Creating market knowledge from big data: Artificial intelligence and human resources

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Abstract

The abundance of social media use and the rise of the Internet-of-Things (IoT) has given rise to big data which offer great potential for enhanced market knowledge for marketers. In the literature, market knowledge has been associated with positive marketing performance. The literature also considers market knowledge as an antecedent to insight which in turn is a strategic asset that can yield a sustained competitive advantage. In summary, market knowledge is important due to its relationship with performance and as a pre-requisite to insight.

Market knowledge (as an outcome) results from market knowledge creation processes which encompasses the activities to create market knowledge. Market knowledge is created by integrating resources, specifically information technology and human resources.

With respect to information technology, the unique characteristics of big data - volume, variety, veracity, velocity and value (the five V's) - make traditional information technologies ill-suited to turn big data into information and ultimately market knowledge. Artificial intelligence (AI) has been discussed as one important information technology for creating market knowledge from big data. The literature suggests that AI is having a profound impact on the creation of market knowledge from big data and calls for more research on understanding the value potential of AI.

Regarding human resources, the primacy of human contributions to the creation of market knowledge has been established in the literature. However, scholars and practitioners alike suggest that AI will change the nature and role of human contributions to creating market knowledge. The literature also suggests that the aspect of AI and human resources in market knowledge has not been adequately studied to date.

Hence, the research problem in this thesis is formulated as "How do marketers create market knowledge from big data using artificial intelligence and human resources?" This research problem is addressed via five research questions (RQs):

RQ 1: How does artificial intelligence contribute to creating market knowledge from big data?

RQ 2: How does artificial intelligence impact the creation of market knowledge from big data and what are the implications for human resources?

RQ 3: How do artificial intelligence and human resources interact in creating market knowledge from big data?

RQ 4: What are the mutual contributions of artificial intelligence and human resources in creating market knowledge from big data?
RQ 5: What are the contributions of artificial intelligence and human resources to different activities in creating market knowledge from big data?

The research in this thesis encompasses two studies and three papers. The three papers are published or forthcoming in peer-reviewed journals. The research adopts an interpretivist paradigm and follows a qualitative research approach. The findings provide three key contributions to the body of knowledge and to theory. First, this thesis provides a non-technical understanding of what AI is, how it works and its implications for market knowledge, thus addressing a gap in the marketing literature.

Second, this thesis posits that AI is a resource that meets the criteria of being 'valuable', 'rare', 'in-imitable', and 'organized' (VRIO) postulated by resource-based theory (RBT). The value of AI as a resource occurs in transforming big data into information and also AI transforming information into knowledge. Human resources are an important capability that improve the productivity of AI as a resource. This thesis provides empirical evidence that the nature of contributions offered by AI as a resource and human capabilities differ and explains how they differ.

Third, this thesis contributes to resource-based theory. It proposes a conceptual model and puts forward five propositions regarding the relationship of AI as a resource, human capabilities and market knowledge. This model and the propositions can be tested in future scholarly work.

This thesis opens with a chapter providing an introduction to the research area, followed by a literature review, a methodology chapter and a chapter discussing the findings and contributions to theory and practice, and outlining opportunities for future research. The papers and studies underpinning this thesis are presented in the last chapter of this thesis.

Keywords
Market knowledge, insights, big data, artificial intelligence, resource-based theory, resources, capabilities, machine learning, natural language processing.

Sammanfattning

Utbredd användning av sociala medier och större tillgång till Internet-of-Things (IoT) har skapat så kallad Big Data, vilket erbjuder stor potential för ökad marknadskunskap för marknadsförare. I litteraturen har marknadskunskap associerats med positiva marknadsföringsresultat. Dessutom föreslår litteraturen att marknadskunskap kan leda till insikt. Insikt är en strategisk tillgång som kan ge varaktiga konkurrensfördelar. Sammanfattningsvis är marknadskunskap viktig på grund av dess relation till resultat och som ett underlag för insikt.

Marknadskunskap (som ett resultat) kommer från skapandeprocesser som inkluderar de aktiviteter som krävs för att uppnå marknadskunskap. Marknadskunskap skapas genom att integrera resurser, särskilt informationsteknologi och mänskliga resurser.

Med avseende på informationstekniska resurser gör de unika egenskaperna hos Big Data – volume (volym), variety (variation), veracity (veracitet), velocity (hastighet) och value (värde) (vilket på engelska kallas de fem V: erna) - traditionella informationsteknologier olämpliga för att omvandla Big Data till information och slutligen till marknadskunskap. Artificiell Intelligens (AI) har diskuterats som en viktig informationsteknologi för att skapa marknadskunskap från Big Data. Litteraturen föreslår att AI i hög grad kan påverka skapande av marknadskunskap från Big Data och erfordrar mer forskning för att förstå AI potential.

Mänskliga resursers bidrag till skapande av marknadskunskap har tidigare fastställts i litteraturen. Men både forskare och utövare antyder att AI kommer att förändra hur människor bidrar till marknadskunskap. Litteraturen antyder också att skapande av marknadskunskap ännu inte har studerats tillräckligt från synvinkel av AI och mänskliga resurser.

Forskningsfrågan i denna avhandling är ”Hur skapar marknadsförare marknadskunskap från Big Data med hjälp av Artificiell Intelligens och mänskliga resurser?”

Denna forskningsfråga behandlas via fem delfrågor:

Fråga 1: Hur bidrar Artificiell Intelligens till att skapa marknadskunskap från Big Data?
Fråga 2: Hur påverkar Artificiell Intelligens skapandet av marknadskunskap från Big Data och vilka konsekvenser har det för mänskliga resurser?
Fråga 3: Hur samverkar Artificiell Intelligens och mänskliga resurser för att skapa marknadskunskap från Big Data?
Fråga 4: Vilka är ömsesidiga bidrag från Artificiell Intelligens och mänskliga resurser för att skapa marknadskunskap från Big Data?
Fråga 5: Vad bidrar Artificiell Intelligens och mänskliga resurser till olika aktiviteter för att skapa marknadskunskap från Big Data?

Forskningen som presenteras i denna avhandling omfattar två studier och tre artiklar. De tre artiklarna har redan eller kommer at publiceras i peer-review-tidskrifter. Forskningen följer en interpretivistisk paradigm med en kvalitativ forskningstrategi. Resultaten från studierna och artiklarna ger tre viktiga övergripande bidrag till kunskap och teori. För det första ger denna avhandling en icke-teknisk överblick av vad AI är, hur den fungerar och dess konsekvenser för att skapa marknadskunskap, därmed fyller den en lucka i marknadslitteraturen.

För det andra postulerar avhandlingen att AI är en resurs som uppfyller kriterierna för att vara ’valuable’ (värdefull), ’rare’ (sällsynt), in-imitable (imiterbar) och ’organized’ (organiserad) (VRIO) i enlighet med resursbaserad teori (RBT). Värdet på AI som en resurs uppstår delvis när AI omvandlar Big Data till information och även när AI omvandlar informationen till kunskap. Mänskliga resurser är en viktig tillgång för att skapa marknadskunskap från Big Data och förbättrar produktiviteten för AI som en resurs. Denna avhandling ger empiriska bevis på att den typ av bidrag som AI tillhandahåller som resurs skiljer sig från mänskliga förmågor. Specifikt ger AI-resurser främst bidrag av analytisk karaktär. Den analytiska beskaffenheten av AI omfattar behandling av data och information för att lösa komplexa, väldefinierade problem, lagrande av resultat från dessa behandlingsaktiviteter, och inlärning, d.v.s. gradvis förbättrande av dess behandlingseffektivitet och verkningsgrad.

Människans förmåga är i första hand av intuitiv och empatisk natur. Den intuitiva rollen omfattar människors förmåga att tänka kreativt och anpassa sig till nya situationer med hjälp av kreativ problemlösning, expertis och intuition. Människans empatiska natur omfattar deras förmåga att förstå det AI matar ut ur ett socialt, interpersonellt eller emotionellt perspektiv. Det omfattar en medvetenhet om ens egna känslomässiga tillstånd, empati, förmåga att bygga relationer och svara med känslomässig lämplighet i marknadsförings- eller försäljningssituationer. Medan AI-system blir alltmer sofistikerade när det gäller att känna igen, tolka och till och med svara på känslor, spelar mänskliga förmågor fortfarande en viktig roll i dessa uppgifter.

För det tredje bidrar denna avhandling till resource-based theory (resursbaserad teori). Den föreslår en konceptuell modell och lägger fram fem propositioner om relationen mellan AI som en resurs, mänskliga förmågor och marknadskunskap. Denna modell och propositionerna kan testas i framtida vetenskapligt arbete.

Denna avhandling är organiserad för att ge en övergripande introduktion till forskningsberättelsen. Första kapitlet ger en introduktion till forskningsområdet, följt av en litteraturöversikt, ett metodikapitel och ett kapitel som diskuterar resultat och bidrag till teori och praktik, samt redogör för möjligheter för framtida forskning. Uppsatserna och studierna som ligger till grund för denna avhandling presenteras i det sista kapitlet i denna avhandling.

Nyckelord
Marknadskunskap, insikter, big data, artificiell intelligens, resursbaserad teori, resurser, kapacitet, machine learning (maskininlärning), natural language processing (naturlig språkbearbetning).

Preface

It takes a village to raise a child, and it takes an entire ecosystem to raise a doctorate. From day one, I was blessed with an extensive network of people who encouraged and supported me throughout this journey. Thank you to the many people that have travelled with me during this voyage.

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Stockholm, April 2020
Jeannette Paschen

List of appended papers and studies

Study A

Paschen, J., Kietzmann, J., and Kietzmann, T. C., “Unpacking artificial intelligence – How the building blocks of artificial intelligence (AI) contribute to creating market knowledge from big data”[1].

Paper B

Paschen, J., Wilson, M., and Ferreira, J. J. M., (2020), “Collaborative intelligence – how human and artificial intelligence create value along the B2B sales funnel”, *Business Horizons*, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1016/j.bushor.2020.01.003.

Study C

Paschen, J., Paschen, U., Pala, E., Kietzmann, J., “Artificial intelligence (AI) and value co-creation in B2B sales: Activities, actors and resources”.[2]

Paper D

Paschen, J. (2019), “Investigating the emotional appeal of fake news using artificial intelligence and human contributions”, *Journal of Product and Brand Management*, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/JPBM-12-2018-2179

Paper E

Paschen, J., Wilson, M., and Robson, K. (2020), “#BuyNothingDay: Investigating consumer restraint using hybrid content analysis of Twitter data”, *European Journal of Marketing*, 54(2), 327-350.

[1] An amended version of study A has since been published in a peer-reviewed journal.
[2] An amended version of study C is under review in a peer-reviewed journal.

Contents

Where is the knowledge we have lost in information? Where is the information we have lost in data? (adapted from T. S. Eliot, 1935, opening verse from "The Rock", cited from Deshpandé, 2001)

Chapter 1: Introduction

1.1 The importance of market knowledge

Marketing is knowledge intensive (Deshpandé, 2001; Glazer, 1991; Kohli & Jaworski, 1990; Li & Calantone, 1998; Lin et al., 2006; Ozkaya, Droge, Hult, Calantone, & Ozkaya, 2015; Shaw et al., 2001). Knowledge, defined as “information, combined with experience, context, interpretation and reflection” (Davenport et al., 1998, p. 43) allows marketing decision makers to effectively tailor their goods, services and communications to individuals’ actual preferences and behaviours, rather than to peoples’ assumed behaviours (Erevelles, Fukawa, & Swayne, 2016; Glazer, 1991; Ozkaya et al., 2015).

Market knowledge, defined as knowledge about customers, competitors and other market stakeholders (Deshpandé, 2001; Glazer, 1991; Kohli & Jaworski, 1990), is among the most important forms of knowledge in marketing and has received much attention in the literature (Deshpandé, 2001). A number of studies have shown that market knowledge is positively related to performance, including innovation, financial performance, new product development, or customer relationship management (De Luca & Atuahene-Gima, 2007; Li & Calantone, 1998; Ozkaya et al., 2015; Wei & Wang, 2011).

In addition, market knowledge has been discussed as an antecedent to insight (Said et al., 2015; Wills & Webb, 2007). Insight - in the literature commonly referred to as customer insight or marketing insight, but simply referred to as insight in this thesis - is viewed as a higher-order form of knowledge (Deshpandé, 2001; Smith et al., 2006; Wills, 2005; Wills & Webb, 2007). Insight can be understood as knowledge that is actionable, i.e., it is applied to influence decision making (Rothberg &

Erickson, 2017; Smith et al., 2006; Wills & Webb, 2007). The literature suggests that insight is a strategic asset that can yield a sustained competitive advantage (Berger et al., 2019; Erevelles et al., 2016; Said et al., 2015; Smith et al., 2006; Thompson, 1997; Wills, 2005; Wills & Webb, 2007). In summary, market knowledge is important due to its impact on organizational performance and as an antecedent to insight.

1.2 Market knowledge creation

Given the importance of market knowledge, the literature has been interested in understanding how it is created. A widely accepted perspective suggests that knowledge as an outcome results from a firm's processes, i.e., activities, to transform data into information into knowledge (Davenport, De Long, & Beers, 1998; Davenport & Prusak, 1998; Rothberg & Erickson, 2017; Smith, Wilson, & Clark, 2006).

Data are representations for describing properties of objects or events (Ackoff, 1989) and can be symbols, numbers, or other, non-numerical writing. Information is data that have a purpose, i.e., data that have been processed to increase their usefulness (Ackoff, 1989; Davenport & Prusak, 1998). Like data, information also describes the properties of objects or events; but unlike data, information is organized into patterns through processing (Ackoff, 1989; Davenport et al., 1998; Smith et al., 2006). Knowledge is information that has been placed into a specific organizational context and has been defined as "information that is combined with experience, context, interpretation, and reflection" (Davenport et al., 1998, p. 43). This transformation process has become known as the 'hierarchy perspective of knowledge', due to the hierarchical relationship between the three core constructs data, information and knowledge (Alavi & Leidner, 2001).

Within the hierarchy perspective, one discourse in the literature has investigated resources as antecedents of market knowledge (Erevelles et al., 2016; Foley & Fahey, 2009; Rakthin et al., 2016; Srivastava et al., 2001; Wade & Hulland, 2004). A number of studies have utilized resource-based theory (RBT) which posits that an organization's resources can yield superior performance and a sustained competitive advantage (Barney, 1991; Wernerfelt, 1984). Market knowledge, it is suggested, results from the activities to integrate different resources, specifically information technology and human resources (Alavi & Leidner, 2001; Fowler, 2000; Seleim & Khalil, 2011). Information technology is defined as computers, including software, hardware and other peripheral tools, to collect, store, transmit or manipulate data or information (Cambridge Dictionary, 2019).

