Empirically Grounded Development of a Maturity Model for AI in B2B Sales

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Abstract

This paper addresses the growing prominence of Artificial Intelligence in B2B software investing and the pressing need for effective AI implementation. Despite the immense potential, evidence shows that most AI initiatives fail. To bridge this gap, this study introduces a B2B sales AI maturity model, leveraging the structured framework of maturity models to help firms prepare for AI adoption. Drawing from the Design Science Research process, the study elaborates on the development of the maturity model through iterative stages, encompassing, for example, a literature review, expert interviews, and case studies. The goal is to enable firms to assess their AI implementation maturity and identify areas for enhancement to effectively integrate AI into their sales functions. The paper highlights the need for a robust framework tailored to AI in B2B sales and highlights the contributions and potential impact of the research on reshaping B2B sales practices in the AI era.

Keywords: maturity model, B2B, sales, artificial intelligence, design science research

Introduction

Venture capitalists suggest that, nowadays, 'basically all' B2B software investing focuses on Artificial Intelligence (AI), and recent research by Goldman Sachs predicts that investments in AI could approach $250 billion globally by 2025. At the same time, survey evidence suggests that the majority of AI initiatives fail (van Giffen and Ludwig, 2023). Field experts argue that many firms are simply not ready for AI and that, unless a company's information systems are prepared for AI, the promises of AI vendors are unlikely to deliver (Early and Bennoff 2020). Hence, for firms to make efficient investments in AI, it becomes crucial to better understand their own maturity for implementing AI (Holmström 2022). In this study, we develop a maturity model for AI in B2B sales to help firms refine and adopt AI.

A maturity model is a structured framework that helps organizations assess and improve their processes, capabilities, and overall performance in a particular area (de Bruin et al. 2005; Fisher 2004). It describes a series of development stages or phases that must be passed through to move from an initial state to a target state, thereby providing a way to measure and understand an organization's current maturity state (Becker et al. 2009; de Bruin et al. 2005). For example, large corporations like IBM use maturity models to understand the current state of their customers and define development goals (IBM, n.d.). One of the most well-known and used maturity models is the Capability Maturity Model Integration (CMMI) (CMMI Product Team, 2010), developed in the late 1990s. It provides a structured approach to assessing and improving an organization's processes, with the goal of enhancing the quality, efficiency, and effectiveness of their products and services, and has been successfully applied in various organizations since. While firms make large investments into AI, the literature provides only little guidance on how to assess firms' maturity in regard to the unique challenges of AI implementations in a B2B context.

AI systems can add value to many types and areas of companies (Desouza et al. 2020), whereas B2B sales poses a particularly beneficial opportunity (Paschen et al. 2020). AI can affect every step of the sales process (Paschen et al., 2020), and therefore offers numerous opportunities to improve efficiency and effectiveness and help companies increase revenue (Chen and Lu 2017; Rodríguez et al. 2020). For example, sales employees can use AI to collect and analyze data about competitors' offers and strategies, create customer profiles, predict buying behavior, and create personalized offers and branding campaigns (Andzulis et al. 2012, Itani et al. 2017). Therefore, it seems evident that AI will change B2B sales (Paschen et al. 2020). Although AI is likely to have a substantial impact on B2B sales, the absence of guidelines and specifications poses hurdles for managers to implement AI. A maturity model aims to facilitate this process by providing a structured framework that assesses firms' readiness to implement AI and guides it along this way (Martínez-López and Casillas 2013). Therefore, scholarly work is needed in this area in particular to provide a supportive understanding (Singh et al. 2019).

Therefore, this research aims to explore the research questions "What are critical factors and prerequisites for AI implementation in a company's B2B sales process?" and "What are different maturity levels of AI implementation in B2B sales processes?".

In this paper, we develop an empirically grounded maturity model for AI in B2B sales, using the Design Science Research (DSR) process of Sonnenberg and vom Brocke (2012). The goal of the maturity model is to enable companies to determine their own maturity level for the implementation of AI in their sales processes, identify optimization potential, and increase their ability to successfully adopt AI within their sales departments. The developed maturity model is based on a comprehensive literature review and a survey of experts and practitioners in sales. As part of the DSR process, we iteratively carried out an eight-step process for developing the maturity model, including several evaluations.

The remainder of the paper is structured as follows. The next chapter provides an overview of the current state of research on the topic of AI in sales and the essential basics of maturity models. The following chapter describes the development of the maturity model, by explaining each step and describing the results obtained immediately afterward to ensure understandability of the complex process of development and evaluation. Afterward, we present the final maturity model and the results of its application in four case studies. We then summarize and discuss the results and conclude the paper with the limitations of our research.

Research Background

AI in B2B Sales

In recent times, AI has increasingly emerged as a promising technology for B2B sales. AI has the capability to process and analyze vast amounts of data, extract insights, and automate decision-making processes. Despite AI's recognized potential in B2B sales and many other industries and applications, the definition of AI in the literature lacks consensus. Various definitions emphasize the ability to imitate human-like behavior or replicate cognitive processes, but no unified definition exists. In this study, we adopt the definition of Paschen et al. (2020), who define AI in a B2B sales context as “information systems that act rationally based on the information available to them in order to solve problems” (p. 405). A growing number of studies on the use of AI in B2B sales have shown that AI can create value in various steps of the B2B sales process (e. g., Alavi and Habel 2021; Bongers et al. 2021; Singh et al. 2019). Referring to the established seven-step sales process of acquisition, preparation, approach, presentation, handling objections, closing, and follow-up (Dubinsky 1981; Homburg et al. 2011), Paschen et al. (2020) show that AI can support humans in every step of the sales process and can even take over some of the tasks completely. Tasks such as lead generation, lead scoring, creating personalized offers, predicting future customer behavior and emerging trends, and identifying new business opportunities have the potential to be automated fully through the usage of AI (Kumar et al. 2021; Syam and Sharma 2018). Apart from the opportunity to automate these tasks, the salesperson remains crucial for fostering interpersonal relationships and engaging in personal interaction with customers (Alavi and Habel 2021). One of the significant advantages of using AI is that it allows salespeople to allocate their time more efficiently. AI, one the one hand, can takes over repetitive, data-intensive, and time-consuming tasks while at the same time providing salespeople with the relevant information at the right time (Bongers et al. 2021; Rodríguez et al. 2020; Singh et al. 2019).

The opportunities AI offers have led to increased interest in the implementation of AI into B2B sales practices to improve sales performance, enhance customer interactions, and gain a competitive edge (Syam and Sharma 2018). Despite the recognized potential of AI in B2B sales, the successful implementation of AI remains a challenge for many companies. B2B sales often involve high-value deals and complex decision-making processes that require human judgment, intuition, and relationship-building skills (Paschen et al. 2020). Sales professionals rely on their experience, negotiation skills, and interpersonal interactions to understand customer needs, build trust, and close deals (Bongers et al. 2021). Replicating these complex human behaviors and decision-making processes accurately in AI algorithms is challenging, however, it is even more difficult to ensure the acceptance of these technologies so that they are actually used in sales (Alavi and Habel 2021). Furthermore, B2B sales data can be complex, heterogeneous, and dispersed across various sources, and external databases. Ensuring data quality, integration, and accessibility for AI applications can be a significant challenge, as it may involve dealing with unstructured data, data inconsistencies, and data privacy concerns (Mikalef and Gupta 2021). AI algorithms rely heavily on data quality and availability to train and optimize their models (Nda et al. 2020), making data management a critical factor in successful AI implementation in B2B sales. Additionally, implementing AI in B2B sales may require organizational processes, structures, and cultural changes. Organizational readiness can be a significant challenge in AI implementation in B2B sales, as it requires alignment across different parts of the organization. Since Wengler et al. (2021) have already found the aspects 'human', 'process' and 'data' to be main success factors of digital transformation in B2B sales, it seems natural that they will also play a significant role in the implementation of much more sophisticated solutions like AI. In addition, studies focusing on AI have shown that data analysis and the required infrastructure are also particularly crucial for AI implementation (Alsheibani et al. 2019; Wright and Donaldson 2002). In the context of AI implementation, technologies related to data analysis and infrastructure thus represent another essential factor (Mikalef and Gupta 2021; Nda et al. 2020). Another challenging factor comes in the differing levels of automation AI solutions for B2B sales can entail. While simpler solutions focus on data analysis, descriptive knowledge, more sophisticated systems can offer predictive or predictive knowledge. These kinds of systems might predict customer behavior and, in turn, prescribe actions to salespeople. The differing degree of possible automation then poses unique challenges to organizational processes and demands differing degrees of acceptance from salespeople.

