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# Artificial Intelligence en Vogue

## Enterprise AI Through the Lens of Management Fashion

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**Abstract:** The purpose of this study is to explore how enterprise AI could be understood from a management fashion perspective. Although management fashion theory has been applied to a myriad of management concepts, the currently hyped phenomenon of artificial intelligence (AI) is not one of them. Furthermore, theoretical conceptualizations of management fashion dynamics lack empirical grounding. To address these research gaps, this study takes on a single-case study approach, based on interviews with members of a Swedish startup developing and selling software to orchestrate enterprise automation solutions. The findings suggest that, although enterprise AI does not originate from a traditional management fashion-setter, it does exhibit typical traits of management fashion – such as interpretative viability. Thereby, not only is enterprise AI found to qualify as a distinct management fashion itself, but it can also be thought of as a domain containing several underlying management fashions. Additionally, the findings serve to illuminate the theoretical understanding of how the management fashion phenomenon manifests itself qualitatively.

**Keywords:** artificial intelligence, AI, enterprise AI, interpretative viability, management concept, management fads, management fashion, RPA

**Supervisor:** Erik Wetter

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# Glossary

**Chat GPT:** an AI chatbot developed by OpenAI which can generate text-responses to human input. It is based on various kinds of machine learning.

**Citation analysis:** a type of bibliometric method that is common in management fashion research, which measures the interest in certain management concepts from various types of publications and considers this a proxy for how fashionable it is over time.

**Enterprise AI:** a branch of AI, consisting of applications that allow certain types of technology to be employed in a business setting.

**Fashion-adopter:** an individual or organization that aligns itself with popularized concepts of management.

**Fashion implementation:** the process of going from adoption to practical use of a management concept.

**Fashion-setter:** an actor in management fashion who creates and promotes ideas about management practice that shape collective beliefs.

**Hype:** the state of something being intensively promoted in a way that is partly centralized and partly fragmented.

**Management concept:** a set of techniques or ideas on how to practice business management, which has been predefined to some extent.

**Management fashion:** a management concept that has been made fashionable in the business community. Management fad is synonymous, but with added emphasis on brevity.

**Management guru:** an individual who has made a name for themselves by coming up with one or several management fashions. They have usually authored bestsellers promoting their work.

**Software vendor:** a company that develops and sells software for enterprise use, usually in a highly standardized format for universal applicability.

# 1. Introduction

According to the most cited article on the subject, "management fashion […] is a relatively transitory collective belief, disseminated by management fashion setters, that a management technique leads rational management progress." (Abrahamson, 1996) These techniques are characterized by a high level of abstraction, which makes them seem intuitively applicable to many organizational contexts, thus offering the potential for a wide appeal to fashion-hungry managers (e.g., Benders & van Veen, 2001; Giroux, 2006). In being of an abstract nature, good management fashion appeals to universal virtues of business, creates urgency around adoption, and creates the sense of being grounded in practice (Kieser, 1997). The reasons why fashionable management techniques are attractive from the perspective of the adopting managers can be connected to the ever-changing nature of challenges faced by the organization, the desire to remain competitive, or even the individual's desire for self-actualization (Huczynski, 1993). When it becomes clear that the promises of the fashionable management practices were exaggerated, the hype dies down (e.g., Birnbaum, 2000; Giroux, 2006).

A phenomenon that is currently enjoying the interest of the business world is artificial intelligence (AI). Having existed as a theoretical concept for the past 70 years (e.g., Turing, 1950), AI is now rapidly making its way onto the radar of business and society at large (von Krogh, 2018). With the launch of ChatGPT in late 2022, millions of people were given first-hand experience of the potential of AI (Murgia, 2023), and the explosive growth of interest is reflected by the Google Trends curve for AI as a search term (see Appendix 1). However, the evolution of AI in business has already been going on behind the scenes for several years. Not only have companies such as Netflix, Airbnb, and Uber built their entire business models around AI (e.g., Brynjolfsson & McAfee, 2017; Cusumano et al., 2020; Lanzolla et al., 2020; Verganti et al., 2020), AI is also permeating into business in general – both as a means of realizing efficiency gains (e.g., Berente et al., 2021; Brynjolfsson & McAfee, 2017; Kaplan & Haenlein, 2020) and as a means of transforming business models altogether (Brynjolfsson & Mitchell, 2017).

Throughout the past two decades, many management concepts have been viewed through the lens of management fashion, for example, knowledge management (e.g., Hislop, 2010; Ponzi & Koenig, 2002), agile (e.g., Cram & Newell, 2016; Madsen, 2020; Näslund & Kale, 2020), and total quality management (e.g., David & Strang, 2006; Soltani, Lai & Garneh, 2005). Despite the apparent hype around it, however, enterprise AI has yet to be examined through the lens of management fashion. Before doing so, a noteworthy characteristic setting AI apart from the management concepts mentioned above is its materiality. In addition to ideational manifestations of AI – a natural consequence of its emergence in research – it now also materializes in the form of tangible enterprise software. This gives AI a kind of scalability that purely ideational concepts could only dream of possessing. Considered along with evidence suggesting that organizational adherence to management fashion can both boost their reputation (e.g., Bermiss et al., 2014; Wang, 2010), and even cause a systematic tendency towards financial over-valuation (Nicolai et al., 2010), this scalability feature means that there is good cause to investigate enterprise AI from a management fashion perspective. The purpose of this study is therefore to explore how enterprise AI could be understood as such, by conducting a single, interview-based case study with a Swedish startup providing software for enterprise automation orchestration.

# 2. Theory

*The following chapter will explain the theoretical context of management fashion through a literature review to identify a research gap (2.1), present the topic of AI (2.2), as well as the theoretical framework and research question of the study (2.3).*

## 2.1 Literature Review

### 2.1.1 Management Fashion: Background and Characteristics of Research

Fads and fashions in management practice have been the subject of academic inquiry for decades, as researchers have recorded the seemingly transient way organizations adopt and abandon concepts of management, noting the similarity to fashion consumption in more aesthetic domains (e.g., Mintzberg, 1979). Total quality management (TQM), management by objectives (MBO), and agile are examples of management concepts that are generally considered management fashion (Carson et al., 2000). The most seminal paper to stem from this avenue of research is that of Abrahamson (1996). Its fundamental departure from previous research is the firm view of management fashion as distinct from purely superficial types of fashion. Abrahamson argues that both cursory fads and guidelines of genuine practical value exist among fashionable management concepts, calling for a conceptual framework that explains the phenomenon. (Abrahamson, 1996)

At its core, Abrahamson's (1996) theory characterizes the management fashion arena as a market. It has a demand side, consisting of organizational managers who adopt new practices to feel and to be perceived as both progressive and rational in response to an ever-changing business environment (Abrahamson, 1996; Huczynski, 1993; Kieser, 1997). It also has a supply side, made up of so-called fashion-setters. Fashion-setters range all the way from academics to management gurus and consultants, and are believed to possess superior management wisdom, which makes them a reliable source of inspiration for rational managers. (Abrahamson, 1996)

To explain how fashion-setters influence the consumption of fashion, Abrahamson (1996) extrapolates from the entertainment media industries to create a model incorporating the four stages of creation, selection, processing, and dissemination. These steps allow fashion-setters to sense incipient demand, make the product that will satisfy it, and push this carefully curated product to the market. If successful, the management concept will become fashionable and thus spread rapidly from status-seeking early adopters, across a wide collective of demand-side managers and organizations. (Abrahamson, 1996) The creation of management fashion has later been conceptualized as a more collaborative process between different supply- and demand-side actors (Clark & Greatbatch, 2003).

Given that Abrahamson's (1996) theory primarily deals with the constructive aspect of management fashions, their decline is best understood as the consequence of creative destruction. The aspect of status differences between demand-side actors adds some nuance to this notion, as it implies that high-status early adopters will abandon a fashionable management practice to escape association with lower-status followers once such actors have adopted the fashion. (Abrahamson, 1996) More technical explanations for fashion decline also exist. In an earlier article, Abrahamson (1991) proposes that management concepts fall out of favor when it becomes clear that attempts at practical implementation fall short of initial promises. At that point, the rhetoric around the concept goes from optimistic to realistic in what Birnbaum (2000) refers to as dissonance resolution. Analogously, Giroux (2006) points to ambiguity in the initially popularized management concept as the reason why it fails in practice. From a broader perspective, management fashions appear to be increasingly characterized by difficulty of implementation the newer they are, precipitating the onset of dissonance resolution and resulting in a pattern of lifespan shrinkage over time (Carson et al., 2000).

Studies of management fashions have tended to rely on the method of citation analysis, through which the transience of these fashions has manifested itself in a bell-shaped curve, reflecting an exponential growth, peak, and subsequent decline in the number of publications dealing with a given concept (Abrahamson, 1996; Abrahamson & Fairchild, 1999; Carson et al., 2000). When abstracts of academic papers from different stages of management fashions have been analyzed, this has shown that emotionally charged and uncritical discourse characterizes the upswings, while critical and rational discourse characterizes the downswings. At its advent, a management fashion is also highly publicized in the popular press. (Abrahamson & Fairchild, 1999; Spell, 2001) This could be interpreted as the academic press initially echoing its popular and optimistic counterpart, only to be left to pick up the pieces once the novelty dissipates.

Interestingly, such a shift in actor make-up would reflect what happens within the context of management fashion practice, at least in the case of TQM. When TQM boomed, the market was flooded with general consulting firms trying to capitalize on organizational demand. Conversely, as the TQM hype died down due to implementation difficulties, the general consultancies fled the market. The consultancies that remained were those with the technical expertise necessary to create value with TQM. (David & Strang, 2006)

### 2.1.2 Applied Management Fashion Theory and Alternative Methods

As previously mentioned, numerous specific management concepts have been assessed through the lens of management fashion over the years (e.g., Carson et al., 2000; Gibson & Tesone, 2001; Pollach, 2022). In line with management fashion research in general, there is an overwhelming reliance on bibliometric methodology (e.g., Baskerville & Myers, 2009; Oswick & Noon, 2014). This method is sometimes complemented by an additional layer of qualitative analysis, such as the scrutiny of abstracts (e.g., Abrahamson & Fairchild, 1999). Moreover, there are instances where meta-studies come into play (e.g., Kumar et al., 2008; Lichtenthaler, 2011). Naturally, these studies are predominantly grounded in citation analysis, rather than empirical observation. While there is some evidence in support of coevolution between publication volumes and instances of practical adoption (Abrahamson & Fairchild, 1999), management fashion research has to some degree taken the connection for granted, resulting in a theory-building that lacks empirical grounding (Madsen & Stenheim, 2013; Newell et al., 2001).

Approaches that lean more towards the qualitative spectrum, such as case studies, are considerably less common. Nevertheless, when such studies have been undertaken, they have often revealed intriguing findings. McCann et al.'s (2015) case study about the behavior of the lean concept at a British hospital, for example, confirms some central propositions of management fashion theory. It shows that hospital representatives on some, especially administrative, levels adopted the concept enthusiastically, while others were more reluctant. The incompleteness of organizational adoption led to the lean concept being used superficially to elicit action, but not in a manner that was true to the meaning of lean. (McCann et al., 2015) Essentially, the concept was co-opted, leading to a dilution of its significance. This represents a pattern in the micro-setting which is strikingly similar to the management fashion lifecycle stage of dissonance resolution, proposed by Birnbaum (2000).

An example of where authors have looked at a potential management fashion by using different methodologies is talent management, a human resource concept that deals with things like recruitment, development, and retention of employees (Iles et al., 2010; Preece et al., 2011). In the first of their two papers, talent management was assessed using citation analysis in two big databases, finding that the number of new publications had consistently grown year by year for the entire period being studied – from 1985 to 2008. This result suggested that if talent management was a management fashion, it had yet to peak. (Iles et al., 2010) It is worth noting that the peak and decline of a management fashion would typically occur within a considerably shorter timespan than the over 20-year upward trajectory identified for talent management (Clark, 2004). In a case study conducted the following year – focused especially on the adoption side of talent management in Beijing – the authors argue against talent management being a management fashion, because the informants were able to rationalize their adoption of it (Preece et al., 2011).

A management fashion that is important to mention in the context of alternative methods is the balanced scorecard (BSC). Although it has been examined with the use of citation analysis (e.g., Braam et al., 2007), a strikingly large portion of the research is qualitative. Ax and Bjørnenak (2005) looked at local literature and conference invitations to understand how local BSC fashion-setters in Sweden modified the original concept of Kaplan and Norton (1992) to fit the local market. A demand-side analogy to this is a multi-case study of adopting organizations in Finland, which concluded that instances of practical BSC implementation can be so unique that it is impossible to determine the extent of implementation on a binary scale. Rather, it is a question of which aspects of the BSC can be identified in each organizational setting. (Malmi, 2001)

### 2.1.3 Identifying a Management Fashion and Going Beyond Abrahamson

To this point, the discussion around what constitutes a management fashion has revolved around Abrahamson's (1996) conceptualization of it. However, because of bibliometric methods that emphasize a retroactive perspective and make assumptions about the qualitative nature of management fashion, the case has also been made that the theory lacks empirical grounding. This calls how one might identify an ongoing management fashion into question. Both Kieser (1997) and Benders and van Veen (2001) have presented lists of features that, according to them, are exhibited by most management fashions. Firstly, management fashions are rhetorically presented as simple and distinct solutions to a wide set of problems. Secondly, they come at a time when managers feel pressured to seek improvement. Thirdly, they stress their general applicability through appeals to universal virtues, such as efficiency gains, and references to success stories and research. (Benders & van Veen, 2001; Kieser, 1997)

In addition to the above, Kieser (1997) also emphasizes that the newness of management fashions absolves managers of any responsibility with regards to not having already applied their principles and that management fashions are framed as so difficult to implement that only the best managers can successfully use them for value-creation. Although admittedly somewhat overlapping with the features of simple rhetoric and difficulty of implementation, Benders and van Veen (2001) include a unique concept in the form of interpretative viability. This particular term was initially coined by Ortmann (1995), but the idea – which is grounded in the hermeneutic notion that the meaning of words can vary over time and across communities – has a well-established presence in the academic literature (Benders & van Veen, 2001). Numerous analogous concepts have emerged over time, such as strategic ambiguity, (Eisenberg, 1984) umbrella constructs, (Hirsch & Levin, 1999) boundary objects, (Star & Griesemer, 1989), and pragmatic ambiguity (Giroux, 2006).

Benders & van Veen (2001) point to interpretative viability as a crucial omission of Abrahamson's (1996) theory. The argument is that, for concepts to stand a chance of diffusion, they must lend themselves to different interpretations by means of ambiguity, vagueness, and generality (Benders & van Veen, 2001; Giroux, 2006; Kieser, 1997). Only then can a particular label be applied to a wide range of practices without sparking controversy, allowing fashion setters to expand the potential market for their concept and increase its likelihood of popular success (Benders & van Veen, 2001).

On the demand side of the management fashion market, the principle of interpretative viability enhances the ease with which managers can identify a fashionable concept as relevant to their own situation. They can cherry-pick those conceptual elements that seem most attractive to them, are most pertinent to their needs, or represent what they interpret as the core idea of the concept. (e.g., Benders et al., 1998; Benders & van Bijsterveld, 2000; Benders & van Veen, 2001; Cram & Newell, 2016) The idea of such active decoupling on the demand side affords the adopting manager more agency than what Abrahamson's (1996) theory does, and although the line of thinking predates the theory (Watson, 1994), it has later turned into its most significant criticism (e.g., Benders & van Veen, 2001; Røvik, 2011; Scarbrough & Swan, 2001).

While interpretative viability facilitates the adoption of a management fashion, it somewhat paradoxically does the opposite for implementation, contributing to the ultimate waning of the concept's appeal (Benders & van Veen, 2001; Røvik, 1998). Organizational change – the inherent goal of all management fashion – is intrinsically complex and prone to pitfalls, meaning that any overly simplified attempt at it is bound to fail. As its association with failure grows stronger, whether in the context of an adopting organization or on the level of the concept itself, the fashion will eventually die off. (Benders & van Veen, 2001) An example of when this has happened is illustrated by the hospital case study which was mentioned in section 2.1.1 (McCann et al., 2015).

