Towards an Integrated IoT Capability Maturity Model

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ABSTRACT: Through the Internet of Things companies obtain more and more data everyday that has potential in creating unique value. However, extracting beneficial information becomes more complex with this huge pool of data. Therefore, organizations need to improve their Internet of Things management and carefully facilitate the transformation from data to useful knowledge. Accordingly, this research aims at developing an integrated Internet of Things capability maturity model in order to provide companies with the self-assessment and guidance for a better Internet of Things management. In this paper, relevant capabilities and existing maturity models are analysed through literature review and combined for a new model creation. The results show that companies need to have a technical department integrated in decision-making activities and establish a very supporting and open culture for enabling information sharing. The article provides a five staged maturity model with explicit descriptions of the requirements and actions in technology, authority and culture, and knowledge management areas. Additionally, it provides the operational steps and suggestions for implementing the model.

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1. INTRODUCTION

The Internet of Things (IoT) is an emerging technology that changes life of people and organizations. It has potential providing value to many areas in the business. In order to gain that value companies have to transform their strategies, structures and culture of the organization. There are plenty of benefits IoT can offer, but there are many challenges and a number of aspects have to be managed carefully: security, customer privacy, data storage and processing, technologies and networking (Rivera & Meulen, 2014). According to Abu-Elkheir, Hayajneh & Ali (2013) data problems will be the biggest challenge in the future and they are not explicitly answered yet and not connected to the networks of organizations. Many companies adopted this new technology and connected many devices and therefore generated plenty of information. However, not all the data is useful and there is a need to differentiate between redundant data and the one that can be implemented. In fact, too many enterprises focus on making the connected system bigger and do not improve their data management (Noronha et al., 2014). Therefore, there is a need for organizational improvements on how to handle the data coming from IoT devices in order to extract value for the company. This research creates an integrated IoT capability maturity model for companies to assess and improve their processes to get the best out what IoT can offer. The paper first explains relevant concepts and a framework, later explores the capabilities needed for a successful IoT management and analyses the existing maturity models, which can contribute to a new model development. Finally, it presents operational steps and advices for successful model's implementation.

2. KEY CONCEPTS

Internet of Things (IoT) is a concept connecting many things and activating communication between them (Said & Masud, 2013). IoT has three characteristics: 1) generation of huge amount of data, 2) the primary data is semi-structured or unstructured, 3) the data is only useful after its analysis (Chen, Mao & Liu, 2014). Such complex system requires many supportive elements which can be grouped in three categories: 1) hardware – the technical parts of IoT that use sensors to collect the data, 2) middleware – mechanism for storage and transforming the data and 3) presentation – tools and applications for data organizing and representation (Cole et al., 2013). In this paper the focus is placed on the last element – more a semantic role of IoT.

Big Data includes a very large amount of advanced but unstructured data that can be very useful to get important information for the companies. It is also great in volume, has various modalities, rapid generation and creates huge but low-density value (Chen, Mao & Liu, 2014). There are many technological difficulties involved in generating hidden value from the pool of data, however managerial challenges are even more important and many aspects of the organizational decisions have to be addressed (McAfee & Brynjolfsson, 2012).

Since IoT is extracting big amounts of data from various sources it can be related to the Big Data concept, which as mentioned is enormous datasets. Chen, Mao & Liu (2014) stated that recently IoT is not the major part of Big Data, which is also generated by other technologies like data centre and cloud computing, but by 2030 it is expected that IoT will take the biggest part of it (p. 177). From the previous concepts' descriptions, it can be seen that the characteristics of IoT and Big Data are similar; they are both great in amount and value. Additionally, Barnaghi, Sheth & Henson (2013) identified IoT data as a type of Big Data, which is constant and very dynamic. Therefore, IoT data and Big Data in this study are considered as one and used interchangeably for describing any complex data organizations are obtaining.

Organizational capability is a business capacity to effectively perform a special business task and it complements the technological elements in the company (Collis, 1994). Gold, Malhotra and Segars (2001) identified two perspectives and their elements of organizational capabilities. The infrastructure capabilities include technology, structure and culture, whereas process capabilities comprise acquisition, conversion, application and protection process (Gold et al., 2001).

