following hypothesis:

Hypothesis 2: The use of the IoTs is positively related to the enhancement of dynamic data and information processing capabilities.

2.2.3. Dynamic data and information processing capabilities and operational agility

Dynamic data and information processing capabilities (DDIPCs) play an important role in achieving operational agility (Heisterberg and Verma, 2014; Perera et al., 2014; Weill et al., 2002). This is one of the core capabilities needed to process and generate knowledge from the huge amount of data coming through the IoTs (Uden and He, 2017). Such capabilities for knowledge generation turn raw data into explicit and useful information that network partners can use to develop their operational agility (Uden and He, 2017; Wixom et al., 2013). Without such capabilities, organizations would be unable to compete effectively and develop the competitive advantages linked to being agile and first in accessing markets (Heisterberg and Verma, 2014; Wixom et al., 2013).

The data coming from the IoTs need to be processed to generate valuable insights; those organizations that do not have the dynamic data and information processing capabilities to generate knowledge and develop and enhance their operational agility are often at a competitive disadvantage compared to those that do. The possession of dynamic data and information processing capabilities to generate knowledge not only enables the collection of valuable data but also helps to store important datasets that can provide marketing actionable insights utilized for operational agility (Uden & He, 2017; Weill et al., 2002; Woerner and Wixom, 2015). Studies also point out that information processing related infrastructures are vital to enhance agility in complicated business operations (Liu et al., 2013; Weill et al., 2002). Such capabilities for dynamic data and information processing are the higher order capabilities needed to develop agility (Heisterberg and Verma, 2014; Teece, 2014b; Zahra and George, 2002), which consists of multiple dimensions (Seebach et al., 2011; Tallon and Pinsonneault, 2011). This discussion leads us to propose that:

Hypothesis 3: DDIPCs are positively related to operational agility.

2.2.3. The mediating role played by DDIPCs

If DDIPCs mediate the relationships between the IoTs and operational agility, the three correlations need to be verified between:

1) The use of the IoTs and operational agility (hypothesis 1)

2) The use of the IoTs and DDIPCs (hypothesis 2)

3) DDIPCs and operational agility (hypothesis 3)

Finally, the first correlation (hypothesis 1) should become insignificant when the three correlations (1, 2, and 3) are verified and the construct (DDIPCs) is controlled (Baron and Kenny, 1986; Preacher and & Hayes, 2008; Sobel, 1982). For each condition, this study develops one hypothesis, each of which is based on the literature that is discussed in Section 2. Fig. 1 presents a graphic version of these hypothesized conditions and their inter-relationships.

Additionally, the use of the IoTs alone may not aid organizations in developing their operational agility, as they would also require in-house capabilities suited to process the vast amount of data and information in a timely manner. Thus, there may be other central mechanisms and underlying processes that, together with the IoTs, can enhance operational agility (Bresciani et al., 2017; Helmsen et al., 2012). One such underlying process and mechanism could be the possession of dynamic data and information processing capabilities suited to enhance the multiple dimensions of internal and external agility and contribute to overall performance. This points at the need for effective in-house dynamic data and information processing capabilities that would enable organizations to take advantage of the huge volume of data processing and information sharing, and would play a central role (i.e., a mediating role) in strengthening the links between the IoTs and operational agility (Bresciani et al., 2017; Chen et al., 2014; Marinagi et al., 2015)..

Although the value of general IT capabilities has been highlighted by practitioners and scholars alike, the knowledge obtained from and the central role played by data and information processing have not been explored. As it is an emerging and complex domain interconnected with many operational dimensions, any mediating roles played in the link between the use of the IoTs and agility therefore remain the subject of debate in the interdisciplinary IT-business literature (Bresciani et al., 2017; Chen et al., 2014; Marinagi et al., 2015; Matthias et al., 2017). This gap and discussion thus lead us to propose the following hypothesis.

Hypothesis 4: The link between the use of the IoTs and operational agility is mediated by DDIPCs.