Maturity Model

Maturity models are a particular class of reference models that deal with the developmental process of organizations. The concept of maturity models gained popularity with the publication of the CMMI in the late 1980s in the field of software development (Humphrey 1988). The model was further developed into the CMMI in the late 1990s and is one of the most well-known maturity models, along with Software Process Improvement and Capability Determination (SPICE) (Ahern et al. 2003). Maturity models are widely used in software development and IT management (Becker et al. 2009). A maturity model includes a sequence of maturity levels that represent the expected, desired, or typical development path of a class of objects. These objects are typically organizations or processes (Becker et al. 2009). The maturity model is used to determine the current maturity with the help of criteria and characteristics. This enables organizations to make an objective assessment of the as-is situation (de Bruin et al. 2005) and to derive possible actions to increase their maturity (Ahern et al. 2003; Iversen et al. 1999; Paulk et al. 1993).

According to de Bruin et al. (2005), maturity models can be divided into descriptive, prescriptive and comparative models. Descriptive maturity models survey the current situation in an organization. This form of maturity models is the most common and is often used as a diagnostic tool by management consultancies (Canetta et al. 2018). Compared to descriptive models, prescriptive maturity models provide concrete recommendations for action to improve maturity based on the current situation (de Bruin et al. 2005). The goal of a comparative maturity model is to be able to make comparisons and benchmarks of different organizational units or companies in an industry or region (de Bruin et al. 2005). The three types of maturity models are not mutually exclusive but can be run through as phases one after the other (de Bruin et al. 2005). According to Fraser et al. (2002), there are six criteria that a maturity model should include. These are (1) the number of stages or maturity levels, (2) a keyword or descriptor for each level, (3) a description or summary of each level, (4) a number of dimensions relevant in the context (e.g., capabilities, technologies, etc.), (5) a number of sub-dimensions describing the dimensions in more detail, and (6) a description of the characteristics of each individual sub-dimension. For the development of maturity models Becker et al. (2009) define eight requirements (R), namely: Comparison with existing maturity models (R1), iterative procedure (R2), evaluation (R3), multi-methodological procedure (P4), identification of problem relevance (R5), problem definition (R6), targeted presentation of results (R7), scientific documentation (R8).

Development of the Maturity Model

The development of the maturity model is guided by the DSR paradigm. DSR is a systematic approach that focuses on solving real-world problems (Hevner et al. 2004). The typical DSR approach is characterized by the practical application of scientific principles and the creation of design knowledge. The creation of design knowledge takes place in the form of artifacts that serve a specific purpose (Gregor and Hevner 2013). Artifacts are objects, processes or services that have been created through DSR (Goldkuhl 2002). In this context, the artifact to be developed represents the maturity model. To develop the maturity model for AI in sales, the DSR approach of Sonnenberg and vom Brocke (2012), in combination with the established requirements for the development of a maturity model by Becker et al. (2009), was applied. Figure 1 shows the combination of these two methodological bases. In the middle, the DSR process of Sonnenberg and vom Brocke (2012) can be seen. R1 to R8 stands for the eight requirements to be considered for the development of a maturity model, according to Becker et al. (2009). Various methods were used to develop the artifact, as shown in Figure 1. The participants in each study differed from each other throughout. Except for Evaluation 4, the same people who used the maturity model in the use phase were interviewed.

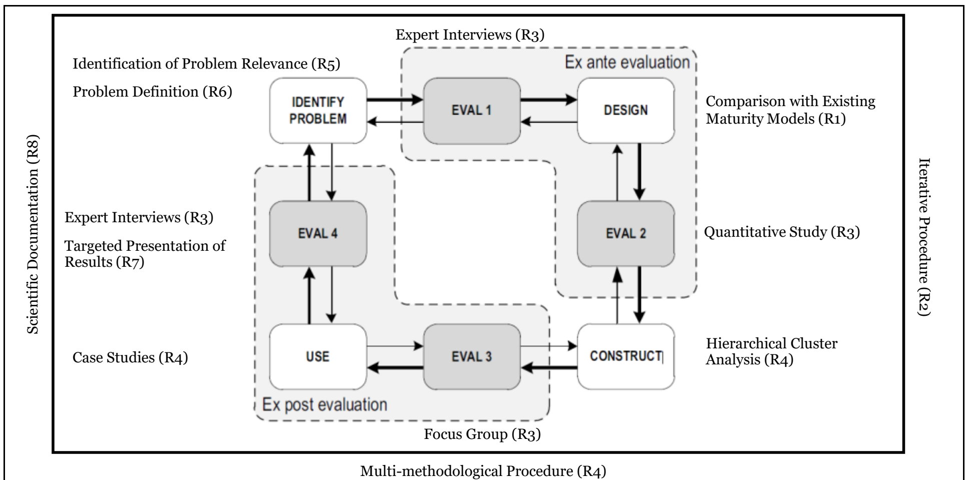

Figure 1: Research approach

Identify Problem and Evaluation 1

In the first step (identify problem) of the DSR process, the research gap was defined. This gap was underscored in the introduction through relevant literature, highlighting the challenge companies face due to the absence of clear guidelines for new technology implementation, especially in the context of AI tools in B2B sales. Possible applications of AI in B2B sales and the necessary prerequisites for implementation are uncertain. This research gap was then reviewed in the context of Evaluation 1 to determine its practical relevance. For this purpose, we conducted interviews with six experts from B2B sales, both sales employees and sales managers. Their in-depth industry experience provides a practical lens through which to evaluate the challenges of implementing new technologies, such as AI, in B2B sales. Their insights offer real-world perspectives on the lack of guidelines and specifications, illuminating the gap's tangible impact on sales operations. The B2B experts were recruited via personal contacts as well as LinkedIn. Interviews were conducted using a semi-structured guide and recorded. The first part of the interviews consisted of determining which tools and systems are currently used to support sales. In addition, the sales employees were asked about changes due to digitalization and the systematic collection of data. Finally, the interview focused on existing challenges and the future of sales. The interviews unanimously reinforced the need for tangible guidelines and specifications, particularly those outlining the prerequisites for successful AI integration. For example, one expert commented as follows:

"We don't know anything about it yet. So when we talk about the use of AI in sales, we as a company would first have to look at where we stand. I mean, what are the prerequisites for implementation? I know you need a lot of data, but otherwise, for us, this is all new."

Design and Evaluation 2

In the process step "Design", we conducted a literature search for existing maturity models. Here, we searched for maturity models related to AI, digital transformation, or Industry 4.0. The aim of the search was to derive relevant main and sub-dimensions for the development of the maturity model and to compare the approach of the identified models. In addition to the generally very well-known maturity models (CMMI and ISO/IEC 15504), we were able to identify a further 17 models, which are shown in Table 1.