A *maturity model* is a tool for assessing and guiding the organization and its processes by presenting an evolutionary improvement pathway consisting of sequenced maturity levels generally starting from the ad hoc activities to the mature and well managed processes (Becker et al., 2009). Each level involves a number of dimensions, which structure the capabilities and incorporates business characteristics, processes and measurement elements (Lahrmann & Marx, 2010).

3. RESEARCH GOAL

The goal of this research is to describe the organizational setting suited for managing and extracting value from data generated from IoT in order to create competitive advantage. The aim is to help companies to improve capabilities dealing with big data by developing an assessing and guiding tool - IoT capability maturity model.

4. THEORETICAL FRAMEWORK

In order to provide a continuous improvement in IoT management for organizations, maturity model framework will be used and therefore it is necessary to explain it for theoretical background of this research. In this section, the resource-based view and the properties and design of the maturity models are described.

4.1 Resource-based View

The importance of organizational capabilities derives from the resource-based view model. Barney (1991) stated that in order to improve company's performance and sustain competitive advantage it is necessary to identify possible organizational key resources. They have to be valuable, rare, inimitable, and non-substitutable (Barney, 1991). However, the resources suggested in that model are rather static and do not take into consideration the rapidly changing environment (Teece et al., 1997). Since IoT is a new and still developing concept it exists in a very demanding environment, therefore in order to have a competitive advantage and create customer value there is a need to address dynamic capabilities which emphasize the strategic management in adapting organizational skills, resources and functional abilities to cope with a rapidly changing business environment (Teece, Pisano & Shuen, 1997). Helfat & Peteraf (2003) stated that "to say organization has a capability means only that it has reached some minimum level of functionality" (p. 999), therefore the authors developed a capability lifecycle. They explained that organizational capability supported by a team evolves over time and reaches from founding stage to the maturity stage (Helfat & Peteraf, 2003).

4.2 Maturity Models

The aforementioned evolution of capabilities can be related to maturity models. In this paper some criteria is applied for their development. According to Becker, Knackstedt & Pöppelbuß (2009) maturity models are considered as artifacts and therefore the guidelines for design science can be applied. In their study the authors translated the design science guidelines provided by Hevner et al. (2004) to the guidelines for the development of maturity models. The criteria are: comparison with existing maturity models, iterative procedure, evaluation, multi-methodological procedure, problem relevance, problem definition, targeted presentation of the results and scientific documentation. There are several types of maturity models developments; in this paper the innovation one is chosen "combination of maturity models towards a new model" (Lahrmann & Marx, 2010, p. 524).

One of the most universal models is the capability maturity model (CMM), which is a framework for the process improvement by describing the key characteristics and capabilities of an effective process, usually applied in software development (Kumta & Shah, 2002). There are five levels of maturity: initial, repeatable, defined, managed and optimizing, those move from immature to mature stages covering application for planning, engineering and managing the software (Kumta & Shah, 2002). In the same study authors summarized the issues in the model implementation. The areas are: management of change, process ownership, awareness, meeting guidelines, decision-making, team evaluation, and knowledge management (Kumta & Shah, 2002). Additionally this framework shows the importance of people in the organizations in relation to technology and processes. Seeing that "people use technology and people work, execute and contribute to the processes" (Kumta & Shah, 2002) makes human resource management a critical success factor (p. 4).

5. METHODOLOGY

The research question of the study is: what are the important organizational capabilities for an effective data management of IoT? In order to reach the study goal, it was necessary to search and indicate IoT capabilities, analyze already existing and relevant maturity models, and integrate the results into a new IoT capability maturity model. For this, a systematic literature review was conducted, which provided secondary data. The existing studies on relevant topics were critically examined, evaluated and built upon. In this paper one of the several types of literature review is used – narrative literature review. According to Baumeister and Leary (1997), narrative literature review can be applied for connecting and integrating the literature about different topics with intention to develop new concepts and/or theory. In the following, there are two methodology descriptions of the sections I used the literature review for.