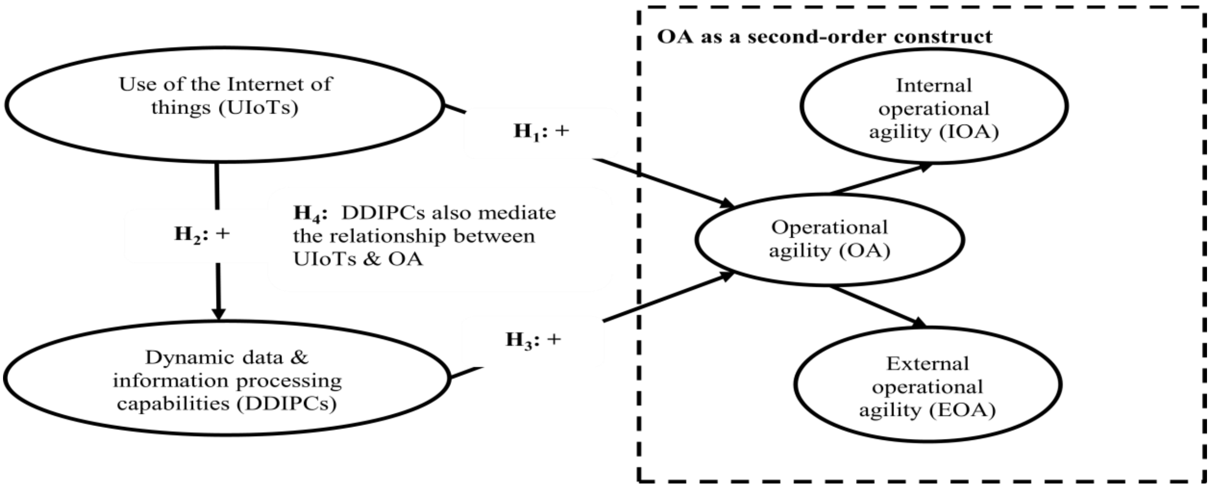


Fig. 1. Inter-relationships between underlying constructs

3. Methods

3.1 questionnaire development, operationalization and respondents

To operationalize the key constructs, we undertook a thorough literature review. This helped to identify the scales used in past studies. The questionnaire items were then reviewed and pilot-tested to ensure content validity. A seven-point scale was used to measure the extent to which the respondents agreed or disagreed (1 = strongly disagree and 7 = strongly agree). Endogeneity biases (Abdallah et al., 2015; Antonakis et al., 2010; Qin, 2015)—such as common-method variance (CMV), measurement error, omitted variables and simultaneous bias—were also addressed (Antonakis et al., 2010; Hamilton and Nickerson, 2003). To deal with common-method variance, the guidelines provided by Tourangeau et al. (2000) and Podsakoff et al. (2003) were also utilized (avoiding unfamiliar words, double-barrelled questions, and technical terms). Additionally, Harman's one-factor test provided multiple factors, which explained greater variance compared to a single factor solution or combinations, and assisted to investigate the CMV. Further, the marker variable technique (the variable being the number of languages known by the respondents) proposed by Lindell and Whitney (2001) and the latent factor approach did not highlight any issues (Malhotra et al., 2006). To deal with the measurement error, we used the maximum likelihood estimate and a multiple indicator approach, which corrected the biasing effects (Frone et al., 1994). To deal with omitted and simultaneous biases, well established theories were used (Antonakis et al., 2014; Antonakis and Dietz, 2011).

The KOMPASS database was utilized to identify and contact a total of 900 respondents working in the selected European IT, telecommunication, and energy companies. After excluding incomplete ones, a total of 205 useable participant responses were subjected to structural equation modelling, and the characteristics of the respondents are shown in Table 1.

Table 1
Respondents and their characteristics.