An alternative, implementation-related explanation for the decline of management fashion – as it manifests itself through bibliometric research methods – is that the process of implementation changes the fashion beyond recognition. This is arguably what is being described in the Finnish study on BSC, which was mentioned in section 2.1.2 (Malmi, 2001). Perkmann and Spicer (2008) propose that management concept implementation is a matter of institutional work, that is, efforts to prime the organization and to adapt the concept to achieve a fit between the two. Røvik's (2011) virus-inspired theory is another influential model that emphasizes organizational change, explaining management fashion diffusion and organizational implementation with a viral metaphor. The virus-inspired theory has been considered to give a more nuanced view of how process management behaves in an organizational setting (Quist & Hellström, 2012). A noteworthy idea in relation to fashionable management concepts changing in the process of implementation is that of management fashion as old wine in new bottles. This is the notion that new management fashions are little more than old management fashions that have been repackaged to become marketable again. (Benders & van Veen, 2001; Spell, 2001)

### 2.1.4 Research Gap

Considering the theoretical contributions to management fashion in their entirety, disagreement mainly seems concentrated to the point where the method of citation analysis takes on a downward trajectory. Abrahamson and Fairchild (1999) assert that citation count is a reliable proxy for organizational adoption, while others argue the opposite (e.g., Benders et al., 2007; Clark, 2004). At the same time, these views may conceivably be reconciled; Modell (2009) suggests that classic management fashion theory might provide a good understanding of how fashionable management concepts behave initially, on a macro level, while other perspectives are better for understanding how they develop in practice. This means that the decline indicated by citation analysis could be explained by numerous phenomena, of which far from all are about failure and abandonment.

An interview study involving both supply- and demand-side actors of the management fashion market for the BSC argued that the management fashion and virus theories could be merged. Critics of this multi-theoretical approach, the authors asserted, would argue that the macro-oriented management fashion theory is inherently irreconcilable with the micro-oriented virus theory. (Madsen & Slåtten, 2015) On the other hand, if the research profession allows the persistence of management fashion theory in defiance of micro-level evidence that contradicts its aggregate representation, it risks promoting a flawed theory. A more judicious course of action would be to explore how the theory can be reasonably amended – either to rectify inherent shortcomings in the original theory or to make adaptations that have become necessary due to circumstantial changes.

An example of the latter is a recent paper by Piazza and Abrahamson (2020), in which it is suggested that the ubiquity of mass communication warrants modification to the idea of the supply side of the management fashion market – which should now be understood as a hybrid of high-status fashion setters and social media actors. This conceptualization of changes to how the management fashion supply-side exhibits itself following the advent of social media is arguably rudimentary. Given that it is proposed by the author of the original management fashion theory (Abrahamson, 1996), a total rejection of that, very popular, theory would also be a surprising conclusion. At the same time, the findings reinforce the notion that management fashion is not well understood on the micro-level.

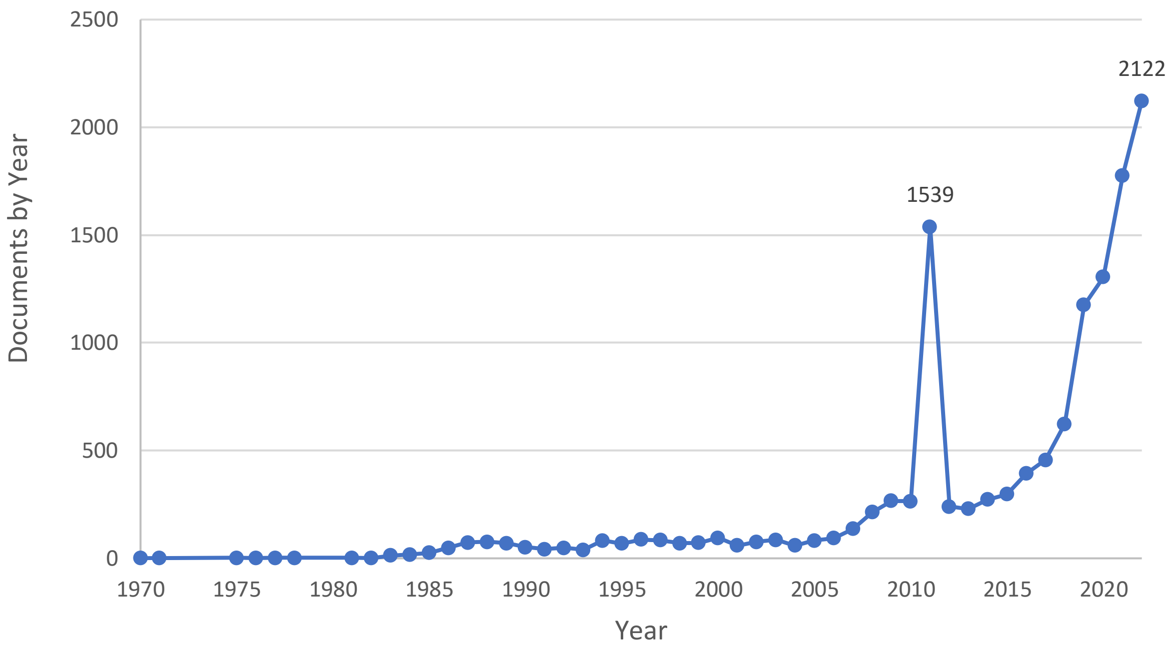
In addition to the fact that management fashion research has never addressed the topic of enterprise AI, this review of the literature hence results in a theoretical research gap. Scientific inquiry must address the mechanisms by which management fashions emerge, diffuse, are adopted, and implemented – at least in a contemporary business context. In light of the apparent need to amend management fashion theory in line with more implementation-oriented theory, this research gap must be addressed through qualitative investigation on a non-aggregated level.

## 2.2 Empirical Setting

The concept of AI has existed for several decades, tracing its roots back to Alan Turing's (1950) seminal paper, "Computing Machinery and Intelligence." In this work, Turing introduces what he calls the imitation game, which has since become widely known as the Turing test. The term artificial intelligence was first coined by John McCarthy during the Dartmouth Summer Research Project on Artificial Intelligence in 1956 (McCarthy et al., 2006). Since then, various forms of AI and related technologies have emerged, resulting in cycles of both hype – AI summers – and periods in which the concept has received little attention and funding – AI winters (Haenlein & Kaplan, 2019). There has recently been a notable resurgence of interest in AI, led by advancements in the emerging field of generative AI which is most notably represented by OpenAI's ChatGPT (Marr, 2023). The Google Trends curve for AI as of May 12th, 2023, reveals a steep rise in search interest starting in late 2022 (see Appendix 1), and Bill Gates has dubbed AI the hottest topic of 2023 (Konrad, 2023). It would hardly be controversial to say that AI is currently enjoying one of its summers.

Therefore, and because of the widespread use of citation analysis in the management fashion literature, a database search for academic articles and conference papers on AI – within the subject area of business, management and accounting – was performed. The results are displayed in Figure 2.1, showing that the topic is currently enjoying a surge in interest from business academics which began around 2016. A temporary peak was recorded in 2011, before returning to the approximate level of the years preceding, not to be surpassed again until 2021. While these are interesting findings, they are of limited significance to understanding enterprise AI from the perspective of management fashion. Its popularity in practice, and the underlying mechanisms that determine its diffusion through the business environment, remain in obscurity.

*Figure 2.1. The number of published papers on AI in business research reveals a current surge in academic interest and a peak in 2011.*




The results of the database search reinforce the idea that enterprise AI needs to be qualitatively examined through the lens of management fashion. To this end, this section serves the purpose of providing a comprehensive overview of the AI concept, its associated terminology, theories, and real-world technologies and applications. This will serve as a foundation to solidify this research endeavor, while also providing any readers to whom the topic is unfamiliar with a brief introduction.

### 2.2.1 Unraveling the AI Enigma: Moving Targets and Evolving Perspectives

Exactly what constitutes AI is not easy to pinpoint. Part of the reason for this is that intelligence itself is difficult to define (Kaplan & Haenlein, 2020). An early perspective, the previously mentioned Turing test, proposed using human intelligence itself as the benchmark against which AI can be evaluated on a case-by-case basis – specifically in the context of language output. If a human cannot distinguish between the output of a machine and that of another human, the machine is to be considered AI (Turing, 1950). While the Turing test offers an elegant and straightforward criterion for defining AI, its reliance on specific conditions prevents it from functioning as a universally applicable definition of AI. Rather, its relationship to human perception serves quite well to frame the so-called AI effect, a phenomenon where technologies initially considered examples of AI gradually seize to enjoy AI status, as humans become familiar with them and begin to take them for granted (Haenlein & Kaplan, 2019). This renders AI, by a definition analogous to the Turing test, a moving target (Kaplan & Haenlein, 2020).

In line with the notion of the AI effect, Berente et al. (2021) argue that AI should be viewed as a process rather than as a static phenomenon. By describing AI as the dynamic frontier of computing, the notion of the moving target is developed to become much more multi-faceted. The factor of inscrutability is intuitive, with the Turing test having just been discussed, as it denotes the degree to which an algorithm eludes public comprehension – essentially its ability to outpace the AI effect. The second factor is autonomy, signifying the ability of an algorithm to operate without human intervention (Baird & Maruping, 2021; Murray et al., 2021). The third and final factor is the concept of learning, that is, the capability of an AI algorithm to improve upon itself through experience and data. (Berente et al., 2021) Learning has been a fundamental aspect of theoretical AI ever since its inception as a field of science (Solomonoff, 1964; Turing, 1950).

### 2.2.2 Exploring the AI Frontier: An Overview of Today's Technologies

Having discussed the theoretical foundations of the AI concept, the following section will serve to outline the practical technologies that represent the current frontier of AI. These are often co-applied in various constellations, meaning that their identities and functionalities overlap to a considerable extent. The following sections should be viewed in this light and be used primarily as a theoretical directory of AI technologies.

#### *2.2.2.1 Machine Learning*

Machine learning (ML) is not only the most widely applied and prominent technology in the field of artificial intelligence but also a term that is frequently used as a synonym for AI, likely due to its historical centrality to theoretical AI. ML allows computers to learn and enhance their performance from experience, without being explicitly programmed. A machine learning algorithm can identify patterns in observed data, such as a growing trend in monthly sales revenue; build models that explain them, such as a correlation between sales and weather conditions; and predict future data points, such as an estimation of future sales growth based on information about weather (Bornet et al., 2020, p. 69).

The most common categorization of machine learning emphasizes the methods by which algorithms learn from data. Examples of such categories are supervised learning, unsupervised learning, reinforcement learning, and deep learning (DL). Supervised learning is a method where algorithms learn from labeled data, using input-output pairs to create a model that predicts outputs for new, unseen inputs. Unsupervised learning, on the other hand, deals with unlabeled data, identifying underlying patterns or structures without any guidance on desired outcomes. In reinforcement learning, an algorithm learns how to optimize its decision-making, by interacting in a training environment where rewards are generated from decisions that produce a predefined desired outcome. (Jordan & Mitchell, 2015; Shalev-Shwartz & Ben-David, 2013, pp. 22-23) Deep learning leverages artificial neural networks, drawing inspiration from the human brain's structure and function, to process and learn from vast volumes of data. Composed of interconnected layers of nodes or neurons, neural networks can discern complex patterns and representations by processing information through these layers and adjusting the connections between neurons based on input data. By processing and extracting features at various levels of abstraction, deep learning models can achieve state-of-the-art performance in tasks such as image recognition, natural language processing, and speech recognition. (Bornet et al., 2020, pp. 148-149; Shalev-Shwartz & Ben-David, 2013, p. 268)

*2.2.2.2 Natural Language Processing*

Natural language processing (NLP) is a theory-driven domain that encompasses a variety of computational techniques dedicated to the automatic analysis, representation, and understanding of human language (Young et al., 2018). While NLP primarily deals with the processing of language input, such as reading or interpreting text or speech, natural language generation (NLG) is concerned with expressing language through text or speech. However, the term NLP is also commonly used to describe both the processing and generation aspects of AI language processing. Key technologies currently utilizing NLP include intelligent chatbots, unstructured information management (UIM), sentiment analysis, and speech analytics. (Bornet et al., 2020, pp.132-142) A prominent example of an NLP model is OpenAI's ChatGPT, which generates human-like responses to text-based prompts and performs various language-related tasks such as translation, summarization, and sentiment analysis (Murgia, 2023). Other typical NLP application features include information extraction; information categorization, such as spam filters; speech-to-text; text-to-speech; predictive text typing; or voice understanding. In the past, NLP was primarily based on a set of predefined rules. However, modern NLP primarily relies on deep learning methods. (Bornet et al., 2020, pp. 132-142)

*2.2.2.3 Computer Vision*

Computer vision refers to technologies that allow computers to perceive, interpret, and comprehend visual elements, such as environments, objects, signs, or letters. It enables the processing of documents, images, videos, and biometric information. It can facilitate the automation of tedious tasks, such as invoice processing or anomaly detection – for example, identifying disease symptoms in medical images. Like NLP, contemporary computer vision primarily relies on the power of deep learning techniques. (Bornet et al., 2020, p. 115; Voulodimos et al., 2018) Key technologies within computer vision include optical character recognition (OCR), intelligent character recognition (ICR), image and video analysis, and biometrics. OCR is used to detect and transform alphabetical or numerical characters in images into a digital format, as long as they are arranged according to a predetermined structure. By contrast, ICR – which is also referred to as intelligent data capture (IDC) or intelligent document processing (IDP) – is capable of processing unstructured documents. It combines OCR for digitizing documents, NLP for information extraction and interpretation, and machine learning for pattern recognition. However, ICR systems need to be trained using supervised learning. This involves feeding the system with a set of data containing scanned example documents and their expected output. While image and video analysis is concerned with obtaining information from digital sources, biometrics revolves around quantifying and analyzing the distinct physical and behavioral features of humans through statistical methods. (Bornet et al., 2020, pp. 115 - 122)

#### *2.2.2.4 Automation*

In the context of AI, automation refers to the process in which software programs or machines perform tasks typically carried out by human workers. Often referred to as robots or bots, these automation programs act as a glue, seamlessly linking various technologies together. For example, they can transfer data, collected through vision or language algorithms, to machine learning algorithms that can generate insights, and use these insights as prompts to implement preprogrammed actions. Key technologies in this field include smart workflow platforms, low-code platforms, and robotic process automation (RPA). Smart workflow platforms are ready-to-use solutions designed to streamline business processes by orchestrating specific data and action flows. Low-code platforms allow individuals to develop applications without having coding skills, by offering chunks of code in a more user-friendly drag-and-drop environment. RPA refers to a programmable software tool, usually called a software robot, that follows business rules and a set of instructions. It engages with computers in a similar manner to a human and automatically performs tasks across a variety of applications. Essentially, such a robot can perform any task that a human could perform on a computer with a mouse or keyboard, so long as it can be programmed in advance. It is often used to automate repetitive and rule-based tasks, such as copying and pasting, opening applications, and sending emails. While all these technologies can work together, it is considered best practice to lay the foundation of a comprehensive automation platform by adopting smart workflow and low-code platforms as core components. RPA comes into play when integrating automation with legacy systems, or when automating bespoke processes. In contrast, intelligent automation (IA), also known as hyperautomation, represents an emerging frontier within the automation domain. IA leverages a new generation of software-based automation with a focus on automating knowledge work. It combines diverse methods and technologies from the fields discussed in this section to autonomously execute complex business processes, even in highly dynamic circumstances. (Bornet et al., 2020, pp. 123-130)

### 2.2.3 Contemporary Theory in AI Application

Having gained an understanding of the technologies in practice, the focus in the following section shifts towards exploring recent application-oriented theories, bridging the gap between theory and practice. While the initial concepts of AI discussed were of a more theoretical nature (Berente et al., 2021; Kaplan & Haenlein, 2020), Bornet et al. (2020) provided a more practical perspective on the definitions of AI. Taking another step in the direction from the theoretical to the practical, AI can also be defined from the context of its application. Davenport & Ronanki (2018) do this by categorizing AI into three distinct types that align with specific business capabilities, rather than technological underpinnings. The first category is process automation, which refers to the automation of both physical and digital tasks. The second category, cognitive insight, is concerned with algorithms that can identify patterns in large data sets and interpret their meaning. The final category, cognitive engagement, revolves around human interaction, mainly using NLP and machine learning. Table 2.1. aims to consolidate the somewhat different perspectives of Davenport & Ronanki (2018) and Bornet et al. (2020), to illustrate the alignment of specific AI technologies with their corresponding business functions and emulated human capabilities. However, it also demonstrates how the various technologies under the AI umbrella are often used in conjunction with one another and are closely intertwined, emphasizing the blurred boundaries that distinguish these technologies.