5.1 Identifying Capabilities

In order to answer the research question there was a need to review IoT related papers. The literature review was used for IoT's explanation and capabilities necessary for its successful implementation. Accordingly, a number of keywords were used in the titles and abstracts in search for required articles. The main search words for the articles explaining IoT challenges and needed capabilities were: IoT data, IoT value, IoT capabilities, IoT and Big Data management including alternations and synonyms of these phrases. The criterion of choosing the paper was: an article that has a non-technical perspective of IoT and its challenges and focuses on knowledge and value extraction. Published studies were found through the search of Google Scholar search engine. An effort was made to focus on the newest articles and since IoT is a relatively new subject, the search was also conducted in the general Google in order to find the newest insights about the issues on websites and in white papers. However, some not directly IoT related capabilities and models were sourced from the older articles as well.

5.2 Analysing Maturity Models

It is important to review already existing maturity models whose insights could be applied in a new IoT maturity model. Therefore, after identifying capabilities necessary for IoT, related fields were selected: business intelligence, business analytics, knowledge management and decision-making in organization. The search for relevant papers included mentioned phrases along with 'maturity model' using Google Scholar. The ones most recent, most cited and able to contribute to the new model with detailed level description were chosen. The content analysis was conducted after identifying the article as relevant: main ideas were highlighted and useful information was documented.

6. FINDINGS

6.1 The Internet of Things Capabilities

It is important to structure IoT field into areas and capabilities in order to develop an organized model. Therefore, after reviewing the IoT data, the following areas for the improvements were identified: business analytics, organizational culture and knowledge management. In this sub-section the important capabilities and actions for each area will be discussed which later will be integrated into maturity model.

6.1.1 Business Analytics

"Big Data and business analytics" is one of the three groups of activities companies should focus on for IoT's successful implementation (Lee & Lee, 2015, p. 433). Grant (1996) stated that IoT related organizations often focus on quantity of the data even if they cannot benefit out of it. Therefore, businesses should create value from the Big Data by improving their business analytics capability (Vidgen, 2014). Vidgen (2014) did a qualitative case study and addressed organizational dimensions needed for this capability and gave suggestions for its utilization. In the study, the author integrates the research framework and states that business analytics capability functions as an intermediary between generated data and value created by enhancing their decisions (Vidgen, 2014). Data and value are grouped together and business analytics capability separated into four elements: 1) analytics management and process, 2) technology, 3) people and tools; some central recommendations are explained in the following. For the data it is crucial to ensure high quality, transparency and anonymisation as well as it is suggested to build partnerships with the entities who need organization's data rather than sell it (Vidgen, 2014). In the management and process, Vidgen (2014) found that "An analytics strategy is needed with a clear articulation of how and where value will be created" (p. 24). Furthermore, machine learning is one of the methods for data analysis, which is known for high-value predictions; it improves the decision-making and therefore increases the competitiveness (Chen et al. 2013).

6.1.2 Organizational Culture

The culture of the company plays also a very important part in IoT improvement. The companies will face organizational change and they will need to change their culture and encourage the innovation (Vidgen, 2014). For the lasting value it is also needed to have a deep field knowledge understanding, mixed team structure and agile development culture (Vidgen, 2014). Additionally, Agarwal & Dey (2016) claimed that in order to extensively adopt the IoT it is important to be involved in the IoT community – in a "truly open source development" (p. 89). Another dimension described by Kaivo-oja et al. (2015) is accountability, which should be horizontal and vertical, that is not only communicating the outcomes to the whole organization, but also reporting it to the connected and external stakeholders. The companies should also encourage the intra-organizational information flow (Kaivo-oja et al., 2015). Yang & Maxwell (2011) stated, "With limited access to and sharing of information and knowledge, organizational members lack the capability to develop integrated solutions to problems" (p. 165). For this reason, they described the three-layered factors influencing the intra-organizational information sharing. Some of the most important factors in the outer layer are organizational structure and culture while the middle layer contains incentives, performance-based rewards, trust, types of information and absorptive capability (Yang & Maxwell, 2011). Member's beliefs are mentioned in the outer layer and it is explained that cost-benefit analysis, self- interest and reciprocity impact the employees' willingness to share the information (Yang & Maxwell, 2011).