With respect to information technology resources, studies have investigated different information technologies, often summarized under the umbrella term 'marketing information system' (Deshpandé, 2001; Kotler & Keller, 2006) as possible antecedents to market knowledge (Alavi & Leidner, 2001; Erevelles et al., 2016; Fowler, 2000; Z. Khan & Vorley, 2017; Wei & Wang, 2011). Information technologies can range from simple, e.g., spreadsheet software, to more complex information technologies, such as applications for advanced analytics, multivariate analysis, marketing intelligence, and data management. The premise is that marketing information systems can help marketers analyse data effectively and efficiently (Ackoff, 1989), thus contributing to advanced information quality and quantity which in turn can impact how market knowledge is created (Alavi & Leidner, 2001; Davenport, De Long, & Beers, 1998; Davenport & Prusak, 1998; De Luca & Atuahene-Gima, 2007; Erevelles, Fukawa, & Swayne, 2016).

In addition to information technology resources, a large body of literature has considered the "human side of … market knowledge … rather than the technical aspects of the information product itself" (Deshpandé, 2001, p. 4). The primacy of human resources in creating knowledge is widely discussed in the literature (Fowler, 2000). Knowledge is viewed as the result of processing by individuals through which information is interpreted and put into context (Alavi & Leidner, 2001; Davenport & Prusak, 1998; De Luca & Atuahene-Gima, 2007; Seleim & Khalil, 2011). Humans make sense of information, question and synthesize it, put into their specific business context, and combine it with existing knowledge. These activities require a variety of human resources, for example, analytical skills, problem-solving skills or domain-specific knowledge (industry knowledge, business expertise, and others).

In summary, the literature has considered a resource-based perspective on the creation of market knowledge. Market knowledge results from the activities to transform data into information and then into knowledge. These activities utilize resources, specifically, information technology and human resources. Following this view in the literature, this thesis adapts a resource-perspective on the creation of market knowledge by investigating resources, i.e., information technologies and human resources, for the creation of market knowledge. This is further explained below.

1.3 Market knowledge creation from big data

The proliferation of social media (Kietzmann et al., 2011) and the rise of the Internet-of-Things (IoT) (Robson et al., 2016) has led to an explosion in data availability from various sources with the potential for enhanced market knowledge for marketers (Balducci & Marinova, 2018; Berger et al., 2019; Erevelles et al., 2016; Said et al., 2015). A large majority of these data are unstructured (Rizkallah, 2017), i.e., they do not have a pre-defined data model or are not organized in a pre-defined manner (Balducci & Marinova, 2018). These data are created at high velocity, variety and in large volumes and are referred to as big data (Marr, 2015b).

Scholars and practitioners alike acknowledge the potential for creating market knowledge from big data (Balducci & Marinova, 2018; Berger et al., 2019; Davenport et al., 2019; Erevelles et al., 2016; Wedel & Kannan, 2016). However, big data have also created challenges for marketers with respect to analysing and organizing these data into information and ultimately creating knowledge: 87% of marketers view data as their most underused asset (Howatson, 2015), and face obstacles in analysing and creating knowledge from these data using traditional data analytics tools and information technologies (Balducci & Marinova, 2018).

Recently, artificial intelligence (AI) has been considered as an information technology with potential to support the creation of market knowledge from big data (Balducci & Marinova, 2018; Berger et al., 2019; Duan et al., 2019; Erevelles et al., 2016; Metaxiotis et al., 2003; Moreira Nascimento et al., 2018). Due to the unique characteristics of big data as outlined in the previous paragraph, previous information technologies are ill-equipped to transform these data into useful information and to support the creation of market knowledge (Erevelles et al., 2016; Russell & Norvig, 2016). In contrast, the emerging technology of AI has potential to fill the gaps in creating market knowledge left by previous technologies (Schwab, 2016).

1.4 Market knowledge creation using artificial intelligence

Artificial intelligence is defined as information technology that acts intelligently (Poole & Mackworth, 2010). AI perceives data inputs, processes these data and returns information as outputs. In the popular media, AI is often equated with emulating human-like intelligence (Russell & Norvig, 2016). This is not the case. Rather, AI considers the data and information available and acts to achieve the best expected outcome. Stated differently, AI is rational if it does the “right thing” given what it knows. The distinction between human and rational behaviour acknowledges that human behaviour is boundedly rational (Simon, 1996), i.e., may include behaviour that may not achieve the best outcome (Kahnemann & Tversky, 1979).

While AI has existed since the 1950s, it was only in the last decade that it has been discussed as a transformative technology that is expected to substantially impact marketing practitioners (Schwab, 2016), specifically how marketers create market knowledge (Davenport & Ronanki, 2018). In B2C, a 2017 Forrester survey among marketing executives revealed that three out of five firms expect to implement AI within the next 12 months (Forrester, 2017). And, according to Gartner's 2018 technology trend survey, AI is listed as the number one strategic technology for creating information and knowledge from big data (Panetta, 2017).

Moreover, AI is also increasingly adopted in B2B. According to a 2018 MIT study, the professional services sector ranked among the top sectors to embrace AI (MIT Technology Review Insights, 2018). For professional service firms in B2B, the premise is that AI can help analyse customer data and use the information to create knowledge about what drives customers' behaviour.

In addition to the relevance for practitioners, AI has been widely investigated in the literature and scholarly interest in AI has been increasing in the last decade (Duan et al., 2019; Martínez-López & Casillas, 2013; Moreira Nascimento et al., 2018). A number of studies have researched different AI systems and their application to organizational decision making contexts (Duan et al., 2019; Moreira Nascimento et al., 2018), such as operations management (Baryannis, Validi, Dani, & Antoniou, 2019; Bottani et al., 2019), finance (Riikkinen, Saarijärvi, Sarlin, & Lähteenmäki, 2018), knowledge management (Fowler, 2000; Metaxiotis, Ergazakis, Samouilidis, & Psarras, 2003) or information systems (Khan, Baharudin, Lee, & Khan, 2010; Meyer et al., 2014). In addition, organizational science scholars have studied AI's role in and its impact on organizational decision making (Aleksander, 2017; Davenport & Kirby, 2016a, 2016b; Jarrahi, 2018; Kaplan & Haenlein, 2019; Lichtenthaler, 2019; Von Krogh, 2018).

Most importantly, and from the perspective of this marketing thesis, AI has received more and more scholarly attention in the marketing discipline (Balducci & Marinova, 2018; Berger et al., 2019; Davenport et al., 2019; Huang & Rust, 2018; Kietzmann et al., 2011; Moreira

Nascimento et al., 2018; Singh et al., 2019; Syam & Sharma, 2018; Wedel & Kannan, 2016). In the service literature, for instance, research has investigated service provisions enabled by AI technologies (Colby, Mithas, & Parasuraman, 2016; Huang & Rust, 2018; Pee, Pan, & Cui, 2019).

Further, marketing scholars have explored the use of AI as a data analysis tool, for instance to analyse user-generated content on social media or review sites (Duan, Edwards, & Dwivedi, 2019; Gupta, Kar, Baabdullah, & Al-Khowaiter, 2018; Liu, 2019; Pitt, Kietzmann, Botha, & Wallström, 2018; Pitt, Mulvey, & Kietzmann, 2018; Tirunillai & Tellis, 2014) or to analyze marketing communications, such as in the context of fake news (Horne & Adali, 2017; Potthast, Kiesel, Reinartz, Bevendorff, & Stein, 2017; Sharma et al., 2018). Research has also investigated the role of AI in and its impact on marketing decision making, including B2C marketing (Kietzmann et al., 2018; Sundsøy et al., 2014; Wirth, 2018; Ye et al., 2009) and B2B marketing (Eitle & Buxmann, 2019; Martínez-López & Casillas, 2013; Singh et al., 2019; Syam & Sharma, 2018).

Many of these extant studies suggest that AI will have a profound impact on human activities and resources. For instance, the article by Syam and Sharma (2018) hypothesizes that the sales practice will be disrupted by AI and specifically points to its impact on human resources in the sales process. The work by Singh et al. (2019) echoes this perspective and suggests that AI will substantially impact the sales profession and sales professionals, and highlights questions pertaining to AI and knowledge as a fruitful area for further investigation.

Other marketing scholars also call for more research on AI for creating market knowledge (Balducci & Marinova, 2018; Berger et al., 2019; Duan et al., 2019; Martínez-López & Casillas, 2013; Metaxiotis et al., 2003; Singh et al., 2019; Syam & Sharma, 2018; Wedel & Kannan, 2016). In addition, the Marketing Science Institute (MSI), in its 2018-2020 report, delineates five key research areas for the advancement of the discipline. Among these five priorities is the call for an increased understanding of the approaches to create knowledge from big data, and specifically highlighting AI as a research focus (Marketing Science Institute, 2018).

In summary, research suggests that AI is becoming increasingly important for the creation of market knowledge (Balducci & Marinova, 2018; Berger et al., 2019; Duan et al., 2019; Martínez-López & Casillas, 2013; Singh et al., 2019; Syam & Sharma, 2018; Wedel & Kannan, 2016). The research presented herein attempts to provide a deeper understanding on the combined roles of human resources and AI in generating market knowledge. In the next section, the overall research problem under investigation in this thesis is described in detail.

1.5 Research problem statement

As outlined earlier in this introduction, market knowledge is important as it is an antecedent to insights. Market knowledge results from the processing and interpretation of information which in turn results from the processing of data. The extant literature acknowledges the importance of human resources and information technology resources for creating market knowledge (Alavi & Leidner, 2001; Davenport et al., 1998; Davenport & Prusak, 1998; Erevelles et al., 2016; Wei & Wang, 2011).

Artificial intelligence has been discussed as an information technology that can effectively analyse big data and support the creation of market knowledge (Duan et al., 2019; Martínez-López & Casillas, 2013; Moreira Nascimento et al., 2018; Singh et al., 2019; Syam & Sharma, 2018). The literature suggests that AI will have a substantial impact on how knowledge is created (Daskou & Mangina, 2003; Fowler, 2000; Lichtenthaler, 2019; Metaxiotis et al., 2003; Singh et al., 2019; Syam & Sharma, 2018) and will change the role and nature of human contributions to creating market knowledge (Duan et al., 2019; Huang & Rust, 2018; Jarrahi, 2018; Singh et al., 2019; Syam & Sharma, 2018).

Hence, the discussion in this introduction so far suggests that a necessary and relevant investigation is a study of how market knowledge is created from big data using AI and human contributions. This is at the core of the research presented in this thesis. Specifically, this thesis seeks to investigate the intersection of AI (the information technology) and human resources for creating market knowledge. Thus, the research problem for this thesis is formulated as:

How do marketers create market knowledge from big data using artificial intelligence and human resources?

1.6 Delimitations

This thesis adopts a resource-based-theory perspective to the study of market knowledge. Specifically, the research in this thesis investigates the contributions, impact and interactions among AI (information technology) and human resources for creating market knowledge. This thesis focuses its scope on market knowledge, defined as knowledge about customers, competitors and other market stakeholders (Deshpandé, 2001; Glazer, 1991; Kohli & Jaworski, 1990). This conceptualization of market knowledge aligns with widely used conceptualizations in the marketing literature (Deshpandé, 2001; Kohli & Jaworski, 1990) and provides a comprehensive understanding by considering customers, competitors and other stakeholders.

Market knowledge has been suggested to be most critical form of knowledge, and Deshpandé (2001, p. 1) goes as far as to term it the “lifeblood of any organization”. In addition, a number of scholars have identified a need for further research on how to create market knowledge from big data using AI (Duan et al., 2019; Huang & Rust, 2018; Martínez-López & Casillas, 2013; Metaxiotis et al., 2003; Moreira Nascimento et al., 2018; Singh et al., 2019; Syam & Sharma, 2018). Moreover, the Marketing Science Institute emphasizes an understanding to generating market knowledge using AI as one of their research priorities (Marketing Science Institute, 2018).

This thesis further focused its scope on creating market knowledge using the perspective that knowledge (an outcome) results from transforming information which results from transforming data (a process). This perspective has been adopted by many scholars (Alavi & Leidner, 2001; Davenport & Prusak, 1998; Erevelles et al., 2016). Key to this transformation process are resources, and this thesis focused its scope on AI (information technology resources) and human resources. To further clarify the focus of this thesis, definitions of key terms used throughout this thesis are presented in Table 1.

Table 1: Glossary of key terms in this thesis

Term	Definition of term	Reference(s)
Artificial intelligence (AI)	Information technology that receives or perceives data inputs, process these data, return information as outputs and act to achieve the best expected outcome.	Russell & Norvig (2016)
Big data	Data that are characterized by unprecedented volume, variety, veracity, velocity and value.	Erevelles et al. (2016)
Capabilities	A subset of an organization’s resources; encompass resources that improve the productivity of other resources.	Kozlenkova et al. (2014); Penrose (1959)
Data	Representations for describing properties of objects or events, such as numbers or symbols.	Ackoff (1989)
Information	Data that are processed and organized into patterns to increase their usefulness.	Ackoff (1989); Davenport & Prusak (1998)
Information technology	Computers, including software, hardware and other peripheral tools, to collect, store, transmit or manipulate data or information.	Cambridge Dictionary (2019)
Insights	Market knowledge applied to solve marketing problems; a strategic resource that can yield a sustained competitive advantage.	Said et al. (2015); Wills & Webb (2007)
Knowledge	Information that has been combined with experience, interpretation and reflection and put into a specific context.	Davenport, De Long, & Beers (1998)
Market knowledge	Knowledge about customers, competitors and other market stakeholders.	Deshpandé (2001); Glazer (1991); Kohli & Jaworski (1990)
Marketing information system	Umbrella term used to summarize different information technologies used in marketing, including internal databases/reporting, market research, marketing intelligence.	Deshpandé (2001); Kotler & Keller (2006)
Resources	“Tangible and intangible assets firms use to conceive of and implement its strategies.”	Barney & Arikan (2001, p. 138)
Structured data	Data that are organized according to a predefined model that organizes data and describes their relationships.	Balducci & Marinova (2018)
Unstructured data	Data that does not have a pre-defined data model or is not organized in a pre-defined manner.	Balducci & Marinova (2018)
VRIO framework	Depicts four criteria of resources with respect to their potential to generate a competitive advantage. Stands for value, rarity, imperfect imitability and organization.	Kozlenkova et al. (2014)

1.7 Thesis structure and presentations

This thesis is organized by means of five chapters which encompass an introduction to the research area, a positioning of the research within the literature, an overview of the methodology and a chapter presenting the findings of the research work, the contributions to theory and practice and future research opportunities. The final chapter includes the two studies and three papers underpinning this thesis. The current section provides an overview of how this thesis is organized, including a summary of each thesis chapter.

Chapter 1 presents an overview of the thesis narrative. It formulates the research problem and introduces the background to and significance of the research problem. It introduces and defines the core constructs and provides explanation on the relevance of the research problem for business and academia. In summary, this chapter encapsulates the rationale for the “what” and the “why” of this thesis.

Chapter 2 discusses the literature underpinning this thesis. It defines market knowledge and discusses its relevance to positive marketing outcomes. Chapter 2 then reviews the literature on market knowledge, market knowledge creation processes, resources and resource-based theory. Chapter 2 concludes with the identification of the research gap and formulates the research questions. Thus, chapter 2 provides a theoretical frame of reference and grounds the research in the existing literature.

Chapter 3 explains the methodology in this thesis. It includes a discussion of the adopted research paradigm, research approach, research design, and methods for each paper and study. It also discusses quality aspects of the empirical studies in this research. In summary, chapter 3 discusses the “how” of this thesis.