*Table 2.1. Mapping exemplified technologies with theoretical categories.*

<table>
<tr><th>Business Capabilities<br>(Davenport & Ronanki, 2018)</th><th colspan="3">Exemplified AI Technologies</th><th>Human Capabilities<br>(Bornet et al., 2020)</th></tr>
<tr><td rowspan="2">Process automation</td><td rowspan="2">Automation</td><td colspan="2">Low code<br>Smart workflow<br>RPA</td><td>Execution</td></tr>
<tr><td>IA</td><td>Automation technologies above with integrations in Computer Vision, ML, & NLP</td><td>Execution, Vision, Language, & Thinking & Learning</td></tr>
<tr><td rowspan="5">Cognitive insight</td><td rowspan="3">Computer Vision</td><td colspan="2">OCR</td><td>Vision</td></tr>
<tr><td colspan="2">Image and video analysis (can involve ML)<br>Biometrics (can involve ML)</td><td>Vision, & Thinking & Learning</td></tr>
<tr><td colspan="2">ICR (involves OCR, NLP & ML)</td><td>Vision, Language, & Thinking & Learning</td></tr>
<tr><td>ML</td><td colspan="2">Supervised Learning<br>Unsupervised Learning<br>Reinforcement Learning<br>Deep learning</td><td>Thinking & Learning</td></tr>
<tr><td rowspan="2">NLP</td><td colspan="2">UIM (can involve ML)<br>Sentiment analysis (can involve ML)<br>Speech analytics (can involve ML)</td><td>Language, Thinking & Learning</td></tr>
<tr><td>Cognitive engagement</td><td colspan="2">Chatbots (can involve ML)</td><td>Language, Thinking & Learning</td></tr>
</table>

### 2.2.4 Synergies, Blurred Lines, and an Operational Definition of AI

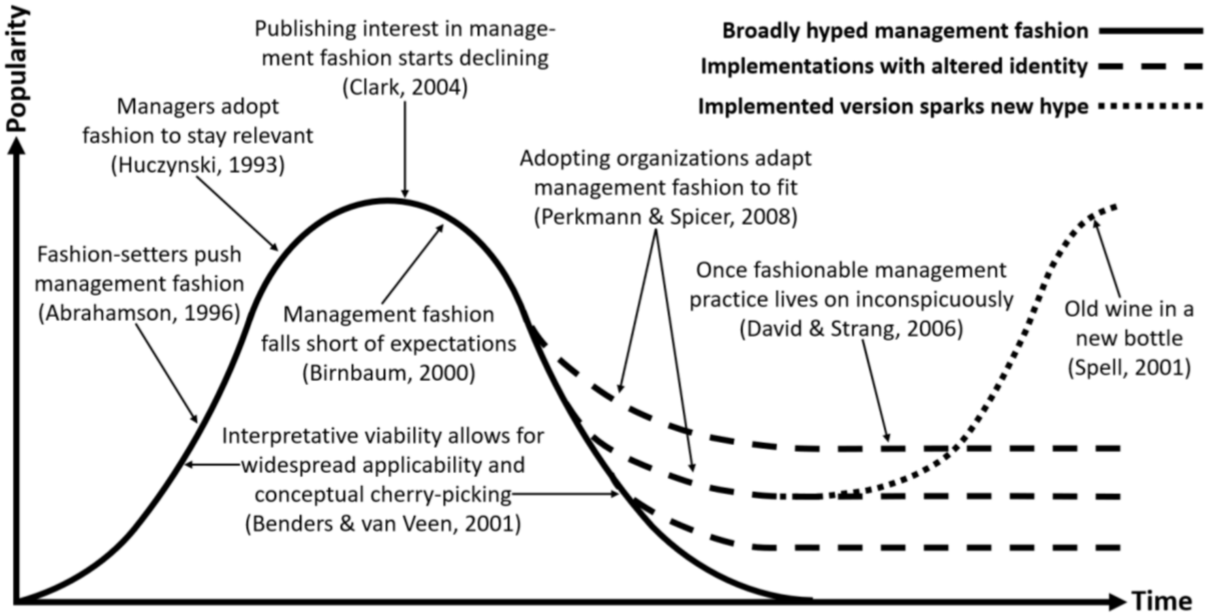
As has been alluded to previously, there is a lot of overlap between technologies that fall under the broader umbrella of AI technologies. This is partly due to the diversity with which they tend to be combined. Adding to the complexity, these combinations change over time as a manifestation of AI's technological development. If this progression is viewed from the business-process perspective proposed by Davenport & Ronanki (2018), it becomes clear that also humans can be considered a part of this wavering equation. This gives rise to the so-called automation-augmentation paradox, where automation denotes the takeover of human tasks by machines, while augmentation refers to human-machine collaboration to perform a task. Rather than being truly paradoxical, however, the relationship between automation and augmentation might be better described as one of interdependency – at least over time. This means that the link between humans and AI should be seen as a coevolutionary process, where the capabilities of humans and machines develop and overlap differently over time. (Raisch & Krakowski, 2021)

While this discussion brings clarity to why AI is so hard to grasp, it does not provide the easily usable operational definition of AI that a study of enterprise AI through the lens of management fashion requires. Therefore, this study will rely on one of the specific technologies within the enterprise AI market as its operational definition of AI. For the sake of tangibility, this choice falls on the most mature enterprise AI technology, RPA. From 2018 to 2020, RPA established itself as the fastest-growing segment within the enterprise software market (Biscotti et al., 2019; Biscotti et al., 2020; Biscotti et al., 2021). Moreover, McKinsey's latest survey on the state of AI, published in December of 2022, confirmed RPA as the most deployed AI technology in business (Chui et al., 2022). As a result, RPA companies can also attain extraordinary valuations; at seven billion USD in 2019, UiPath became the highest-valued AI company at the time (Wheatly, 2019).

## 2.3 Theoretical Framework and Research Question

The theoretical framework of this study aims to present a nuanced view of management fashion theory, by consolidating the different views presented in section 2.1. Figure 2.2 shows how the bell curve proposed by many authors (e.g., Abrahamson & Fairchild, 1999; Carson et al., 2000) can be adapted to account for different perceptions within management fashion theory, especially regarding the decline phase of a fashionable management practice. A crucial concept in enabling this consolidation of perspectives is that of interpretative viability. It implies that the literal meaning of a popular management concept may change over time and depending on context. On the one hand, this will broaden the appeal of a management concept in its popularized form. On the other hand, it will enable management concepts to change and even take on a different identity through practical implementation. It also means that cases of long-term management fashion implementation may exist without being visible in the sense of being fashionable, by extension even allowing evolutions of old management fashions to be re-launched under completely new guises.

*Figure 2.2. Visual representation of how a management fashion might develop over time, according to a synthesis of the literature review. The authors given within parentheses represent examples of the mechanisms or phenomena described.*




The different types of lines in Figure 2.2 signify qualitative changes that a management fashion can undergo, from solid lines to long-dashed and short-dashed lines. Although Figure 2.2 suggests that such qualitative change would occur in stage-like shifts, the changes would realistically be highly incremental. Furthermore, each of the three long-dashed lines in Figure 2.2 represents a unique development path from the original management fashion – represented by the solid line.

For the present study, this theoretical model allows for the identification of a management fashion based on the following four characteristics. Firstly, the management fashion environment will be marked by the presence of fashion-setters and adopting organizational managers in some kind of interplay. Secondly, the popularized management concept in question will be highly open to interpretation, meaning different things to different people and in different contexts. Thirdly, implemented versions of the management concept will differ from the original, theoretical view of what it is, as well as from each other. Lastly, some such developmental offshoots can be expected to turn into management fashions of their own.

This practical model of the theory allows enterprise AI to be examined through the lens of management fashion, to determine the ways in which it can be considered as such. Furthermore, this examination will serve to establish an understanding of how features that are unique to AI, in relation to conventional management fashions, manifest themselves through the theoretical perspective in question, and thereby contribute to the development of said theory. The key distinction of interest in this case is that management fashions typically manifest as purely ideational constructs (Benders & van Veen, 2001), while enterprise AI – comprising applications that harness the theoretically heavy technological field that is artificial intelligence in a business setting – has significant material components to it.

While enterprise AI applications have fundamentally been made possible by the advancements in processing power that have allowed the up to 70-year-old theories of AI to materialize, other kinds of technological development are of equal importance. For example, cloud computing – which is a phenomenon made possible by new communication technology – is what allows the hyper-scalable software as a service (SaaS) business model to exist (Chung, 2021). Still, although material components as manifested through phenomena like SaaS should be considered news in relation to how management fashions are typically thought of, they are not unique to enterprise AI. Hence, understanding the potential peculiarities of enterprise AI from a management fashion point of view is a first step towards extending management fashion theory to incorporate modern genres of business fads that are not solely ideational, but also have tangible, scalable, and highly marketable features. In such cases, management fashion can be mass-marketed in a distilled format. Considered against the background of what mere adherence to management fashion can mean for organizational reputation and valuation (e.g., Bermiss et al., 2014; Nicolai et al., 2010; Wang, 2010), such extension of the theory is decidedly relevant.

In summary, the aim of this thesis is to leverage the nuanced and intelligible theoretical model presented above, not only to see how enterprise AI fits with the theory of management fashion, but also to discuss how its inherent and apparent deviations from conventional management fashions may serve to illuminate the theory by means of empirical grounding. This prompts the research question of the study:

*RQ: How can enterprise AI be understood through the lens of management fashion, and how can management fashion theory be developed by studying the case of enterprise AI?*

# 3. Methodology

*This chapter describes and discusses the methodological considerations and methods with which this study was conducted. The structure is inspired by the research onion proposed by Saunders et al. (2012, pp. 126-207). Beginning with research design, the first section covers the study's research philosophy, research approach, methodological choice, and research strategy (3.1). Next is an explanation of how the literature was approached (3.2), a section on how the data was collected and analyzed (3.3), and finally a discussion about the quality of the study (3.4).*

## 3.1 Research Design

### 3.1.1 Research Philosophy and Approach

Provided that the literature review leads to a research gap regarding the empirical grounding of management fashion research in modern-day business, the theory is debated to such an extent that it cannot be considered entirely established. Out of their three archetypes, Edmondson and McManus (2007) would likely characterize it as intermediate or even nascent. As a result, further work within the stream of research should maintain an open-ended stance in relation to data (Edmondson & McManus, 2007). When also considering that the reality of fashion is inherently socially constructed, subjective meanings are essential to understanding how it works. It is, therefore, suitable to adopt an interpretivist research philosophy (Saunders et al., 2012, pp. 127-143). In the context of theoretical debate, the natural approach to research is one of iteration. Alternating between theory and empirical observations not only serves to refine the theory, but it is also necessary to be able to apply theory that is indistinct to a new empirical context (Saunders et al., 2012, p. 148).

### 3.1.2 Methodological Choice and Research Strategy

In order to stay consistent with the research approach, a qualitative method is most appropriate for this study. Quantitative approaches do not offer the in-depth understanding of phenomena that is necessary to oscillate between empirical observations and theory in a constructive way (Bryman & Bell, 2011, pp. 401-406). Within the context of qualitative research, case study method is appropriate when the goal is to understand complex phenomena with a strong social component to them (Yin, 2003, pp. 1-2).

One of the most influential thinkers on case study research is Eisenhardt (1989). Her highly positivist approach relies on multiple cases to induce theory that is generalizable to populations, and therefore quantitatively testable. Consequently, the main strength of this method is its claim to the discovery of general truth. On the one hand, this is undoubtedly a goal worth aiming for. On the other hand, attaining it is predicated on breaking free from contextual detail, so that aspects that are unique to any specific case do not affect findings in an undue manner. (Welch et al., 2011) This means that carrying out a case study in accordance with the principles of Eisenhardt relies on a high level of contextual awareness which, as demonstrated in section 2.2, can be difficult to maintain in the case of AI. A lower-risk approach to studying enterprise AI through the lens of management fashion is therefore one where the prevalence of contextual uniqueness can be viewed as a source of strength, rather than one of interference.

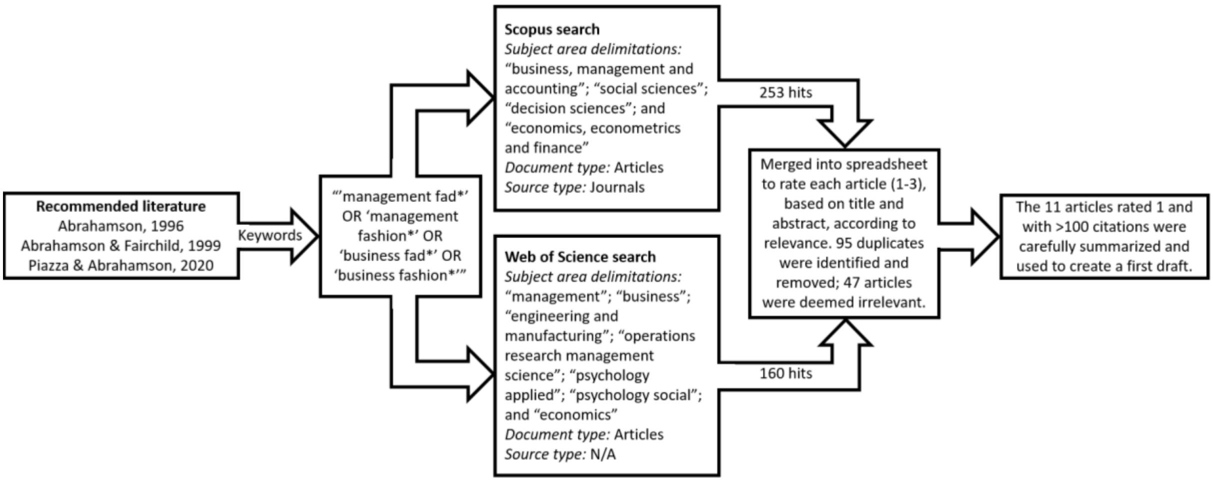
Compared to Eisenhardt, Yin (2003) offers up a broader concept of what case study research can entail, including, for example, the option of carrying out single-case studies that emphasize context. While still positivist in the eyes of Welch et al. (2011), Yin (2003) arguably broadens the avenues of possibility regarding how case study research is to be conducted, so long as the approach is well argued for. Considering the complexity of the empirical setting under study, a single case approach – that confines the scope of inquiry to one form of enterprise AI and one organization that deals with it – is a suitable way to control contextual ambiguity. This choice naturally reduces the generalizability of findings and limits their nuance to the perspective of the chosen case organization, but these are reasonable aspects to trade off in favor of clarity. Future research can always increase its ambition of scope, but never make up for a lack of precision in earlier work.

Therefore, the decision was made to anchor this study in what is arguably the most mature form of AI, RPA. In light of this, the choice of case organization from which to sample informants fell on a startup that is developing and selling software to orchestrate enterprise automation, with a specific focus on RPA. Being promoters of a product which in and of itself reflects the relative maturity of the RPA market, the case organization can be considered critical (Yin, 2003, pp. 39-53). Furthermore, focusing the informants' technological perspective on AI should reduce the level of interference that is to be expected from the complexities nested within the empirical context. Such clarity is arguably an underlying theme of Flyvbjerg's (2006) defense of single-case studies as a research method. Although RPA has been around for several years, it is merely used as a vehicle to understand what is currently going on in AI, meaning that this study is to be considered cross-sectional rather than longitudinal (Saunders et al., 2012, pp. 190-191).

## 3.2 Approach to the Literature

When conducting a case study, the first step of a rigorous methodological path is a thorough literature review (Saunders et al., 2012, pp. 90-105). With respect to the abductive nature of the inquiry (Bryman & Bell, 2011, pp. 11-14), this might intuitively be better approached as a narrative review than as a systematic review (Bryman & Bell, 2011, pp. 94-103). Without considerable experience with the research craft (Daft, 1983), however, some aspects of systematic review might sensibly be incorporated into the process (Bryman & Bell, 2011, pp. 101-103). In line with the approach suggested by Bryman and Bell (2011, p. 110), the initial inquiry into the field of management fashion was based on the recommendation to read three articles by the most prolific researcher in the context of management fashion. Figure 3.1 gives an overview of the study's approach to the literature review.