Study	Author	Title	Journal/Conference/Book
1	De Carolis et al. (2017)	Guiding Manufacturing Companies Towards Digitalization (DREAMY)	International Conference on Engineering, Technology and Innovation (ICE/ITMC)
2	Colli et al. (2018)	Contextualizing the outcome of a maturity assessment for Industry 4.0	IFAC-PapersOnLine
3	Berghaus and Back (2016)	Stages in Digital Business Transformation: Results of an Empirical Maturity Study	Mediterranean Conference on Information Systems (MCIS)
4	Canetta et al. (2018)	Development of a Digitalization Maturity Model for the Manufacturing Sector	2018 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)
5	Schumacher et al. (2016)	A Maturity Model for Assessing Industry 4.0 Readiness and Maturity of Manufacturing Enterprises	Procedia of the International Academy for Production Engineering (CIRP)
6	Jung et al. (2016)	An Overview of a Smart Manufacturing System Readiness Assessment	International Conference on Advances in Production Management Systems
7	Leyh et al. (2016)	SIMMI 4.0 – A Maturity Model for Classi-fying the Enterprise-wide IT and Software Landscape Focusing on Industry 4.0	Federated Conference on Computer Science and Information Systems
8	Gökalp et al. (2017)	Development of an Assessment Model for Industry 4.0: Industry 4.0-MM	International Conference on Software Process Improvement and Capability Determination
9	Gentsch (2019)	AI business: framework and maturity model	Palgrave Macmillan
10	Kreutzer and Sirrenberg (2020)	Understanding Artificial Intelligence: Fundamentals, Use Cases and Methods for a Corporate AI Journey	Springer International Publishing
11	Saari et al. (2019)	AI Maturity Web Tool Helps Organisations Proceed with AI	VTT White Paper
12	Coates and Martin (2019)	An instrument to evaluate the maturity of bias governance capability in artificial intelligence projects	IBM Journal of Research and Development
13	Abele and D'Onofrio (2020)	Artificial intelligence – the big picture	Springer Vieweg
14	Lichtenthaler (2020)	Five maturity levels of managing AI: from isolated ignorance to integrated intelligence	Journal of Innovation Management
15	Yablonsky (2019)	Multidimensional data-driven artificial intelligence innovation	Technology Innovation Management Review
16	Burgess (2018)	Starting an AI journey	Springer International Publishing
17	Alsheibani et al. (2019)	Towards an artificial intelligence maturity model: from science fiction to business facts	Pacific Asia Conference on Information System (PACIS)

Table 1: Analyzed maturity models from the literature

We examined the maturity models using criteria and characteristics from literature. In their study, Sadiq et al. (2021) provided an overview of such characteristics, which we applied in this study. The first criterion analyzes whether a new maturity model was developed or an existing one was validated or applied in the study. The criterion (two) "scope" refers to the object of study and the level of analysis that are the focus of the maturity model. The methodological approach of the study is elaborated in criterion three. Criterion four refers to the design approach chosen in developing the maturity model. A distinction is made here between the top-down and bottom-up approaches (de Bruin et al. 2005). Another criterion is the architecture (criterion five) of the maturity models examined. Criterion six relates to the purpose of use, whereby a distinction can be made between descriptive, prescriptive, and comparative. In the context of typology (criterion seven), the type of measurement instrument is analyzed. The last criterion (eight) considers the individual components, such as levels and dimensions of the maturity models. According to Becker et al. (2009), the design strategy of the maturity model to be developed should also be derived from the comparison of existing maturity models. Since the analyzed maturity level models from the literature do not focus on the sales organization and/or have not been developed in sufficient detail and on a scientific basis, we decided to develop a new maturity level model for the design strategy.

Previous literature has shown that the areas of "human", "process", "data" and "technologies", play a central role in the implementation of digital technologies (e.g. Wengler et al. 2021). We therefore assume that for the implementation of AI, an even more sophisticated technology, these areas will also be main success factors. Based on this assumption, we examined the dimensions of the analyzed maturity models with regard to these four areas. We found that significant parts of the models we analyzed overlap with these areas. Hence, for the maturity model we develop in this study, we defined “Human”, “Process”, “Data” and “Technology” as the four main dimensions for the maturity model we develop in this study. In addition, we analyzed the sub-dimensions specified in the maturity models from the literature. Table 2 shows the main dimensions and the sub-dimensions we derived from the respective maturity models.

Main dimension	Sub-dimension	Reference
Technology	Infrastructure	Alsheibani et al. (2019), Berghaus and Back (2016), Canetta et al. (2018), Colli et al. (2018), De Carolis et al. (2017), Gökalp et al. (2017), Jung et al. (2016), Saari et al. (2019), Schumacher et al. (2016)
	Data analysis	Berghaus and Back (2016), Colli et al. (2018), Gentsch (2019)
Data	Data collection	Alsheibani et al. (2019), Berghaus and Back (2016), Coates and Martin (2019), Gentsch (2019), Gökalp et al. (2017), Saari et al. (2019)
	Data retrievability	Alsheibani et al. (2019), Coates and Martin (2019), Gökalp et al. (2017), Saari et al. (2019)
	Data storage	Alsheibani et al. (2019), Colli et al. (2018), Gentsch (2019), Gökalp et al. (2017)
Human	Attitude	Berghaus and Back (2016), Colli et al. (2018), Gentsch (2019), Schumacher et al. (2016)
	Competence	Alsheibani et al. (2019), Berghaus and Back (2016), Canetta et al. (2018), Colli et al. (2018), Gentsch (2019), Schumacher et al. (2016)
	Transformation Management	Alsheibani et al. (2019), Berghaus and Back (2016), Colli et al. (2018), Schumacher et al. (2016)
Process	Process definition	De Carolis et al. (2017), Jung et al. (2016), Schumacher et al. (2016)
	Process measurement	Berghaus and Back (2016), De Carolis et al. (2017), Jung et al. (2016)
	Process control	De Carolis et al. (2017), Jung et al. (2016)
	Process innovation	Berghaus and Back (2016), Canetta et al. (2018), Jung et al. (2016)

Table 2: Main dimensions and sub-dimensions with the respective literature

With regard to the main dimension “technology”, we were able to identify two aspects in the literature. First, the need for an infrastructure as the basis for new digital products or services (Berghaus and Back 2016). Alsheibani et al. (2019) also state that the prerequisite for realizing a data-driven enterprise is a suitable technological infrastructure. Similarly, in Jung et al. (2016), the dimension 'IT maturity' is understood as IT resources that are available and functioning. Second, in the context of this main dimension, reference was made to data analytics technologies. The point here is that technologies for data analysis are available so that possible strategic decisions can be made based on this (Berghaus and Back 2016). Colli et al. (2018) see great added value in these technologies, as valuable information can be generated that contributes to the understanding of business processes. Therefore, we defined the two sub-dimensions infrastructure and data analytics.

The main dimension “data” is used in maturity models with a focus on artificial intelligence (cf. Alsheibani et al. 2019; Gentsch 2019; Saari et al. 2019). Following Alsheibani et al. (2019), the main dimension “data” in this paper refers to aspects related to both the amount and the structure of data. In particular, the collection and availability of data play an essential role. Furthermore, the structure and standardized collection of data (Alsheibani et al. 2019; Colli et al. 2018; Gentsch 2019), as well as the need for good availability of data so that AI systems can use it (Alsheibani et al. 2019; Gökalp et al. 2017), are addressed. Based on this, we defined the sub-dimensions of data collection, data retrievability, and data storage.

The main dimension “people” could be found in many of the maturity models analyzed. Among other things, aspects of employee attitudes are addressed. These include aspects such as the openness of employees and their acceptance of embracing new technologies (Colli et al. 2018; Schumacher et al. 2016). Gentsch (2019), for example, speaks of a 'data-driven mindset' in this context. Furthermore, the aspect of competence plays a central role (Alsheibani et al. 2019; Berghaus and Back 2016; Colli et al. 2018). In addition to internal expertise such as IT knowledge, this also involves further training opportunities (Alsheibani et al. 2019; S. Berghaus and Back 2016). In addition, AI implementation requires transformation management, where managers accompany the change and clearly define roles and responsibilities (Berghaus and Back 2016). Colli et al. (2018) also consider the “willingness toward the digital transformation from the management side” in their model (p. 1348). For the main dimension, “people”, we have therefore derived the three sub-dimensions of attitude, competence and transformation management.