Chapter 4 discusses the findings regarding each research question. It outlines the contributions to theory, followed by managerial implications. It concludes with a review of the limitations and suggestions for further research.

Chapter 5 presents the papers and studies.

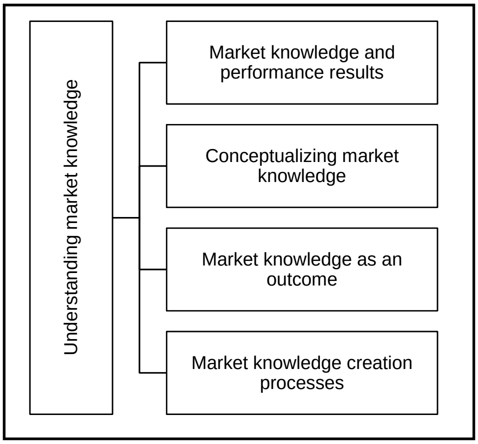
1.8 Chapter summary

The current chapter provided an introduction to the research presented in this thesis. It outlined the significance of the proposed research for scholars and marketing practitioners. This chapter also outlined the research problem and presented the delimitations of the current research. The chapter ended with an overview of the chapters included in this thesis.

Chapter 2: Literature review

This thesis seeks to explore AI and human resources for creating market knowledge from big data. The current chapter defines the key constructs underpinning this research and discusses the relevant literature. The chapter begins with a discussion of the performance outcomes from market knowledge. This is followed by a review of how market knowledge has been conceptualized in the extant literature. Market knowledge has been viewed as an outcome (a result) and as a process in which data is transformed into information, which is then transformed into knowledge. The transformation processes consist of resources, specifically information technology and human resources, and activities to translate data into information into knowledge. Market knowledge stocks are the end result of market knowledge creation processes. Figure 1 presents an overview of how the literature review is structured. Following the literature review, the research gap is identified, and the research questions aimed at addressing this gap are formulated.

Figure 1: Understanding market knowledge – overview of literature review



2.1 Market knowledge and performance results

Market knowledge has been a central construct in the marketing literature (Berger et al., 2019; Deshpandé, 2001; Erevelles et al., 2016; Jaworski & Kohli, 1996; Kohli & Jaworski, 1990; Narver & Slater, 1990; Slater & Narver, 1994). A number of studies provide evidence that market knowledge is positively related to organizational performance, such as innovation, marketing effectiveness, new product development, customer relationship management or financial performance (Chang, Mehta, Chen, Polsaq, & Mazur, 1999; Li & Calantone, 1998; Ozkaya, Droge, Hult, Calantone, & Ozkaya, 2015; Taylor, Kim, Park, Kim, & Moon, 2008; Wei & Wang, 2011). An overview of this literature is presented below.

Wei and Wang (2011) suggest that market knowledge and its use are positively related to B2B firms' performance. Building on Kohli and Jaworski's (1990) work, the authors test a conceptual framework linking market knowledge to strategic marketing decisions which impact marketing mix performance and financial performance. The empirical results from 1,800 survey responses suggest that market knowledge is positively related to firm performance through enabling a firm's market-driven actions and a competitive marketing advantage (Wei & Wang, 2011).

In another study, Ozkaya et al. (2015) found empirical evidence that acquiring information about a firm's market and the activities to transform this information into knowledge are positively related to innovation and firm performance (Ozkaya et al., 2015). Li and Calantone (1998) provide empirical evidence that a firm's processes to generate and integrate market knowledge are positively related to new product advantage. This positive relationship was found in earlier scholarly work as well (Day, 1994; Slater & Narver, 1994). Other studies have examined market knowledge and the organizational activities to create, integrate and apply market knowledge and positively linked these constructs to operating effectiveness and cost efficiency (Chang, Mehta, Chen, Polsaq, & Mazur, 1999), customer relationship management (Taylor, Kim, Park, Kim, & Moon, 2008), innovation (Han, Kim, & Srivastava, 1998; Matear, Osborne, Garrett, & Gray, 2002), and marketing decision making (Cao, Duan, & Banna, 2019; Mavondo & Farrell, 2003).

Moreover, the marketing literature considers market knowledge as an antecedent to insight (Said et al., 2015; Wills & Webb, 2007). Insight, commonly termed market insight or customer insight, but simply called insight in this thesis, has been defined as knowledge applied to solve marketing problems (Rothberg & Erickson, 2017; Smith et al., 2006; Wills & Webb, 2007). Knowledge and insight are different, yet related constructs. In the literature, insight has been described as encompassing different types of knowledge – explicit declarative knowledge ('know what'), tacit procedural knowledge ('know how') and explanations of anomalies or failures ('know why'). In addition to these three dimensions of knowledge, insight encompasses a fourth dimension; this fourth dimension encompasses the underlying meanings and reasons for decision making ('care why'). The marketing literature suggests that insight, generated from market knowledge, represents a strategic asset for firms that can yield a sustained competitive advantage (Berger et al., 2019; Erevelles et al., 2016; Said et al., 2015; Smith et al., 2006; Thompson, 1997; Wills, 2005; Wills & Webb, 2007).

2.2 Conceptualizing market knowledge

Market knowledge has received much attention in the marketing literature. The current section first discusses the 'market' construct before defining market knowledge. Market knowledge has been central to the market orientation literature (Day, 1994; Deshpandé et al., 1993; Kohli & Jaworski, 1990; Liao et al., 2011; Narver & Slater, 1990; Ozkaya et al., 2015; Slater & Narver, 1995) which has received much interest in the past three decades (Liao et al., 2011). In their seminal paper, Kohli and Jaworski (1990), emphasize that market is defined as a "broader concept than customers' verbalized needs and preferences in that it includes an analysis of exogenous factors that influence those needs and preferences." (Kohli & Jaworski, 1990, p. 4). A market, according to Kohli and Jaworski (1990) encompasses customers, competitors and other external stakeholders that may impact customers' preferences and behaviours.

A broad conceptualization of the market construct has been echoed by other marketing scholars (Day, 1990, 1994; Deshpandé et al., 1993; Narver & Slater, 1990; Slater & Narver, 1995). Narver and Slater (1990) use the notion of "customer and competitor orientation" (Narver & Slater, 1990, p. 21) to emphasize the importance of acquiring and disseminating knowledge about customers and competitors.

In a later publication, Slater and Narver (1995) express concerns about a too narrow conceptualization of the 'market' construct prevailing at that time which viewed a market primarily as consisting of customers and competitors (Day, 1994; Deshpandé et al., 1993; Kohli & Jaworski, 1990). "A business must be careful not to underestimate the potential contributions of other learning sources, such as suppliers, businesses in different industries, consultants, universities, government agencies, and others that possess knowledge valuable to the business" (Slater & Narver, 1995, p. 68). They subsequently suggest broadening the market construct to include all stakeholders that have the potential to contribute to superior customer value or the potential to threaten an organization's competitive advantage. Specifically, they suggest that "The conception of "market" should be broadened to encompass all sources of relevant knowledge and ideas pertaining to customers and customer value creating capabilities" (Slater & Narver, 1995, p. 68).

Moreover, the current definition of 'marketing' by the American Marketing Association (AMA) reflects this broader conceptualization of the market as well: "Marketing is the activity, set of institutions, and processes for creating, communicating, delivering, and exchanging offerings that have value for customers, clients, partners, and society at large." (AMA, 2019).

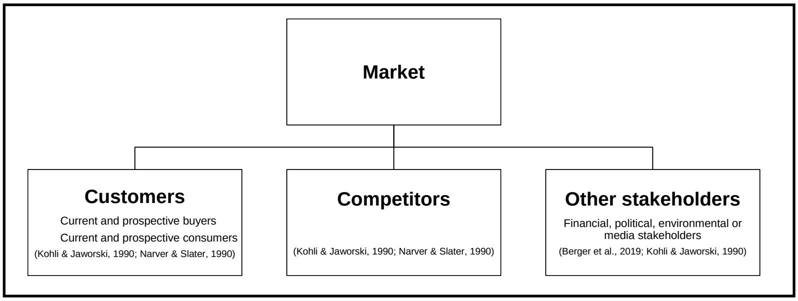
Despite the differences in conceptualizing the market construct, there exist commonalities. First, the discussed conceptualizations view a market as an exogenous construct. Thus, a market is an a-priori entity which is assumed to exist outside of an organization (Coviello & Joseph, 2012). As such, the literature highlighted above is focused on knowledge *about* the market (Day, 2011).

Second, the above discussion suggests that a market consists of multiple stakeholder groups, including customers, competitors and other, external stakeholders. The literature considers customers as an important stakeholder group; after all, customers, are the primary focus of any marketing activity (Campbell, 2003; Kohli & Jaworski, 1990; Salojärvi et al., 2010). Customers include buyers (individuals or businesses who purchase a product) and consumers (individuals or businesses who consume or use a product, regardless of whether they purchased it or not) (Berger et al., 2019; Day, 1994; Kohli & Jaworski, 1990; Narver & Slater, 1990). Thus, marketers need to create knowledge about customers (Abrell et al., 2016, 2017; Chatterji & Fabrizio, 2014; Pedeliento et al., 2018).

Third, the literature emphasizes competitors as another important stakeholder group in a market (Kohli & Jaworski, 1990; Narver & Slater, 1990; Ozkaya et al., 2015; Slater & Narver, 1995). Knowledge about competitors is important as it provides an understanding of competitors' behaviours, their strategy, new product, or marketing initiatives, and competitors' actions may in turn impact customers' preferences and behaviours (Calof & Wright, 2008; Narver & Slater, 1990; Rakthin et al., 2016).

Lastly, the literature considers other stakeholders as part of a market about which marketers should create knowledge. These 'other' stakeholders may include financial, political, environmental, or media organizations (Berger et al., 2019; Frow & Payne, 2011; Kohli & Jaworski, 1990). Creating knowledge about these other stakeholders is important as they may influence buyer and consumer preferences and behaviours (Day, 1994; Deshpandé et al., 1993; Kohli & Jaworski, 1990; Narver & Slater, 1990). Following this discussion, a market in this thesis is conceptualized as an exogenous construct, encompassing customers, competitors and other external stakeholders (see Figure 2).

Figure 2: Conceptualization of the 'market' construct in this thesis



Having delineated the market construct, the discussion now turns to a review of the studies on market knowledge. This thesis defines market knowledge as knowledge about customers, competitors and other market stakeholders (Deshpandé, 2001; Glazer, 1991; Kohli & Jaworski, 1990). The literature offers different perspectives on market knowledge which can be grouped in terms of market knowledge as an outcome (an end result in terms of knowledge stocks) and market knowledge creation processes (Alavi & Leidner, 2001; Archer-Brown & Kietzmann, 2018; Joshi & Sharma, 2004; Li & Calantone, 1998). Market knowledge as an outcome results from market knowledge creation processes. Each of these two perspectives is discussed below.

2.3 Market knowledge as an outcome

Given that market knowledge is defined as knowledge about customers, competitors and other stakeholders (Deshpandé, 2001; Glazer, 1991; Kohli & Jaworski, 1990), the starting point for understanding market knowledge is knowledge. Knowledge and how it is created has been considered in the marketing and knowledge management literature, and as such both disciplines are considered in the discussion.

Within the literature, alternative perspectives on knowledge as an outcome exist. The seminal article by Alavi and Leidner (2001) differentiates between six perspectives: Knowledge as (1) an object, (2) the application of expertise, (3) a condition of having access to information, (4) a capability, (5) a state of mind or (6) the hierarchical view of knowledge. Each of these perspectives is presented below.

The knowledge as an object view treats knowledge as an entity that can be acted upon (Carlsson, 2003). According to this view, knowledge can be captured, stored, organized, manipulated and communicated (Alavi & Leidner, 2001; Archer-Brown & Kietzmann, 2018; Fahey & Prusak, 1998; McQueen, 1998). The knowledge as an object view has also been widely considered in the marketing literature. Li and Calantone (1998, p. 14) view market knowledge as “organized and structured information about the market”, endorsing the perspective that market knowledge is an object that can be captured, organized and applied. Similarly, more recent literature in highly-ranked marketing journals echo the perspective of knowledge as an object (Balducci & Marinova, 2018; Berger et al., 2019).

A second view posits that knowledge can be viewed as knowing and acting (Alavi & Leidner, 2001; McQueen, 1998; Zack, 1999). Here, knowledge reflects the application of expertise by individuals or organizations. In another view, knowledge is viewed as a condition of having access to information (Alavi & Leidner, 2001; McQueen, 1998). According to this perspective, knowledge stocks develop through accessing information captured in documents, databases, wikis and other information storage tools. This view can be thought of as an extension of the knowledge as an object view, with a particular emphasis on the accessibility of the objects that hold knowledge (Alavi & Leidner, 2001).

The knowledge as a capability view suggests that knowledge is the capacity to use information for decision making, such as the ability to interpret information and to ascertain what information is necessary in decision making (Alavi & Leidner, 2001; Watson, 1999). The fifth view, knowledge as a state of mind, describes knowledge as a condition of knowing, with knowing being understanding gained through experience (Alavi & Leidner, 2001; McQueen, 1998). According to this view, knowledge happens in humans, and its storage or codification is therefore not possible (McQueen, 1998).

The sixth perspective adopts a hierarchical view of knowledge (Alavi & Leidner, 2001) by distinguishing between data, information and knowledge. This view suggests that data, information and knowledge are different, but related constructs and a hierarchy between data, information and knowledge is presumed in these views (Ackoff, 1989; Alavi & Leidner, 2001; Davenport, De Long, & Beers, 1998; Davenport & Prusak, 1998; Zins, 2007). Data are raw numbers or symbols that represent the properties of events or objects; when these data are processed in useful ways, they become information; knowledge is information that has been interpreted and contextualized. According to this hierarchy view, data are the inputs for information, and information is the input for knowledge. Stated differently, data are something less than information and information is something less than knowledge. Moreover, it is assumed that data needs to exist before information can be created, and that knowledge can be created once information exists (Tuomi, 1999).

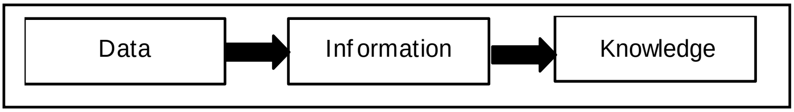
The hierarchy perspective of data, information, knowledge has also been discussed in the marketing literature, specifically in the literature on marketing information technologies and marketing analytics (Cao et al., 2019; Erevelles et al., 2016; Glazer, 1991a; Salojärvi et al., 2010; Wedel & Kannan, 2016). Table 2 summarizes the different perspectives on knowledge.