Categories		Numbers	percentages
Job titles	IT directors	97	47
	IT operations manager	65	32
	Implementation managers	43	21
Company types	IT	91	44
	Telecommunication	62	30
	Energy	52	26
Employees	>250	109	53
	>50&<250	96	47
Turnover($m)	> €50 million	110	54
	< €50 million	95	46
Total		205	100

3.2. Measurement models and quality checks

Multiple items were used to develop the measurement models. The construct, Use of the Internet of Things (UIoTs), was measured using ten items, followed by Dynamic Data and |Information Processing Capabilities (DDIPCs) assessed through eight items. The second-order construct, Operational Agility (OA) was measured by two sub-constructs, called Internal Operational Agility and External Operational Agility, each consisting of four items. Three control variables (Respondent Types, Industry Types, and Company Sizes) were also used to ensure the quality of this study; these are given in Table 1. Table 2 presents the constructs, items, reliability measures, average variance explained, and loadings. These statistics provide acceptable psychometric properties of our scales. Additionally, we found that there was no non-response bias in our sample. Discriminant validity was measured by using two methods. First, the correlation between the constructs did not exceed 0.85, and ranged between 0.27 and 0.57 (Kline, 2011) as listed in Table 3. Second, the square of the correlation (ϕ^2) between each pair of constructs was less than the average variance explained (AVE) (Chiang et al., 2012; Sekaran, 2000). The descriptive statistics and correlation matrix of the constructs are shown in Table 4.

Table 2
Measurement models and reliability statistics.

Constructs, items' brief description, sources and reliability measures	λ
Use of Internet of Things, UIoTs (Kim et al., 2012; Liu et al., 2013; Miorandi et al., 2012; Yang et al., 2013) [Cronbach's α = 0.95 ; AVE =0.66 ; CR = 0.94]	
UIoTs provides us real-time solutions (UIoTs1)	0.73
UIoTs wirelessly provides us comprehensive data about the surroundings (UIoTs2)	0.78
We are highly depend on IoTs in order to track and trace our objects (UIoTs3)	0.72
We use IoTs to monitor our operational environments (UIoTs4)	0.75
We frequently get data through IoTs-devices (UIoTs5)	0.76
Our IoTs technology effectively identifies the required objects (UIoTs6)	0.94
UIoTs continuously assists to innovate our business operations (UIoTs7)	0.94
Integrating advanced IoTs is the main part of our business strategy (UIoTs8)	0.88
UIoTs improves the connectivity of networks (UIoTs9, deleted due to low loadings)	-----
We often collect unstructured data via IoTs (UIoTs10)	0.75
Dynamic data and information processing capabilities, DDIPCs (Chou et al., 2007; Hazen et al., 2014; Kim et al., 2012) [Cronbach's α = 0.93 ; AVE = 0.61; CR = 0.93]	
We have excellent expertise to process structural data (DDIPCs1)	0.93
Our analytics personnel (i.e., team) actively get insights from unstructured data (DDIPCs2)	0.71
The programming skills of our personnel greatly helps us to get analytical insights from the large datasets produced from smart-devices we use regularly (DDIPCs3)	0.77
Our personnel effectively get insights from web-based data (DDIPCs4)	0.66
We effectively process complicated data & information (DDIPCs5)	0.89
We effectively use real-time information for day-to-day operations (DDIPCs6)	0.82
Our IT infrastructure strongly focuses on information integration by using advanced technology (DDIPCs7)	0.69
We frequently disseminate useful information across our departments (DDIPCs8)	0.73
Operational agility, OA (Agarwal et al., 2006; Sambamurthy et al., 2003; Seebach et al., 2011; Tallon and Pinsonneault, 2011) [Cronbach's α = 0.72 ; AVE = 0.67; CR = 0.80]	
Internal operational agility, IOA [Cronbach's α = 0.90 ; AVE = 0.67; CR = 0.89]	0.87
Reliability of our offerings [i.e., services and products] has increased (IOA1)	0.81
Our day-to-day operations are flexible for customized demand (IOA2)	0.77
Our offerings are more cost-efficient than competitors (IOA3)	0.84
We accomplish greater speed in delivering our offerings (IOA4)	0.86
External operational agility, EOA [Cronbach's α = 0.93 ; AVE = 0.76; CR = 0.93]	0.76
Our response to market changes is very reliable (EOA1)	0.94
We have greater flexibility in our offerings to adopt market changes (EOA2)	0.83
We efficiently redesign our offerings to adopt market changes (EOA3)	0.95
We are very quick to adopt market opportunities (EOA4)	0.74

Cronbach's alpha, α = items reliability; λ = loadings; AVA =average variance explained; C.R =construct reliability

Table 3
Discriminant validity.