The fourth main dimension "process" refers to the influences of AI on the processes in B2B sales. The maturity models analyzed focus in particular on the structure and definition of processes (De Carolis et al. 2017). In addition, the internal and external coordination of processes and the definition of responsibilities are also named in this context (Berghaus and Back 2016). Further essential aspects represent the measurement of sales processes (De Carolis et al. 2017) and an analysis based on this (Berghaus and Back 2016; Jung et al. 2016). Berghaus and Back (2016) also see process control based on data as relevant, building on the analysis. Another factor mentioned in the literature is the innovation of processes (Berghaus and Back 2016). In addition to a required adaptability (Canetta et al. 2018), the further development of processes is also addressed (Jung et al. 2016). We have grouped the aspects identified in the literature under the sub-dimensions of process definition, process measurement, process control and process innovation.

For the subsequent determination of the individual characteristics for a more detailed description of the sub-dimensions, we also used other literature in addition to the maturity models analyzed. This was particularly necessary because the existing maturity models often do not provide a very detailed description of the dimensions they contain. When searching for suitable literature, we made sure that the studies could be assigned to the thematic area of this work (AI, (B2B) sales, information systems). For the main dimension “technology” we were able to identify 15 characteristics, across all sub-dimensions. For the sub-dimensions of the main dimension “data” we defined 12 characteristics in total. The main dimension “human” consists of 18 characteristics and the main dimension “process” of 16. Table 3 shows an excerpt from the subdimension "attitude" of the main dimension "human" and gives examples of characteristics and the corresponding items.

Sub-dimension	Characteristic	Item	Level
Attitude	The use of AI is considered sensible	Our sales team perceives the use of an AI-based information system as sensible.	1
	Positive attitude towards AI	Our sales team has a positive attitude towards the use of artificial intelligence (AI).	2
	Willingness to change	Our sales team is willing to adapt to changes in their workplace.	3
	Acceptance of AI suggestions	Our sales team is willing to accept the decisions proposed by an AI-based information system.	4
	Acceptance of AI decisions, even if they differ from their own	Our sales team is willing to accept the decisions suggested by an AI-based information system, even if they differ from their own assessments.	5

Table 3: Excerpt from characteristics of sub-dimension “Attitude”

The aim of the quantitative study (evaluation 2) was to validate the items for the previously defined characteristics and to determine the difficulty with which they can be achieved by companies. For this purpose, we developed a questionnaire containing the items of the characteristics. To determine the difficulty of the respective items, the participants were asked to indicate the current state of the item in their respective company and the desired state that this item should achieve on a five-point Likert scale. Following Lahrmann et al. (2011), we calculated the median of the desired states and were thus able to map the significance of the respective item for the entirety of the companies in our sample. We then formed a delta between the median of the desired states and the individual assessment of the actual states, which allowed us to determine the difficulty of each item by applying the Rasch algorithm. The Rasch algorithm has already been used for the development of maturity models (Raber et al. 2012), as the difficulty of the items can be used to assign maturity levels to them (Lahrmann et al. 2011). The Rasch algorithm was performed in R using the package eRm. A rating scale model was implemented to determine the measure (of difficulty), standard error, and infit and outfit. If infit and outfit are between 0.5 and 1.5, the measurement data are considered productive (Raber et al. 2012).

We recruited the participants for our study via Amazon Mechanical Turk (MTurk), an approach that has been used in various other studies (e. g., Hibbeln et al. 2017; O'Leary et al. 2014). MTurk allows the selection of participants with respect to their job functions, therefore, in line with the scope of our study, we set the following job functions as criteria for participating in our study: Marketing, Sales, and Business Development. Additionally, only MTurk Masters - people who consistently deliver high-quality results - were eligible for participation to ensure the quality of their responses. Following Jia et al. (2017) we incorporated several control questions in our questionnaire to screen out people who have not completed the questions diligently. This left us with a total of 174 participants. The characteristics of the sample is shown in table 4.

Position		**Industry**	
Managing Director	20	Industrial Goods	50
Area Sales Manager	17	Service	48
Marketing Manager	75	Pharma	19
Sales Manager	25	Financial Services	36
Sales Representative	25	IT and telecommunications	18
Marketing Staff	12	Other	3
Revenue in Mio $		**Number of employees**	
0-49	64	1-49	14
50-99	26	50-249	40
100-249	39	250-499	48
250-499	30	500-999	50
500-999	11	1000-5000	16
>1000	4	>5000	6

Table 4: Sample characteristics

An excerpt of the results is shown in Table 5. For each item, we assess their respective difficulty, standard error, infit, and outfit. Of the 63 items, only three items did not meet the criterion that infit and outfit must be between 0.5 and 1.5 (Raber et al. 2012). Thus, the data set meets the quality criteria according to Dekleva and Drehmer (1997). We kept the items not meeting the infit outfit criteria in our data sample, as it does not compromise the quality of our data set and allowed us to discuss these items later on in the process with the experts in the focus group.

Infit	Outfit	Difficulty	Item
0.951	0.901	0.22248357	Our sales team perceives the use of an AI-based information system as sensible.
0.985	0.894	0.28674512	Our sales team has a positive attitude towards the use of artificial intelligence (AI).
0.742	0.698	0.07066503	Our sales team is willing to adapt to changes in their workplace.
0.969	1.02	0.18520627	Our sales team is willing to accept the decisions proposed by an AI-based information system.
1.164	1.233	0.30489262	Our sales team is willing to accept the decisions suggested by an AI-based information system, even if they differ from their own assessments.

Table 5: Excerpt of the results of the Rasch-Algorithm from the main dimension “Human”

Construct and Evaluation 3

In the next step (construct) of our analysis, we clustered the items into maturity levels. In addition to the relevance of the items, the degree of difficulty per item could also be determined by the Rasch algorithm (Lahrmann et al. 2011). This value is a measure of how difficult it is for companies to achieve the respective item. To objectively cluster the determined proficiencies and their items, we performed a hierarchical cluster analysis (Lahrmann et al. 2011; Marx et al. 2012). Cluster analyses are used as an exploratory procedure to identify similarity structures in data (Kaufman and Rousseeuw 1990). Within a cluster, the data should be highly homogeneous, and between clusters as heterogeneous as possible (Gordon 1996). The goal of the hierarchical cluster analysis was to divide the items, and thus the associated proficiencies, into maturity levels. In this work, Ward's method (squared Euclidean distance) was used for clustering (Lahrmann et al. 2011; Marx et al. 2012). Ward's method belongs to the agglomerative methods and to the group of variance methods. In agglomerative methods, each data point initially forms a single cluster. Successively, these are then combined into larger clusters (Bouguettaya et al. 2015). We implemented the cluster analysis using the package sci-kit learn in Python, where the items, the difficulty of each item and the number of maturity levels served as inputs. As this work is based on the CMMI, which is comprised of five maturity levels, we also set the number of maturity levels to five. Defining the number of maturity levels based on the CMMI is a commonly used way in many other studies that develop maturity models (Lahrmann et al. 2011). We ran the cluster analysis accordingly; therefore, the analysis resulted in five clusters encompassing items from the four main dimensions.

The first maturity level includes ten items from the sub-dimensions of infrastructure, data analysis, data collection, data storage, attitude, and transformation management, thus covering the dimension of technology, data, and human. The second maturity level covers 13 items from the sub-dimensions of infrastructure, data analysis, data collection, data storage, data retrievability, competence, attitude, transformation management, process control, and process innovation, which cover all four dimensions. The third maturity level encompasses nine items from the three dimensions technology, human, and process from the sub-dimensions infrastructure, data analysis, attitude, process definition, and process measurement. The fourth maturity level has 17 items assigned to it, covering the four dimensions and including the sub-dimensions infrastructure, data analysis, data retrievability, attitude, transformation management, process definition, process measurement, and process control. The fifth maturity level includes 12 items from the four dimensions while covering the sub-dimensions infrastructure, data analysis, data storage, competence, attitude, and process definition.

