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Research-in-Progress

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Abstract

Artificial intelligence (AI) has become increasingly prevalent in organisations in different sectors. The rapid development of AI technology has rendered it essential to understand strategies for its implementation. Despite current trends, the uncertainties in the process required to establish strong AI capabilities are the major concerns for high level management. Therefore, this research-in-progress aims to understand AI practices in organisations through the development of an organisation-level AI maturity model (AIMM). However, to the best of our knowledge, no fully developed and theoretically derived AI maturity model currently exists. This research, therefore, represents an early attempt to develop an AI maturity model at the level of organisations; the results of this research will provide organisations with insights into the successful evolution and adoption of AI and can be used as a theoretical foundation for future research.

Keywords: Artificial Intelligence, Maturity model, AI maturity model, Industry 4.0

Introduction

Artificial Intelligence (AI) plays a crucial role in strategic planning and has been used by organisations to gain a competitive advantage over their rivals (Varian, 2018). AI has transformed from an 'old' but emerging technology to a management reality (Alsheibani et al.,2018). The progress made in AI has motivated organisations to become part of the Fourth Industrial Revolution or industry 4.0. According to the World Economic Forum (2018), AI is the engine technology that drives the Fourth Industrial Revolution and will be the primary disruptor in this new phase of change (Clark, 2019).

An explosion of networks and increased data processing speeds together with advances in hardware are reshaping industries and have brought AI to a commercial level (Cockburn, 2018). According to Gartner (2018), AI is ranked first as a strategic technology for organisations. This is supported by Google, Amazon, IBM, Facebook, Apple, and others, all of whom have leveraged AI to deliver better customer experiences and improve productivity. Every industry has massive opportunities in this respect (Gartner, 2018). It has improved decision-making and ecosystems, and has become increasingly commercialised; however, uncertainty and the need for managerial guidance prevail. Organisations worldwide are facing substantial challenges as a result of economic and technological developments in

AI (Goolsbee, 2018). To be competitive and benefit from the opportunities promised by AI, organisations must adapt to these new circumstances and develop new capabilities. Furthermore, they need to have a holistic view of how these transformative changes will redraw the boundaries of future work (Gruner and Csikszentmihalyi, 2019). Therefore, this study aims to develop a maturity model (MMs) to enhance organisational performance for the assessment and improvement of capabilities created by AI.

Due to the lack of theoretical foundation and documentation in most of the analysed models (e.g. Gartner 2018, Ovum, 2017), the relations between an AI maturity model and organisational capability is still unclear (Andrews et al. 2019; Vanson, 2017). However, to the best of our knowledge, no fully developed and theoretically derived AI maturity model currently exists. For this reason, it is essential to build a maturity model to assess the organisational level of AI capability. This research-in-progress is one of the early attempts to develop an AI maturity model (AIMM) at the organisational level. Thus, the result of this research will provide organisations with insight into the successful evolution and adoption of AI. Using an AIMM can help organisations visualise and identify the steps that need to be taken in order to mature in their usage of AI. To achieve this objective, this study addresses the following research question:

How can AI maturity be expressed through maturity domains and maturity levels? Specifically, the following sub-research questions will be addressed: What are the significant components of AI maturity? How could the developed maturity model be applied? How can AI maturity be expressed through specific levels? Which specific individual(s) will be participating? (Becker et al., 2009). The focus of this study is to present the first development guidelines and empirical step towards a maturity model for AI. The paper will be structured as follows: First, the theoretical foundation is presented in order to provide a theoretical structure for AIMM. Second, the research methodology and producer guidelines used to further develop the AIMM are presented. Third, the proposed model is introduced. Finally, the proposed methodology and future research directions are discussed.

Theoretical Foundation

Artificial Intelligence

AI is an 'umbrella term' for both AI terminology (e.g. Machine Intelligence, De Silva, 2000; Computer Intelligence, Barr and Feigenbaum, 1981; Intelligent Behaviour, Schalkoff, 1990) and AI technologies (e.g. Deep Learning, Personal Assistants) and used to develop AI applications (Purdy and Daugherty 2016). AI was developed in the 1950s as a computer science discipline in the United States (US). It has remained a persistent theme in science fiction ever since its introduction by Professor John McCarthy at a conference held at Dartmouth in 1956, where he described AI as the 'science and engineering of making intelligent machines, especially intelligent computer programs'(McCarthy, 1955). Debate on the risks of AI grow primarily on the topic of employment displacement (Rotman, 2013), failure of autonomous machines (Buchanan, 2005) and loss of privacy (Brey, 2005). Today, the focus of AI is very different from that of the past 60 years (Cockburn, 2018). AI has become an increasingly popular area of research in numerous fields and various industries including education (Hunter, 2018), healthcare (Yu and Kohane, 2018), finance (Agrawal, 2018), business, accounting, finance, marketing, economics, and law (Brynjolfsson and Mcafee, 2017). The development of AI is already being applied to such endeavours as the self-driving car, healthcare, and new media (Bollier, 2017). The success of AI has also increased the responsibilities of decision-makers and policy analysts (Cockburn, 2018).