Table 2: 'Knowledge as an outcome' perspectives in the literature (adapted from Alavi & Leidner, 2001)

Perspective Knowledge as...	**Description of perspective**	**Reference(s)**
(1) An object	Knowledge is an entity that can be captured, stored, organized, manipulated and transmitted.	Balducci & Marinova (2018); Berger et al. (2019); Carlsson (2003); Fahey & Prusak (1998); Li & Calantone (1998); McQueen (1998)
(2) An application of expertise	Knowledge is the application of expertise; knowledge is knowing and acting.	McQueen (1998); Zack (1999)
(3) A condition of having access to information	Knowledge is a condition of accessing information.	McQueen (1998)
(4) A capability	Knowledge is the potential to influence future action.	Watson (1999)
(5) A state of mind	Knowledge is the state of understanding.	McQueen (1998)
(6) Hierarchical view of knowledge	Data are raw facts; information is processed data; knowledge is contextualized interpreted information.	Ackoff (1989); Cao, Duan, & Banna, (2019); Davenport, De Long, & Beers (1998); Davenport & Prusak (1998); Erevelles et al. (2016); Glazer (1991); Salojärvi, Sainio, & Tarkiainen (2010); Wedel & Kannan (2016); Zins (2007)

The perspective relied upon most in this thesis is the hierarchy view of knowledge (see Figure 3), which differentiates between data, information and knowledge: Data are raw facts; information is processed data while knowledge is information that has been interpreted and applied to a specific context. This view relates to other knowledge perspectives, mostly perspective (1) (knowledge as an object) and perspective (3) (knowledge as information access). The hierarchy perspective is widely accepted in the literature and has received substantial scholarly attention (Alavi & Leidner, 2001; Cao et al., 2019; Erevelles et al., 2016; Wedel & Kannan, 2016) as shown by this quote: "A great deal of emphasis is given to understanding the difference among data, information, and knowledge and drawing implications from the difference" (Alavi & Leidner, 2001, p. 110).

Figure 3: Hierarchy view of knowledge adopted in this thesis (adapted from Metaxiotis, Ergazakis, Samouilidis, & Psarras, 2003)



2.4 Market knowledge creation processes

Understanding market knowledge creation processes involves studying how knowledge (as an outcome) comes to be by transforming data into information and information into knowledge. To gain an understanding of how market knowledge is created, this section first defines market knowledge creation processes and clarifies the underlying constructs ‘data’, ‘information’ and ‘knowledge’. The discussion then turns to the processes, which includes the resources and activities to create market knowledge (Li & Calantone, 1998).

2.4.1 Data, information, knowledge

Market knowledge creation encompasses the processes by which market knowledge as an outcome is created. Processes include the resources and activities that transform data into information into knowledge (Davenport & Prusak, 1998; Li & Calantone, 1998; Ozkaya et al., 2015). In this section, the three underlying constructs of market knowledge creation – data, information, knowledge – are reviewed first, before discussing the resources and activities that transform data into information into knowledge.

Data

Data are representations for describing properties of objects or events (Ackoff, 1989) and can be symbols, numbers or other, non-numerical writing. Data are merely facts and do not have a meaning or utility per se

(Ackoff, 1989; Davenport & Prusak, 1998; Glazer, 1991; Salojärvi et al., 2010). For example, census takers collect data about a population of interest; marketers collect data about customer demographics.

In the marketing literature, data is classified based on the ease of adding structure to it to allow for quantitative analysis (Balducci & Marinova, 2018; Wedel & Kannan, 2016). According to this classification, data can be plotted along a continuum from 'highly structured' to 'highly unstructured' (Balducci & Marinova, 2018). Highly structured data is defined according to a pre-existing, numerical model, for example age, income, or sales transaction data. Structured data, while non-numerical but still well defined, can be converted into numbers with fairly little effort by the researcher. Survey data, such as satisfaction scores or likelihood to purchase, are examples of structured data that can fairly easily be converted into numbers.

Unstructured data is defined as data that "does not have a pre-defined data model or is not organized in a pre-defined way." (Balducci & Marinova, 2018, p. 557). Examples of unstructured data in marketing include user-generated content on social media (posts, comments, videos, photos), reviews or blog posts. Three characteristics describe unstructured data (Balducci & Marinova, 2018). First, unstructured data are non-numeric, i.e., they lack numeric representations for the constructs of interest. As a result, unstructured data do not lend themselves to quantitative analysis about a construct of interest per se; rather unstructured data require the researcher to manually or automatically code them into numerical values, prior to quantitative analysis.

Second, unstructured data is multi-faceted, enabling the researcher to analyze one or more facets depending on the research objectives (Balducci & Marinova, 2018; Berger et al., 2019). For instance, text data contain multiple facets, including words, syntax (sentence structure), semantics (relationships between words or symbols), and pragmatics (context of word use). One or more of these facets can be of interest to the researcher, for example to understand what was said or how it was said.

Third, unstructured data maintain concurrent representation, i.e., may represent multiple phenomena at the same time. For example, voice data may contain information about the sender's affective state or the persuasiveness of the message itself. Table 3 summarizes the three characteristics of highly unstructured in comparison to highly structured data (Balducci & Marinova, 2018).

Table 3: Characteristics of highly unstructured data and highly structured data (adapted from Balducci & Marinova, 2018)

Characteristic		Explanation
Highly unstructured data	**Highly structured data**	
Non-numeric	Numeric	*Highly unstructured data:* No pre-defined numeric representations of the construct(s) of interest. Quantitative analysis possible after researcher assigns numerical values (manually or automatically). *Highly structured data:* Pre-defined numerical representations of the construct(s) of interest, thus allowing for quantitative analysis.
Multi-faceted	Single-faceted	*Highly unstructured data*: Multiple facets, each enabling unique information. *Highly structured data*: Single-faceted, each enabling one, and only one piece of information.
Concurrent representation	Non-concurrent representation	*Highly unstructured data:* Due to being multi-faceted, different phenomena can be represented simultaneously. *Highly structured data*: Due to single-faceted nature, one phenomenon is represented at any point in time.

The last two decades saw an unprecedented growth in data (Marr, 2015b), and the term 'big data' was coined in 2005 (van Rijmenam, 2019). The majority of big data are (highly) unstructured (Rizkallah, 2017). Big data can be described in terms of five properties (Erevelles et al., 2016; Wedel & Kannan, 2016), often referred to as the "five V's" of big data: volume, velocity, variety, veracity, and value. Each of these five properties of big data is defined and explained below.

Volume

Volume refers to the sheer size of big data sets (Erevelles et al., 2016). In 2013, IBM estimated that 2.5 exabytes of data were being created daily (Jacobson, 2013); by 2020, the volume of big data is expected to have increased ten-fold compared to 2013 (IDC, 2014). A key contributor to this rapid growth in volume is the rise of the IoT (Erevelles et al., 2016; IDC, 2014; Robson et al., 2016), whereby devices are connected to the internet with the potential to share data with other devices connected to the internet (Osmonbekov & Johnston, 2018; Turunen et al., 2018). This, as well as the growth in social media (Kietzmann, Hermkens, McCarthy,

& Silvestre, 2011) and pervasiveness of mobile technology has led to an influx of structured data and to a rapid growth in unstructured data (Balducci & Marinova, 2018; Wedel & Kannan, 2016). The majority of the world's data volume is unstructured, with estimates suggesting that unstructured data compose between 80 to 95% of the data in existence today (Berger et al., 2019; Rizkallah, 2017). In addition, unstructured data are estimated to grow at a rate 15 times faster than structured data (Nair & Narayanan, 2012).

In addition to these external data sources, organizations have been collecting an increasing amount of data from internal sources, spurred by more sophisticated enterprise reporting systems or customer relationship management programs (Rothberg & Erickson, 2017).

<u>Velocity</u>

A second property by which to describe big data is velocity. It encompasses the speed at which data are created or travels (Erevelles et al., 2016). At the time of writing this thesis, every second, 75,000 Google searches were performed, 8,500 tweets and 2.8 million emails were sent globally (Internet Live Stats, 2019). Many types of data have a limited shelf-life where their value can erode in a short period of time. Thus, velocity also relates to the time required to process data, in addition to the time required to utilize data (Dykes, 2017; Erevelles et al., 2016).

<u>Variety</u>

Variety refers to the diversity of big data (Erevelles et al., 2016). In particular, and as explained above, unstructured data are multifaceted, offering multiple ways for interpretation (Balducci & Marinova, 2018). For example, voice data contain many facets, such as speed of speech, intonation, pitch, in addition to the syntax (i.e., the structure of a sentence), semantics (i.e., the relationships between words, phrases and sentences) and pragmatics (i.e., the context in which words or phrases are used). Each of these facets can convey unique information about the speaker or the message, such as affective state, persuasiveness, or behavioural information.

<u>Veracity</u>

Veracity refers to the degree to which data is accurate, precise and reliable (Erevelles et al., 2016). The veracity property of big data underscores the need to be aware of their quality. Big data is often viewed as certain and trustworthy, partially due to its volume (the more, the better), however, estimates suggest that up to 80% of big data can be uncertain in terms of their quality (Puget, 2015). This uncertainty can come from a variety of sources, such as measurement error in the case of sensor data, or lacking credential in the case of social media sourced data.

Value

The increasing volume, variety and veracity of big data have raised the question of the value of big data and value is the fifth characteristic to describe big data. Value refers to big data's ability to be useful in deriving information and knowledge and context-specific interpretation (Erevelles et al., 2016), with some arguing that value is the most important property of big data (Marr, 2015).

Information

When data is processed, so that it becomes organized and useful, it becomes information (Ackoff, 1989; Davenport & Prusak, 1998; Glazer, 1991; Salojärvi et al., 2010). As Glazer (1991, p. 2) notes “"Information" can be defined as data that have been organized or given structure”. The processing of data into information refers to the organization of a set of otherwise independent symbols or numbers into a pattern that corresponds to an external reference system. For instance, census data may be processed to determine the socio-demographic profile of a city or town. Marketers may process customer demographics and sales transaction data to determine which customer segments purchased which products and how these purchases change over time.

Like data, information also describes the characteristics of objects or events, but it does so in a useful way (Ackoff, 1989). While data and information are identical in terms of their structure, the key difference between the two lies in their functional nature. For example, a firm may track visits to their website and collect data related to website visits. When these data points are processed, an organization could derive information about how visits to its website change over time and establish a trend.

Knowledge

Conceptualizations of knowledge differ in the extant literature. The definition adopted in this thesis defines knowledge as “information that has been combined with experience, context, interpretation, and reflection” (Davenport, De Long, & Beers, 1998 p. 43). In their highly cited article, Alavi and Leidner (2001) define knowledge as “personalized information … related to facts, procedures, concepts, interpretations, ideas, observations, and judgements” (Alavi & Leidner, 2001, p. 109). In another widely cited work in the *Journal of Marketing*, De Luca and Atuahene-Gima (2007) posit that “information about the market environment, particularly about customers and competitors, is the source of stimulation for the firm’s knowledge … This implies that a firm that correctly identifies, collects, and uses information about customer and competitor conditions is deemed to be knowledgeable about the market.” (De Luca & Atuahene-Gima, 2007, p. 97).

The work by Davenport and colleagues (1998) view knowledge as originating from and applied in the minds of individuals (Davenport et al., 1998; Davenport & Prusak, 1998). “Knowledge is a fluid mix of framed experience, values, contextual information, and expert insight that provides a framework for evaluating and incorporating new experiences and information.” (Davenport & Prusak, 1998, p. 4).

Despite the differences, there exist commonalities in these definitions. First, all definitions emphasize that knowledge results from processing information, which, in turn, results from processing of data. Second, knowledge is the meaning given to information, and is context-specific. Stated differently, knowledge is the result of processing of information based on an individual’s experience, expertise or skills and within a specific context (Alavi & Leidner, 2001).

2.4.2 Activities and resources

The processes to turn data into information into knowledge have received substantial consideration in the scholarly literature (Berger et al., 2019; Davenport et al., 1998; Deshpandé, 2001; Shaw et al., 2001; Wedel & Kannan, 2016). Processes include the activities and resources that transform data into information into knowledge; in other words, market knowledge as an outcome results from the processes (Erevelles et al., 2016; Kozlenkova et al., 2014).

2.4.2.1 Activities

Activities encompass *what* marketers do to create knowledge from information and data (Li & Calantone, 1998; Ozkaya et al., 2015). In the literature, activities for creating market knowledge have been described as collecting, analysing and interpreting data or information (Erevelles et al., 2016; Wedel & Kannan, 2016). Collecting data encompasses the acquisition of data from internal or external sources (Bordeleau et al., 2018), such as customer-relationship management, e-commerce, or point-of-sale systems. In addition, marketers acquire data from external sources, for example, through surveys, social media, or other sources. Collection also includes storing data, i.e., loading data into a database, often a data warehouse, for further analysis (Bordeleau et al., 2018).

Analysing data encompasses categorizing data, and performing calculations, typically with the help of statistical methods (Davenport & Prusak, 1998; Wedel & Kannan, 2016). These analyses transform data into information by giving data meaning or purpose (Davenport & Prusak, 1998). Data analysis can be descriptive, diagnostic, predictive, or prescriptive (Wedel & Kannan, 2016). Descriptive analyses perform statistical calculations on data to understand what happened, for example to describe a decrease in sales performance over a specific time.

Diagnostic analyses help transform data into information by 'digging deeper' and analyzing why certain trends happened, using data exploration and correlation analyses. For example, using diagnostic analyses, marketers may determine that the decline in sales may be strongly correlated with one customer segment in one specific geographical region and with a competitor's increased advertising spend in that region. Predictive analysis employs historical data to predict future performance, and prescriptive analysis provides recommendations to marketers on what to do next. In the above example, predictive analysis may forecast that the decline in sales trend may continue based on the focal firm's current advertising efforts, while prescriptive analyses may suggest changes to the focal firm's advertising strategy and tactics to reverse the downward trend. Through any of these analyses, data is transformed into information by assigning meaning and purpose to data.

Analysing also includes presenting the information, for example in reports, alerts, dashboards or interactive visual displays (Bordeleau et al., 2018).

Market knowledge is created by interpreting information within a specific context and combining information with expertise, previous knowledge and background (Davenport et al., 1998). Using the above example, a marketing decision maker may interpret the information about the sales decrease based on his business expertise, for instance, regarding effectiveness of different advertising strategies, budget availability, upcoming product launches or others.

2.4.2.2 Resources

The literature has given substantial attention to the role of different resources in creating market knowledge (Chuang, 2004; Erevelles et al., 2016; Fink et al., 2017; Kozlenkova et al., 2014). A number of studies have used resource-based view (Barney, 1991; Wernerfelt, 1984) and the resultant resource-based theory (RBT) (Kozlenkova et al., 2014) to explain knowledge creation processes and outcomes (Kozlenkova et al., 2014). RBT posits that a firm's resources can facilitate superior firm performance and a competitive advantage (Erevelles et al., 2016). Specifically, RBT posits resource heterogeneity across firms and suggests that resources that are valuable, rare, in-imitable and organized can yield a sustained competitive advantage (Barney, 1991). The current section first defines the key terms before discussing the logic and assumptions underlying RBT. Following this is a discussion on how RBT has been applied for market knowledge creation with a particular focus on information technology and human resources.