Overall, the hierarchical cluster analysis achieved a conclusive classification. However, we noticed slight inconsistencies in the three sub-dimensions. In the sub-dimension data analysis, the expression "decision-making through descriptive analyses" was categorized as level five, but this would be more likely to be attainable at a lower level. The sub-dimension attitude of the main dimension human showed a particularly large number of items at level 5. Similarly, all items in the process definition sub-dimension were at least at level 3, leaving no items of this sub-dimension at levels 1 and 2. Therefore, we selected these sub-dimensions for further discussion in the focus group in the following step. Following the classification of the characteristics into maturity levels, we developed a first draft of the descriptors and descriptions for each level. We used the descriptors of the CMMI as orientation and adapted to the scope of our maturity model. We defined „initial“, „assessable“, „scalable“, „adaptable“ and „optimizable“ as the descriptors of our five maturity levels. These were also subject to the discussion in the focus group.

Focus Group

To evaluate the findings from the cluster analysis, we conducted a focus group (evaluation 3). A focus group is a moderated discussion with several participants. It allows the researchers to ask for the participants' opinions, experiences, and assessments of a specific topic. In an open discussion, participants can respond to each other's statements, exchange information among themselves, and discuss them from their different perspectives (Schulz et al. 2012; Stewart and Shamdasani 2017). We held the focus group to evaluate the results from the previous steps and discuss the inconsistencies that we noticed in the results of the hierarchical cluster analysis.

Six experts participated in the focus group. Four of the experts are employed by companies that deal with the implementation of AI (three persons in the context of a consulting firm and one person as an employee of a provider of AI solutions). The two other participants are employees in sales. This group of experts was able to cover both the expertise on the implementation of AI in companies and the expertise in the area of sales. The focus group discussion was conducted online and lasted one hour.

We started the focus group with a short introduction to the maturity model to ensure a uniform understanding of the concept before we continued by shortly presenting the developed maturity model. First, we presented the participants with the names of the five stages of the maturity model and their descriptions and asked for feedback on the stages. The participants agreed with both the designations and the descriptions so that no need for change arose. As explained previously, the sub-dimensions data analysis, attitude, and process definition were the focus of the subsequent discussion, with each sub-dimension being covered separately. Additionally, we discussed the items that did not fit the infit and outfit criteria from the quantitative analysis.

Regarding the sub-dimension “data analyses”, the experts agreed that the characteristic "decision-making through descriptive analyses" is not correctly assigned to level 5 and should be moved to level 1. The experts argued that a possible reason for the incorrect assignment could be the similar-sounding words "descriptive", "predictive," and "prescriptive". In their experience, these are often confused with each other, and they suggested that the respondents in the preceding step of the study encountered the same issue. Consequently, the experts suggested moving the characteristic “decision automation through prescriptive analysis” to level 5. In this context, we addressed the characteristic decision-making by means of predictive analyses since this did not fulfill the criteria according to Raber et al. (2012). The experts again referred to the problem of word similarities and rated the characteristic to be relevant. We followed the advice of the experts, retained this characteristic, and rearranged the others.

Next, we discussed the sub-dimension attitude in the context of the main dimension “human”. The experts agreed that the items and characteristics of this sub-dimension could be quite difficult to achieve as most of them were assigned to higher maturity levels. On the other hand, the experts argued that the requirements represented by the items would be indispensable for implementing an AI. Hence, the experts considered the characteristic “AI use is considered useful” as a mandatory prerequisite, therefore we moved it from level 5 to level 1. A similar argument was put forward for the characteristic “positive attitude toward AI”. The experts recommended moving the characteristic from level 5 to level 2. According to them, successful implementation is only possible if employees have a positive attitude toward AI and show the necessary acceptance. Additionally, the experts suggested placing the two characteristics, “acceptance of AI suggestions” and “acceptance of AI decisions,” at level 4 instead of level 5. They argued that especially in comparison to the characteristic “Acceptance of AI decisions, even if they differ from their own” located at level 5, the rearrangement allows for mapping the development in attitudes among employees.

The third sub-dimension we discussed in detail was “process definition”. In total, we moved four characteristics to a different level. In particular, the experts quickly agreed that the “definition of objectives" was a minimum requirement for the implementation of AI. We, therefore, moved the characteristic to level 1. The experts also suggested assigning three characteristics, “internal interfaces defined”, “external interfaces defined”, and “tasks defined” to level 2. According to the experts, the interfaces are relevant for ensuring smooth processes and should therefore be known and defined as early as possible in addition to the tasks and work steps. For this reason, we placed the two characteristics “referring to internal and external interfaces'' on the same level. The experts were also in favor of keeping the external interfaces defined in the maturity model since it is a useful addition to the internal interfaces and represent the starting point for the implementation of AI for several use cases.

Throughout the whole discussion, the experts had the opportunity to look at all areas of the maturity model. They were encouraged to openly address inconsistencies or discrepancies. At the end of the focus group, we asked the experts again whether they had noticed any other aspects that they would like to discuss. The participants did not raise any further conspicuities and thus, we did not make any further changes.

Final Maturity Model

Based on the results from the focus group, we created the final maturity model. Figure 2 shows the 5 levels with the respective descriptors and a short description for each level.

The sales department contains the basic elements for the use of AI. Internal data is used for analysis.	The sales department can evaluate the use of AI. The necessary internal and external data is systematically collected and accessible.	The sales department can control the use of AI. Roles and authorities are assigned, and there is readiness for change.	The sales department is set up in such a way that it can react flexibly to changes and adjust the use of AI according to the situation.	The sales department is optimized for the use of AI. Employees have knowledge about AI and accept decisions made by AI.

Figure 2: Final Sales AIvation Maturity Model

A measuring instrument is used to apply the maturity model. This measuring instrument is based on the items of the individual characteristics. The items are part of a questionnaire, which is divided into the individual main and sub-dimensions. When applying the maturity model, the individual items of the questionnaire are to be evaluated on a five-point Likert scale. For the evaluation, the individual items are first assigned to the respective levels. The mean values of the individual items per level are then determined. In accordance with the principle of a stage model, a higher maturity level can only be reached when the previous one has been fully completed. In this context, complete means that the company achieves a value of at least 3.5 or higher. The smallest level of the four main dimensions then determines the overall maturity level. This logic is based on the assumption that successful AI implementation can only succeed in the interaction of all dimensions (Wengler et al. 2021).

Evaluation of the Maturity Model

Case Studies

The aim of the case studies was to test the developed maturity model in practice (use). Case studies can help apply theories and concepts to real-world situations, which is important for the transferability of research findings (Eisenhardt 1989; Gerring 2006; Stake 1995; Yin 2009). For this, the relevant information of a particular event or person is collected and analyzed to gain a better understanding of a particular situation.

In this work, the maturity model was used in four companies. All four companies were before implementing AI in sales at the time of the research. By using the maturity model, the respective maturity of the companies for the implementation of an AI could be identified. Building on this, further action should be taken as needed based on the results. The choice of the point in time related to where the companies were (in the process), i.e., before the implementation of an AI, could be considered as very suitable for the application of the maturity model. To determine the maturity level, a questionnaire with the items was provided to the companies online. In pairs or threes, employees from sales answered the questions together. For each item, the employees rated the current situation in the company on a five-point Likert scale. The mean values of the answers were then calculated for the individual main dimensions. These values were used to classify the sales organization in the maturity model.

The results of the first company are described below as an example. In the main dimension “Technology”, the company has an average score of 4.5 in level 1 and an average score of 2.3 in level 2. This means that level 2 has not yet been fully achieved and a classification at the higher level 3 is not yet possible. For the main dimension “Data”, the company achieved an average score of 3.8 at level 1. This level is therefore considered to be fulfilled. An average value of 3.0 was determined for level 2. Since the average value for level 2 is below 3.5, this level is not considered complete. In the main dimension “Data”, the company therefore achieves a maturity level of 2. In the main dimension “Human”, the company achieved an average value of 4.0 on level 1. Level 2 is also considered to be completed with a value of 3.5. An average value of 4.0 was also achieved at level 3. At the following level 4, an average value of 3.3 was determined. The maturity level of the main dimension “Human” can therefore be defined as level 4. For the fourth main dimension “Process”, both level 1 and level 2 can be classified as completed, with average values of 5.0 and 3.8 respectively. For stage 3, the company currently achieves an average value of 3.4 and is thus just below the threshold of 3.5. The maturity level of the main dimension “Process” is thus at stage 3. Following the minimization principle, this results in an overall maturity level of 2 for the company.