Based on the AI definitions from literature, the concept of AI is defined as a set of tools and technologies that has the ability to augment and enhance organisational performance. This is achieved by creating "artificial" systems to solve a complex environmental problem in an arena where "intelligence" refers to the simulation of human-level intelligence. This definition reflects our understanding of AI in a way that AI represents a complex technical system for which both technological and organisational elements need to be considered.

Maturity Model

As part of the hype surrounding industry 4.0, several maturity models (MMs) have been devised and applied to check the progress of industry 4.0 initiatives (Lichtblau, 2015; Ganzarain and Errasti, 2016; Lanza et al., 2016). The terms 'maturity' and 'immaturity' are usually used to continually compare and determine a path or roadmap in a given state (Andersen and Henriksen 2006). They were initially proposed during the 1970s by Gibson and Nolan (1974). MMs are commonly used as benchmarks to assess and improve organisational capabilities (Schumacher et al., 2016). The emergence of the maturity concept has been widely studied by scientists and practitioners in relation to software development, e-learning and supply chain management (Schriek et al., 2016). Over the last four decades, many different types of MMs have been developed (Mettler and Rohner, 2009). For example, MMs as classification structures, the Capability Maturity Model (CMM) developed by Carnegie Mellon University in the software industry (Paulk et al., 1993) to improve organisational capabilities (Schumacher et al., 2016) and project management maturity model (PMMM) (Ibbs and Kwak, 2000) and Quality Management Maturity Grid (QMMG) Crosby (1979). In information systems (IS) academic research MMs are defined as "a measurement tool to evaluate the capabilities of an organisation" (De Bruin et al., 2005, p. 1). Initially proposed in the 1970's (Mettler and Rohner 2009), over a hundred different IS maturity models have been applied in many different fields such as business intelligence (Raber et al., 2013), cloud computing (Weiss, 2013), and ERP system (Holland and Light, 2001). Pöppelbuß and Röglinger (2011), describes three basic kinds of MMs; descriptive (examining the status of capabilities through current characteristics), prescriptive (providing guidelines and measures) and comparative model (providing organisations with the opportunity to benchmark). MMs have proven to be a significant tool to guide organisations in improving their capabilities and the organisation's process orientation (Schriek et al., 2016). Although existing models cover several aspects of relevance for IS domains, AI aspects are not yet covered.

Research Methodology

The design and development of the AI maturity model (AIMM) was based on the procedure proposed by Becker et al. (2009) and design science research (DSR) guidelines developed by Hevner et al. (2004) which can be seen as the foundation of the entire artefact and to develop a model with a sound theoretical foundation. This study aims to develop a new IS artefact called AIMM. Becker et al. (2009) describe seven steps in the development of MMs. In this research, the first four steps are considered: step 1) problem definition, step 2) comparison of existing models, step 3) development strategy, and step 4) Iterative Maturity Model Development. The remaining steps of the procedure model that involve transfer, implementation and evaluation will be addressed in future research. Figure. 1 shows the critical design steps in the development of an AIMM (adopted from Becker et al., 2009).