Key terms in resource-based theory

Assets and capabilities are key constructs in RBT (Barney, 1991). Resources are generally categorized as assets, i.e., something of value to an organization and can be tangible or intangible. "Resources are the tangible and intangible assets firms use to conceive of and implement their strategies." (Barney & Arikan, 2001, p. 138). Assets can be inputs into a process, or the outputs of a process, and can be classified into physical, human, and organizational assets (i.e., resources) (Barney, 1991). Physical resources include equipment, financial capital, buildings, or information technologies, such as software or hardware infrastructure to collect, analyze, and interpret data and information. Human capital resources concern the people component of resources (Barney, 1991) and include their knowledge and skills to capture data and extract information along with their judgement, expertise, and experience to interpret the information. Organizational resources relate to the configuration of a firm in various parts and may include formal reporting relationships as well as informal interdepartmental relationships (Barney, 1991).

Capabilities are a subset of an organizations resources that improve the productivity of other resources (Kozlenkova et al., 2014; Srivastava et al., 2001). Capabilities are assortments of assets that are integrated (Grant, 1991; Kozlenkova et al., 2014). Capabilities encompass resources that can be used to modify assets. Capabilities are viewed as the primary source of value and are often viewed as a converter of resources/assets into a competitive advantage (Kozlenkova et al., 2014). “They are generally information-based, tangible or intangible processes that enable a firm to deploy its other resources more efficiently and therefore enhance the productivity of those resources.” (Kozlenkova et al., 2014, p. 5). Thus, a firm’s capabilities encompass its ability to utilize valuable assets that complement each other.

Logic and assumptions in resource-based theory

RBT posits that resources are the key to understanding firm performance (Barney, 1991; Wernerfelt, 1984). The work by Penrose (1959) can be viewed as an early contribution to what became later knows as RBT. Wernerfelt’s (1984) contribution is widely seen as the first major contribution to RBT (Barney & Arikan, 2001; Kozlenkova et al., 2014) which was subsequently developed further by Barney (1991) and other scholars (Kozlenkova et al., 2014). Wernerfelt (1984) argues that the key to understanding how firms achieve a competitive advantage is not by viewing firms based on their outputs, as was the perspective at the time (Darroch & McNaughton, 2002), but rather by viewing firms based on their resources. Wernerfelt (1984) conceptualizes resources as tangible and intangible assets that can be considered a strength or a weakness of a firm, including, for example, brand names, human capital, machinery, or knowledge, among others.

The work of Barney (1991) demarcates a critical point in the further development of RBT (Kozlenkova et al., 2014). Barney (1991) explains that tangible and intangible resources may yield a sustained competitive advantage and identifies characteristics of such resources. Specifically, resources that are valuable, rare, imperfectly imitable, and non-substitutable can facilitate an organization's performance and may yield a sustained competitive advantage (Barney, 1991). A 'valuable' resource improves an organization's effectiveness or efficiency, for instance when the resource generates something of value to customers or by improving an organization's profitability (Barney, 1991). A 'rare' resource is one that is not abundant, i.e., is not possessed by a large number of competitors (Barney, 1991).

These two criteria, valuable and rare, are necessary but not sufficient for a sustained competitive advantage (Kozlenkova et al., 2014). In other words, these two criteria alone may generate a competitive advantage, but do not generate a sustained competitive advantage. Sustainability of a competitive advantage only occurs if a resource cannot easily be copied (the 'imperfectly imitability' characteristic of a resource) (Barney, 1991). If a resource is valuable and rare but easy to imitate, then exploiting it will result in a temporary competitive advantage for the firm. Once competing firms obtain or substitute and exploit this resource, any competitive advantage dissipates (Kozlenkova et al., 2014). Thus, a resource must be simultaneously valuable, rare, and imperfectly imitable.

In his original work, Barney (1991) outlined a fourth criterion of a resource that may generate a sustained competitive advantage: 'non-substitutability' of the resource, i.e., rivals cannot substitute the resource (Barney, 1991). Hence, the criteria of RBT resources were originally described via the VRIN (valuable, rare, imperfectly imitable and non-substitutable) framework (Erevelles et al., 2016; Kozlenkova et al., 2014).

The contemporary view of RBT subsumes the 'non-substitutability' criteria under the 'imperfectly imitable' criteria and proposes a different fourth condition. This fourth condition pertains to the organizational processes and procedures to exploit the resource (commonly referred to as the 'organization' criteria) (Kozlenkova et al., 2014). Thus, a resource must be valuable, rare, imperfectly imitable and a firm must organize to exploit the competitive potential of the resource. More updated discussions of RBT refer therefore to the VRIO (valuable, rare, imperfectly imitable and organization) framework to describe RBT resources.

The refinement of RBT with the addition of the organization criteria has also addressed one point of criticism toward RBT (Kozlenkova et al., 2014). Specifically, critiques had claimed that the theory is static and does not address the impact of organizational actions (Kozlenkova et al., 2014; Srivastava et al., 2001). "Even RBV's most vociferous proponents admit to the relative inattention in the RBV literature to unraveling the black-box by which resources are converted into something of value to external stakeholders." (Srivastava et al., 2001, p. 782). The VRIO framework – versus the VRIN framework – acknowledges the importance for organizations to effectively manage the resources, as opposed to simply possessing or controlling them (Kozlenkova et al., 2014). Table 4 summarizes key RBT terminology and assumptions.

Table 4: Key terms and assumptions in resource-based theory (adapted from Kozlenkova et al., 2014)

Term	Explanation	Reference(s)
Resources	“Tangible and intangible assets firms use to conceive of and implement its strategies.”	Barney & Arikan (2001, p. 138)
Capabilities	A subset of an organizations resources and encompass resources that improve the productivity of other resources.	Kozlenkova et al. (2014); Penrose (1959)
VRIN framework	Depicts four criteria to analyse resources with respect to their potential to generate a competitive advantage. Stands for value, rarity, imperfect imitability and non-substitutability.	Barney (1991)
VRIO framework	Depicts four criteria to analyse resources with respect to their potential to generate a competitive advantage. Resulted from refinement of VRIN framework. Stands for value, rarity, imperfect imitability and organization.	Kozlenkova et al. (2014)
Valuable resource	Enables a firm to improve its efficiency or effectiveness.	Barney (1991)
Rare resource	Non-abundant, i.e., resource that is not possessed by a large number of current or potential competitors.	Barney (1991)
Imperfectly imitable resource	Cannot easily be copied by other firms.	Barney (1991)
Non-substitutable resource	Cannot easily be substituted for by other firms.	Barney (1991)
Organization	Processes and procedures to exploit the potential of valuable, rare and imperfectly-imitable resources.	Kozlenkova et al. (2014)
Competitive advantage	Value creation strategy by a firm that is not simultaneously implemented by other firms.	Barney (1991)
Sustained competitive advantage	Value creation strategy by a firm that is not simultaneously implemented by other firms and these other firms are unable to duplicate the value creation strategy by the focal firm.	Barney (1991)

This thesis focuses on physical resources, specifically, information technologies, and human resources in creating market knowledge from big data. Information technologies have received substantial attention in the literature with respect to knowledge creation, however, currently there is a gap in our understanding on AI as an information technology for knowledge creation (Berger et al., 2019; Duan et al., 2019; Kietzmann et al., 2018; Singh et al., 2019; Syam & Sharma, 2018). As a result, and as will be explained in the following section, scholars are calling for more research on AI and market knowledge creation.

Moreover, the relevance of human resources to knowledge creation has been acknowledged in the literature, and scholars are calling for more research to jointly investigate human and information technology resources (Duan et al., 2019; Lane et al., 2006; Metaxiotis et al., 2003; Singh et al., 2019; Syam & Sharma, 2018). The following sections will discuss the current literature on human and information technology resources for market knowledge creation. Following this, a discussion of the literature on AI and human resources for market knowledge creation is provided, from which the research gap addressed in this thesis will be identified.

2.4.3 Human resources and market knowledge creation

Human resources consider people's expertise and skills, in addition to their experience and judgement (Barney, 1991). The relevance of human resources for knowledge creation has been widely discussed in the literature. As discussed earlier, knowledge results from the processing of information by individuals (Davenport & Prusak, 1998; Fowler, 2000). The ability of humans to assign meaning to information, based on their experiences and talents, make humans instrumental in creating knowledge. People are simultaneously the creators and consumers of knowledge because individuals consume knowledge from various sources on a constant basis, in addition to creating knowledge through their cognitive processing, writing, speech, or other output (Fowler, 2000).

The literature provides evidence of the relevance of human resources for market knowledge creation. For instance, using an inductive, grounded theory research design, the study by Verona and Ravasi (2003) found that employees' skills and expertise positively impact knowledge creation, integration, and reconfiguration. Menguc et al. (2013) investigate leadership style and its impact on knowledge creation. The empirical results from their survey provides support that managements' empowering leadership positively impacts sales teams' customer knowledge creation capability.

Lane et al. (2006) emphasize the role of human resources for knowledge creation. Based on the results from a literature review of 289 articles published in fourteen highly ranked journals, the authors posit that the unique and valuable ways in which humans interpret information, combine and apply knowledge is key to realizing knowledge's positive performance impact. "But what creates competitive advantage out of knowledge is the unique and valuable ways in which it is combined and applied. This uniqueness arises from the personal knowledge and mental models of the individuals within the firm, who scan the knowledge environment, bring the knowledge into the firm, and exploit the knowledge in products, processes, and services." (Lane et al., 2006, p. 854).

Other researchers echo the importance of human resources, particularly in terms of identifying what specific knowledge is needed for marketing decision making (Berger et al., 2019; Lane et al., 2006), in terms of utilizing the underlying IT systems, interpreting information for a specific business context and creating relevant knowledge from data and information (Rothberg & Erickson, 2017).

2.4.4 Information technology resources and market knowledge creation

The value of information technology resources for market knowledge creation processes and outcomes has been demonstrated widely in the literature (Alavi & Leidner, 2001; Erevelles et al., 2016; Wade & Hulland, 2004; Wedel & Kannan, 2016; Wieneke & Lehrer, 2016). Information technologies have been considered as important enablers of knowledge creation processes (Alavi & Leidner, 2001; Erevelles et al., 2016; Fowler, 2000; Nguyen et al., 2019; Wedel & Kannan, 2016), as illustrated in the following quote "Technology holds a pivotal position both as a domain for knowledge possession and creation and as a possible contributor to the knowledge proliferation and management processes... Hence, although the primacy of the human resource, as the originator and developer of knowledge, is firmly established in the KM [knowledge management] canon..., it is also necessary to contemplate the role and interaction of technology" (Fowler, 2000, p. 109).

Similarly, Alavi and Leidner (2001) stress the importance of knowledge and a firm's "ability to effectively apply the existing knowledge to create new knowledge and to take action that forms the basis for achieving competitive advantage from knowledge-based assets. It is here that information technologies may play an important role... Advanced information technologies (e.g., the Internet, intranets, extranets, browsers, data warehouses, data mining techniques, and software agents) can be used to systematize, enhance, and expedite large-scale intra- and inter-firm knowledge management." (Alavi & Leidner, 2001, p. 108).

In summary, information technology has large potential to improve the creation of market knowledge by supporting the collection, analysis and interpretation of data and information. Previous research suggests that information technology can impact knowledge creation from the deployment of IT-based resources, such as data mining, marketing analytics and more broader business intelligence applications (Berger et al., 2019; Erevelles et al., 2016; Tirunillai & Tellis, 2014; Wedel & Kannan, 2016; Wei & Wang, 2011; Wieneke & Lehrer, 2016). Table 5 provides an overview of information technologies and how they support the creation of market knowledge.

Table 5: Information technologies and market knowledge creation processes (adapted from Alavi & Leidner, 2001; Antonova, Gourova, & Nikolov, 2006)

Information technology	Explanation	Supports market knowledge creation activity	Reference(s)
Data mining	Exploration and analysis of large data volumes to discover patterns and relationships; primarily descriptive, diagnostic and predictive.	Collecting, analysing	Berry & Linoff (2004)
Expert system	Captures human expertise in specific domains of knowledge, usually in a set of "if / then" rules.	Collecting, analysing, interpreting	Alavi & Leidner (2001)
Database	Organizes and centrally stores data to efficiently serve many applications (e.g., business intelligence, reporting, etc.).	Collecting	Alavi & Leidner (2001)
Decision support system	Utilizes data and models to solve unstructured problems; often allows for "what if" analyses, i.e., assessing the sensitivity of marketing decisions relative to the assumptions in the input data and information.	Collecting, analyzing, interpreting	Noori & Hossein Salimi (2005)

2.5 Market knowledge creation from big data using artificial intelligence

The volume, variety, and velocity of big data offers potential for marketers to create valuable knowledge about customers, competitors, or other market stakeholders (Balducci & Marinova, 2018; Berger et al., 2019; Kietzmann et al., 2018; Wedel & Kannan, 2016). In particular, the literature suggests that unstructured data offers great potential for creating market knowledge (Balducci & Marinova, 2018; Berger et al., 2019; Erevelles et al., 2016; Wedel & Kannan, 2016). Balducci and Marinova (2018), for instance suggest that unstructured big data can enable managers and researchers to conduct analyses of different phenomena simultaneously. In addition, unstructured data allows for more flexibility for theoretical discovery for scholars, and rich and deep knowledge for insight creation and managerial decision making.

While many scholars agree on the potential value of unstructured data for market knowledge, there are also some challenges. First, given the sheer volume and variety of data from a variety of sources, there exist challenges in identifying the more important data for knowledge creation and managerial decision making (Rothberg & Erickson, 2017). In addition, many marketing practitioners acknowledge the value potential of big data, but suggest data is underutilized, noting challenges to derive value from unstructured data from different sources (Balducci & Marinova, 2018). One reason for these challenges may be that traditional information technologies were primarily designed to collect, store and analyse structured data. However, these technologies are ill-equipped to deal with the unique characteristics of unstructured data outlined earlier in this chapter (Duan et al., 2019; Syam & Sharma, 2018).

In recent years, AI has been discussed as an information technology that can deal with the volume, variety, velocity, and veracity of unstructured data and can support the creation of market knowledge (Berger et al., 2019; Duan et al., 2019; Fowler, 2000; Kietzmann et al., 2018, 2018; Metaxiotis et al., 2003; Moreira Nascimento et al., 2018; Wedel & Kannan, 2016). This is discussed in the following two sections of the literature review. The next section conceptualizes AI while the ensuing section reviews the literature on AI and knowledge creation.

2.5.1 Defining artificial intelligence

In the human context, the literature considers intelligence as a person's ability to learn, to deal with new situations, to understand and handle abstract concepts, and to adapt to one's environment (Huang & Rust, 2018; Legg & Hutter, 2007; Sternberg, 2017). Gardner (1993) views intelligence as a person's ability to process information to achieve goals. Stated differently, intelligence is defined as a person's ability to perceive data from their environment, process it to develop information and ultimately knowledge, and use this knowledge towards goal-directed behavior. Psychologists suggest that intelligence draws upon a number of processes, including perception, problem solving, reasoning, learning, memory, and goal-directed decision making (Humphreys, 1979). The literature discusses AI as 'machine intelligence' that mimics the above described human intelligence, such as the ability of computers to perceive, reason, problem solve, learn, adapt, and act (Huang & Rust, 2018).