*Figure 3.1. Visual representation of the systemic literature review.*




From the recommended literature, the most relevant keywords were identified. These were then turned into search strings, including the word "business" for added breadth. Two databases were searched using the strings, yielding a total of 413 hits. The articles were exported and merged into one spreadsheet, allowing duplicates to be removed and the remaining articles to be rated according to relevance. The word that had been added for breadth rendered few additional results of relevance, suggesting that the keywords derived from the recommended literature were representative of the terminology used in management fashion research. Moreover, the significant overlap between the databases indicated that the topic had been well-covered by the two searches. Additional articles were then found by means of snowballing (Greenhalgh & Peacock, 2005).

In addition to the recommended literature, eleven of the articles that were rated as highly relevant – for dealing directly with the conceptualization of management fashion – had over 100 citations. These were carefully reviewed, summarized, and used to write a first draft of the literature review. Moving forward, iterations of the literature review made sure to include more recent articles to account for the bias towards older articles that is inherent to both citation count and snowballing.

## 3.3 Data Collection and Analysis

The dataset comprises 16 semi-structured interviews which, with the exception of two, involve eight members of the case organization. This means that six informants were interviewed twice. Before being interviewed, each informant was told that the interviews were part of a master's thesis, that their participation was voluntary and anonymous, and that they were free to withdraw their consent to participate at any time. The interviews conducted are summarized in Appendix 2, providing an overview of participants and additional relevant information. The following section describes the process of data collection and analysis in more detail.

### 3.3.1 Qualifying the Case Organization

The first two interviews were held with the company's CEO and CSO, and mainly served the purpose of qualifying the organization as a case to study, after it had been identified as an actor in the enterprise AI market segment of interest. A tentative interview guide had been prepared, leveraging the theoretical framework. To mitigate potential participant bias, deliberate efforts were made to refrain from explicitly disclosing the theoretical basis of the study (Saunders et al., 2012, pp. 192-193). Based on the insights gathered from the first two interviews, the interview guide was refined (see interview guide in Appendix 3).

### 3.3.2 Main Data Collection Round and Informant-Centric Coding

With the next five interviews, seven of the eight organizational members who had been identified as potentially relevant were covered. These interviews were transcribed and coded, using the coding tool Quirkos. The analysis method was inspired by Gioia et al. (2013). The initial, informant-centric codes were generated by both authors individually, resulting in a very large number of codes. These were then reduced and tentatively categorized into themes, between which significant overlap could be observed.

### 3.3.3 Refining Themes by Leveraging Theory and Additional Interviews

Next, the developed themes were considered in relation to management fashion theory. This guided the interpretation of observations in a way that allowed superfluous themes to be removed, and new themes to be developed to reconcile overlapping themes. This step can be likened to Charmaz's concept of focused coding (Saunders et al., 2012, pp. 567-572). This was a highly abductive process in the sense that it fueled additional interviews that could add nuance to the material. As part of these continued interviews, two informants from a prospective customer of the case company were added. Nuance was thereby added to the data in the form of an embedded unit of analysis (Yin, 2003, pp. 39-53). The customer organization is a large communications technology enterprise, with a well-established internal automation and AI division. Both informants were managers from this division. One new employee of the case company was interviewed, and five of the six that had already been interviewed were interviewed a second time. This activity echoes Yin's (2003, pp. 120-122) explanation building technique; in the second-round interviews, the coding system that was undergoing change was used as the interview guide, and then continuously developed to incorporate findings from previous interviews.

## 3.4 Quality of the Study

### 3.4.1 Construct Validity

Construct validity is about finding the appropriate operational instruments to measure what is being studied (Yin, 2003, pp. 33-39). Given the study's explorative nature and interpretivist research philosophy, satisfying the criterium of construct validity is not entirely straightforward. In part, it is addressed by the literature review, which demonstrates the fragmentation of ideas that exist in the space of management fashion theory. In part, by virtue of being the overarching validity measurement, it is addressed in the following sub-section.

### 3.4.2 Internal and External Validity

Although Yin (2003, pp. 33-39) argues that the matter of internal validity is only relevant for causal studies, and thus not for this explorative one, it still deserves to be mentioned in the context of the present study. Part of this study's research question asks how AI might be understood as a management fashion, meaning that the results must be compared to the propositions of theory. To this end, the previously mentioned triangulation of literature, data collection, and analysis – through which an understanding of AI as a management fashion was gradually built – constituted a form of explanation building that increased internal validity

(Yin, 2003, pp. 120-122). The use of theory in this process also contributed to external validity (Yin, 2003, pp. 33-39).

### 3.4.3 Reliability

The study's claim to reliability can be traced in the level of detail with which the research methods are exhibited in the present chapter. Furthermore, the empirical results pair quotes with clarifications of the meaning that was derived from them, adding transparency to the interpretation of raw data. Finally, the use of the interview guide (see Appendix 3) asserts that the interviews were conducted in a non-biased way, especially with regard to asking leading questions. (Yin, 2003, pp. 33-39)

# 4. Empirical Findings

*This chapter presents the empirical findings of this study, structured in accordance with four dimensions. These are based on the themes which are, in turn, derived from informant-centric coding. Each informant-centric code is exemplified with a quote, which is also commented on in-text. The first section is dedicated to the feature of the versatility of AI as a concept (4.1). Next, the most important actors in the management fashion market for enterprise AI are presented (4.2). Then the factors promoting the adoption of hyped enterprise AI are displayed (4.3). Finally, the way that the enterprise AI space is characterized by commoditization is considered (4.4).*

## 4.1 The Versatility of AI as a Concept

In the way that management fashion theory has been conceptualized in this study, the rise and subsequent decline of management fashions can largely be ascribed to ambiguity – or interpretative viability – within such management concepts. As discussed in the literature review, this characteristic allows concepts to reach a wide audience, while also making them flexible through implementation. The observations of this study suggest such ambiguity to be present in the case of enterprise AI, and this section aims to present the different ways in which it manifests itself as such.

### 4.1.1 AI Concept is Open to Interpretation

The first and perhaps most central way that enterprise AI is an elusive concept is how it is open to interpretation. In other words, it lacks a singular, fixed meaning, resulting in the permeation of diverse meanings to it. The empirical findings show two ways in which this appears to be the case. These are explored below.

Firstly, AI functions as an umbrella term, which encompasses many different technologies. The first example quote in Table 4.1 compares enterprise AI to strategy, four decades ago, in the sense that people talk about it, but nobody knows what it means. The informant attributes much of this confusion to the lack of clear definitions with regard to technology that is generally considered to be AI.

The second observation is that the informants all define AI in different ways and acknowledge this themselves. Quote number two in Table 4.1 shows that there are as many definitions of AI as there are people. This implies that the overlap in the enterprise AI space is not only technological but also terminological, making it impossible to draw any firm lines between different facets of AI.

*Table 4.1. Quotes illustrating how the concept of AI is open to interpretation.*

| **Concept** | **Exemplifying Quote** |
|---|---|
| AI is an umbrella term encompassing many different technologies | *"I mean, it is like […] in the 80s […], everyone talked about strategy. But it wasn't very clear what does strategy actually mean. We're seeing similar things with AI at the moment. There is confusion around what does it actually mean? And it does mean a lot of different things to a lot of different people. There isn't enough clarity, and that taxonomy under AI hasn't been defined to my knowledge."* – COO |
| Informants define AI in many different ways | *"Hmm. It's a really good question, right? And I guess to some extent it doesn't make sense to ask the question because you will get different answers whoever you talk to, right?"* – CEO |

### 4.1.2 AI as a Buzzword

Another theme, which illustrates how the ambiguity of the AI concept contributes to its appeal, is that it is being used as a buzzword. This means that it is being used frequently even though its meaning is not clear. The findings of this study offer three observations that help to illustrate this. These are presented below.

The first observation is that the term AI is overused to the extent that its meaning is becoming diluted. The corresponding example quote in Table 4.2 demonstrates how this is a consequence of software vendor marketing departments associating their products with AI in a vague manner. Another informant took it further, by drawing the argument to how all manner of consumer products are now sold as driven by AI.

Next, enterprise AI is being sold as something that is easy to implement. The second quote in Table 4.2 exemplifies how RPA was being sold as a cheap, quickly implemented way to create additional value. This represents an oversimplified view of what enterprise AI is and what it can do, as suggested by the end of the quote as well as the rest of the interview data.

Thirdly, substantiating the notion of AI as a buzzword is the aspect of over-promising. The last quote in Table 4.2 is about how technology associated with AI has been oversold in relation to what it can really do, and the informant is saying that this is now becoming clear. This indicates that there is a bubble of expectations around AI that has now reached the point of bursting.

*Table 4.2. Quotes showing how AI functions as a buzzword.*

| **Concept** | **Exemplifying Quote** |
|---|---|
| Overuse and Dilution of the Term AI | *"I don't think there is a really good understanding [of AI] yet, and I think that's primarily because marketing has done a really good job at making AI this catch-all term, this panacea for every problem that an organization has, right? If you look at any technology that is marketed today, they're all saying: 'This is what we do, this is our SaaS software powered by AI' and that's such a nebulous term. It's so vague and nobody really understands what that means. So, I think marketing is to blame for that."* – VP of Sales |
| Over-simplifying the AI Concept for Sales | *"If you look at automation, initially it was sold as something that was super simple. It would go really fast, and there would be no pickups, and there will be low cost and you will be done in two weeks. But that is not the reality in a big enterprise. Then it might have turned out to be costlier, slow, and maybe not as value-generating."* – CSO |
| The enterprise AI space has been characterized by overpromising | *"There's been this overpromise and under-delivery, and with this overpromise, there have been over-inflated costs and it didn't work. And now everyone's like, 'well, as I'm looking at my budget, I can get rid of all this stuff. I don't need it anymore.' […] It's big companies and small companies who have over-promised on their tech, under-delivered and over-charged. And so, now when people aren't coming back, there is no cushion there, because everything was so inflated to begin with."* – Head of Marketing |

### 4.1.3 The Gap Between AI Marketing and Reality

The next theme that signals ambiguity in the concept of AI is that there is a big gap between the reality of enterprise AI and the way it is being marketed. On the marketing level, AI is simpler and more exciting than it is on a technical level. This pattern is identifiable based on three observations. These are presented next.

To begin with, AI has been dramatized to make it more interesting. As the first quote in Table 4.3 illustrates, the realities of AI work would not make for a particularly interesting movie, because it is all about math and statistics, which is not generally thought of as exciting. With this movie metaphor, the informant is saying that enterprise AI marketing has to sell a vision of itself that is more emotionally appealing than the underlying truth.

Closely related to the first, the second observation is that the realities that fall into enterprise AI can be too simple to be marketable. In other words, what is being done is so straightforward that it would not make sense to market it transparently. The example quote in Table 4.3 is about how the value of an AI solution risks being lost in the simplicity of the means to get there. Therefore, enterprise AI marketing is sometimes about obscuring the simplicity of solutions.

The third and final observation is that the discussion around AI happens on several different levels of sophistication. As the last quote in Table 4.3 illustrates, one informant characterizes the AI discussion as happening on two levels of sophistication – one that takes place on social media and another that happens at the universities. The former kind is marked by fragmentation and loose definitions, which adds to the confusion around what AI means.

*Table 4.3. Quotes demonstrating the gap between AI marketing and reality.*

| **Concept** | **Exemplifying Quote** |
|---|---|
| AI has been dramatized in order to make people care | *"I think that it's not as attention-grabbing. It would be a really boring movie to watch people figure out all of the data science steps and the mathematical computations. That's not nearly as exciting as the Terminator, right? No one's going to click and be like, 'Look, we found a better way to process this algorithm'"* – Head of Marketing |
| The real work behind AI is sometimes too straightforward for marketing | *"It just doesn't have to be as sophisticated as everyone wants to make it sound. 'How cool would this be?' you're like, 'I just need this Excel file to be analyzed once a month.' There's a software developer out there saying, 'I could do an API call. I'll be done with that in 30 minutes.' It's not pretty, not fancy, you can't make a video about it, and people aren't going to read an article about how you did that to solve a problem, but that's where people are in the real world."* – Head of Marketing |
| The discussion around AI happens on several levels of sophistication | *The discussion is at two levels, I feel. There is a discussion at a more consumerish [sic] level. In the last three months, or maybe more, we have had more experts on AI on LinkedIn than there ever existed in the world. […] So, I think there are two levels of discussion. I see university level discussions around AI, where AI is being researched, and that's very interesting to watch and learn from. And then there is this massive cloud of confusion around AI that exists, particularly in social media. And now also in the mainstream press, that we see reporters picking up on nomenclature that they've read about on AI and sort of throwing it around, which creates much more confusion, I feel, in the market than clearing it up.* – COO |

### 4.1.4 AI Definition as a Function of Communication Objectives

The final theme reinforcing the notion of AI being an ambiguous concept, is that the way that it is being discussed depends on the goal of the communication. That is, the reason for talking about AI dictates what is said about it. The empirical findings contain three aspects that go into this, and they are explained below.

Firstly, the idea that AI does not even need to be defined on a general level emerged. The first example quote in Table 4.4 shows this, as an informant asks why and for whom such a definition is necessary. Such a sentiment makes the AI concept inherently ambiguous because it puts the substance of the term second to what one hopes to achieve by using it.

Secondly, the selling of enterprise AI software relies on a narrative that can appropriately position the product in the minds of the right stakeholders. Example quote number two in Table 4.4 illustrates this by explaining that the product must be presented in a way that is relevant to the audience, that will make them engage, and understand the relationship between them and the product. This means that the messaging will move somewhat freely around the core substance of the product.

Finally, the aspect of AI hype can be understood from a goal-of-communication perspective. As the last quote in Table 4.4 shows, hype serves to give the topic the attention that its proponents think it deserves – even though the terminology used is not understood in a consistent way. This translates to the purpose of hype being the attraction of attention in an early stage, which can lead to a meaningful level of understanding and productive engagement with time.

*Table 4.4. Quotes showing how the use of AI in communication is goal-dependent.*

| **Concept** | **Exemplifying Quote** |
|---|---|
| AI does not need to be defined on a general level | *"For whom does AI need to be defined, and why does it need to be defined?"* – COO |
| When selling AI software, a narrative is important to position the product to relevant stakeholders | *"You have to think about who your audience is and what they need to hear. [...] like what are their pain points? How are we going to help them? What's going to make them read something and say, 'Wait, that might be me'? It's sort of like, how do we put this in a language that our buyers and our users, our target audience in both of those segments, are going to care about and that it will resonate with them?"* – Head of Marketing |
| Hype is good because it generates high-level attention | *"I think the hype is great because it gets the focus it deserves, this technology. It is very powerful."* – Head of Enterprise AI* |

***** Customer of the case company

## 4.2 Catalysts for Fashion

A central proposition of the management fashion literature is that management concepts go into style as the result of active promotion on behalf of certain actors. Exactly who these actors are and how they relate to each other has been the subject of debate and may differ between cases. In the context of this study, no clear supply and demand roles in relation to AI could be identified and tied to certain types of actors. Rather, by virtue of contributing to hypes in a decentralized manner, players were found to be better described as catalysts for fashion. The empirical results presented in this section describe the main types of actors which appeared in this study, beginning with two that are somewhat unique to enterprise AI and ending with two that are arguably present in any case of management fashion.

### 4.2.1 Software Vendors Striving for Market Positions

One type of catalyst in the fashion market for enterprise AI is software vendors, of which the case organization is an example. These are companies that sell various types of systems, programs, or applications using AI, or at least claiming to do so. Their contribution to the hype around AI can be understood based on three observations, explored below.

The first observation can be understood as sales being the number one priority of any software vendor, meaning that any hype that can be appropriated to that end will be taken advantage of. As the first example quote in Table 4.5 shows, the case company consciously looks for what is trending – using Google searches as a proxy – and tailors its web content accordingly to create and strengthen the perception that they are aligned with the trend.

The second observation is an extension, and partial explanation, of the first. To the extent that a software vendor is a startup, such as the case company, selling a vision of what they might one day become is key to securing funding, as this enables the product development that is necessary to attract paying customers. Table 4.5 features a quote that exemplifies how software vendors try to associate themselves with broader ideals to make themselves more tangible and appealing, thus ensuring that they survive into the future.

The third observation is that the tangible software product component of the enterprise AI environment invites investors who drive hype to promote their investments. The final quote in Table 4.5 demonstrates how they do this by being very public about their investments, using media as an intermediary. As exemplified by the end of the quote, the sheer size of an investment can be enough of a message to the audience.