	Statistics			Condition met
Constructs	ϕ	ϕ^2	AVE	ϕ^2 < AVE
UIoTs & DDIPCs	0.40	0.16[a]	0.64[b]	Yes
UIoTs & IOA	0.29	0.08	0.67	Yes
UIoTs & EOA	0.32	0.10	0.71	Yes
DDIPCs & IOA	0.34	0.12	0.64	Yes
DDIPCs & EOA	0.27	0.07	0.69	Yes
IOA & EOA	0.57	0.32	0.72	Yes

ϕ=correlation between factors, [a]ϕ^2, 0.40*0.40 = 0.16; [b]AVE, (0.66+0.61)/2 = 0.64 (UIoTs & DDIPCs)

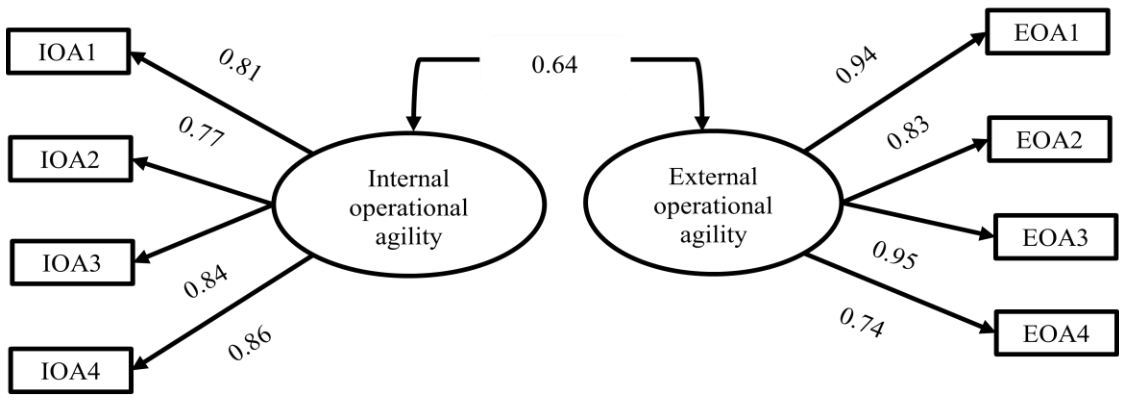
Table 4
Descriptive statistics and correlation matrix.

Constructs	$\bar{x}$	σ	UIoTs	DDIPCs	IOA	EOA	OA
UIoTs	6.16	0.37	1				
DDIPCs	6.27	0.39	0.40	1			
IOA	6.29	0.45	0.29	0.34	1		
EOA	6.33	0.51	0.32	0.27	0.5	1	
OA	6.31	0.42	0.35	0.34	0.8	.90	1

$\bar{x}$ (mean); σ (standard deviation); all correlations are significant at $p < 0.01$

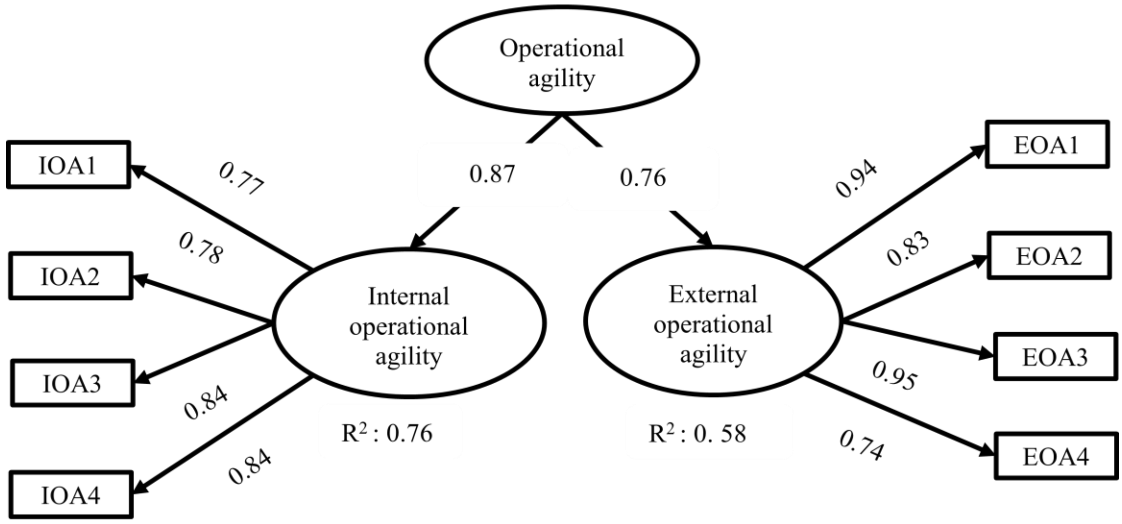
3.3. Establishing a second-order construct for structural results