According to Kaivo-oja et al. (2015), organizations have to see their operating environments as open systems and become members of a network rather than acting as hierarchy single organizations. To continue, in the same study by Kaivo-oja et al. (2015), foresight-based resilience is mentioned to be adopted as an organizational coping mechanism for the big data utilization enhancement. Furthermore, the innovation philosophy should be open while change management – intrinsic and emergent, and in the production logic the customers has to be considered first rather than productivity (Kaivo-oja et al., 2015).

6.1.3 Knowledge Management

Knowledge management is another area, which needs close attention for IoT management. The authors argued that "smart organizations do not rely on knowledge production, but focus on knowledge integration instead" and there is a need for "a new understanding of organizations functioning in the framework of open systems" (Kaivo-oja et al., 2015, p. 510). Grant (1996) defines three process aspects of knowledge integration in his framework: breadth, efficiency and flexibility. The smaller scope and the more sophisticated common knowledge exists, the easier the integration is; flexibility refers to the way in which the company can combine its cross-functional knowledge (Grant, 1996).

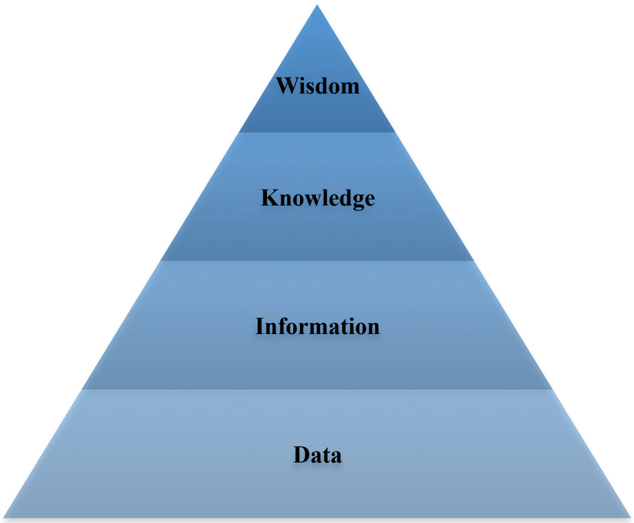

Figure 1. 'Knowledge pyramid'

'Knowledge pyramid' is a widely known model for understanding the process of data transfer to the actionable knowledge (Rowley, 2007); it is shown in the Figure 1. This chain shows how the raw data becomes a wisdom, which is used for decision-making. Barnaghi et al. (2012) related this framework to the IoT and argued that this knowledge management is fundamental for capturing 'rich data'. Similarly, Xu (2015) identified knowledge management as a crucial process for companies dealing with Big Data and pinpointed that "Knowledge management in big data times is no longer a pure technical matter, but becomes a social issue" (p. 168). Abu-Elkheir et al. (2013) developed a framework for data management for IoT in which they included a management layer with three suggested positions: transaction manager, recovery manager, and security manager; these positions could be helpful in managing the transformation from data to wisdom.

6.2 The Analysis of Maturity Models

In order to create a fine maturity model it is important to analyse existing models related to IoT field. The choices for maturity models derived from the literature review in the previous section. After identifying the capabilities necessary for a successful Big Data management, relevant maturity models were captured. First, their key process areas were identified in order to find the relevance to the IoT and use them for selecting the areas for the new model. Second, key success factors present the logic for moving from one stage to another. Lastly, levels were pinpointed for level integration and a fine stage creation of the new model. All the summarized models according to the explained attributes can be found in the Table 1. In this section, some viewpoints of the models will be emphasized and discussed, which will later be integrated into an IoT maturity assessment tool.