*Table 4.5. Quotes exemplifying the role of software vendors in the enterprise AI arena.*

| **Concept** | **Exemplifying Quote** |
|---|---|
| Software vendor marketing departments need to frame their products as exciting by latching onto new hypes within AI | *"We analyze what people are searching for, and then we write our content to optimize. […People are] still searching for, "what is AI?", "what is machine learning?" […] It had nothing to do with our content and our positioning. So, we kind of have to play the algorithms from a marketing perspective like that. Looking at, 'what are people asking Google?' and then, 'how do we put that in our web experience just to get them there?'"* – Head of Marketing |
| Software companies need to sell in the near-term if they want to develop and thrive in the long-term | *"[…] you're at the point with the company this early where you're trying to get people to buy into your idea. […] you try to put some kind of vision – like tangible thing you can see – to your idea, but the idea isn't done. So, there's this much of the idea and the product, which fits this much of the market. And so […] you can get more money and you can build from there."* – Head of Marketing |
| Software vendors get support from their investors | *"Let's not forget investors […], they are really hyping stuff, […] because they invest, and they want the valuation to increase. […] They talk a lot with journalists […] about the investments they do. […] They have a very strong influence on the hype itself. […] When [Microsoft invests] 10 billion dollars in ChatGPT, that's a signal. That's part of the hype."* – CEO |

### 4.2.2 Analyst Firms as Corrupt Gatekeepers

A second type of catalyst in the fashion market for enterprise AI solutions is analyst firms, such as Forrester and Gartner, who play an important role in the promotion of software products. The empirical findings suggest that there are three mechanisms by which they contribute to the AI hype. These are elaborated on below.

The first factor to consider with analyst firms is that they specialize in the generation of hype, by creating catchy concepts to promote new products. The first quote in Table 4.6 shows that this is what happened with RPA; the concept itself was the result of a collaborative effort between Blue Prism – an RPA software vendor – and the analyst firm Horses for Sources. Other observations suggest that this is only one of several instances of automation being repackaged by analyst firms.

Strongly related to the phenomenon described in the previous paragraph, the second aspect to consider with analyst firms is their revenue model. They do not promote new products out of the goodness of their hearts, but because software vendors pay them to do so. The second exemplifying quote in Table 4.6 implies that there is a strong relationship between what software companies spend on analyst firms and how the analyst firms portray them in return. One informant revealed that the case company has in fact paid for an article to be written about them.

The third observation is that, despite the nature of their business, analyst firms enjoy the trust of people in the enterprise AI market – and erroneously so since the analyst firms are evidently not as objective as they try to appear. The last quote in Table 4.6 exhibits the degree to which software buyers rely on analyst reports to support their purchase decisions. While the informant who explained this was generally very critical of analyst firms, he realized that he had himself been referring to their data in the same interview. Together, these mechanisms effectively render the analyst firms the corrupt gatekeepers of the enterprise AI market.

*Table 4.6. Quotes demonstrating how analyst firms function as corrupt gatekeepers.*

| **Concept** | **Exemplifying Quote** |
|---|---|
| Analyst firms help launch catchy concepts to create hypes around products | *"I think RPA got very hyped when they coined the term robots. Before it was a UI automation, and that doesn't seem so sexy, but robots seem very sexy. So, I think the pictures of robots working in the back-office setting, that actually attracted my interest."* – CSO |
| Analyst firms are pay to play | *"Oh, they're one hundred percent paid for, right? […One of my previous employers] had a massive analyst relations team and a massive analyst relations budget, […] you know, tens to hundreds of thousands of dollars to analyst firms. And then we're magically always a leader, or we're always briefing them, and we're always talking to them.* – Head of Marketing |
| People in the enterprise AI market erroneously trust what the analyst firms say | *Me being on the selling side, I've […] had multiple prospects tell me, 'Oh, yeah, I'm looking at you guys because you guys are in the top right quadrant. 'That's literally the only reason that they're talking to us, […] and they're vetting the top right quadrant and all those players against each other. That's how they're making their decision."* – VP of Sales |

### 4.2.3 Early Adopters: Diverse Approaches to Implementation

A third kind of player in the fashion market for enterprise AI solutions is organizations that adopt these technologies in their business. The empirical findings reveal four patterns for how such companies play into the AI hype. Explanations of these patterns follow.

Firstly, although AI has heavy IT components to it, successful adoption comes from approaching it with a business process transformation mindset. The first example quote in Table 4.7 emphasizes the notion that enterprise AI adoption takes a long time. Budget allocation and cultural alignment are other aspects that make it a difficult thing to do.

As a result of the first observation, the second is that successful enterprise AI adopters have developed new needs in relation to the topic. As illustrated by the second quote in Table 4.7, the adoption of for instance RPA led to the creation of new activities, the automation of which is the case company's raison d'être. This creates a natural progression into enterprise AI for organizations that invest heavily in it.

However, thirdly, organizations that have adopted RPA have rarely realized its full potential. Table 4.7 contains an example quote that shows this to be the case, despite RPA being the most mature niche in the enterprise AI market. This ties back to the first observation, in that the reason why companies are not doing well is that they approach RPA with the wrong mindset.

Finally, stories of failure and hardship relating to enterprise AI are not easily accessible. The last quote in Table 4.7 says that such information is only revealed if deliberately sought out from informal interactions at conferences. Officially, everyone is doing well with enterprise AI implementation and value creation.

*Table 4.7. Quotes illustrating the role of early adopters in driving hype.*

| Concept | Exemplifying Quote |
|---|---|
| Successful adopters approach AI with a business transformation mindset, not as a separate IT project | *"You need to have the right mindset, that this will not generate lots of business value in a six-month time period. This is something that you need to consistently invest in over many, many years and build a good model to execute."* – CSO |
| Successful early adopters in enterprise AI have developed new needs in relation to their continued development | *"[…] what happened around 2015, 2017 is that many companies started to build new workflows on top of existing systems, as these systems were not really actually automated in a process. […] Now the companies [have] started to automate these processes using RPA and IDP and AI and other tools."* – CSO |
| Very few RPA adopters have exhausted their opportunities | *"[…] RPA is the most mature in the market, but the market for RPA itself is still very immature. And what you see here […] is that most companies fail, or maybe not fail, but they are not even close to realizing the full potential of automation […] and it's not a technology question, it is more of a management question."* – CSO |
| Failure stories are not broadcasted, they have to be sought out | *"You don't really hear those stories. It's really only when you go to the conferences, and you talk to other people in the automation space, the guys and gals who are actually in those centers of excellence […] They'll tell you the nightmares, the battle scars. They'll tell you, 'Yeah, this has been really, really difficult, it's stressful, we're not deploying as much as we should.'"* – VP of Sales |

### 4.2.4 Consultancies Defending Their Status

The fourth and last type of player that emerges as an actor in the fashion market for enterprise AI solutions is management consultancies. These companies make their money by assisting organizations in the adoption and implementation of enterprise AI solutions, and the empirical results indicate that they thereby contribute to the AI hype in four ways. These are presented below.

Firstly, in terms of their function, consultancies can be viewed as a bridge between software companies and enterprise AI adopters – thus echoing the agenda of the software companies. Table 4.8 starts with an example quote that explains how consultancies are better suited for this role than software vendors. In other words, the informant sees this as value-creating.

The second way that they contribute to the hype represents a more cynical perspective, that consultancies are focused on short-term sales, which they achieve by using hyped buzzwords. The second quote in Table 4.8 illustrates this, emphasizing the urgency for consultancies of selling engagement over time. This is how they generate revenue, and also how they manage to stay relevant in the eyes of others.

Thirdly, on the topic of staying relevant, one of the ways in which general strategy consultancies have responded to the AI hype is by launching AI-focused subunits. The example quote in Table 4.8 explains how this helps them convince client organizations of their expertise. Such expertise does not necessarily exist, as the same informant also recounted that one of his clients had employed the consultancy AI subunit mentioned in the quote for some time, but that they had eventually ended the engagement with nothing to show for it.

Finally, it seems as though consultancies have neither the incentive nor technical expertise necessary to help their clients succeed with AI implementation. The quote in Table 4.8 shows that they are more inclined towards billing than creating value for the client. Part of the reason seems to be that consultancies are not generally the most well-suited type of actor to induce value-creation in this context.

*Table 4.8. Quotes about how consultancies function in the context of enterprise AI.*

| Concept | Exemplifying Quote |
|---|---|
| Consultancies act as a bridge between adopters and software companies | *"[…] consultants are in a unique position to go in, and they can sit on-site with the customer, and get that access to their data, and talk one-on-one to people and help them build stuff. And they still need all of those tools that the technology companies are providing, but they can kind of be a bridge [that] the technology companies don't want to be."* – Head of Marketing |
| Consultancies primarily aim to sell time-bound engagement, leveraging buzzwords to create urgency. | *"But you know, they're revenue-seekers. They have to find a way of getting really sticky into these accounts and pushing these types of things and more services to create ongoing revenue and stay relevant."* – VP of Sales |
| Strategy consultancies have launched AI subunits in response to hype | *"Look at Deloitte […], they specialize in so many things, right? They're a jack of all trades, but they have their own automation and AI division, that will help go consult on these things, right? So, I think they've made a really strong push at making organizations feel like they need it or need to look into it."* – VP of Sales |
| Management consultancies lack both incentive and the technical expertise necessary to help clients to succeed in AI implementation | *"I think these consultancies are failing. So even if you pay McKinsey 20 million, they might not come up with a strategy or operating model to be able to realize value. They might come up with three use cases that they build with super expensive internal resources that lead nowhere because they can't go live."* – CSO |

## 4.3 Openness to Adopting Hype

Provided that management fashion theory conceptualizes the environment for new management concepts as a market with supply- and demand-side actors, it proposes that the demand side adopts management fashion in order to seem progressive and rational. Since the present study seeks to empirically ground the theory further – and seeing as the supply-demand dichotomy has already been called into question in the previous section (4.2) – what makes the so-called catalysts adopt enterprise AI deserves to be explored. The empirical findings in this section delve into four motivations that drive the adoption of enterprise AI.

### 4.3.1 Fear of Missing Out

The first motivation which emerges from the data is fear of missing out (FOMO). This means that adoption is driven by a worry that enterprise AI presents a rare opportunity that, if not taken, will be missed forever. There are three observations in the empirical findings which exhibit FOMO. These are explained below.

The first observation is that the hype around AI garners the attention of top executives, who unconsciously see it as the solution to their problems and adopt it out of FOMO. The first quote in Table 4.9 gives the example of a CFO, who will generally have a hard time ignoring RPA due to its association with cost savings. Because a CFO is constantly looking for ways to cut costs, they will want to believe that a new solution promising just that can deliver.

Another observation is that FOMO can be triggered by conspicuous examples of AI technology demonstrating impressive features, making the phenomenon impossible to ignore. The second example quote in Table 4.9 is about how ChatGPT proved itself to be sophisticated enough to be useful in the daily lives of people, and how it thereby changed the way people do certain things. This took people by surprise and made them feel like they had to investigate the AI phenomenon further.

Finally, a new hype such as enterprise AI might present individual managers with the opportunity of carving out a new career path. The FOMO in the case of enterprise AI can be that the new career path is a viable one, while the manager might fear the current career path will be made obsolete by enterprise AI itself. The third quote in Table 4.9 tells the story of a manager who went from being an accountant to now making a career for himself in enterprise AI.

*Table 4.9. Quotes demonstrating how actors are open to hype out of FOMO.*

| **Concept** | **Exemplifying Quote** |
|---|---|
| Hype gets the attention of C suite executives who adopt out of FOMO and see what they want to see | *"[…] because there was that hype, it fostered that sense of FOMO. And I think that's why it caught the attention of a lot of people in C suite, particularly your CFOs [because] people cost is one of the biggest costs, […] if not the biggest cost of an organization, then if I can displace that, by using bots which are a fraction of the price of a human being, then that makes a lot of sense."* – VP of Sales |
| ChatGPT has increased the accessibility of AI and made it impossible to ignore | *"It was very interesting. I think the hype became real when the technology got at a level of sophistication where […] it could start affecting our daily work, or our daily lives. […] It's actually revolutionized the way I take in information, right? The ChatGPT, of course, I'm speaking of it now, but it's revolutionized the way we search for information."* – Head of Enterprise AI* |
| Individual managers might adopt a hype to carve out a new career path | *"There's an old story […] they wanted to start their automation initiative and […] they started it in their accounting department. […] and this woman there […] was like 'Yeah, I'll do it, this is cool, I want in.' So, she ended up leading the digital automation practice, it became a big thing, and it started spreading out to all these different units. Now, her right-hand guy, when she retired, he took over and now you can see him going from one job to another, and he started as an accountant. Right, and now he's got this other body of knowledge [allowing him to future-proof himself]."* – VP of Sales |

***** Customer of the case company

### 4.3.2 Desire to Seem Relevant

In addition to FOMO, the adoption of enterprise AI can also be understood from the perspective of fashion catalysts wanting to appear relevant. Adoption is then driven by a desire to be associated with what is new and cutting-edge. Two observations demonstrate this pattern; they are outlined next.

To begin with, individuals use buzzwords to seem in tune. The first quote in Table 4.10 shows how an individual might work a new, hyped buzzword into a conversation simply to cement their status as belonging at the forefront of managerial development. The interview data suggests that this type of behavior reveals a naïve attempt at personal brand-building.

The other observation relates to the organizational level and is about how companies look to adopt the language around hypes to signal their progressiveness. The second quote in Table 4.10 implies that it might in some cases even be dangerous not to appropriate the hype around AI, at least verbally. The implication is that if an organization does not associate itself with the latest trends, it will appear dated.

*Table 4.10. Quotes exemplifying hype adoption as a means of seeming relevant.*

| **Concept** | **Exemplifying Quote** |
|---|---|
| Individuals use buzzwords to seem in tune | *"At my last job at Trey.io, I literally had a guy from Udemy say, 'Hey, what are you guys doing to accelerate hyperautomation?' And I was like, 'you mean just automation?' Like, just fucking [sic] call it automation. […] it's so weird to me that […] we heard it as a buzzword and people are like, 'well, that's the word I have to start using now', because also people want to be relevant too. You don't want to be the guy that's just talking about RPA."* – VP of Sales, case company |
| Companies have to adopt the language to appear relevant | *"I can't say it's dangerous not to include AI, because I don't know if AI would be great for every DAS application out there, right? There might be like some software that just simply doesn't require it, I don't know. […] I think it just goes back to the point that […] if you want to seem more forward thinking as a solution, incorporating some AI component into what you're doing is helpful.* – VP of Sales |

### 4.3.3 Pressure to Constantly Improve

Staying on the organizational level, another theme for openness to adopting enterprise AI is rooted in the continuous growth ideal that characterizes enterprises. This translates into a pressure on companies for constant improvement. The empirical findings exhibit this on two accounts. These are explained below.

Firstly, managers in adopting organizations use buzzwords such as those associated with AI to identify change in the market, which they should pay attention to. The first of the two quotes in Table 4.11 illustrates this with the example of how regional banks in the United States would find out about new trends in automation from the big banks' communication of buzzwords. By scanning their business environment in this way, companies can make sure that they are staying on par with the market leaders of their industry.

Secondly, when knowledge of enterprise AI begins to permeate through an organization, the adoption of it increasingly becomes seen as an imperative to succeed. The second of the two quotes in Table 4.11 shows that the hype around AI means that every company feels compelled to adopt it. This has resulted in essentially all enterprises investing in AI over the past few years, although not all have had favorable results.

*Table 4.11. Quotes showing how pressure to improve makes adopters receptive to hype.*

| **Concept** | **Example quote** |
|---|---|
| Managers use buzzwords as indicators of changes in their competitive landscape, signaling that they need to take action to stay competitive | *"So those are like the types of like trendy things that they hear out there that their competitors are doing. And in order to stay competitive, that might [make them] gravitate towards these things and start to research them. Back when I was at Blue Prism, we used to get these calls all the time, [from] smaller regional banks [saying], 'What is this, what is this RPA thing? What is this automation thing? What can you do with it? Show me what it looks like!' There's like this, they didn't know what it was conceptually."* – VP of Sales |
| When managers become aware of AI, they feel that adoption is imperative in order to grow | *"All the companies need to constantly improve. So then of course, there's also a bit of a hype, or push, that everybody wants to do AI, everybody wants automation. So, any large enterprise, they have all been invested in automation and AI for the last five years to become better, basically, and some are successful, some are less successful, some have big deployments, some have small deployments."* – CSO |

### 4.3.4 Sense of Urgency Driving Companies to Adopt AI

The fourth and final theme in explaining why enterprise AI is adopted by the catalysts of its fashion is a sense of urgency. This is a feeling induced by external forces, making companies rush into enterprise AI without deliberation. The theme emerges from the interview data in two ways. These are described below.