It was imperative to establish a second-order construct (i.e., OA) before running for the structural model. Fig. 2a shows the first order construct, which provides acceptable measures to establish a second-order one, and the fit indices listed underneath Fig. 2a also support the data. The second-order construct, its loadings, R^2 values, and relevant fit indices are depicted in Fig. 2b.



All loadings were significant at $p < 0.01$; $\chi^2/df = 1.962$; CFI = 0.988; TLI = 0.980; IFI = 0.988; RMSEA = 0.069

Fig. 2a. First-order constructs for operational agility.



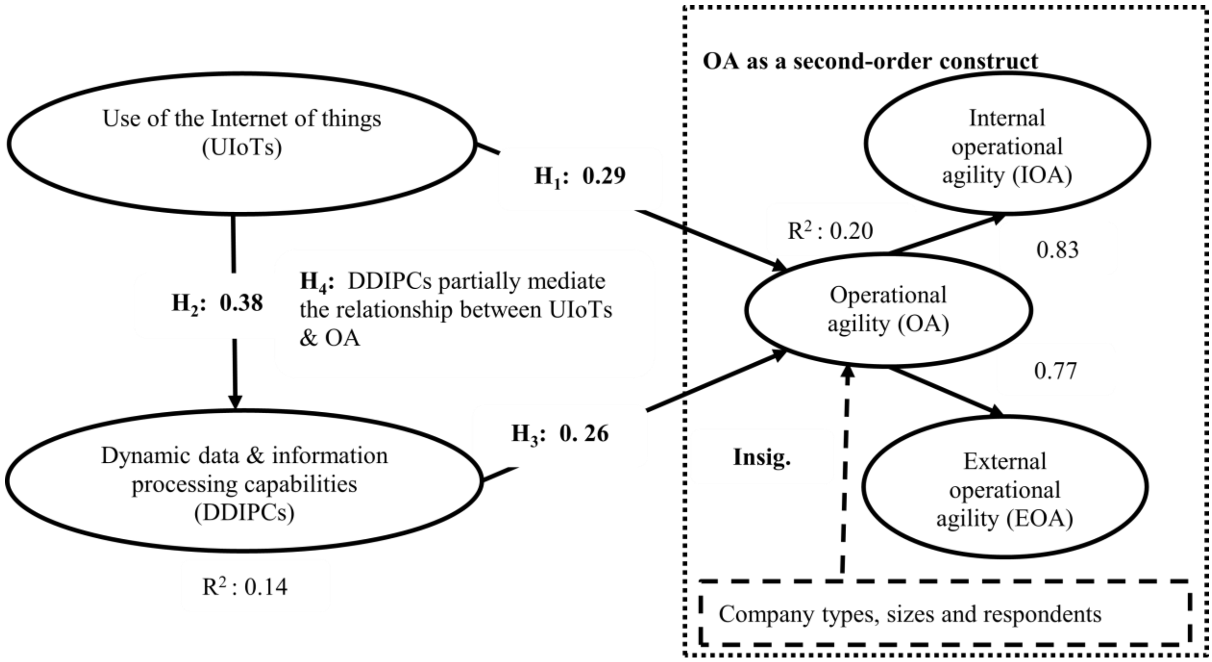
All loadings were significant at $p < 0.01$; $\chi^2/df = 1.838$; CFI = 0.990; TLI = 0.983; IFI = 0.990; RMSEA = 0.064

Fig. 2b. Operational agility as a second-order construct.