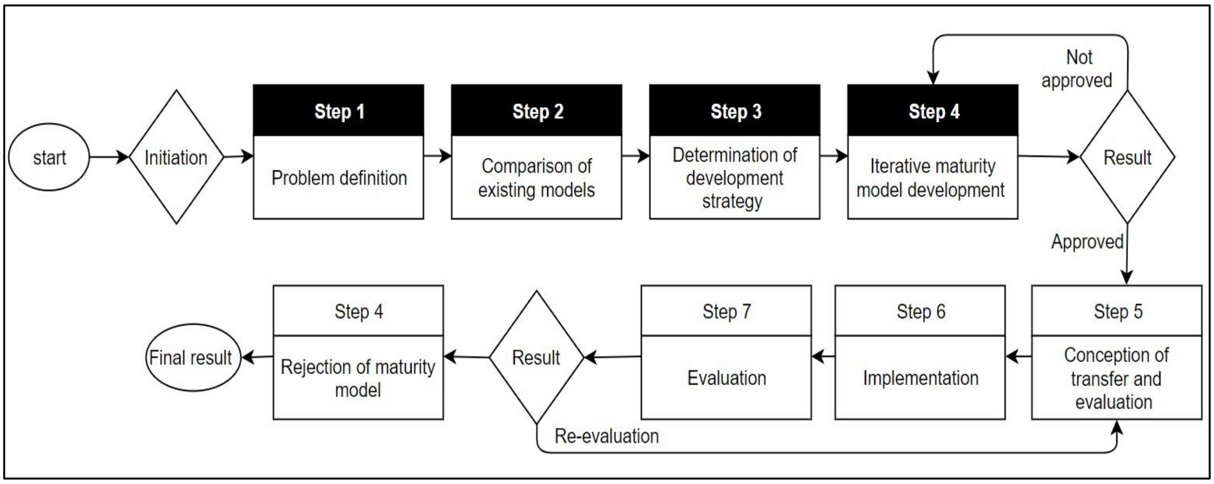

Figure 1. Procedure model for developing a maturity model adopted from (Becker et al. 2009)

Developing AI Maturity

Step 1 - Problem Identification The first step in developing an MMs starts with an initial definition of the problem (Becker et al., 2009). In the defining the principle of an MM, Hevner et al., (2004) outline a problem as the difference between the current state and the target system level. Despite its novelty, AI has already had a substantial economic impact (Purdy & Daugherty, 2016). AI is transitioning from science fiction to a commercial entity that is core in enabling businesses to stay competitive. Vanson Bourne's (2017) report on 260 large organisations shows that 80 % are investing in AI however, commercialisation of AI is still in its early stages. Additionally, a recent Gartner (2018) study states that how to align AI into a business strategy is unclear in terms of it capability. Moreover, the definition of AI is unclear; organisations are facing difficulties in identifying and adopting AI applications. This leads us to an awareness of the significant gaps between organisations which already understand and have adopted AI and those that are lagging. To achieve this, organisations must continually improve their capabilities and reshape their business models (De Bruin et al., 2005). Maturity in the field of AI indicates the degree of development and the strength of the organization's performance measures to mitigate risks that threaten its assets. Therefore, they must identify the level of maturity so they can leverage AI to give them a competitive advantage. Objective or development strategy allows for the maturity model of a variety of different objects. An AIMM has been designed to evaluate the maturity level of organisations that have implemented or partially adopted AI. The design strategy of AIMM for the field of AI can be used as the basis for future research and application-specific maturity models by following a scientifically-valid development model.

Step 2- Comparison of Existing Maturity Models To compare existing AI maturity models and develop the initial MMs for this research, a systematic literature review was conducted. The theoretical background and literature review was based on the work of Webster and Watson (2002). This review covered the fields of computer sciences, information system/information technology, and business. The keywords used to search for relevant articles included "Artificial intelligence capability model", "AI maturity model" and combinations thereof. The focus was on IS MM literature from 2011 to 2018. Only articles written in English and published in leading peer-reviewed journals were chosen. To conduct the search, a research database containing top-level IS journals/conferences and online technical AI reports was used. The outcomes of existing AI maturity models (e.g. Gartner AIM, Andrews et al. 2018; Ovum, 2017) found that the absence of theoretical foundation and lack of documentation in most of the analysed models are almost completely ignored. Therefore, we decided to develop an entirely new model because all the established and accepted model have deficits according to the requirement of the procedure model.

Step 3- Determine Development Strategy According to Becker et al. (2009), the development of MMs needs to be justified according to one of the following strategies: designing a new model; improving an existing model; combining several existing models into a new model; transferring structures or applying contents from existing models to new domains. The development of a new model should transfer valid structure and content from existing models while remaining aware of what is lacking in these models (De Bruin et al., 2005). However, because no empirical AIMM exists, a new MMs will be designed based on the construction approach proposed by Becker et al. (2009) and De Bruin et al. (2005).