To begin with, the adoption of enterprise AI tends to precede a thorough understanding of what it means. The first quote in Table 4.12 is an example of this, as it shows how companies would invest heavily into the adoption of RPA first, then go to a conference to learn how to derive value from it. They do this because the hype around that genre of enterprise AI was strong enough to convince them that it must be valuable, despite not knowing why.

Next, some companies go into new domains of enterprise AI out of fear of creative destruction. That is, they have a business model which suddenly becomes threatened by innovations in enterprise AI. The second example quote in Table 4.12 illustrates this in the case of Google, which was forced to respond to the launch of ChatGPT by releasing its own intelligent chatbot, Bard. It had most likely been under development for some time, but the launch was prompted by ChatGPT rather than by the product being finished.

*Table 4.12. Quotes illustrating how a sense of urgency can explain hype adoption.*

| **Concept** | **Exemplifying Quote** |
|---|---|
| Adoption of new AI hypes tends to precede understanding | *"I heard some like keynote speakers, and there's so much hype around automation, and people have really drunk the Kool-Aid. […] people were just so gung-ho and so passionate about it at this conference […] This is an example to me, what I saw, is that the hype was so great that people were willing to adopt these technologies without […] even knowing, really, all the best practices, or how do you do it, or how do you derive value?"* – VP of Sales, case company |
| Fear of creative destruction forces incumbents into AI | *"The advent of [ChatGPT] is forcing companies to adopt this. […] Google had Bard, which is like the equivalent of ChatGPT. They've probably been sitting on it for a while, [but] if there's no […] force to change and they're making money […], someone might think to themselves, 'well, if it's not broken, why fix it?'"* – VP of Sales |

## 4.4 Commoditization of Enterprise AI

Part of what enables management concepts to become fashionable is that they take on an almost product-like form. In the case of enterprise AI, as is partially demonstrated in the choice of case organization, the centrality of software products has been implied. Still, how that factor plays out in the context of enterprise AI as a hype warrants further explanation. This sub-section will explore the aspect of commoditization by looking at three themes that can be derived from the interview data.

### 4.4.1 Enterprise AI Hypes in Succession

The first theme revolves around the notion that AI can be seen as an umbrella term for many different technologies, as explored in section 4.1.1, which means that there is room for several distinct hypes within the context of enterprise AI. Below are the three ways in which the interview data suggests that these hypes relate to each other.

Firstly, there is a succession of hypes within enterprise AI, which build on incremental technological development but serve the purpose of making the progress appear more radical. The first quote in Table 4.13 explains how Excel macros gradually led to .NET, RPA, and finally automation solutions with intelligent features.

Turning to the adoption side of enterprise AI solutions, the notion of incremental technological progress is reflected in the way that enterprise AI adoption usually begins with RPA and then progresses towards more advanced technologies. In the second example quote in Table 4.13, the informant describes this condition with the metaphor of having to crawl before proceeding to run. Generally, the informants consider RPA the most accessible type of enterprise AI.

Finally, the enterprise AI sub-hypes that are created to make incremental progress seem more radical is the product of analyst firms promoting new software. The last quote in Table 4.13 conveys an idea of what the process looks like. This phenomenon was discussed in more detail in section 4.2.2.

*Table 4.13. Quotes showing how hypes in enterprise AI succeed each other.*

| **Concept** | **Exemplifying Quote** |
|---|---|
| Succession of AI sub-hypes reflect incremental technological progress | *"So, we have seen a lot of shifts in the technology where we started from Excel macros, then .NET, and then to RPA, now to AI. […] Because when RPA was started, there was no intelligence built into it. […] I would say it's an enhanced version of Excel macro […that] is more secure because Excel macro, you can just go and interrupt it. But RPA can just put that in the server, and it can run a remote machine."* – Customer, Director of Intelligent Analytics & AI* |
| AI adoption usually starts with RPA to then move on to more advanced technologies | *"Any enterprise that wants to adopt a digital transformation initiative, […] I usually see that they start with automation. So, you have to start with automation. Nobody really starts with AI […] because you have to crawl before you run."* – VP of Sales |
| Analyst are paid to create AI sub-hypes to promote new software | *"The hype gets created [by analyst firms] from a new category, they put out data around it, the consultants pick it up, they start putting it out there, the buzz gets created and then now customers are talking about it, and then that becomes their buzz."* – VP of Sales |

***** Customer of the case company

### 4.4.2 Modularization of Hyped AI Technologies

The second theme feeding into how the enterprise AI hype manifests itself in the form of products is the modularization of software. Different parts of enterprise AI are made available on a piece-by-piece basis. This is observable from four different perspectives, which are described below.

The first observation to substantiate this theme is that the RPA hype saw software companies adding RPA modules into their product suites as a means of staying relevant. The first quote in Table 4.14 exemplifies two software-as-a-service companies that added RPA modules to their products as a response to seeing that it was being hyped. RPA functionality is now seen as a hygiene factor in many legacy software suites.

Additionally, the case company – whose product is mainly based on RPA – is currently adding AI functionality to its offering. The second exemplifying quote in Table 4.14 is about how the case company is portraying its product as powered by AI. Most of this functionality remains under development.

Thirdly, software companies are not only adding new technology modules themselves, but they are also building their products in such a way that they are compatible with new technology to be bolted on by others. Quote number three in Table 4.14 describes how an automation flow can be expanded by adding intelligent document processing technology onto what is essentially RPA. All of this is indicative of a modularization trend.

Lastly, the nature of the case company product itself adds to the modularization argument. Its purpose is to orchestrate assemblages of enterprise AI technology within organizations, the existence of which points to some degree of modular compatibility across the board. The example quoted in Table 4.14 describes it as an intelligent layer on top of deployed solutions.

*Table 4.14. Quotes demonstrating how enterprise AI hypes can manifest themselves as software modules.*

| **Concept** | **Exemplifying Quote** |
|---|---|
| During the RPA hype, software companies added RPA modules to their existing products to stay relevant | *"When robotic process automation was becoming really popular, what a lot of SaaS software companies started to notice is, 'Hey, we are starting to see that automation is a big thing, it's a big deal, enterprises want it, they're demanding it.' […] Now they have all these cool automation features built in. […That] helped them stay relevant, because in this world of automation […], they knew that if they weren't gonna [sic] add automation features, somebody else was gonna [sic] do it, and then that would make them less relevant, and replaceable."* – VP of Sales |
| Case company is adding AI modules to derive benefit from the current generative AI hype | *"AI's gonna [sic] be the same thing […] Our product is actually no different, […] the way we're marketing it is: it is automation for automation centers of excellence that's powered by AI. We use AI to help manage your ecosystem of intelligent automation methodologies and softwares [sic]."* – VP of Sales |
| Software solutions have been made compatible with new AI technology to be bolted on for additional intelligence | *"In that example that I gave, […of] invoice processing, we want to process and automate those, and make them quicker, and free up accountants. Then […] I need an IDP technology to bolt onto my automation technology, my base automation technology, which is RPA."* – VP of Sales |
| Case company product is designed to facilitate the orchestration of enterprise technology modules | *"What we try to accomplish is to put kind of an intelligent layer and operational layer on top of a deployed solution, and a deployed solution can be a robot, it can be an AI model, it can be a low code solution, it can be a chat bot […] – the more the merrier – and then to be able to automatically optimize and manage these solutions."* – CEO |

### 4.4.3 Standardization in AI Product Development

The final theme that goes into the commoditization feature of enterprise AI revolves around product development. Creating these products is about standardization. This is illustrated by the two observations explained below.

To begin with, software companies work closely with their customers, listening to them to identify common requirements which might be indicative of broader market appeal. The corresponding example quote in Table 4.15 is a description of how the case company observes the customer organization in their day-to-day activities to identify pain points, while balancing the need to solve specific problems with the broader perspective of standardizing for wide market viability. In addition to listening to the customers directly, there is an emphasis on observation which can help the case company identify needs that the customer is unable to articulate.

Observation number two is about how the market for enterprise AI software develops over time. To some extent, the standardization efforts described above lead to different providers within a given category of enterprise AI software eventually becoming interchangeable. The second quote in Table 4.15 explains that this is likely to happen with generative AI, based on the number of large language models that are currently being launched. An important factor in this standardization trend is that software providers look to each other for inspiration on how to improve, which leads to functional convergence and subsequently commoditization.

*Table 4.15. Quotes exemplifying how enterprise AI product development is about standardization.*

| **Concept** | **Exemplifying Quote** |
| --- | --- |
| Software companies listen to customers to find common requirements | *"So, we capture their requirements […and] day-to-day activities, […as well as the] limitations [that] they find in the existing solutions […]. We try to understand that and try to see what best we can accommodate here. At the same time, […we] get into a productization mode rather than doing a customization for each customer. What we try to do is standardize these features, understand these requirements, and then move it into a standard product feature for which will be suitable for all the customers as well."* – Director of Client Success |
| Different software providers within each enterprise AI product category become interchangeable as the category matures | *"It's getting commoditized. I think AI will go down that path. I mean, there are so many LLMs that are being launched, right? […] So, I think the proliferation of these LLMs is going to drive down the incremental cost of intelligence […], it will go down to nearly zero."* – COO |

# 5. Discussion

*In this chapter, the empirical findings presented in the previous chapter are analyzed using the theoretical framework presented in section 2.3. The question of how enterprise AI can be understood through the lens of management fashion, how it diverges, and the implications of that for the development of the theory will thereby be answered. Firstly, the discussion will address the aspect of interpretative viability in the context of AI (5.1); secondly, the nature of actors in the fashion market for enterprise AI will be dealt with (5.2); thirdly, the ways that enterprise AI might one day go out of fashion will be considered (5.3); fourthly, the manifestation of conventional management fashion dynamics in a feature unique to enterprise AI is discussed (5.4); and finally, the way that enterprise AI might better be described as a domain of management fashion than a management fashion in its own right is debated, showing how that notion fits with the theoretical framework of the study (5.5).*

## 5.1 Naturally Occurring Interpretative Viability

It has already been posited that enterprise AI may exhibit some differences from theoretical management fashion, by virtue of AI not being the product of a management bestseller but a 70-year-old field of scientific inquiry. A credible explanation for why AI can act as a buzzword in spite of its age is perhaps the phenomenon known as the AI effect (Haenlein & Kaplan, 2019), which was explained in section 2.2. Its essence resides in the fact that the meaning of AI changes over time – as technology progresses – which is clearly analogous to the hermeneutic foundation of interpretative viability: that the meaning of words can vary over time and across communities (Benders & van Veen, 2001; Ortmann, 1995). Despite not consciously being given the feature of interpretative viability by a management fashion-setter, AI can therefore doubtlessly be said to possess it.

As the results presented in section 4.1 show, the meaning of AI is not only open to interpretation, but it can also consciously be applied in different ways depending on the goal that its use aims to attain. For example, the concept can be utilized as a buzzword on a high level to garner the attention of managers who, as established in section 4.3.3, use buzzwords as indicators of change in their business environment. It can also be used for marketing in a way that is oriented more towards eliciting action, for instance by obscuring the undramatic or even simple nature that enterprise AI is sometimes characterized by. This points clearly in the direction of interpretative viability being used to ensure the widespread applicability of enterprise AI solutions.

How interpretative viability plays into the adoption side of enterprise AI as a management fashion is less clear – nothing in the empirical findings points clearly to what was referred to as conceptual cherry-picking in section 2.3. A natural explanation for this might be found in the database search presented in Figure 2.1, suggesting that if the case of enterprise AI is on its way to manifesting itself in the form of a bell curve, it is still in the early phases of that development. If this is considered from the perspective of Abrahamson and Fairchild (1999), it is probable that the type of adoption and implementation that is currently taking place is enthusiastic and uncritical, meaning that adopters are not yet likely to be particularly discerning – or prone to cherry-picking.

## 5.2 Catalysts in a Democratized Management Fashion Arena

Another aspect to bring up in relation to the unique history of AI, and its implications for enterprise AI as a management fashion, is the actors who operate on the proverbial market for this management fashion. As was stated in the empirical findings, the supply-demand dichotomy proposed by Abrahamson (1996) could not be clearly observed from the interview data. Rather, the various kinds of actors who contribute to the hype around enterprise AI were found to be better characterized as catalysts for fashion, because the roles of fashion-setter and fashion-adopter were intertwined. In this way, Røvik's (2011) criticism of conventional management fashion is strengthened.

To understand how this works, it is useful to consider the reasons why individuals and organizations are open to adopting enterprise AI. The observations presented in section 4.3 do not only relate to the pressure to always grow and improve, or the fear of missing out on tangible opportunities. The empirical findings also suggest that the adoption of enterprise AI is driven by a desire to seem relevant – essentially to become a fashion-setter. An understanding of this ambition may be promoted by recent developments in management fashion theory, particularly that which introduces social media to the fashion-setter environment (Piazza & Abrahamson, 2020). In light of this development, it is natural that the role of management fashion-setter is now open to a much broader set of actors than it once was. As exemplified in section 4.1.3, the launch of ChatGPT has sparked a dramatic upsurge of self-proclaimed AI thought leaders on LinkedIn. While this is a new occurrence to the management fashion phenomenon, it is not new to theory. For one thing, Røvik's (2011) notion of the active host elicits an image of management fashion adopters recklessly roaming social media, spreading the enterprise AI virus. For another thing, it was theorized already in the 1990s that management fashion adoption was driven by the desire to feel and be perceived as progressive and rational (Abrahamson, 1996; Huczynski, 1993; Kieser, 1997). The only difference now is that fulfillment of this desire can more easily be expressed, effectively blurring the line between fashion-setter and fashion-adopter as essentially any kind of adoption inherently leads to some degree of broadcasting. This is especially true on an organizational level, where early adopters can use their own communication channels – such as social media accounts and websites – to advertise their progressiveness.

However, this does not only lead to typical fashion adopters becoming fashion-setters. By lowering the barriers to becoming a fashion-setter, the ubiquity of mass communication also leads to increased competition for fashion-setter status. Hence, traditional fashion-setters such as management consultancies must now compete to be seen as a source of superior business knowledge. The prime example of this is the observation that general management consultancies have launched their own automation and AI subunits in response to the hype around enterprise AI. This is indicative of them playing a reactive role, considering that the only virtue the informants see in consultants seems to be their ability to act as a bridge between enterprise AI software vendors and organizations looking to implement their products. Outside of that function, not only is their ability to help companies succeed with enterprise AI called into question, but also their willingness to do so – given that selling engagement is the only thing they are incentivized to do.

Why academics are not identified as a category of fashion catalysts in the empirical findings, despite being considered a type of fashion-setter in the literature (Abrahamson, 1996), warrants some explanation. While the pattern displayed in Figure 2.1 suggests a high level of activity around AI in business research, the empirical findings in section 4.1.3 point to there being several levels of sophistication in the AI discourse. The level represented by universities is then characterized by being very detail-oriented and accurate. In other words, it is the antithesis of AI as a buzzword.

## 5.3 The Decline Phase Remains Multi-Faceted

As demonstrated by the database search presented in Figure 2.1, there is no sign of a loss of interest in enterprise AI from the world of academics. Therefore, investigating the decline phase of AI as a management fashion initially appears impossible to do. This is not the case, however, as this study has revealed several of the patterns proposed by theory – the first of which is the bluntness of bibliometric methods of analysis as a proxy for real-life adoption of management practices. The truth to this claim is nested in the observations that suggest fluctuations in the practical adoption of enterprise AI, in relation to the popularity curve presented in Figure 2.1. Most of these observations fall under the buzzword feature of enterprise AI, presented in section 4.1.2.