4. Hypotheses and results

Fig. 3 presents the results against proposed hypotheses, R^2 values, and fit indices. Hypothesis 1 proposes that the use of IoTs is positively related to operational agility. This hypothesis is supported at $p < 0.01$ with $\beta = 0.29$. Hypothesis 2 (the use of IoTs is positively associated with dynamic data and information processing capabilities, DDIPCs) and hypothesis 3 (DDIPCs positively links with operational agility) are also supported with β =

0.38 (p < 0.01) and β = 0.26 (p < 0.01) respectively. Additionally, the fit indices strongly support the model and the R^2 values, which ranged from 14% to 40%, are given below in Fig. 2, showing stronger support to the final model.



All loadings were positively significant at p < 0.01; χ^2/df = 1.181; CFI = 0.990; TLI = 0.987; IFI = 0.990; RMSEA = 0.032

Fig. 3. Structural results for hypotheses, R^2 values and fit indices.

H_4 [mediating analysis, DDIPCs mediate the relationship between the use of IoTs and operational agility] was tested by utilizing three approaches; a) the causal-steps approach (Baron & Kenny, 1986), b) Sobel typed-tests (Sobel, 1982), and c) Bootstrapping (Preacher and Hayes, 2008). The causal-steps approach showed that the independent variable (UIoTs) significantly affects the dependent one (Operational Agility, OA) with β = 0.35 and t-value = 5.24 at p < 0.001. The independent variable also significantly affects the mediating one (DDIPCS), as β = 0.41 and t-value = 6.35 at p < 0.001. Further, DDIPCS (mediator) significantly affects OA with β = 0.34 and t-value = 5.13 at p < 0.001. Finally, when the model was controlled for DDIPCS, the previous relationship (i.e., between UIoTs and OA) was reduced (β = 0.25 and t-value = 3.53 at p < 0.001), the results thus yielded a partial, rather than a full mediation as the relationship was still significant. The Sobel test also depicted that the indirect effect of the independent variable on the dependent one via the mediator is significantly different from zero at $p < 0.001$. Additionally, the Aroian and Goodman tests provided similar results.

The bootstrapping method with 5,000 samples and a 95% confidence interval was also used (Preacher and Hayes, 2008). First, it was found that the use of IoTs was positively associated with ES [($\beta = 0.40$, t = 5.24, $p < 0.001$)] total effects. It was also found that the use of IoTs was positively associated with DDIPCs [($\beta = 0.42$, t = 6.35, $p < 0.001$)], and the mediator (DDIPCs) was positively associated with OA [($\beta = 0.26$, t = 3.38, $p < 0.001$)]. Additionally, the results showed that the direct effect of the use of IoTs on OA was reduced [($\beta = 0.28$, t = 3.53, $p < 0.001$)] when controlled for DDIPCs, thus, it was partially mediated, with a confidence level between 0.036 and 0.21.

5. Discussion and conclusions

5.1. Summary of findings

The aim of this research is to understand the role played by the Internet of Things (IoTs) and its links with dynamic data and information processing capabilities (DDIPCs) and operational agility, which are two of the key factors involved in dealing with dynamic and competitive environments (Yang et al., 2013). The IoTs has emerged as one of the main technologies of the modern era, with companies from various industrial settings utilizing connected devices with various sensors and data processing technologies to glean useful data to develop competitive advantages (Atzori et al., 2010; Wortmann and Flüchter, 2015). Despite the IoTs' potential, the research in this area is in its infancy and the field lacks a clear understanding of the particular mechanisms and underlying processes through which the IoTs can develop and enhance organizational operational agility. Such technologies are enabling organizations to utilize both structured and unstructured data and information coming through the IoTs, creating valuable knowledge that can be utilized to develop and enhance business operations and improve both operational agility and manufacturing scalability (Christopher, 2000; Heisterberg and Verma, 2014; Lou et al., 2011; No et al., 2015).