Expert Interviews

To evaluate the use of the maturity model (evaluation 4) in the case studies, we interview conducted interviews with each company. Here, too, Sonnenberg and vom Brocke (2012) consider expert interviews, among other methods, to be suitable for evaluation. We conducted the interviews following an interview guide. In the first part of each interview, we discussed the applicability of the maturity model and the results of each company in general. In the second part, we examined the results of the companies in more detail, going over every dimension and discussing possible courses of action. In total, we conducted and recorded four interviews. The average duration of the interviews was 51:09 minutes. For company one, we spoke to the CEO and the Marketing Manager, for company two to the CEO, in company three we talked to the Head of Sales and the Head of Marketing and in company four to the Business Director and the Sales Manage.

The results of the application of the maturity model were available to the respective company. The evaluation was aimed at the applicability of the maturity model and was also intended to verify whether the maturity model correctly reflects the actual situation in the companies. Based on the interviews, it became clear that the current maturity could be determined for all companies. Table 6 shows an overview of the benefits of the maturity model that were mentioned in the interviews.

Benefits	**Company 1**	**Company 2**	**Company 3**	**Company 4**
Current maturity regarding the implementation of an AI can be determined	√	√	√	√
Optimization progress can be measured with multiple use	√		√	
Relevant areas for the implementation of an AI can be identified	√	√	√	√
The maturity model with the associated measurement model can be easily applied by the companies	√	√	√	√
Different opinions about certain aspects became apparent		√		√
Encouraged companies to address different topics that had not yet been dealt with	√	√		√
Common understanding for the implementation of an AI can be built	√	√		
The maturity model shows development potential in a meaningful way		√	√	

Table 6: Benefits of the maturity model mentioned in the interviews

The companies had no difficulties in applying the maturity model and also found the questions easy to understand. In addition to the current maturity, the relevant aspects and areas for the implementation of an AI could be identified. On the basis of the different characteristics, the companies were able to derive weaknesses and thus identify potential optimization needs. In some interviews, the possibility of using the maturity model again to measure the development progress was also mentioned. Some interviewees also mentioned the great added value that resulted from the discussions during the use of the maturity model. On the one hand, this resulted in an exchange about topics that were otherwise not in the focus of the company, and on the other hand, different opinions regarding individual aspects and areas became clear. Overall, a common understanding for the implementation of an AI could be built up in the company in this way.

Conclusion and Implications

The result of the present work is the Sales AIvation Maturity Model (SAIM). The model is based on a comprehensive research process in which a fully evaluated and practically applied model was developed through several empirical studies. The studies identified relevant factors and prerequisites for AI implementation in B2B sales. This enables companies to assess their current status with regard to AI implementation in sales and to take targeted measures to increase their maturity. Compared to other maturity models, the one we developed is based on a systematic analysis of existing literature (e. g. Berghaus and Back, 2016; Alsheibani, 2019) as well as a broad survey of experts and practitioners in sales. Compared to other maturity models, this one combines the two areas of sales and AI and is based on a rigorous DSR approach and validated by multiple data sources. The maturity model of Alsheibani et al. (2019), for example, focuses only on the aspect of AI, while the maturity model developed by Voss et al. (2022) focuses on the area of sales, although this does not specifically consider the implementation of AI. The originality of this maturity model can thus be justified on the basis of the focus on AI and B2B sales in combination with the multi-method research approach.

The evaluations have shown the great added value of the maturity model for practice. Among other things, the application of the maturity model has shown that conflicts of interest can be avoided when using measurement tools developed outside the organization (Fraser and Vaishnavi 1997). However, too much focus on formalizing improvement activities can have an inhibiting effect on people's innovative thinking (Herbsleb and Goldenson 1996). The interviews showed that the companies also benefited in particular from the joint discussion in answering the questions in the measurement instrument. In the interviews, it was communicated that different opinions about certain aspects became apparent in the discussions. In this way, a common understanding for the implementation of an AI can be built up in the company, possible ambiguities can be eliminated, and knowledge differences can be reduced. However, it is important to emphasize that the specific context and the needs and requirements of a company must always be considered when applying the model. This means that level 5 does not have to represent the desired goal for all companies. The strategic orientation of a company can lead to a conscious decision for a lower level as the target. This is also explicitly mentioned in the paper by Berghaus and Back (2016). They highlight that each company has to weigh the feasibility of the stages depending on the respective industry, business model and competition. The descriptor "optimal" of level 5, therefore only refers to the content of the maturity model with regard to the implementation of AI in B2B sales. In this context, it is not meant that this level represents the optimum for all companies.

Considering the main dimensions, it can be seen that the two dimensions data and process, in particular, have many characteristics at the lower levels. This circumstance suggests that aspects of data and process are essential prerequisites for implementing AI in sales. This underlines the importance of data collection, availability, and storage for the use of AI. Companies should address this issue early to enable successful AI implementation, especially in B2B sales, where data can be complex, heterogeneous, and dispersed across various sources, and external databases. Additionally, companies need to be able to describe and define their processes first to know where to implement AI and, secondly, to enable value creation with AI. The characteristics of the dimensions technology and people are more evenly distributed across the different maturity levels. It becomes evident from the structure of the maturity model that technology and especially humans play a crucial role on high levels of maturity. For companies, this implies that they need to involve their employees in the early stages of planning and implementing AI to foster acceptance and understanding.

Limitations

In this work we developed a maturity model for the implementation of AI in B2B sales, which is relevant for both practical and research purposes. However, certain limitations need to be considered when interpreting the results. First, the identified maturity models often did not apply the same methodological standards as those implemented in this work. Frequently, the necessary transparency was missing from the documentation of existing maturity models, making it difficult to understand the dimensions and their development as stated in the studies. Despite this, these models were used to derive the main and sub-dimensions as they covered content relevant aspects. Also, we cannot rule out the possibility that we have not considered comparable studies because they do not explicitly develop maturity models. Additionally, the small sample size of one focus group and four companies should be considered a limitation. However, we considered heterogeneity within the focus group to cover all perspectives (developer, salesperson, etc.) and the companies varied in their field of application, industry, and size. Moreover, for the quantitative study, the participants were recruited via MTurk. MTurk offers a diverse group of people mainly from the United States or India (Jia et al. 2017). This aspect may also support the applicability of the maturity model in an international context. Recruiting participants through MTurk is subject to a variety of methodological biases, similar to data collection using traditional methods. In this work, participants from the marketing, sales, and business development fields were selected. However, it cannot be ruled out that other people were included in the study due to incorrect information. Particularly in the case of recruitment through MTurk, the monetary incentive to participate in the study can lead to bias. Jia et al. (2017) have shown that MTurk participants may have difficulty paying attention because they want to complete the studies quickly to maximize their income. To address this problem, we used control questions in our study. If these were not answered correctly, the data of that person was deleted from the dataset. The last aspect to note is that the maturity model was developed for B2B sales. It can be assumed that some areas of the model are identical or similar for sales as a whole, but the generalizability would have to be investigated in further research.

References

Abele, D., and D'Onofrio, S. 2020. "Artificial Intelligence – The Big Picture," in Cognitive Computing, E. Portmann and S. D'Onofrio (eds.), Wiesbaden: Springer Vieweg, pp. 31–65.

Ahern, D. M., Clouse, A., and Turner, R. 2003. CMMI Distilled: A Practical Introduction to Integrated Process Improvement, (2. Auflage.), Boston: Addison-Wesley Professional.

Alavi, S., and Habel, J. 2021. "The Human Side of Digital Transformation in Sales: Review & Future Paths," Journal of Personal Selling & Sales Management (41:2), pp. 83–86.