Step 4 - Iterative Maturity model The AIMM design process has undergone different iterations. Bacher et al. (2009) determine four sub-characteristic structures of the proposed new maturity model: design level, model approach, model selection and assessment. Design level refers to the fundamental structure. For example, the principle concept of maturity, the structure of levels, single or multi-dimensions, and sub-dimensions of the maturity model. In general, the design process can follow a top-down or a bottom-up approach (Bacher et al., 2009). A bottom-up approach first defines dimensions and characteristics representing maturity, then derives descriptions from it. In the case a top-down approach, this first specifies the levels and their descriptions. Given the characteristics of AI discussed above, a bottom-up approach seems most adequate for mature domains (De Bruin et al., 2005). In the context of maturity models, the dimensions are used to structure the subject of analysis (Hansmann, 2016). The dimension is emphasized in two basic approaches: a one-dimensional sequence of discrete steps and a multi-dimensional approach regarding the maturity steps. This answers the basic questions of "what needs to be measured" and "how it can be measured" (Becker et al., 2009). Hence, determination of the design level dimensions depends on the model scope determined from the literature. To conceptualize AI, several classifications or dimensions have been proposed to identify different technology of AI (McCarthy, 1956; Nilsson, 2014; Millington, 2016; Corea, 2017). According to Hansmann (2016), the initial model dimension or domain can be justified based on existing literature or expert knowledge. A number of AI dimensions are identified in the literature by labelling key characteristics and related topics for each level (Chen et al., 2012); it can be argued that they are highly important and relevant to the research context. Furthermore, we argued that organisational aspects represent the challenges that are posed AI implementation. Therefore, AI dimensions can be structured via the following categories: AI functions, data structures, people, and organisational. A conceptual definition of the four dimensions of AI is presented in Table 2. The selection of AI dimensions is used as a basis for the further identification of topics and and will be discussed with the focus group involving AI and IT experts step number five.

Table 2. Definition of AI dimensions

AI dimension	Definition	Reference
AI functions	AI functionality refers to the tools and technologies that are required to handling AI at scale	Russell et al. (1995)
Data structure	Data refer to containing both the amount and structure of the data to getting AI systems to work by enabling high-velocity capture, discovery or analysis.	Nilsson, (2014)
People	People refers to all those individuals within an organisation to create artificial intelligence technologies.	Rich,(1983); Corea, (2017)
Organisational	Describes business characteristics and resources that might influence AI process such as firm size, managerial structure, decision-making and communication.	Tornatzky and Fleischer (1990)

AI dimension items were identified from an analysis of the IS and maturity model literature. In addition to the theoretical side, a number of AI characterizations were identified from an industry background (e.g. Gartner 2018, Ovum, 2017). According to Chui and Francisco (2017) two main characteristics of the data dimension should be taken during evaluation 1) the source and structure of the data 2) adjunctive abilities. Therefore, to identify the process relevant data sources and implementation details will be discussed with the AI experts during Delphi techniques. Second, selecting the model approach or population method defines the maturity assessment, which includes the specification of instruments. This answers the questions of what needs to be measured and how this can be measured in the maturity assessment. Following Becker et al. (2009), a literature review on related approaches is performed to determine design level dimensions. Next, the validation of measurements model can be carried out using qualitative (ex Delphi studies and expert interviews) or quantitative (ex survey) approaches (De Bruin et al., 2005). Becker et al. (2009) indicate that in a bottom-up approach, a questionnaire is needed to gather the relevant input data. Therefore, items identified based on the literature will be discussed with the focus group of an AI and IT expert. The measurements of the four AI dimensions represent different maturity levels. The initial domains for AI capabilities is shown in Table 2 below. Third, the model selection involves designing an AIMM for the organisations and justifying its maturity level. In line with Becker's et al. (2009) definition the model is a general model. Such a broad level design allows a greater number of organisations and industry experts to participate in the model construction process. The AIMM combines the dimensions for AI maturity described above with a five-level maturity scale based on practice of prominent MMs like the Capability Maturity Model Integration (CMMI). The five-levels are used as a basis for the further identification of topics and related measurements. In this step the items are assigned to different levels. The structure of the initial AIMM is shown below in Table 3. The elements of five-level maturity scale are described below.