Based on the responses obtained from 205 top managers from various European knowledge intensive and IT-oriented industries (IT, Telecommunications, and Energy companies), we find support for the four hypotheses. The findings indicate that the use of the IoTs (Hypothesis 1) is indeed vital for the development and enhancement of organizational operational agility (Atzori et al., 2010; Del Giudice and Straub, 2011; Miorandi et al., 2012; Uden and He, 2017; Yang et al., 2013). Those companies that rely more on the IoTs are in a better position to improve their operational agility compared to those that are lagging behind in such aspect. The IoTs enhances the former's network connectivity and makes their business more agile and responsive to the changing business requirements of the 21st century. This finding is interesting as existing studies and media reports point out that IoTs-devices are important for the accumulation of important data and information (Uden and He, 2017); yet, there is a very limited empirical support for claims of how the generation and accumulation of valuable knowledge from the large volume of data can be utilized to improve operational agility (Bresciani et al., 2017; Chen et al., 2014; Marinagi et al., 2015; Matthias et al., 2017). Thus, our findings provide an important piece of evidence to support claims that the IoTs is imperative for operational agility.

Our findings also support our second hypothesis, which states that the use of the IoTs is important for the development and enhancement of DDIPCs. Generic dynamic capabilities have been widely studied in the strategic management literature and other related fields. However, little research has investigated modern DDIPCs linked with the use of the IoTs (Kim et al., 2012; Liu et al., 2013; Miorandi et al., 2012; Uden and He, 2017; Xu et al., 2016; Yang et al., 2013), which can effectively be used for both internal and external dimensions of agility. The data produced by the IoTs are utilized for actionable insights that may be helpful to enhance operational agility. The IoTs does not only enable the collection of valuable data but also assists in producing real-time information useful for operational agility. These IoTs-enabled capabilities are vital to building DDIPCs (Wang et al., 2017; Xu et al., 2016).

The findings further indicate that DDIPCs play a key enabler role for the development and enhancement of organizational operational agility. Dynamic capabilities are suggested to be the key in developing a competitive advantage, and also aid in competing in highly changeable and turbulent business environments. Thus, those organizations that invest in their dynamic data and information processing capabilities can find themselves in better positions to take advantage of data and information to enhance their operational agility (Agarwal et al., 2006; Sambamurthy et al., 2003; Seebach et al., 2011; Tallon and Pinsonneault, 2011; Xu et al., 2016). The use of the IoTs alone may not provide full benefits. In this paper, we have also argued that those organizations that make timely investments in the development of their dynamic data and information processing capabilities will be in a better position to effectively and efficiently utilize the vast amount of data made available by the use of the IoTs. Thus, we advance a novel perspective by proposing important mechanisms, linked with DDIPCs, that may explain the differential effect of the IoTs on the enhancement of operational agility. The findings support the proposed mediating effect of DDIPCs on the link between the use of the IoTs and operational agility. By proposing and testing this novel mediating effect, the results provide important insights into the underlying mechanisms through which the use of the IoTs can affect operational agility via the mediating role of DDIPCs, which, so far, had not been theorized and tested in the existing studies on this topic, as such advanced capabilities are still emerging (e.g., big data analytics and unstructured data) (Bresciani et al., 2017; Chen et al., 2014; Marinagi et al., 2015; Matthias et al., 2017; Xu et al., 2016).

5.2. Contributions and implications

This study contributes to the existing debate on the usefulness of the IoTs in four important ways. First, it contributes theoretically by advancing arguments based on traditional dynamic capability perspectives (e.g., Teece, 2007; Teece et al., 1997) and modern dynamic capability requirements (e.g., Mikalef and Pateli, 2017; Wang et al., 2017; Xu et al., 2016; Yang et al., 2013), proposing a framework that utilizes various literature streams such as the IoTs, a dynamic capability-based view and agility to advance the understanding of the important relationships that exist between the use of IoTs, dynamic data and information processing capabilities, and operational agility (Atzori et al., 2010; Xu et al., 2016). So far, the research on IoTs and its impacts had not been established on sound underlying theoretical bases (Atzori et al., 2010; Wang et al., 2017; Xu et al., 2016; Yang et al., 2013), therefore, the contribution of our empirical findings to these aspects substantially closes such research gap.