Alsheibani, S., Cheung, Y., and Messom, C. 2018. "Artificial Intelligence Adoption: AI-Readiness at Firm-Level," in Proceedings of the Pacific Asia Conference on Information Systems (PACIS). 37, Japan.

Alsheibani, S., Cheung, Y., and Messom, C. 2019. "Towards An Artificial Intelligence Maturity Model: From Science Fiction To Business Facts," in Proceedings of the Pacific Asia Conference on Information Systems (PACIS). 46.

Andzulis, J. M., Panagopoulos, N. G., and Rapp, A. 2012. "A Review of Social Media and Implications for the Sales Process," Journal of Personal Selling & Sales Management (32:3), pp. 305–316.

Becker, J., Knackstedt, R., and Pöppelbuß, J. 2009. "Developing Maturity Models for IT Management. A Procedure Model and Its Application," Business & Information Systems Engineering (3), pp. 213–222.

Berghaus, S. and Back, A. 2016. "Gestaltungsbereiche der Digitalen Transformation von Unternehmen: Entwicklung eines Reifegradmodells," Die Unternehmung (70:2), pp. 98–123.

Berghaus, S., and Back, A. 2016. "Stages in Digital Business Transformation: Results of an Empirical Maturity Study," in Proceedings of the Mediterranean Conference on Information Systems (MCIS). 22.

Bongers, F. M., Schumann, J. H., and Schmitz, C. 2021. "How the Introduction of Digital Sales Channels Affects Salespeople in Business-to-Business Contexts: A Qualitative Inquiry," Journal of Personal Selling & Sales Management (41:2), Routledge, pp. 150–166.

Bouguettaya, A., Yu, Q., Liu, X., Zhou, X., and Song, A. 2015. "Efficient Agglomerative Hierarchical Clustering," Expert Systems with Applications (42:5), Elsevier, pp. 2785–2797.

de Bruin, T., Rosemann, M., Freeze, R., and Kaulkarni, U. 2005. "Understanding the Main Phases of Developing a Maturity Assessment Model," in Proceedings of the Australasian Conference on Information Systems (ACIS). 109, Australasian Chapter of the Association for Information Systems.

Burgess, A. 2018. "Starting an AI Journey," in The Executive Guide to Artificial Intelligence: How to Identify and Implement Applications for AI in Your Organization, A. Burgess (ed.), Cham: Springer International Publishing, pp. 91–116.

Canetta, L., Barni, A., and Montini, E. 2018. "Development of a Digitalization Maturity Model for the Manufacturing Sector," in IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC), Stuttgart, Germany: IEEE, June.
Chen, I.-F., and Lu, C.-J. 2017. "Sales Forecasting by Combining Clustering and Machine-Learning Techniques for Computer Retailing," Neural Computing and Applications (28:9), pp. 2633–2647.
CMMI Product Team 2010. CMMI for development, Version 1.3. https://resources.sei.cmu.edu/library/asset-view.cfm?assetid=9661
Coates, D. L., and Martin, A. 2019. "An Instrument to Evaluate the Maturity of Bias Governance Capability in Artificial Intelligence Projects," IBM Journal of Research and Development (63:4/5), 7:1-7:15.
Colli, M., Madsen, O., Berger, U., Møller, C., Wæhrens, B. V., and Bockholt, M. 2018. "Contextualizing the Outcome of a Maturity Assessment for Industry 4.0," IFAC-PapersOnLine (51:11), pp. 1347–1352.
De Carolis, A., Macchi, M., Negri, E., and Terzi, S. 2017. "Guiding Manufacturing Companies towards Digitalization a Methodology for Supporting Manufacturing Companies in Defining Their Digitalization Roadmap," in International Conference on Engineering, Technology and Innovation (ICE/ITMC), Funchal: IEEE, June, pp. 487–495.
Dekleva, S., and Drehmer, D. 1997. "Measuring Software Engineering Evolution: A Rasch Calibration," Information Systems Research (8:1), pp. 95–104.
Desouza, K. C., Dawson, G. S., and Chenok, D. 2020. "Designing, Developing, and Deploying Artificial Intelligence Systems: Lessons from and for the Public Sector," Business Horizons (63:2), pp. 205–213.
Dubinsky, A. J. 1981. "A Factor Analytic Study of the Personal Selling Process," Journal of Personal Selling & Sales Management (1:1), pp. 26–33.
Early, S., & Bennoff, J. 2020. "Is Your Data Infrastructure Ready for AI?" Harvard Business Review. https://hbr.org/2020/04/is-your-data-infrastructure-ready-for-ai
Eisenhardt, K. M. 1989. "Building Theories from Case Study Research," Academy of Management Review (14:4), Academy of Management Briarcliff Manor, NY 10510, pp. 532–550.
Fisher, D. M. 2004. "The Business Process Maturity Model A Practical Approach for Identifying Opportunities for Optimization," Business Process Trends (9:4), pp. 11–15.
Fraser, M. D., and Vaishnavi, V. K. 1997. "A Formal Specifications Maturity Model," Communications of the ACM (40:12), pp. 95–103.
Fraser, P., Moultrie, J., and Gregory, M. 2002. "The Use of Maturity Models/Grids as a Tool in Assessing Product Development Capability," in IEEE International Engineering Management Conference, Cambridge, UK, August, pp. 244–249.
Gentsch, P. 2019. "AI Business: Framework and Maturity Model," in AI in Marketing, Sales and Service: How Marketers without a Data Science Degree Can Use AI, Big Data and Bots, Cham: Springer Nature Schwitzerland, pp. 27–78.
Gerring, J. 2006. Case Study Research: Principles and Practices, New York, USA: Cambridge University Press.
Gökalp, E., Şener, U., and Eren, P. E. 2017. "Development of an Assessment Model for Industry 4.0: Industry 4.0-MM," in Software Process Improvement and Capability Determination (Vol. 770), Communications in Computer and Information Science, A. Mas, A. Mesquida, R. V. O'Connor, T. Rout, and A. Dorling (eds.), Cham: Springer International Publishing, pp. 128–142.
Goldkuhl, G. 2002. "Anchoring Scientific Abstractions–Ontological and Linguistic Determination Following Socio-Instrumental Pragmatism," in Proceedings of European Conference on Research Methods in Business and Management (ECRM), UK.
Gordon, A. 1996. "Hierarchical Classification," in Clustering and Classification, P. Arabie, L. Hubert, and G. De Soete (eds.), World Scientific Publishing, pp. 65–121.
Gregor, S., and Hevner, A. R. 2013. "Positioning and Presenting Design Science Research for Maximum Impact," MIS Quarterly (37:2), pp. 337–355.
Herbsleb, J. D., and Goldenson, D. R. 1996. "A Systematic Survey of CMM Experience and Results," in Proceedings of IEEE 18th International Conference on Software Engineering, IEEE, pp. 323–330.
Hevner, March, Park, and Ram. 2004. "Design Science in Information Systems Research," MIS Quarterly (28:1), pp. 75–105.
Hibbeln, M. T., Jenkins, J. L., Schneider, C., Valacich, J., and Weinmann, M. 2017. "How Is Your User Feeling? Inferring Emotion Through Human-Computer Interaction Devices," MIS Quarterly (41:1), pp. 1–22.
Holmström, J. 2022. "From AI to Digital Transformation: The AI Readiness Framework," Business Horizons (65:3), pp. 329–339.

Homburg, C., Müller, M., and Klarmann, M. 2011. "When Should the Customer Really Be King? On the Optimum Level of Salesperson Customer Orientation in Sales Encounters," Journal of Marketing (75:2), pp. 55–74.

Humphrey, W. S. 1988. "Characterizing the Software Process: A Maturity Framework," IEEE Software (5:2), pp. 73–79.

Itani, O. S., Agnihotri, R., and Dingus, R. 2017. "Social Media Use in B2b Sales and Its Impact on Competitive Intelligence Collection and Adaptive Selling: Examining the Role of Learning Orientation as an Enabler," Industrial Marketing Management (66), pp. 64–79.