As identified in Section 6.1.2, business analytics is one of the areas that needs attention from the organizations dealing with IoT. For this reason, the business analytics capability maturity model developed by Cosic et al. (2012) was chosen. The authors first identified the relevant BA capabilities and grouped them in the following areas: governance, culture, technology and people, which can be also integrated to an IoT maturity model as they cover most areas of IoT capabilities. In addition, there is a number of IT capabilities that are suitable for an organizations dealing with IoT data. It is stated that the companies should possess dynamic BA capabilities in order to have a continuing learning (Cosic et al., 2012). Furthermore, the strategy of BA has to be aligned with the overall business strategy and all the insights incorporated into people's values (Cosic et al., 2012). Also the data-driven decision-making is a part that has to be commonly integrated, therefore another crucial capability for BA is "evidence-based management" (Cosic et al., 2012, p. 6). In the paper by Cosic et al. (2012), all types of skills and knowledge is included in "people" category, however as knowledge management is usually emphasized in IoT it could become a separate area for the new maturity model.

Business intelligence deals with structured and unstructured data, its collection and management, which is analysed and used for an organizational decision making and planning support (Negash, 2004). Since data and its progress to useful knowledge is one of the most important elements in IoT management, the Business Intelligence/Performance Management Maturity Model developed by AMR research was included to complement business analytics model. The main takeaway from this model is that the more mature the company is, the more technology becomes just a tool and members realize how changes in one part of the business affect the other parts, therefore the attitude towards performance has to be aligned in all the units of organization (Hagerty, 2006). Furthermore, it stated, "at the highest level of maturity, they fuse culture, philosophy, and technology in a grand coalition", this determines all the business parts integration being optimized (Hagerty, 2006, p.1). Similarly, an Enterprise Business Intelligence Maturity Model (Chuah, 2010) explains the integration of the technology, but also focuses on the data management and the quality, which is useful for IoT.

Since in the previous section knowledge management was identified as another required capability for IoT, a maturity model by Lee & Kim (2001) was chosen. The main point from knowledge management maturity model is that companies become more mature when the knowledge in an organization is understood as a core value and it is effortlessly spread across the business and to the external parties for an inter-business collaboration (Lee & Kim, 2001). Many points from this model can be included in knowledge management area of the new model, except IT systems, which may be a part in technology. The next model can also contribute to the IoT model creation. Knowledge-based decision-making capability maturity model by Kaner & Karni (2004) adopted decision-making and knowledge management maturity models and provided an explicit description of a new integrated levels and dimensions. The approaches in handling the knowledge are supplementary to the previous research.

7. THE INTEGRATED IOT CAPABILITY MATURITY MODEL

In the previous section mentioned models are suitable for IT related activities assessment, however they are too specific in one field and do not provide a wider picture. For example, knowledge-based decision-making capability maturity model explains many valuable attributes efficient organizational knowledge use, however it does not include any data management or more technical part related solutions. As IoT requires the integration of all business parts, it is practical to combine those maturity models and merge the most important aspects from each into a new capability maturity model. In this section, the integrated capability maturity model of the IoT will be presented. First, I will identify the maturity levels of the model and the key interest areas for structuring the capabilities. Second, each area will be described in detail in every level in order to provide the IoT maturity assessment. Lastly, the operational steps for model application will be provided.

7.1 Elements

The basic capability maturity model consists of five levels: 1) initial, 2) repeatable, 3) defined, 4) managed, and 5) optimizing (Paulk et al., 1993). The stages for IoT derived from the

Table 1. Maturity model analysis

Attributes Maturity Models	Key Process Areas	Key Success Factors	Levels
Business Analytics Capability Maturity Model (Cosic et al., 2012)	Governance, culture, technology, people	Level of capabilities development: from not having a capability to an integrated capability	Non-existent, initial, intermediate, advanced, optimised
Business Intelligence/Performance Management Maturity Model, Version 2 (Hagerty, 2006)	Technology, process, culture/philosophy	Moving from technology-focused to multilayer effort and reaching the integration to the company's culture	Reacting, anticipating, collaborating, orchestrating,
An Enterprise Business Intelligence Maturity Model (Chuah, 2010)	Data warehouse, information quality, knowledge process	Increase of data quality understanding, becoming more formal towards knowledge related activities, data aligned and shared throughout the departments	Initial, repeatable, defined, managed, optimizing
Knowledge Management Maturity Model (Lee & Kim, 2001)	Organizational knowledge, knowledge workers, knowledge management process, IT systems	Integrated and networked knowledge sharing	Initiation, propagation, integration, networking
Knowledge-Based Decision-making Capability Maturity Model (Kaner & Karni, 2004)	Decision-making: formality, foundation, favour and feedback Decision Knowledge management: acquisition, arrangement, appraisal, application	Identification of a problem or opportunity, explore and evaluate the alternatives, choose and apply the approved decision	Ad-hoc, planned, defined, controlled, sustained