Second, we advance the understanding of operational agility; the existing studies had narrowly focussed on operational agility and its dimensions. We extended the traditional operational agility concept with multiple dimensions linked with internal and external operational agility rooted in the micro and macro environments (e.g., Sambamurthy et al., 2003) of the operational sides of modern businesses. Third, the article contributes to the dynamic capabilities literature by proposing and testing the influence of DDIPCs on operational agility. This is an important contribution because, although the existing studies had highlighted the important role played by traditional dynamic capabilities, there was hitherto limited empirical support for how modern data and IT-driven capabilities affect operational agility (Kim et al., 2012; Tan et al., 2015; Wang et al., 2017; Xu et al., 2016). Finally, the article provides important insights into the underlying mechanisms through which the IoTs impact operational agility by proposing a mediation effect of DDIPC, which provides an important basis for future studies (Bresciani et al., 2017; Chen et al., 2014; Marinagi et al., 2015; Matthias et al., 2017).

The findings of this article have important implications for practitioners. First, they highlight the important role played by the IoTs for operational agility, thus indicating the need for managers to invest in such disruptive technologies and improve the IT organizational infrastructure of their companies in order to take advantage of vast amount of data and information coming through the devices connected to the internet in order to develop both operational agility and manufacturing scalability. The era of the IoTs may significantly change the IT-industry, as it facilitates real-time data and information sharing for operational purposes. Second, the article points toward the importance of having DDIPCs in order to utilize the data and information coming through the IoTs for the generation of vital knowledge. Thus, companies may benefit by improving their internal DDIPCs and recruiting relevant employees equipped with data and information-driven skills. The use of the IoTs alone may not be enough to get the maximum operational benefits; organizations often need in-house human capabilities for data processing and information sharing. These capabilities, together with the IoTs, may provide managers with better opportunities to get greater operational benefits. Managers with such capabilities may take advantage of large datasets, which can unpack actionable insights for operational benefits—such as improving customer service, product quality, speed, product reliability, and supply chain visibility. In fact, effective DDIPCs can play a central role in bridging the gap between the IoTs and operational benefits. The value of general human-IT capabilities has been highlighted by practitioners. However, general business managers may not be fully aware of the valuable knowledge generated by modern DDIPCs, as it is an emerging domain and mainly remains the subject of IT departments. Contemporary business operations are inundated with structured and unstructured data and modern businesses rely on new tools and techniques to process data and share information; this challenges traditionally minded managers to equip themselves with these tools to achieve better operational outcomes. Continuous learning can help such managers to tackle those challenges. Lastly, investing in DDIPCs and systematically improving IT-related capabilities is important for the development and enhancement of operational dimensions, which is a key message that managers should take on board.

5.4. Limitations and future research

Despite the important contributions, this article has several limitations that offer important opportunities for future research. First, it utilizes information collected from three European-based key knowledge intensive and IT-oriented industries (IT, Telecommunications, and Energy). Future studies need to test the proposed framework in other industrial and geographical contexts by comparing less IT-oriented industries with highly IT dependent ones. This could also be performed by comparing developed and emerging economies. Second, there could potentially be other variables that can influence organizational operational agility, such as the skills needed to deal with the IoTs/data and information processing, and internal cultural barriers to such modern implementations. Third, future studies could build on this one and examine other potential mediating and moderating variables. Fourth, there is the need to utilize social network techniques and understand how network partners improve their operational agility by being widely connected through various digital technologies and internet devices and how knowledge-related resources flow through such networks and impact their members' agility. Lastly, future studies need to combine qualitative case studies and large scale surveys to disentangle the impact of the IoTs and of dynamic data and information processing capabilities on operational agility. A potential contribution would be made by case studies based on the large unstructured datasets that are produced by the IoTs.

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