Extant conceptualizations in the literature view AI as "computational agents that act intelligently" (Poole & Mackworth, 2010, p. 3). In this definition, the notion of computers acting intelligently refers to acting rationally (Huang & Rust, 2018; Russell & Norvig, 2016). This view suggests that the performance of AI is not measured in terms of conformity to human intelligence (Russell & Norvig, 2016). Rather, AI is intelligent, i.e., rational, if it does the "right thing", given what it knows. Stated differently, AI acts to achieve the best expected outcome. Human behaviour, on the other hand, may not always be achieving the best expected outcome, due to being influenced by intuition and emotions, and due to peoples' limited processing capability for data and information.

The second key element in the notion of AI is 'computational agent'. An agent perceives its environment, processes its perceptions from the environment, and acts upon the environment based on the goals it is designed to achieve (Russell & Norvig, 2016). Human agents perceive through their eyes, ears, and other organs, process via various cognitive processes, and act using their hands, legs, or voice. Computer agents use sensors, such as cameras or keystrokes to perceive inputs, use algorithms to process the inputs and act by writing files, moving objects, or displaying output on a screen. Thus, considering the notion of

computational agents, this suggests that AI acts intelligently in practice as opposed to only in principle (Russell & Norvig, 2016; Tecuci, 2012).
In summary, intelligence encompasses an ability to perceive data, process it to develop information and ultimately knowledge, and use this knowledge towards goal-directed behavior in rational ways. Following these conceptualizations in the literature, AI in this research is defined as information technologies that receive or perceive data inputs, process these data, return information as outputs and act to achieve the best expected outcome (Russell & Norvig, 2016).

Artificial intelligence in this thesis describes "narrow" AI, i.e., AI information technology that is optimized for a given task. On the other hand, "strong" AI, also known as "artificial generalized intelligence", includes AI technology that is capable of solving any intellectual task, much like a person, does currently not exist and is excluded from the discussion.

2.5.2 Market knowledge and artificial intelligence

Artificial intelligence has seen substantial growth in scholarly interest in the last decade, particularly in the management discipline (Duan et al., 2019; Moreira Nascimento et al., 2018), including knowledge management (Fowler, 2000; Metaxiotis et al., 2003) and in marketing (Huang & Rust, 2018; Martínez-López & Casillas, 2013; Wirth, 2018). A number of scholars have empirically investigated the use of AI for knowledge creation processes, by studying how AI can analyze large and complex datasets and convert these data into information which can then be used for subsequent statistical analyses.

For instance, Tirunillai and Tellis (2014) demonstrate the use of AI to extract quality information from a large dataset of user-generated brand reviews. The results from this analysis are subsequently used for deriving perceptual maps of the brands. In an empirical study conducted by Liu (2019), the author demonstrates the use of AI to transform unstructured big data into structured information. Specifically, using machine learning and natural language understanding algorithms, AI is capable of extracting sentiment values contained in 84 million tweets from more than 20 million Twitter accounts. Through subsequent statistical

analyses, the study determines the impact of sentiment on stock performance for more than 400 companies.
A case study by Pee, Pan and Chui (2019) explores the use of AI in knowledge work, using healthcare service as their empirical context. They conclude that AI plays four, mutually non-exclusive roles in knowledge management: (i) expediting, i.e., automating human tasks; (ii) equipping, i.e., assisting human efforts; (iii) emancipation, i.e., enacting human cognition; and (iv) expansion, i.e., augmenting human cognition (Pee et al., 2019).

Fowler (2000), using empirical data from a case study, proposes a five-stage knowledge activity cycle and illustrates the potential and limitations of AI in terms of its capabilities to support knowledge activities. The author suggests that AI serves as a facilitator of human processes in knowledge generation (Fowler, 2000). Artificial intelligence provides a mechanism to support and enable knowledge creation processes through creating means to capture and transmit data and information effectively and quickly. In addition, AI is capable of processing and analyzing data and producing higher-order information. As such, it contributes to the development of knowledge. However, AI does not substitute or replace human interaction in knowledge creation.

Other scholarly research has studied AI and its impact on knowledge creation processes conceptually. Metaxiotis et al. (2003) suggest that AI can improve knowledge management effectiveness and efficiency through supporting knowledge generation and knowledge application. The authors assert that AI can play a strong supporting role in knowledge creation processes and call for more research on this topic, as illustrated by this quote: “It is our belief that there is still a need for deeper understanding of the use of AI in decision support through knowledge management.” (Metaxiotis et al., 2003, p. 220).

Von Krogh (2018) conceptually explores the potential of AI for managerial decision making and problem solving, both tasks relying on knowledge. Here, AI’s potential lies in processing large, complex datasets, sorting and classifying or de-duplicating data. In addition, AI can help in predicting consumer behaviour variables in marketing, for example, the likelihood that a prospect may convert into a lead. However, AI cannot offer an explanation or justification for the proposed solution, nor creatively put previous experience to use for solving novel problems (Von Krogh, 2018).

Among these conceptual articles, a number of scholars have explored AI and its relationship to and impact on human resources. For instance, Huang and Rust (2018) examine AI in service and propose that AI will and already is replacing lower intelligence service tasks, such as mechanical and analytical tasks. The authors contend that AI will eventually progress to performing higher intelligence tasks, such as tasks requiring empathy and intuition. This progression of AI shifts the relative importance of the different intelligences for service employees over time.

In their study, Jarrahi (2018) conceptually explores the complementarity of humans and AI in the context of organizational decision making and posit that AI capabilities outperform those of humans in data analysis and information processing. Humans, on the other hand, have an upper hand when it comes to evaluating matters where past experience, insight, and a holistic perspective are needed. Both are essential activities to knowledge creation processes (Davenport et al., 1998). Jarrahi (2018, p. 8) calls for a "human-AI collaboration" suggesting that each, AI and human resources, are important for knowledge creation. Lichtenthaler (2019) proposes a framework integrating human contributions and AI and suggests that the application of both intelligence types can yield successful marketing outcomes and can result in a firm's competitive advantage.

With regard to knowledge creation in marketing specifically, Syam and Sharma (2018) conceptually explore AI and its implications for the sales process and conclude that AI will profoundly impact the sales process through advanced information access and application. Singh et al. (2019) conceptually discuss AI in sales and conclude that AI enables the generation and updating of sales knowledge by harnessing the information held in complex data sets. Table 6 displays illustrative studies from the literature along with key findings.

Table 6: Literature on knowledge creation, artificial intelligence and human resources

Reference	Article type	Key finding(s)
Fowler (2000)	Empirical	AI enables knowledge creation processes through capturing data and converting data into information effectively and efficiently. AI does not substitute for human processes in knowledge creation.
Metaxiotis et al. (2003)	Conceptual	AI supports knowledge creation processes, e.g., by codifying existing knowledge in a knowledge base, processing data, and combining existing knowledge to generate new knowledge.
Tirunillai & Tellis (2014)	Empirical	AI can analyze user-generated data and extract information on product quality dimensions from these data. The results are used for subsequent statistical analyses, particularly brand positioning.
Huang & Rust (2018)	Conceptual	AI will replace lower intelligence service tasks, such as mechanical and analytical tasks first, and will eventually progress to performing higher intelligence tasks, such as tasks requiring empathy and intuition. This progression changes the relative importance of different intelligences for employees.
Jarrahi (2018)	Conceptual	AI enables the processing and analyzing of large datasets which supports knowledge creation through extending humans' cognition when addressing complexity. Humans offer a more holistic, intuitive approach in dealing with uncertainty and equivocality.
Syam & Sharma (2018)	Conceptual	AI is transforming the B2B sales process through advanced information access and application.
Von Krogh (2019)	Conceptual	AI effectively processes large, complex datasets, by sorting, classifying or de-duplicating data and transforming data into information. AI cannot offer an explanation or justification for its outputs and has limited potential for solving novel problems.
Lichtenthaler (2019)	Conceptual	The combination of human intelligence and AI may provide an important basis for competitive advantage. In order to create a sustained competitive advantage, firms need to develop meta-intelligence, i.e., intelligence for dynamically transforming human intelligence and AI in alignment with firm strategies.
Liu (2019)	Empirical	AI applications are able to analyze large unstructured datasets from user-generated content and predict the impact of user-generated content on firms' stock performance. The study demonstrates step-by-step guidelines on how to use different AI applications to process and transform unstructured big data into information for subsequent statistical analyses.
Pee et al. (2019)	Empirical	AI plays four roles in knowledge creation processes: (i) expediting, i.e., automating human work; (ii) equipping, i.e., assisting human efforts; (iii) emancipation, i.e., enacting human cognition; and (iv) expansion, i.e., augmenting human cognition.
Singh et al. (2019)	Conceptual	AI enables the generation and updating of sales knowledge by harnessing the information held in complex data sets.

2.6 Research gap identification

Moreira Nascimento et al. (2018) perform a systematic literature review on the topic of AI in management published between 1984 and 2017 in eight high-ranked journals. The authors conclude that half of the extant research has examined AI in the context of information systems and that research on AI in marketing were considerably less prevalent (Moreira Nascimento et al., 2018). They conclude that research "has only been scratching the surface of the potential outcomes and impacts of AI techniques in business management. In other words, it appears that these subfields and techniques have not been researched and reported to the extent of their rising importance to management" (Moreira Nascimento et al., 2018, p. 7).

A literature review by Duan et al. (2019) echoes the view of Moreira Nascimento et al. (2018) that much of the existing research has focused on technical aspects of AI. Duan et al. (2019) argue that one of the most important applications in AI's history has been its use for human decision making, including for tasks that traditionally were relying heavily on human resources. "As the progress of AI technology enables researchers to create advanced machines, it is possible for AI to undertake more complex tasks that require cognitive capabilities such as making tacit judgements, sensing emotion and driving processes which previously seemed impossible." (Duan et al., 2019, p. 67). The authors conclude that much is left to be understood about the interaction of AI with human decision making and call for rigorous empirical work to address the extant research gaps. Duan et al. (2019) offer 12 research propositions to advance scholarly understanding about AI; among these propositions, inquiries to advance the body of knowledge on the topic of AI-human interaction featured strongly across their propositions (see Table 7). Specifically, of the 12 propositions outlined by Duan et al. (2019), seven are related to AI and human decision making and the relationships between AI and human resources.

Table 7: Research propositions suggested by Duan et al. (2019)

Theoretical development	AI-human interaction	AI applications
Proposition 1 – Defining AI can be difficult, so it is necessary and beneficial to re-define the concept of AI and related terms to reflect the changing nature of AI development and applications in the era of Big Data.	Proposition 4 – AI can play multiple roles in decision making, but AI will be mostly accepted by human decision makers as a decision support/augmentation tool rather than as the automation of decision making to replace them.	Proposition 8 – There are a set of critical factors that will significantly affect AI's success for decision making.
Proposition 2 – Measuring the benefit of AI and its impact is very difficult, but possible. Therefore, there is a need to develop and test theoretically sound and practically feasible AI impact indicators to measure its benefits.	Proposition 5 – The ergonomic design of AI systems is important for their success, but the ergonomic issues are different between supporting, augmenting, replacing, or automating systems.	Proposition 9 –There is a necessity to fully understand the synergy of AI and Big Data and its implications for AI research and practice.
Proposition 3 – It is necessary to theorise the use of AI and its impact on decision making, therefore an integrated conceptual framework is needed to provide a systematic understanding of AI for decision making.	Proposition 6 – AI systems performance for decision making can be refined and improved by deep learning while the systems are in use by decision makers.	Proposition 10 – The acceptance of AI for decision making can be affected by different cultures and personal values.
	Proposition 7 – AI users' personal traits and knowledge and understanding of AI will significantly affect the use and success of AI.	Proposition 11 – The acceptance and successful application of AI for decision making may result in a change of culture in organisations and in individual behaviour.
		Proposition 12 – Government plays a critical role in safeguarding the impact of AI on society.

Other scholars have also emphasized a call for research to advance the body of knowledge on the relationship between AI and human resources (Jarrahi, 2018; Kaplan & Haenlein, 2019; Lichtenthaler, 2019; Wirtz et al., 2018), particularly for knowledge creation (Fowler, 2000; Huang & Rust, 2018; Metaxiotis et al., 2003; Pee et al., 2019). Jarrahi (2018) suggests that "with the resurgence of AI, a new human-machine symbiosis is on the horizon and a question remains: How can humans and new artificial intelligences be complementary in organizational decision making?" (Jarrahi, 2018, p. 579). Lichtenthaler (2019) emphasizes the need for scholarly research to empirically investigate the interplay of AI with various types of human intelligence.

In the marketing literature, the topic of human-AI interaction also features strongly across scholarly calls for research (Daskou & Mangina, 2003; Davenport et al., 2019; Jörling et al, 2019; Huang & Rust, 2018; Singh et al., 2019; Syam & Sharma, 2018; Wirth, 2018; Wirtz et al., 2019). Huang and Rust (2018), for instance, suggest that future research topics include an investigation of what tasks require what composition of intelligences - human or AI - and what tasks require the combination of these (Huang & Rust, 2018). Wirtz et al. (2018) explore the role of robots in service delivery and provide an understanding of the types of service tasks dominated by robots, where humans will prevail and areas where humans and robots will be likely to collaborate. Martínez-López and Casillas (2013) perform a literature survey of the topic of AI in the journal *Industrial Marketing Management* and conclude that this "research theme has received scarce attention in journals that primarily deal with business and management issues" (Martínez-López & Casillas, 2013, p. 489).

Singh et al. (2019) identify research priorities that would benefit from further exploration. These research priorities are organized into three research problem areas: (1) organizational issues motivated by AI, i.e., the changing nature of the sales function and the structure of the sales organization; (2) individual issues, i.e., the changing role of the individual sales professional triggered by AI; and (3) value creation issues, i.e., the changing nature of value creation motivated by AI (Singh et al., 2019). Research questions related to knowledge and the relationship between human resources and AI feature strongly across all three areas identified in this work (see Table 8).

The work by Syam and Sharma (2018) suggests a number of avenues for research; future research investigating the role of AI and human contributions for knowledge creation are emphasized as a research priority (Syam & Sharma, 2018).

Table 8: Research priorities on AI and knowledge in sales (adapted from Singh et al. (2019)

Research problem area	Illustrative research questions
(1) AI and knowledge – individual issues	What are the effects of AI on salesperson's knowledge and performance?
	How will salespeople react to the codification of their tacit knowledge enabled by AI?
	How can AI support knowledge transfer among salespeople in the same organization?
(2) AI and knowledge - organizational issues	How will knowledge be created and utilized in the changing environment?
	How can companies capture market knowledge that resides with customers or channel partners or is embedded in networks?
	How can technology and AI be leveraged to develop market sensing capabilities?
	How can technology and AI be used to facilitate the conversion of local knowledge to collective knowledge within an organization?
	What are the benefits and downsides of sales function owning and controlling knowledge within the network of intra-organizational entities that are involved in the sales process?
(3) AI and knowledge - value creation issues	How will AI change the knowledge and learning processes in the value creation process?
	How effectively can AI process tacit and explicit knowledge?
	How can AI facilitate customerr knowledge at each stage of the marketing and sales process?
	How can AI facilitate external market knowledge, for example, when the external environment undergoes dynamic, rapid and unforeseen change?
	How can AI help capture market knowledge that resides outside of the organization (e.g., with customers, with channel partners, in networks)?
	How can AI be leveraged to develop market sensing capabilities?