original levels and from the analysed models are: 1) primitive, 2) preliminary, 3) transitional, 4) harmonious, and 5) maximizing. The dimensions for each level are: technology, authority and culture, knowledge management.

7.1.1 Primitive Level

Technology: the technology adoption is very basic at this stage, in fact the innovation diffusion is very static and all the IoT sensors/tools and data matters are limited to the IT/technical department. The focus is to connect devices and collect data. The quality of the data depends on the technicians (Chuah, 2010).

Authority and culture: as in level 1 of Business Intelligence/Performance Management MM (Hagerty, 2006), everyone is independent and improving their own tasks with a minimal control just over the productivity. Performance measures do not exist at this point.

Knowledge management: this capability is not present at the company. Knowledge is obtained and retained by one person and "is used only by the individual to carry out a knowledge-based activity" (Kaner & Karni, 2004, p. 241), usually for day-to-day short-term activities.

7.1.2 Preliminary Level

Technology: starts to extract information and structure it, however still within the same department, although the recognition that different parts of the business are interrelated increases. The need for expanding and improving the existing tools and practices arises.

Authority and culture: the need for improvement is also recognized at the management level. The organization becomes more strategic towards the knowledge management and therefore starts to create visions and set goals. Decision-making is still informal and derives from personal experience (Kaner & Karni 2004).

Knowledge management: knowledge management capability and its problem recognition rises. Company starts to seize an opportunity to obtain knowledge, for this reason the information owned by individuals begins to flow within team circles and an effort to record it is made.

7.1.3 Transitional Level

Technology: The ways of managing the data are shared within the company and data becomes treated as "a corporate asset" (Chuah, 2010, p. 306), therefore various departments and their performances are more aligned. The quality control is important at this stage.

Authority and culture: the reward systems are built in order to increase the motivation and participation in data-driven environment development. There are meetings organized for sharing the knowledge to create an open and encouraging atmosphere. The decision making process becomes formal, clearly defined and based on a model approved by the whole team, however the model is closely fixed and it is applied for most of the decisions with minor adjustments.

Knowledge management: an organization understands what kind of knowledge is needed to support the company's strategy and structures it into areas. The team understands that 'rich data' does not come from the IT department alone, but only in corporation with all the business units, therefore it develops knowledge related goals derived from the company's strategy and key performance indicators.

7.1.4 Harmonious Level

Technology: a shared awareness exists that technology is just a tool for data extraction and there is a need for its environment improvement. Therefore, technical specialists are trained to understand knowledge management and help to extract and maintain insights from the data for decision-making support.

Authority and culture: the decision-making process is controlled and well documented for the evaluation. The culture is more open and members share and discuss the information. It is clear what gives the value and how to create it.

Knowledge management: all the knowledge is continuously revised and the best practices are spread and integrated within a whole organization. There is a responsible person for facilitating and communicating the data-to-wisdom transformation.

7.1.5 Maximizing Level

Technology: IT department is continuously improving its performance and participating in a decision-making team. Innovation becomes an important aspect. At this stage productivity is not an issue anymore; it is maximized and stable. The company adopts and masters machine learning for its data analysis.

Authority and culture: decisions are made based on the case reasoning approved by a team (Kaner & Karni, 2004). The vision and strategy are IoT data related and clearly communicated throughout organization. The value creation through IoT management is incorporated in the company's philosophy. The management group adopts a formal "evidence-based management" (Cosic et al, 2012, p. 6). Additionally, change management is optimized and recovering after problems is quick.