To begin with, the theoretically aligned observation that enterprise AI has tended to be over-simplified in the interest of selling (Kieser, 1997), exemplified by the case of automation in section 4.1.2, not only connects to the aspect of interpretative viability. It also goes together with the observation of overpromising and under-delivery that holds true on a more general level for the enterprise AI industry. These phenomena imply imminent underperformance in relation to expectations, which is what theory refers to as dissonance resolution (Birnbaum, 2000). When this happens, a once fashionable management concept falls from grace and is forgotten (Abrahamson, 1991). The potential exists within the enterprise AI space for overly simplistic sales pitches to inspire an adoption approach that is too myopic to truly facilitate successful outcomes. As shown in section 4.2.3, effective enterprise AI implementation requires a business process transformation mindset and a long investment horizon. At the same time, this sentiment on the part of a case company representative lines up perfectly with the management fashion characteristic that only great managers can derive value from them (Kieser, 1997).

Another theoretical view on why methods like citation analysis record a popularity decline for management fashion, in a way that is at least to some extent erroneous, is that management fashions change their identities through the process of implementation. This could imply, for example, that measuring the level of practical adoption of a management fashion comes down to tracing fragments of it (Malmi, 2001). Examples of such transformation were not observed in the interviews per se; however, it is arguably implied by the finding that the concept of AI is open to interpretation. It was established in section 4.1.1 that informants tended to define AI in different ways. For the sake of this argument, the most interesting form of divergence in the informants' definitions of AI is the view of RPA – this study's operational definition of AI. Some informants made a point of including it in their definition of AI, while others differentiated between the two. An obvious reason for the inclusive definition of RPA is that the informants would want to associate a technology that is integral to their business with AI, yet some did not. A viable explanation the exclusive definition of RPA might be the AI effect (Haenlein & Kaplan, 2019). In other words, being intimately familiar with RPA as a result of working with it on a daily basis might mean that its inner workings have become completely unobscured, separating it by definition from AI. In the context of enterprise AI adoption, this would play out as a case of enterprise AI becoming unidentifiable as AI post-implementation.

To understand how this could manifest itself on the broader level of enterprise AI, it is useful to consider the findings that explain why AI marketing is necessary. The case company head of marketing not only considered the realities of enterprise AI too boring for anyone to be expected to care about it, but at times also too straightforward to be marketable transparently. This means that hype might be necessary to get adopters over the hurdle of implementation, but that it will then lose its utility. In other words, when an organization has in some way ingrained the management fashion of enterprise AI into itself, continued success is no longer dependent on hype, but on well-informed labor. This is a natural result of a management fashion having been adapted for alignment with the adopting organization (Perkmann & Spicer, 2008). At this point, the organization will be privy to the gap between hype and reality, which might even generate fatigue in relation to the hyped terminology. The observation in section 4.1.2 about the overuse and dilution of the term AI would certainly point in that direction. Much like in the case of TQM, the enterprise AI market would then live on in a more anonymous format (David & Strang, 2006).

## 5.4 Novel Expressions of Conventional Fashion Market Dynamics

A unique type of actor in the management fashion market for enterprise AI, compared to most management fashions in the literature, is the prevalence of software vendors. As fashion-setters, they arguably offer something more tangible than fashion-setters in the context of purely theoretical management fashion – such as agile, TQM, or MBO. Although this category of management fashion catalysts does exhibit cases of reactiveness, such as when they launch technology modules to capitalize on new hypes, they for the most part resemble fashion-setters in the way they are described in theory.

The clearest example of this manifests itself in the way that software vendors carry out product development. To give direction to their development efforts, software vendors interact with presumptive users – providing them with both explicit and implicit pain points to address. On an aggregated level, these pain points then aid in the creation of a standardized product with wide market appeal. This is very similar to how management gurus go into the world to collect inspiration for new management fashion from managers, according to Clark and Greatbatch (2003). In the case of producing management bestsellers, the authors describe further development and commercialization as a collaborative process with the publishing industry

(Clark & Greatbatch, 2003). The publishing industry equivalent in the case of enterprise AI would be analyst firms, whose official job is to objectively cover the enterprise AI market, but who are really in the business of packaging new software products into appealing categories and creating hype in exchange for sponsorship from the software vendors. Still, followers of analyst firms look at their output as more or less objective. Viewed together with the apparent ambition of some individuals to become enterprise AI fashion-setters, this trust in analyst firms might even translate to active promotion on behalf of followers – for example in the form of social media report-sharing. While the ubiquity of mass-communication is speculated to constitute a threat to management consultancies, it might thus be advantageous to analyst firms. They can hence be expected to remain firmly in their role as gatekeepers of fashion.

Based on this position of analyst firms, an interesting premise within management fashion can be empirically observed. As explained in section 4.4.1, the broad concept of AI is not the only thing to enjoy hype in the enterprise AI space. Hypes also occur around more specific technologies, product categories, or software products – because the analyst firms are incentivized to create such hypes. While these hypes are sold as radical, they reflect an underlying progression that is linear due to the predominantly incremental nature of product development. An example of this is the technological evolution from Excel macros to intelligent automation provided in section 4.4.1. This represents a direct reflection of the idea that management fashions in a sequence largely build on each other, meaning that the practical evolution of management knowledge and tools are gradual and unidirectional (Clark, 2004). As indicated in the theoretical model in Figure 2.2, other authors have conceptualized this management fashion phenomenon as the selling of old wine in new bottles (Benders & van Veen, 2001; Spell, 2001).

This deliberate strategy of product development and hype generation, coupled with the marketplace's trust in the output of this machinery, is an embodiment of management fashion theory within the context most unique to the empirical setting of enterprise AI. A plausible explanation for this could be that the tangible nature of software products, as opposed to abstract management concepts, presents a barrier to entry for aspiring fashion-setters. An additional factor that reinforces software vendors' fashion-setter status – by virtue of their products' tangibility – is that they are somewhat bankable. As shown in section 4.2.1, investors can thereby have a stake in enterprise AI as a management fashion. This gives them a clear incentive to contribute to any hype that is associated with their investments, and to the extent that an investor has a strong brand – like Microsoft does – their contribution to hype can be especially impactful.

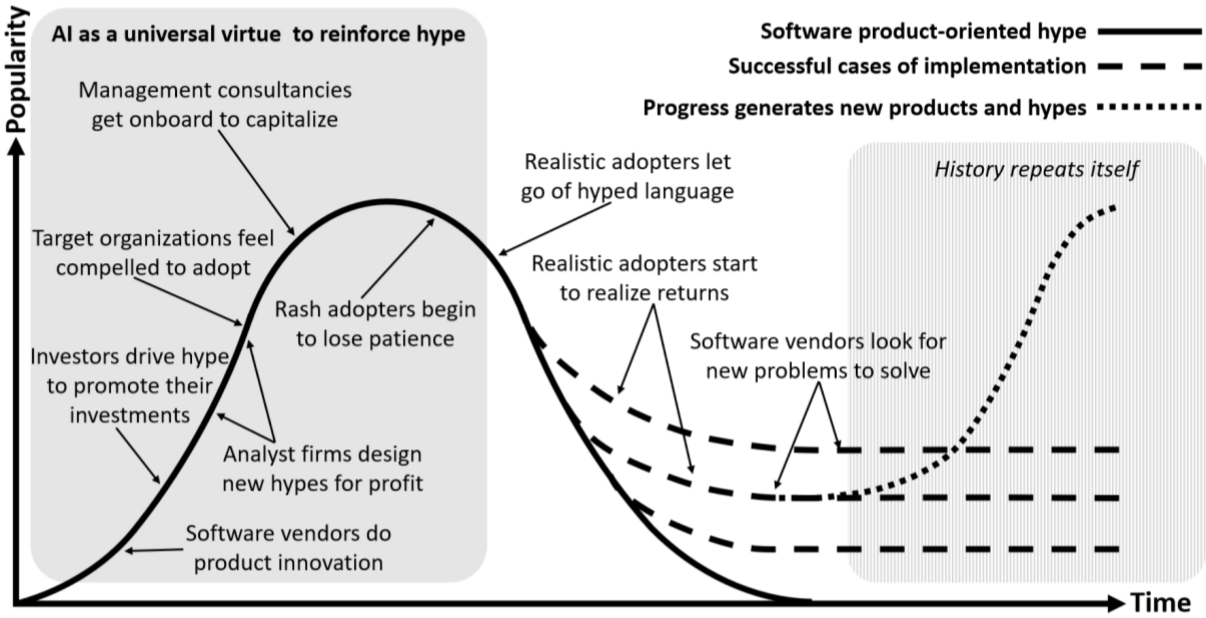
## 5.5 Enterprise AI as a Domain of Management Fashion

The apparent emergence of traditional patterns of management fashion in the context of enterprise AI software products invites a more nuanced discussion of what management fashion might entail in relation to the topic. It might conceivably be wise to look within, rather than at, enterprise AI for management fashion. Hypes, as discussed in the previous section as well as explicitly by the informants in section 4.4.1, do not center around the concept of AI per se as much as categories of technology. As such, they have a strong supply-side productization component to them, seem to build on each other, and are eagerly adopted by ill-informed demand-side actors – meaning that they fit well into the management fashion framework.

The question, then, is what significance the concept of AI has. It would be rash to say that it does not play a role, considering its prevalence in the empirical findings of this paper. For example, it explicitly works as a communicative tool for high-level messaging, as shown in section 4.1.4. Perhaps, though, the interpretative viability discussed in section 5.1 can also be thought of differently to better account for the meaning of the AI concept in the setting described in section 5.4. Both in section 4.1.2 and section 4.2.1, the tendency of software vendors to link themselves to the concept of AI as a means of promoting themselves and their products was touched upon. This can be viewed as a case of association with universal virtues as a means of emphasizing their general relevance – a clear attribute of management fashion (Kieser, 1997). If AI is then characterized by interpretative viability, it has it to such a degree that it can be considered a universal virtue in some circles. Presumably, these circles are somewhat narrower than those where the virtues proposed by Kieser (1997) can be considered universal. While, for example, efficiency is a universal virtue in all of business, AI might be the same in technologically progressive sectors of business. To illustrate further, a virtue such as courage might be universal on the level of society.

With this new insight, it is possible to fully paint the picture prompted by the theoretical framework of this study with enterprise AI. In Figure 5.1, the conceptualization of management fashion presented in Figure 2.2 has been stripped of examples from the literature and populated with empirical observations from this study instead.

*Figure 5.1. Visual representation of how a product-oriented hype might be instigated by linking to the concept of AI as a universal virtue, develop over time, and lead to the generation of new products and hypes.*



# 6. Conclusion

At present, the subject of AI is undoubtedly enjoying societal attention on an extraordinary level. The business environment presents no exception to this condition. Examining AI through the lens of management fashion is therefore a compelling proposition. This study has done so by means of a single-case case study, based on interviews with an early-stage software vendor in the RPA orchestration space. While AI as a genre of management practice distinguishes itself substantially from typical examples of management fashion – in the sense that its foundation is not the theoretical product of a management guru but a computer science phenomenon dating back more than half a century – the present study has proven that it is possible to draw lines between the two.

The theoretically central aspect of interpretative viability proved itself to be present even though the concept of AI, as it manifests itself today, exists independently of its creators. There is enough ambiguity to the term for aspiring management fashion-setters to appropriate it for a wide range of goals. Who these aspiring fashion-setters could be turned out to be more open-ended than what theory might predict, as the omnipresence of mass-communication ability now means that any kind of fashion consumption inherently translates to some degree of fashion broadcasting. One implication of this is that some theoretically conventional fashion-setters must work hard to keep their fashion-setter status as enterprise AI becomes part of their business. As for the decline of enterprise AI as a management fashion, it seems like that event is still far from becoming reality. However, all the patterns that theory associates with fashion decline were identified to some extent, meaning that the study echoes the calls for nuance, regarding that lifecycle stage, that have been put forth in the literature.

While the overall findings of the study point away from the supply-demand dichotomy of the management fashion market, at least in the case of enterprise AI as a whole, the market as conceptualized in conventional management fashion theory does exhibit itself in relation to hypes occurring within the context of enterprise AI. This phenomenon is explained by the tangibility of the software products intrinsic to the industry, which constitutes a barrier to entry into the fashion-setter role for some actors and an invitation for others. Adoption in this environment also appears to be highly uncritical. The role played by the concept of AI in this context was found to be that of the universal virtue to which the management fashion appeals. In conclusion, in addition to indicating that enterprise AI in its entirety can be understood as a management fashion, this study suggests that enterprise AI as a domain also constitutes fertile ground for future management fashion research.

# 7. Contributions & Future Research

*This chapter will cover the theoretical contributions of the study (7.1), its managerial implications (7.2), its limitations (7.3), and suggestions for future research (7.4).*

## 7.1 Theoretical Contributions

The present study contributes to theory in three ways. Firstly, it extends the theoretical field of management fashion to the empirical setting of enterprise AI and similarly scalable business phenomena. Secondly, it introduces a conceptual model representing a more nuanced view of the literature than what has previously been published. Through the application of the proposed conceptual model, the study also emphasizes the centrality of interpretative viability as a feature of management fashion – a feature whose role can arguably be investigated further. Finally, by applying qualitative research methods, the study addresses the theory's purported lack of empirical grounding with regard to its dynamics. These contributions should be seen in the light of Flyvbjerg's (2006) view of the single-case study, as a partial mapping of uncharted grounds.

## 7.2 Managerial Implications

Considering that the results of this study provide a strong indication of enterprise AI being a management fashion, and the nature of this condition from an empirical standpoint, there are two practical implications that managers should take into account. The first one is that they should be cautious in how they interpret available information about enterprise AI. This is especially important in light of evidence suggesting that this management fashion remains in its early stages, meaning that the discourse is likely to be uncritical and characterized by emotion (Abrahamson & Fairchild, 1999). The second implication is that the complex, ambiguous, and somewhat elusive nature of the AI concept makes it difficult to decipher; its specific, practical meaning is likely to differ from one case to another. The overview provided in section 2.2 of this paper can be of use in addressing this challenge.

## 7.3 Limitations

The qualitative approach adopted in this study facilitated the acquisition of comprehensive and nuanced data. This fostered an in-depth understanding of the case company's unique context, the perspectives and experiences of the informants, and the broader enterprise AI market. This methodological approach was chosen to circumvent some of the weaknesses associated with quantitative methods. There are, however, also limitations to it. One significant constraint is the inherent subjectivity of the information gathered. Despite efforts to accurately represent the perspectives of the interviewees, complete elimination of subjectivity is irreconcilable with a study of this kind. Furthermore, considering that this investigation is anchored on a single case study company and its immediate stakeholders, it may exhibit a restricted diversity of viewpoints concerning the enterprise AI market. Rather than presenting a diverse array of industry perspectives, the investigation predominantly mirrors that of the case company itself, limiting the nuance of industry perceptions. This implies that either over- or underemphasis on various aspects of the enterprise AI market, and its relationship to management fashion theory, are likely to have occurred to at least some degree. Moreover, the responses of interview participants may be shaped by their individual biases or perspectives, which could, in turn, affect the interpretation of the data collected. Hence, these responses may not necessarily represent the broader sentiments within the market, implying that the findings' generalizability could be limited to the unique context of the case company.

Moreover, while the professional experience of the informants in the case company lent significant depth to the understanding of the enterprise AI market, it is important to consider that a company in the early stages of developing its enterprise AI software may not fully encapsulate the wider landscape of enterprise AI, especially as it pertains to implementation. Insights gathered from either more established software vendors or companies playing other roles in the enterprise AI market could contribute to a richer, more comprehensive perspective on the implementation of enterprise AI. At the same time, the choice of case organization – particularly as it pertains to its size and maturity – must be weighed against the probability of gaining access to its top executives, who represent the most strategic perspectives in the organization.

One could contend that it may still be premature to examine AI as a fashion. In relation to the framework constructed for this study, and against the background of the current hype around AI tools like ChatGPT, the phenomenon could be considered to still be on an upward trajectory, meaning that its status as a management fashion has yet to prove itself in a popularity decline. Even so, the findings of this study suggest that it possesses several characteristics consistent with traditional management fashions, as detailed in section 5. Moreover, the investigation uncovered evidence of various interconnected sub-hypes within the AI domain, as exemplified by the many precursors to RPA. This implies that the progression outlined in

Figure 2.2 is not necessarily linear, at least not for the entire AI domain, meaning that enterprise AI can be identified in the hype and decline phase simultaneously.