In addition, recent publications in the *Journal of Marketing* and the *Journal of the Academy of Marketing Science* call for more research on AI and market knowledge creation (see Table 9). Balducci and Marinova (2018), Davenport et al. (2019) and Wedel et al. (2016) discuss opportunities for knowledge creation from unstructured data and suggest a number of future research opportunities and specifically highlighting AI. Berger et al. (2019) discuss opportunities for marketing analytics from big data; AI also features strongly across their future research avenues.

Table 9: Research priorities on AI and knowledge in marketing

Reference	Research problem area	Illustrative research questions
Wedel & Kannan (2016)	Big data	How can AI and machine learning be combined with econometric methods to facilitate estimation of causal effects from big data at high speeds?
		How can AI, deep learning and cognitive computing techniques be extended for analyzing and interpreting unstructured marketing data?
Balducci & Marinova (2018)	Methodological advances	How can AI and deep learning techniques detect patterns in voice of user-generated content videos to determine customer sentiment?
		How can interdisciplinary research on AI computing techniques advance marketing research with unstructured data in substantial areas?
Berger et al. (2019)	Methodological advances	How can AI, deep learning and natural language processing-based approaches enable researchers to better understand semantic relationships among entities from text data?
		How can AI, deep learning and natural language processing-based approaches enable researchers to better understand latent states or latent constructs from text data, such as the writer's emotions, personality, or motivations?
		How can AI, deep learning and natural language processing-based approaches help personalize the customer-firm interaction by describing and predicting consumer traits, (e.g., personality), states (e.g., urgency, irritation) and traits associated with value to the firm (e.g., customer lifetime value).
Davenport et al. (2019)	Methodological advances	How well do AI-driven algorithms predict new product demand for really new products in new markets where training data is unavailable?
		How can AI combine text and other communication data (e.g., voice data), actual customer behavior, and other data (e.g., behaviors of similar customers) to predict repurchases?
	AI-human interaction	How can marketers best combine AI-driven insights with human judgment?

The discussion in the current section so far shows a number of calls for research to advance scholarly understanding on the topic of AI and human resources for creating market knowledge from big data. This thesis responds to these calls for research. Specifically, five research questions were formulated and are presented in the following section.

2.7 Development of research questions

This thesis addresses the following research problem: How do marketers create market knowledge from big data using artificial intelligence and human resources? Five research questions were formulated to address the overall research problem and are explained below.

2.7.1 Development of research question 1

As discussed earlier, the literature suggests that AI will significantly impact knowledge creation processes and outcomes (Balducci & Marinova, 2018; Berger et al., 2019; Duan et al., 2019; Kietzmann et al., 2018; Metaxiotis et al., 2003; Moreira Nascimento et al., 2018; Singh et al., 2019; Syam & Sharma, 2018). Artificial intelligence has been studied extensively in the literature with a focus on the technical aspects of AI. Scholars are calling for more research to understand AI in marketing, specifically for creating knowledge from big data (Wedel & Kannan, 2016), to explicate methodological approaches of using AI (Balducci & Marinova, 2018; Berger et al., 2019; Davenport et al.,2019;), and to understand human-AI aspects for market knowledge creation (Berger et al., 2019; Duan et al., 2019; Singh et al., 2019). Given the focus of this thesis, a research opportunity exists to describe the implications of AI for market knowledge creation. This research opportunity is dealt with via research question (RQ) 1 which is formulated as:

RQ 1: How does artificial intelligence contribute to creating market knowledge from big data?

Research question 1 is addressed in study A. The research objectives of study A are two-fold: First, to explain 'what AI is and how it works' in non-technical terms. Extant studies investigate AI in the field of information systems and are grounded in information systems literature and terminology. Studies describing 'AI and how it works' from a non-technical perspective are currently scarce (Duan et al., 2019; Martínez-López & Casillas, 2013; Moreira Nascimento et al., 2018). The answer to RQ 1 via study A aims to address this gap.

The second research objective of study A is to tie understanding of AI to the marketing literature, specifically to the literature on market knowledge. Specifically, study A conceptually explores how AI contributes to creating market knowledge. In line with the conceptualization of the 'market' construct in this thesis, study A hypothesizes how AI can contribute to knowledge about customers (existing and potential buyers and consumers), competitors and other external market stakeholders (political, environmental, competitors, media stakeholders). Thus, a potential contribution of study A to this thesis is an understanding of AI in non-technical terms and hypothesizing how AI contributes to market knowledge creation.

2.7.2 Development of research question 2

Study A establishes an umbrella of both scope and relevance to subsequent papers and studies in this thesis; thus, study A serves to explain AI and the opportunities for using AI to create market knowledge. Research question 2 explores how AI impacts the creation of market knowledge from big data and discusses the implications of AI on human resources. Thus, RQ 2 is formulated as:

RQ 2: How does artificial intelligence impact the creation of market knowledge from big data and what are the implications for human resources?

Research question 2 is addressed in paper B of this thesis. The research presented in paper B builds on the explanations of AI and its contributions to market knowledge from study A. In terms of the research context, paper B examines one specific form of market knowledge: customer knowledge in B2B sales. The B2B sales process (Järvinen & Taiminen, 2016; Syam & Sharma, 2018) was chosen as a context for RQ 2 for a number of reasons: First, AI is seeing increasing use among B2B sales professionals (MIT Technology Review Insights, 2018). The premise is that AI can help translate vast data volumes into knowledge about customers; which has been difficult in the past due to a longer and complex sales process with multiple influencers and changes in the market that are occurring frequently (Cotter et al., 2018; Ingram, 2004).

Second, in the current literature, scholars are calling for more research on AI and sales research and practice (Eitle & Buxmann, 2019; Singh et al., 2019; Syam & Sharma, 2018).
In response to these calls, paper B has two research objectives: First, to explore how AI changes the creation of knowledge in the B2B sales process which traditionally has been human-centric (Syam & Sharma, 2018); this is termed the ‘AI-enabled sales process’. Second, to explicate the implications for human resources at each stage of the AI-enabled sales process. Thus, a potential contribution of paper B is a conceptual exploration of how AI impacts the creation of market knowledge in addition to hypothesizing the implications for human resources.

2.7.3 Formulation of research question 3

Research question 3 explores the interaction of AI and human resources in the context of creating competitor knowledge in B2B sales. A study of the interaction of different resources has been identified as a fruitful area for further research (Badrinarayanan et al., 2019). In response to this identified future research, RQ 3 was developed as:

RQ 3: How do artificial intelligence and human resources interact in creating market knowledge from big data?

Research question 3 is addressed in study C of this thesis. The research presented in study C builds on study A and explores competitor knowledge as one particular form of market knowledge. The research objective of study C is to empirically investigate how AI and human resources interact to create competitor knowledge in B2B sales.

To achieve this objective, study C empirically explores the actors, activities and resources that interact during the creation of competitor knowledge. Thus, a potential contribution of study C is to provide empirical evidence of the interactions of AI and human resources in creating competitor knowledge using AI and human resources.

2.7.4 Formulation of research question 4

Research question 4, which is addressed in paper D, explores the mutual contributions of AI and human resources in creating market knowledge from big data. Thus, RQ 4 was formulated as:

RQ 4: What are the mutual contributions of artificial intelligence and human resources in creating market knowledge from big data?

Research question 4 focuses on external market stakeholders and examines text data created by mass media news organizations as one form of big data. Extant literature suggests that mass media communications are an important influencer on individuals' private or business lives, for instance through cognitive, affective or behavioural effects (Ball-Rokeach & DeFleur, 1976; Carroll & McCombs, 2003; McCombs, 2018). Thus, knowledge about mass media communications is important for marketers as it can moderate or mediate customers' attitudes and behaviours (Ball-Rokeach & DeFleur, 1976; Johnson-Cartee, 2004).

More specifically, the research context for RQ 4 was fake news. Fake news is defined as news communications that intentionally present misinformation with the intent to deceive the audience (Horne and Adali, 2017). Fake news communications can have substantial consequences for brands and organizations (Pitt & Berthon, 2018). For instance, Pepsi's stock declined when a fake news story about its CEO telling Trump supporters to "take their business elsewhere" went viral. Moreover, an organization's or brand's image can be impacted if it is associated, consciously or unintentionally, with fake news. Since fake news can threaten the viability of a brand or organization (Pitt & Berthon, 2018), it is important for marketers to understand how their organizations and brands are portrayed in mass media news and detect any evidence of fake news.

In the academic literature, studies have investigated the use of AI for fake news identification (Horne et al., 2018; Horne & Adali, 2017; Strickland, 2018). More recently, calls to use AI in conjunction with human approaches to fake news identification emerge (Pitt & Berthon, 2018). The premise is that AI algorithms can effectively assist humans in the important task of identifying fake news (Baly, Karadzhov, Glass, & Nakov, 2018; Graves, 2018; Hao, 2018; Pitt & Berthon, 2018; Strickland, 2018) and scholars are calling for more research to investigate human and algorithmic approaches to fake news identification (Pitt & Berthon, 2018). Research question 4 responds to this call for research.

2.7.5 Formulation of research question 5

The increasing use of social media (Kietzmann et al., 2011) has led to a large increase of text data created on social media sites. Every 60 seconds, users post 510,000 comments on Facebook and share close to 475,000 tweets a minute (Domo, 2018), with the potential to influence current or potential customers' preferences, needs, and behaviours.

In addition to the large volume, in the popular press, communications on social media sites have been credited for mobilizing significant social events such as the 'Arab Spring' (Brown, Guskin, & Mitchell, 2012) or the Stanley Cup Riots in Canada in 2011 (Stueck, 2018). In the scholarly literature, communications shared on social media sites, such as Twitter, have been found to impact audience attitudes towards organizations and brands and organizational performance (Burch et al., 2015; Jin & Pua, 2014; Liu, 2019; Qin, 2015; Wieneke & Lehrer, 2016).

Thus, big data on social media sites offer valuable opportunities for marketers to create knowledge about the creators of these data. Relative to surveys, social media content is spontaneous, widely available, low cost, easily accessible, and live (Tirunillai & Tellis, 2014) and may be based on a large number of individual contributions as opposed to only a select number of audience participants. Content analysis is one effective methodology to analyse the written narratives created by individuals (Su et al., 2017).

Marketing researchers have long relied on both, human and automated (i.e., computerized) content analysis techniques. However, there exist trade-offs between human and automated content analysis techniques in terms of validity, reliability and efficiency of coding process (Su et al., 2017). Reliability encompasses the degree to which two or more coders agree on classifying content (Krippendorff, 2004). Reliability is important in content analysis to minimize bias by human coders and enhance the generalizability of the results. However, achieving high reliability is challenging when relying on human coding only, particularly for coding of large datasets (Su et al., 2017). This challenge is due to the potential for human coders to make mistakes and due to the subjective, and differing, judgements of the coders.

These challenges may be overcome by using automated content analysis techniques; however, automated techniques come with other trade-offs, which may impact validity. Validity, defined as the degree to which the coding accurately measures the construct that it intends to measure (Krippendorff, 2004), is crucial to generalizability of results. Human coders are often viewed superior due to their ability to comprehend the nuances and underlying meaning in a piece of text, by considering semantics, pragmatics and semantics (Su et al., 2017), particularly when coding text for latent constructs, such as motivations, sentiment or values. Thus, human content analysis may result in stronger validity compared to automated content analysis.

In summary, each content analysis method has its own benefits and limitations. Some scholars are calling for a hybrid approach to content analysis in which human and automated content analysis methods are jointly used (Lewis et al., 2013; Su et al., 2017). In response to this call, RQ 5 is formulated as:

RQ 5: What are the contributions of artificial intelligence and human resources to different activities in creating market knowledge from big data?

Research question 5 is addressed in paper E. Paper E builds on paper B and demonstrates the benefits AI and human coding by using both in the paper's methodology. While RQ 4 examined the contributions of AI and human resources overall, RQ 5 focuses on the contributions of AI and human resources to different *activities* in creating market knowledge.

The research objectives for paper E are to demonstrate a methodological approach using AI and human resources to create market knowledge from unstructured text data on Twitter. Twitter was chosen due to its large active user base worldwide (Twitter, 2019) and its potential impact on audience opinions and attitudes as investigated in other scholarly research (Jin & Pua, 2014). With respect to the type of market knowledge, paper E focused on external market stakeholders, specifically the general public.

The research context for paper E was to investigate themes around consumption restraint behavior, defined as the purposeful practice of restricting consumption. Consumption restraint was chosen as it is an increasingly popular movement among the general public and has received increasing attention in the marketing literature (Balderjahn et al., 2018; Cronin et al., 2015; Galvagno, 2011; Lee et al., 2011; Odou & de Pechpeyrou, 2011; Pentina & Amos, 2011). Specifically, paper E investigates motivations to participate in and human values expressed in 'Buy Nothing Day' (BND) tweets.

To summarize, the research in this thesis provides an understanding of the contributions, impacts, and interactions between AI and human resources in creating market knowledge. In doing so, it explores both the processes (activities) and the outcome of market knowledge resulting from the processes. Study A focuses on describing AI in non-technical terms and its implications for market knowledge creation. Paper B explores the impact of AI on human resources, while study C studies the interactions of AI and human resources. Paper D explores the contributions of AI and human resources to market knowledge generation more generally, while paper E investigates the contributions of AI and human resources for different knowledge creation activities. Thus, this thesis provides a comprehensive investigation of resources in creating market knowledge via five research questions that are addressed in this thesis. Table 10 summarizes the research questions and their potential contributions.

Table 10: Overview of the research questions and potential contributions

Type of market knowledge	Paper/Study	Research question	Potential contribution
Customers, competitors, other external market stakeholders	Study A	RQ 1: How does artificial intelligence contribute to creating market knowledge from big data?	An understanding of AI in non-technical terms; hypothesizing how AI contributes to market knowledge creation.
Customer knowledge	Paper B	RQ 2: How does artificial intelligence impact human resources in creating market knowledge from big data?	A conceptual exploration of how AI impacts the creation of market knowledge and its implications for human resources.
Competitor knowledge	Study C	RQ 3: How do human and artificial intelligence resources interact in creating market knowledge from big data?	An empirical understanding of the activities, actors and resources in creating market knowledge using AI and human resources.
Knowledge about external market stakeholders – mass media news	Paper D	RQ 4: What are the mutual contributions of artificial intelligence and human resources in creating market knowledge from big data?	An empirical understanding of the joint contributions of artificial intelligence and human resources in creating market knowledge.
Knowledge about external market stakeholders – the general public	Paper E	RQ 5: What are the contributions of artificial intelligence and human resources to different activities in creating market knowledge from big data?	An empirical understanding of the contributions of using AI and human resources for market knowledge creation activities.

2.8 Chapter summary

The current chapter provided a review of the literature underpinning this thesis. The chapter discussed the relevance of market knowledge through delineating its positive outcomes and conceptualized market knowledge. Then, this chapter discussed the literature on market knowledge as an outcome and market knowledge processes. Specifically, the creation processes are delineated by its activities and resources, which was discussed using RBT as a theoretical lens. The chapter concluded with the identification of the research gap from the literature and formulated five research questions that this thesis addresses.