Knowledge Management: the company owns and continuously obtains 'rich data' necessary for the decision support. The way from unstructured data to the wisdom is defined and communicated. Knowledge is smoothly shared not only within the company but also to the external environment creating networking unions.

7.2 Implementation

In order to use this model effectively, some implementation steps and suggestions will be provided in this section. The operational steps for this model's application are adapted from capability maturity model by Paulk et al. (1993). The company has to begin with choosing and training the team for the implementation of the model (Paulk et al., 1993). Secondly it is crucial to become familiar with all the levels provided in IoT model and fairly decide at which stage your organization is in. Lastly, the team has to find the main strengths and weaknesses for each of the areas according to the level descriptions and start the process towards an IoT mature organization.

There are a number of factors that need close attention for maturity model integration, these are: process and project management, engineering, and support (Herndon, 2003). Each area has to be considered when starting to implement IoT maturity model. For the process and project management, it is important to define and plan the process and to establish integrated monitoring, control and risk management (Herndon, 2003). It is also helpful to have an implementation strategy and focus on change management. Engineering category has to be also well organized. Before the start of model implementation, the company has to be sure that all the process tools are stable and technical department is capable and ready for the change (Herndon, 2003). Finally, the whole organization has to be aware of the goal to become mature and get the best support for it. Communication channels have to be clear, improvements have to be announced and close analysis of the process has to be performed (Herndon, 2003).

8. CONCLUSION

"IoT and Big Data most definitely are key factors affecting societal development in the future" (Kaivo-oja et al., 2015, p. 510), therefore companies working with the IoT are challenged to keep up with the evolving innovation. The reason for this is that many companies have reached the point where they generate loads of data, however they do not know how to create value and become unique within an industry. Accordingly, this research attempted to define the capabilities and activities, which companies could obtain in order to improve their performance and generate more useful results from IoT data.

IoT is quite a new concept and not many studies have been conducted about its improvement, except of explaining the idea and challenges. There are many theories developed for organizational improvement, which can be related to the IoT, therefore integrating them can narrow the research gap. In this study, the IoT capabilities were presented and a number of related maturity models were analysed in order to build a new integrated IoT maturity model, which can be used to assess the company's level in IoT and guide for advancement.

The main finding from the IoT capabilities literature review was that companies need to change the understanding of data collection; and see it as a value creating process with technology being just a tool and therefore improve it to a point where it is fully integrated and the whole organization is supporting it. Furthermore, the environment in the IoT dealing companies has to be open and all the knowledge has to be shared inside and outside the organization. The main finding from the maturity models' analysis was that in order to reach the higher stage of maturity, the IT companies have to include technical department into a decision-making group and make the data-driven philosophy an organizational value. Additionally, before starting to implement an IoT capability maturity model it is important to get the team ready and take into account the successful integration factors: process and project management, engineering, and support (Herndon, 2003).

The five-level IoT maturity model integrated the insights gained from the already existing literature, which can be implemented by the companies that want to gain a competitive advantage in the IoT industry. It can be used as an assessment tool in order to know where the company stands and can provide guidance for getting to the highest maturity stage.

9. LIMITATIONS AND FURTHER RESEARCH

There are several limitations of this study that will be mentioned in this section and the recommendations for the further research will be presented. First of all, the time of the research was limited, which could have had an impact on the number of articles reviewed and the conclusions made. Secondly, as the narrative literature review was conducted, it is possible that the findings are subjective, because the choice of theories, analysis and conclusions made based on one author. Furthermore, the search was conducted only in English, which could limit the scope of the research. Finally, some important information could be missing due to restricted availability of the articles. They were accessed through the UTWENTE library.

IoT is still and emergent technology, therefore there is a need for more researches on this topic in the future in order to have an up to date solutions for the companies dealing with IoT. Additionally, researchers could collaborate and collect qualitative data from the companies about their success cases implementing and managing this technology and therefore publish the empirical research.

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