Finally, it is important to acknowledge that there are valid arguments challenging the decision to prioritize RPA as the primary definition of AI in this paper. As discussed in section 5.3, existing views and interpretations of what RPA is are diverse, especially in terms of how it relates to the concept of AI. Consequently, this poses a constraint on the discussion surrounding RPA as an exemplification of enterprise AI. However, it is unlikely that the AI effect would not impact other operational definitions of AI in the same way. Complete avoidance of a trade-off is therefore implausible. Either the operational definition is highly tangible, with the risk of having been outrun by the AI effect; or it is commonly considered AI, with resulting loss of precision in terms of what that means to different individuals. Therefore, while it is advisable to focus on some specific subset of AI as an operational definition for any study such as this, substantial gains can most likely be realized by making this choice carefully.

## 7.4 Future Research

The present study is expected to facilitate future research within the field of management fashion, particularly in relation to enterprise AI. Its findings can serve as a basis for scholarly investigations, encouraging further research to test the developed theoretical framework in diverse organizational contexts. Future research endeavors could build upon this work by conducting multi-case studies, performing in-depth analyses of various case companies representing each type of catalyst for fashion outlined in section 4.2. This approach would help mitigate bias and provide a more thorough understanding of AI as a management fashion. Additionally, a longitudinal study capturing the evolution of the phenomenon over time could provide a more robust understanding of the dynamics at play. By conducting interviews at multiple points in time, researchers could record how experiences and perspectives of the enterprise AI market and the dynamics of its fashion component evolve or persist over time. Furthermore, future research could explore alternative methodological approaches, such as employing ethnographic methods to capture the adoption of AI in its natural setting. By employing ethnographic techniques, researchers could document participants' daily routines, rituals, and behaviors, providing a precise and valid understanding of how AI is integrated into business. This approach goes beyond the reliance on interviews alone and allows for a more holistic exploration of the social, cultural, and contextual factors that shape AI adoption.

Moreover, the selection of RPA as the primary reference for AI in this study should encourage future research to investigate other subsets of AI within the enterprise market. While RPA has been the focal point in this research, exploring additional subsets of AI, as discussed in section 2.2, could provide valuable insights and a more complete understanding of the AI landscape. By examining various enterprise AI applications and technologies beyond RPA, future research endeavors can shed light on different dimensions of the AI enterprise market, uncovering more unique features that add nuance to the theory.

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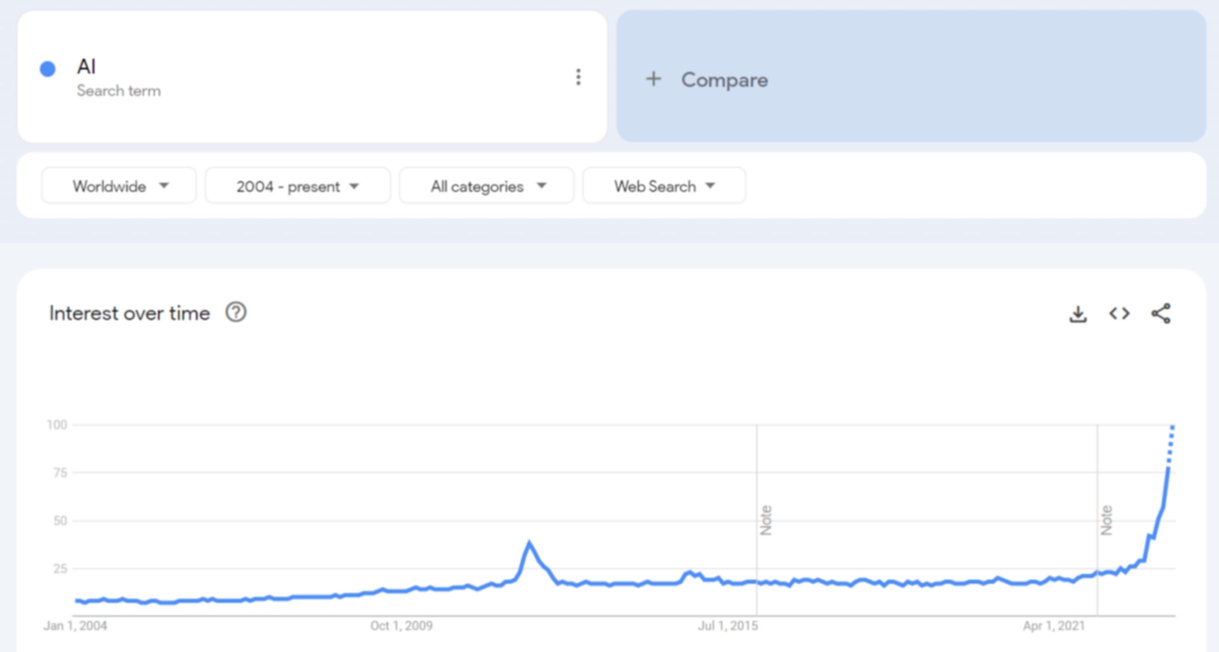
# 9. Appendices

## Appendix 1. Google Search Trend for AI




*Screenshot was taken on 12.05.2023.*

# Appendix 2. Overview of Interviews

| Participant | Role | Referred to as | Case Company | Interview | Interview Format | Duration | Date |
|---|---|---|---|---|---|---|---|
| 1 | Chief Strategy Officer | CSO | Yes | First | In person | 32 min | 2023-03-07 |
| 2 | Chief Executive Officer | CEO | Yes | First | Microsoft Teams | 38 min | 2023-03-08 |
| 3 | Chief Operating Officer | COO | Yes | First | Microsoft Teams | 33 min | 2023-03-27 |
| 4 | Vice President of Sales | VP of Sales | Yes | First | Microsoft Teams | 57 min | 2023-03-28 |
| 5 | Head of Marketing | “ | Yes | First | Microsoft Teams | 67 min | 2023-03-29 |
| 6 | Chief Executive Officer India | CEO India | Yes | First | Microsoft Teams | 57 min | 2023-03-30 |
| 7 | Director of Client Success | “ | Yes | First | Microsoft Teams | 57 min | 2023-03-30 |
| 8 | Director of Intelligent Analytics & AI | “ | No | First | In person | 65 min | 2023-04-04 |
| 9 | Head of Enterprise AI | “ | No | First | Microsoft Teams | 32 min | 2023-04-06 |
| 10 | Chief Strategy Officer | CSO | Yes | Second | Microsoft Teams | 63 min | 2023-04-14 |
| 11 | Vice President of Sales | VP of Sales | Yes | Second | Microsoft Teams | 66 min | 2023-04-14 |
| 12 | Chief Technology Officer | CTO | Yes | First | Microsoft Teams | 37 min | 2023-04-17 |
| *****14 | Chief Operating Officer | COO | Yes | Second | Microsoft Teams | ~ 30 min | 2023-04-17 |
| 13 | Chief Executive Officer India | CEO India | Yes | Second | Microsoft Teams | 35 min | 2023-04-18 |
| 15 | Director of Client Success | “ | Yes | Second | Microsoft Teams | 33 min | 2023-04-18 |
| 16 | Chief Executive Officer | CEO | Yes | Second | Microsoft Teams | 27 min | 2023-04-19 |

***** *Recording tool failure: no transcript available, only interview notes*

## Appendix 3. Interview Guide

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**Briefing**

- Introduction to the interviewers and thesis topic
- Overview of interview procedure (recording, confidentiality & consent, structure)

**Introduction**

- Could you describe your background and current role within [case company]?

**The Meaning of AI and the Surrounding Discourse**

- How would you define AI?
- How do you feel about the way that AI is talked about in general?
- Where is the enterprise AI discussion being conducted?
- What values would you say are closely linked to the concept of AI?

**The Hype Around AI**

- How did the hype around AI come into being?
- Who is responsible for the buzz around AI?
- How would you describe the current state of the AI hype?
- When AI was first becoming popular, how would you say it was being sold?

**Case Company Product and Industry**

- Could you briefly describe your product?
- Can you describe the rationale for how the term AI is used in [the company's] communication, for example on the website?

**Organizational Adoption and Implementation of Enterprise AI**

- What factors influence organizations to adopt AI?
- What kind of problems is enterprise AI being aimed at?
- Who is leading the adoption of enterprise AI?
- Could you describe the success factors in the organizational implementation of enterprise AI solutions?
- Could you describe the stories you have heard of companies adopting enterprise AI?

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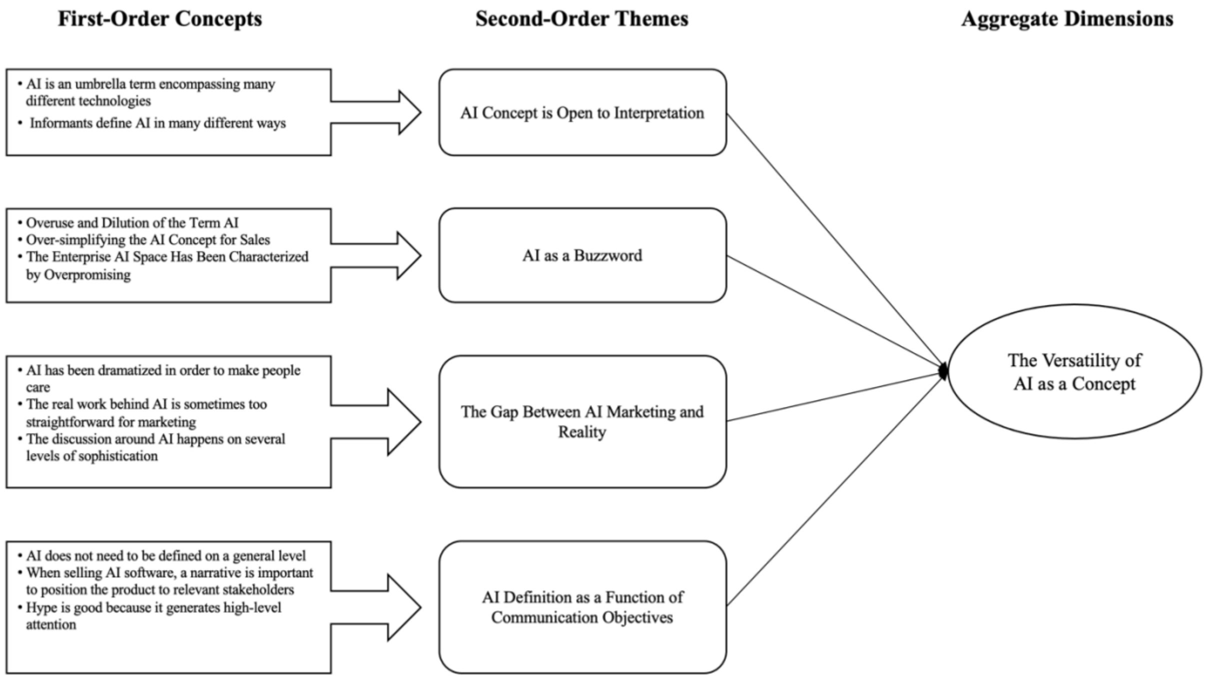
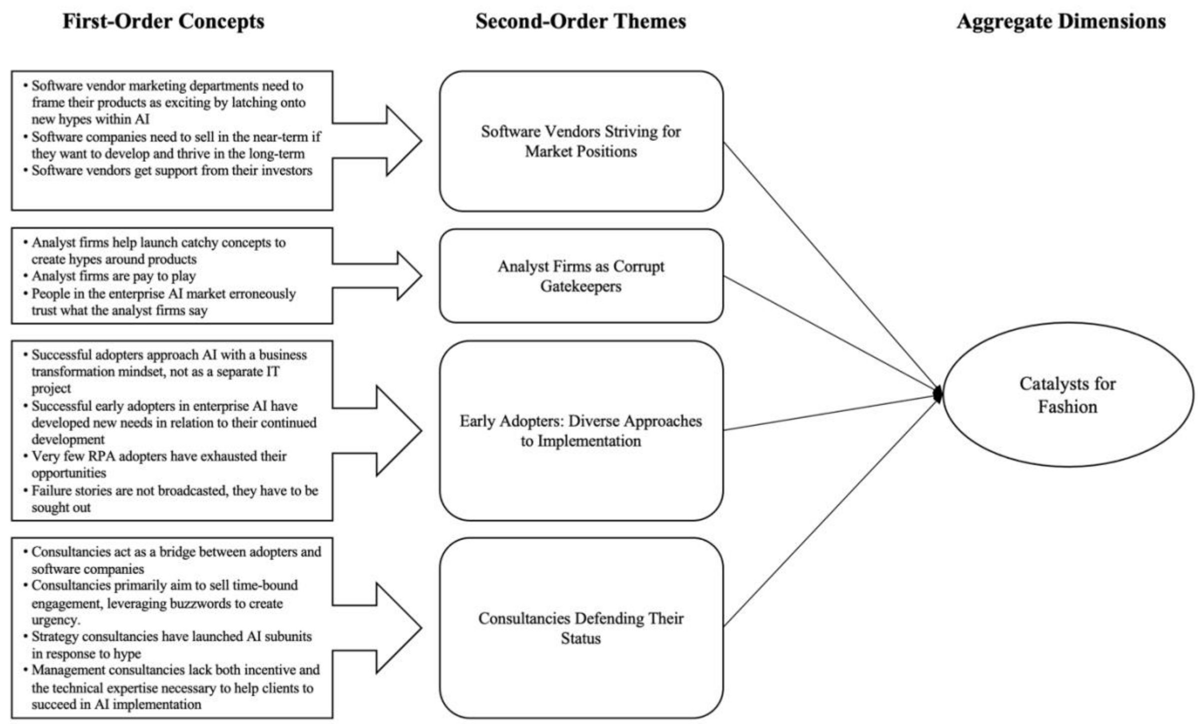
# Appendix 4. Data Structure from Concepts to Themes to Aggregate Dimensions

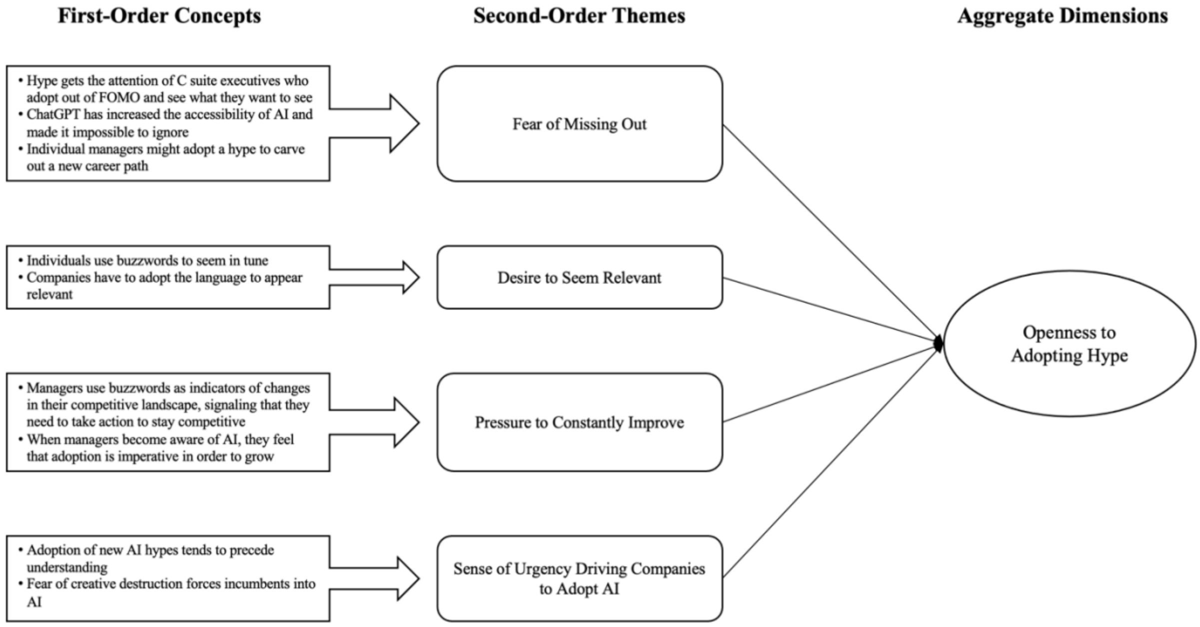
## Appendix 4.1. Aggregate Dimension 1 - The Versatility of AI as a Concept




## Appendix 4.2. Aggregate Dimension 2 - Catalysts of Fashion



## Appendix 4.3. Aggregate Dimension 3 - Openness to Adopting Hype




## Appendix 4.4. Aggregate Dimension 4 - Commoditization of Enterprise AI