Level 1 ***initial***. Organisations associated with maturity level one - the capability exists but there is a lack of organisational knowledge. AI responsibilities are decentralised and have no dedicated unit for AI. It is essentially used by individual's function or team without the clear awareness of the organisation about the actual usage. Since there is a lack of organisational awareness about the usage, it cannot be sufficiently measured and control by the organisational IT. Therefore, there is no AI related governance or regular principles of operation which are extended to AI services by the users themselves. Level 2 ***assessing***. Here, the capability is well-developed and the organisation has decided to move towards AI - with some initial steps in that direction. The AI substructure is already functioning centrally and basic capabilities such as ad hoc analyses are provided. Organisation initial AI strategy; for each AI application, and defined a value proportion is one of the main drivers of AI adoption. However, decentralised solutions still exist and the organisation is faced with AI restrictions issues. Level 3 ***determined***. Based on the knowledge obtained in level 2, the organisation becomes more conscious of inherent risks and opportunities for AI. Organisations that achieve this level have an AI strategy focused on technology and tools. The organisation has standard operating procedures that cover AI scenarios; change management is introduced. The organisation also employs AI talent and resources are provided. This level has strong top management which influences the challenge of aligning the AI with organisational goals; IT capabilities can be addressed. Level 4 ***managed.*** Organisation capability is very well developed. In terms of achieving the primary goal for this stage there is a well-defined value to support and full top management support. Regarding the data dimension, the increase of data regarding the source and structure. Additionally, appropriate data science exists to make critical business decisions using AI Level 5 ***optimised*** organisations are at the final level of AI maturity. They are realising the full role; responsibilities and accountability are clearly defined within each AI project. Data structure is flexible and pro-active to achieve business impact. Altogether, the initial model will be discussed with the AI expert regarding the potential maturity level errors could be found.

Table 3. Artificial Intelligence Maturity Model

level	**AI functions**	**Data structure**	**People**	**Organisation**
Level 1 Initial	Very limited or no AI function exists and has no plans	Regular data structure; no data exists to train AI	Regular IT skills; Organisations lack the skills to evaluate, build and deploy AI solutions	No business case related to AI; existing structure are used informally
Level 2 Assessing	Discovery AI Technology	Integration of current usage of AI into data required to train AI	AI related training; Assessment of existing infrastructure with regard AI	Organisation initial AI strategy; for each AI application, have defined a value proportion
Level 3 Determined	AI project is at an advanced stage; determination of infrastructure needed to further implement AI	Custom AI data are introduced; data standardised are exist	Active management support; resources are provided, AI related employees training	Organisation has standard operating procedures that cover AI scenarios; change management is introduced
Level 4 Managed	AI process are defined throughout the organisations	Appropriate data science exists to make critical business decisions using AI	AI is being fully realised as employees' productivity	There is a well-defined value to support and full top management support
Level 5 Optimise	Full AI infrastructure adoption and standardisation	Proactive data analysis; Data is available in real time	Employees are engaged; centralised leadership	Role, responsibilities and accountability are clearly defined within each AI project; AI culture

Proposed Methodology and Future Work

To our knowledge, this research represents the first attempt to initiate the development of an AI maturity model at the level of organisations. The AIMM is well grounded based on the construction approach of maturity models design by Becker et al. (2009). It presents a procedural approach for developing a maturity model identifying the key dimensions influencing organisation AI maturity. The AIMM combines the dimensions for AI maturity described above with a five-level maturity scale based on practice of prominent MMs like the Capability Maturity Model Integration (CMMI). The initial AI maturity model is the starting point for the model evaluation. The next step of this procedure is testing and validating the proposed maturity model over several iterations of empirical work including a quantitative approach using an online survey instrument, a Delphi study involving AI and IT experts of SMEs in both private and public service organisations in Australia. To measure the model dimensions of each AI capability, a quantitative approach using an online questionnaire instrument drawing on the (Chow, 2005) approach will be the preferred method for data collection as a bottom-up method has been selected. To validate the model, a Delphi techniques based on Analytic Hierarchy Process (Saaty, 2013) is strongly recommended (Becker et al. 2009; de Bruin 2009). A panel of IT, industry experts will be interviewed. In-depth case studies of Australian SMEs will be used to evaluate further and refine the AIMM. The initial AIMM contributes to the IS body of knowledge, in particular to the research field of the maturity model and AI. The AIMM has the potential for several essential contributions in practice. First, the value to organisations of measuring their AI capability at a point in time. Organisations can also recognise some critical existing AI domain capabilities by benchmarking against other advanced organisations. Second, this study provides insights to business managers by helping organisations to adopt AI and express AI maturity accordingly. Additionally, the model also allows organisations to assess and ultimately improve their AI capabilities. This paper also offers several directions for future research. First, we have proposed an initial AI capability, which will provide the appropriate guidelines for future AI maturity within an organisation. Second, future researchers can build a proposed model and enhance the structure, dimensions, or maturity measures. Finally, the outcome of this research can be used to bridge the theoretical gap associated with AI maturity.

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