Iversen, J., Nielsen, P. A., and Norbjerg, J. 1999. "Situated Assessment of Problems in Software Development," ACM SIGMIS Database: The DATABASE for Advances in Information Systems (30:2), pp. 66–81.

Jia, R., Steelman, Z., and Reich, B. H. 2017. "Using Mechanical Turk Data in IS Research: Risks, Rewards, and Recommendations," Communications of the Association for Information Systems (41), pp. 301–318.

Jung, K., Kulvatunyou, B., Choi, S., and Brundage, M. P. 2016. "An Overview of a Smart Manufacturing System Readiness Assessment," in Advances in Production Management Systems. Initiatives for a Sustainable World, IFIP Advances in Information and Communication Technology, I. Nääs, O. Vendrametto, J. Mendes Reis, R. F. Gonçalves, M. T. Silva, G. von Cieminski, and D. Kiritsis (eds.), Cham, Schwitzerland: Springer Nature, pp. 705–712.

Kaufman, L., and Rousseeuw, P. J. 1990. Finding Groups in Data: An Introduction to Cluster Analysis, Wiley Series in Probability and Statistics, Hoboken, New Jersey, USA: John Wiley & Sons, Inc.

Kreutzer, R. T., and Sirrenberg, M. 2020. Understanding Artificial Intelligence: Fundamentals, Use Cases and Methods for a Corporate AI Journey, Management for Professionals, Cham, Schwitzerland: Springer Nature.

Kumar, V., Ramachandran, D., and Kumar, B. 2021. "Influence of New-Age Technologies on Marketing: A Research Agenda," Journal of Business Research (125), pp. 864–877.

Lahrmann, G., Marx, F., Mettler, T., Winter, R., and Wortmann, F. 2011. "Inductive Design of Maturity Models: Applying the Rasch Algorithm for Design Science Research," in Service-Oriented Perspectives in Design Science Research (Vol. 6629), Lecture Notes in Computer Science, H. Jain, A. P. Sinha, and P. Vitharana (eds.), Berlin, Heidelberg: Springer-Verlag, pp. 176–191.

Leyh, C., Schäffer, T., Bley, K., and Forstenhäusler, S. 2016. "SIMMI 4.0 – A Maturity Model for Classifying the Enterprise-Wide IT and Software Landscape Focusing on Industry 4.0," in Federated Conference on Computer Science and Information Systems (Vol. 8), October 2, pp. 1297–1302.

Lichtenthaler, U. 2020. "Five Maturity Levels of Managing AI: From Isolated Ignorance to Integrated Intelligence," Journal of Innovation Management (8:1), pp. 39–50.

Martínez-López, F. J., and Casillas, J. 2013. "Artificial Intelligence-Based Systems Applied in Industrial Marketing: An Historical Overview, Current and Future Insights," Industrial Marketing Management (42:4), pp. 489–495.

Marx, F., Wortmann, F., and Mayer, J. H. 2012. "A Maturity Model for Management Control Systems: Five Evolutionary Steps to Guide Development," Business & Information Systems Engineering (4:4), pp. 193–207.

Mikalef, P., and Gupta, M. 2021. "Artificial Intelligence Capability: Conceptualization, Measurement Calibration, and Empirical Study on Its Impact on Organizational Creativity and Firm Performance," Information & Management (58:3), Nr. 103434.

Nda, R. M., Tasmin, R., and Abdul Hamid, A. 2020. "Assessment of Big Data Analytics Maturity Models: An Overview," in Proceedings of the 5th NA International Conference on Industrial Engineering and Operations Management, pp. 10–14.

O'Leary, M. B., Wilson, J. M., and Metiu, A. 2014. "Beyond Being There: The Symbolic Role of Communication and Identification in the Emergence of Perceived Proximity in Geographically Dispersed Work," MIS Quarterly (38:4), pp. 1219–1244.

Paschen, J., Wilson, M., and Ferreira, J. J. 2020. "Collaborative Intelligence: How Human and Artificial Intelligence Create Value along the B2B Sales Funnel," Business Horizons (63:3), pp. 403–414.

Paulk, M. C., Curtis, B., Chrissis, M. B., and Weber, C. V. 1993. "Capability Maturity Model for Software, Version 1.1:," Fort Belvoir, VA: Defense Technical Information Center, February 1.

Raber, D., Winter, R., and Wortmann, F. 2012. "Using Quantitative Analyses to Construct a Capability Maturity Model for Business Intelligence," in Proceedings of the Hawaii International Conference on System Sciences (HICSS), Maui, HI, USA: IEEE, January, pp. 4219–4228.

Rodríguez, R., Svensson, G., and Mehl, E. J. 2020. "Digitalization Process of Complex B2B Sales Processes – Enablers and Obstacles," Technology in Society (62), p. 101324.
Saari, L., Kuusisto, O., and Pirttikangas, S. 2019. "AI Maturity Web Tool Helps Organisations Proceed with AI," VTT Technical Research Centre of Finland, VTT White Paper.
Sadiq, R. B., Safie, N., Abd Rahman, A. H., and Goudarzi, S. 2021. "Artificial Intelligence Maturity Model: A Systematic Literature Review," PeerJ Computer Science 7:E661.
Schulz, M., Mack, B., and Renn, O. 2012. Fokusgruppen in der empirischen Sozialwissenschaft: Von der Konzeption bis zur Auswertung, Wiesbaden: VS Verlag für Sozialwissenschaften.
Schumacher, A., Erol, S., and Sihn, W. 2016. "A Maturity Model for Assessing Industry 4.0 Readiness and Maturity of Manufacturing Enterprises," Procedia CIRP (52), pp. 161–166.
Singh, J., Flaherty, K., Sohi, R. S., Deeter-Schmelz, D., Habel, J., Le Meunier-FitzHugh, K., Malshe, A., Mullins, R., and Onyemah, V. 2019. "Sales Profession and Professionals in the Age of Digitization and Artificial Intelligence Technologies: Concepts, Priorities, and Questions," Journal of Personal Selling & Sales Management (39:1), pp. 2–22.
Sonnenberg, C., and vom Brocke, J. 2012. "Evaluation Patterns for Design Science Research Artefacts," in Practical Aspects of Design Science (Vol. 286), Communications in Computer and Information Science, M. Helfert and B. Donnellan (eds.), Berlin, Heidelberg: Springer, pp. 71–83.
Stake, R. E. 1995. The Art of Case Study Research, sage.
Stewart, D. W., and Shamdasani, P. 2017. "Online Focus Groups," Journal of Advertising (46:1), pp. 48–60.
Syam, N., and Sharma, A. 2018. "Waiting for a Sales Renaissance in the Fourth Industrial Revolution: Machine Learning and Artificial Intelligence in Sales Research and Practice," Industrial Marketing Management (69), pp. 135–146.
van Giffen, B., and Ludwig, H. 2023. "How Siemens Democratized Artificial Intelligence," MIS Quarterly Executive, 22(1), Article 3.
Voss, M., Jaspert, D., Ahlfeld, C., and Sucke, L. 2022. "Developing a digital maturity model for the sales processes of industrial projects," Journal of Personal Selling & Sales Management, pp. 1-21.
Wengler, S., Hildmann, G., and Vossebein, U. 2021. "Digital Transformation in Sales as an Evolving Process," Journal of Business & Industrial Marketing (36:4), pp. 599–614.
Wright, G., and Donaldson, B. 2002. "Sales Information Systems in the UK Financial Services Industry: An Analysis of Sophistication of Use and Perceived Barriers to Adoption," International Journal of Information Management (22:6), Elsevier, pp. 405–419.
Yablonsky, S. A. 2019. "Multidimensional Data-Driven Artificial Intelligence Innovation," Technology Innovation Management Review (9:12), pp. 16–28.
Yin, R. K. 2009. Case Study Research: Design and Methods, (Vol. 5), sage.