Chapter 3: Methodology

Research methodology encompasses ways to systematically solve research problems (Kothari, 2004). Research methodology includes the research methods, i.e., the techniques a researcher uses in data collection, measurement and data analysis, and the rationale for choosing a particular method. The aim of this chapter is to explain the methodology options available, to describe the methods adopted in this thesis and to clarify the logic for choosing these methods.

This chapter begins with a presentation of the research paradigm, research approach and research design and how these are applied to the research problem in this thesis. Next, the discussion continues to explain the methods employed in each study and each paper, followed by an explanation of the research quality considerations. Thus, at the aggregate level, this chapter presents and discusses the research methodology that has been chosen to solve the research problem (the 'how' of this thesis).

3.1 Research paradigm

A paradigm is a set of beliefs or assumptions about the nature of the world and its individuals (Guba & Lincoln, 1994). A paradigm describes a "worldview that defines, for its holder, the nature of the 'world', the individual's place in it, and the range of possible relationships to that world and its parts, as, for example, cosmologies and theologies do. The beliefs are basic in the sense that they must be accepted simply on faith (however well argued); there is no way to establish their ultimate truthfulness" (Guba & Lincoln, 1994, p. 107). A paradigm is thus a comprehensive belief system or framework that guides research and practice in a field.

When describing a particular paradigm, it is important to consider the philosophical underpinnings related to ontology and epistemology (Guba & Lincoln, 1994; Weber, 2004). Ontology is concerned with the beliefs about the nature of reality, and therefore with the question 'what is there that we can potentially know about'? If, for example, the existence of an objective reality is assumed, then what can be potentially known is 'how things really are' and 'how things work'. Thus, scientific inquiry is concerned with questions that pertain to capturing this objective reality.

Epistemology focuses on ways of knowing and is concerned with the relationship between the researcher and the world around her and how knowledge develops. The epistemological relationship is not independent from the ontological view. If, for example, an objective reality is assumed, then the role of the researcher is to be objective and assume a detachment from her object of inquiry in order to discover 'how things really are' and 'how things work'.

Positivism and interpretivism are two paradigms applied in the social sciences (Weber, 2004; Willis, 2007). Positivism is based on the assumption that an objective and quantifiable reality exists and that this reality exists independently from the researcher observing it (Weber, 2004; Willis, 2007). Positivists consider the researcher and the research object (the phenomena in the world that a researcher investigates) to be separate. The goal of research, according to a positivism paradigm, is to build objective knowledge, or an understanding of phenomena that is impartial and unbiased and based on a view from 'the outside' without personal involvement of the researcher (Willig, 2001).

An interpretivist paradigm assumes there is no single, objective reality; instead, the world and the individual who observes it cannot be separated (Creswell, 2013; Weber, 2004). Interpretivists argue that a researcher's perceptions about the world are inseparable from the experiences they have had throughout their lives. Interpretivism aims to understand phenomena in their natural settings and from the perspective of the researcher (Leitch et al., 2010). Thus, an interpretivist researcher seeks direct contact with the phenomena of interest and in-depth investigation. Knowledge develops from trying to make sense of the world, recognizing that this sense-making occurs within the framework of the researcher's own life-worlds, i.e., her previous expertise, experiences, motivations or goals (Weber, 2004).

This thesis follows an interpretivist paradigm. Unlike phenomena studied in the natural sciences, social phenomena are defined by the actors involved in the phenomena, their activities, interactions and relationships (Heracleous, 2004). Given the exploratory nature of the research problem in this thesis, an interpretivist paradigm is well-suited to address this research problem. Moreover, the study of knowledge as contextualized information based on experience, skills and expertise lends itself to an interpretivist paradigm (Jakubik, 2011).

3.2 Research approach

The choice of paradigm and the assumptions associated with each paradigm have important implications for the choice of research approach and how research operations are conducted (Guba & Lincoln, 1994). A research approach encompasses a plan and the procedures for research (Creswell, 2013). Three research approaches are available to social scientists when conducting empirical research: quantitative, qualitative and mixed methods research.

Quantitative research usually follows the positivism paradigm and focuses on objectivity of and causality between phenomena of interest (Creswell, 2013; Guba & Lincoln, 1994). Quantitative research often involves gathering numerical data, using structured measures, and statistically analysing empirical data. The aim of inquiry for quantitative research is explanation or prediction of phenomena (Guba & Lincoln, 1994). Quantitative research is often used when theoretical models about the relationship between phenomena of interest exist and the researcher aims to analyse the relationship between variables, test hypotheses or validate existing theories or models. Quantitative research relies on deductive reasoning in which the researcher starts with theory, develops hypotheses and then collects observations to test the theory, controlling for alternative explanations and focusing on generalizability and replicability of the findings (Creswell, 2013; Hair, Wolfinbarger, Money, Samouel, & Page, 2011).

Qualitative research typically follows the interpretivism paradigm and does not assume the existence of an objective reality. The aim of qualitative inquiry is understanding (Guba & Lincoln, 1994). A qualitative research approach is discovery-oriented, focusing on exploring and understanding human or business phenomena (Creswell, 2013; Guba & Lincoln, 1994). Qualitative research approaches are used to generate ideas or theories and rely on inductive reasoning in which the researcher identifies themes, patterns or relationships from specific observations to reach conclusions and build theory (Creswell, 2013; Hair et al., 2011).

Mixed methods research involves a research study that combines qualitative or quantitative methods, techniques or concepts into a single study or a series of linked studies (Creswell, 2013; Fakis, Hilliam, Stoneley, & Townend, 2014; Hurmerinta-Peltomäki & Nummela, 2006). The main premise is that the integration of the above two approaches provides a more comprehensive understanding of the phenomenon of interest than either approach alone. In addition, researchers using mixed methods may seek to address one research problem from different perspectives or find answers to diverse questions where little guidance on the most suitable research approach exists (Fakis et al., 2014). Mixed methods research uses inductive, deductive and abductive reasoning, where the latter is concerned with uncovering the 'most likely' or 'best available' explanations among a set of reasons for understanding one's results (Johnson & Onwuegbuzie, 2004). Abductive reasoning yields a plausible conclusion, but it does not positively verify it as deductive reasoning does.

Given the interpretivist paradigm adapted, a qualitative research approach was chosen in this thesis. This choice of research approach was deemed most effective at addressing the research problem posed in this thesis (Johnson & Onwuegbuzie, 2004). The overall research problem of this thesis is exploratory in nature, and the goal of this thesis is inquiry and developing understanding, rather than developing causal explanations or predicting phenomena. Moreover, the phenomena of AI and human resources for market knowledge creation are currently not well understood; hence, a qualitative approach was deemed most effective.

3.3 Research design

The research design includes a plan on how to conduct a study, collect and analyse data to ensure that the evidence collected allows the researcher to answer the research question as unambiguously as possible (De Vaus, 2001).

Research designs can be categorized as exploratory, descriptive or explanatory design. Exploratory research allows the researcher to explore a problem or idea to provide deeper level insights and understanding (Malhotra & Birks, 2007). Exploratory research design is often useful when there is little extant knowledge about a phenomenon. In such situations, the researcher may use an exploratory research design to further the understanding on a particular topic and lay the groundwork for future studies. Descriptive research is used to describe a phenomenon, such as describing market characteristics. The aim of descriptive research is to better understand the 'what' of the phenomenon under investigation.

Explanatory research (also referred to as causal research) aims to answer the "why question", i.e., why is a certain phenomenon happening. Answering the "why question" requires the researcher to develop causal explanations, i.e., determine cause and effect relationships between phenomena of interest.

The research design employed in this thesis encompasses exploratory research. This research design was deemed most appropriate for the research problem and research questions under investigation. The research problem in this thesis focuses on creating a deeper level understanding of the 'how' of creating market knowledge from big data. Currently, there exist little research on AI and human resources in marketing in general, and for creation market knowledge specifically (Duan et al., 2019; Metaxiotis et al., 2003; Moreira Nascimento et al., 2018; Singh et al., 2019; Syam & Sharma, 2018), thus an exploratory design was deemed most suitable.

3.4 Research method

The research method encompasses the form(s) of data collection, analysis and interpretation chosen by the researcher (Creswell, 2013). Since there is little theoretical or empirical research on AI and human resources for market knowledge specifically or marketing more broadly (Duan et al., 2019; Metaxiotis et al., 2003; Moreira Nascimento et al., 2018; Singh et al., 2019; Syam & Sharma, 2018), there is no precedent regarding the most effective research methods. In the absence of a standard research method, Hurmerinta-Peltomäki and Nummela (2006) suggest choosing a method that is appropriate for the research question. Consequently, the method in each paper was chosen based on its appropriateness for the research question.

3.4.1 Research method study A

Study A answers RQ 1: How does artificial intelligence contribute to creating market knowledge from big data? Study A is conceptual in nature; data relating to AI and market knowledge were gathered from the existing literature. No empirical method was employed in study A.

3.4.2 Research method paper B

Paper B answers RQ 2: How does artificial intelligence impact the creation of market knowledge from big data and what are the implications for human resources? Paper B is conceptual; data for paper B were gathered from the literature.

3.4.3 Research method study C

Study C was developed to answer RQ 3: How do artificial intelligence and human resources interact in creating market knowledge from big data? Given the exploratory nature of the study, a qualitative research approach using semi-structured interviews was deemed best suited for study C.

Interviews enable an in-depth understanding of how individuals perceive interactions (Creswell, 2013), such as their perceptions related to the interaction of different resources. In addition, semi-structured interviews let a researcher follow up on initial responses, asking informants to clarify or elaborate. This flexibility allows a deep understanding of the informants' answers while providing structure to organize and understand the data collected.

Furthermore, the literature calls for more research that is grounded in the "context of discovery (i.e., discovering and/or developing concepts, frameworks, hypotheses, and theories)" (Badrinarayanan et al., 2019, p. 25) which is currently under-represented in the research using RBT as a lens (Badrinarayanan et al., 2019). The exploratory research design chosen in this study is aligned with this discovery-oriented focus called for in the literature.

Sample and data collection

A purposive sample was used for this research. Specifically, the informants were employed at a North American start-up company that licenses AI to its clients. The AI information technology collects data from publicly available online sources, as well as from internal sources, and then analyses the data and information for use by clients. Specifically, data is collected, de-duplicated, categorized, assessed for relevance and deposited in a knowledge base. After this, the information becomes ready for review and further analysis, termed 'curation' in study C, by the client's employees. These professionals are primarily sales enablement staff, including product marketers, competitive intelligence and market research professionals. Following curation sales staff consume and apply the information and knowledge as part of their roles. The users of the AI technology work in corporate sales (or corporate sales enablement) of information technology products and services. For further clarity, informants were employed at the company licensing the AI technology to their clients who work in corporate sales of information technology.

Informants included employees in a range of roles, including Sales Development Representatives, Account Executives, Customer Success employees, Marketing Coordinators, Head of Marketing, Front End and Back End Technology Developers, and the Chief Technology Officer. The researchers were given access to interviewees for scheduled interview times by teleconferencing software. Interviews were booked in 30-minute appointment slots.

The researchers utilized the guidelines of Lincoln & Guba (1985) in determining when data collection should be terminated which suggest that data collection should end after at least one of the four conditions are met: (i) that no further data sources are available, (ii) that theoretical saturation has been reached, (iii) that regularities have emerged and a sense of integration has been achieved, or (iv) that collecting new information is beyond the scope of the research question.

After interviews with 14 employees were complete, conditions (i), (ii) and (iii) were met and data collection for study C was ended. Thus, the final dataset consisted of interviews with 14 employees (Table 11). Interviews lasted for an average of 31 minutes each, with a range of 16 to 41 minutes. The total interview time was approximately 7.25 hours.

Table 11: Overview of informants' functional areas

	Number of interviews		
Informant functional area	**Senior management**	**Team member**	**Total**
Marketing	1	2	3
Sales	2	2	4
Customer success	1	1	2
IT development (front-end)	2	1	3
IT development (back-end)	1	1	2
Total	**7**	**7**	**14**

The first step of data collection consisted of developing draft interview questions; these were reviewed by other scholars not involved in the research and their feedback was used to modify the interview questions. Subsequently, two interviews were conducted using the updated interview questions. Following these initial interviews, the interview questions were again modified taking into account the flow of the conversation and feedback from informants. This led to the creation of a final version of the interview questions that was used to guide the remainder of the data collection. The final semi-structured interview process began with a question about the respondent's role and tenure within the target company, followed by a general question about their definition of AI. After informants had given their initial response to a question, the researcher followed up with clarification questions. The interview questions focused on the benefits of AI in B2B sales in general, followed by in-depth questions on how the specific AI information system is used by clients, the role of human contributions during use and whether they perceived limitations of AI in B2B sales.

Immediately after an interview, the interviewer wrote a memo that summarized initial impressions of the interview, as well as any aspects of the interview that stood out and how the conversation fit in with previous interviews. The audio-recordings of the interviews were transcribed into MS-Word files using a professional transcription service. One researcher reviewed a sample transcription, compared it word-for-word with the original audio data, and concluded that the MS-Word files represented an accurate representation of the audio files. The interview transcripts and the researcher memos served as the dataset for this study.

Data Analysis

Data analysis encompassed a thematic analysis approach (Fereday & Muir-Cochrane, 2006) as the appropriate method, as it enables a search for themes by recognizing patterns within the data and facilitates the organization and description of the data in rich detail. Data collection and analysis were conducted simultaneously to allow for flexibility. Throughout this process, the data were analyzed using aspects of grounded theory (Glaser & Strauss, 2017; Strauss & Corbin, 1997).

Data analysis followed the phases of thematic analysis as described by Braun and Clarke (2006). Each transcript was systematically reviewed by one researcher and initial, first order codes that were informant-centric were developed. The aim then was to generate initial codes that were subsequently collated into themes; constant comparison of these labels allowed higher-order labels to be extracted.

This iterative process led to the identification of core categories, which were then utilized in the next stage of coding: axial coding (Strauss & Corbin, 1997). In this stage, similarities and differences and the relationships among and between the categories were sought. Finally, results of the analysis were examined using negative case analysis to enhance the rigor of the investigation. This involved re-examination of each interview after the analysis was completed in order to determine whether the emergent themes were indeed applicable. This process revealed no disconfirming evidence. The final review substantiated that the themes reflected the meanings evident in the dataset as a whole.

3.4.4 Research method paper D

Paper D answers RQ 4: What are the mutual contributions of artificial intelligence and human resources in creating market knowledge from big data? Paper D employs the AI application 'IBM Watson' to analyse the differences in the emotional message appeal between fake and real news communications, followed by hypothesis testing.

Sample and data collection

One-hundred-and-fifty news articles (75 fake and 75 real news articles) were content-analysed with the AI application 'Watson'. The dataset in paper D had been employed in a previous study by Horne and Adali (2017) and had been made publicly available by the authors. This dataset was downloaded, thus following the two-step data collection process employed by Horne and Adali (2017) previously.

Step 1 involved identifying the appropriate source for each of the two news categories from published lists of news outlets that have previously been deemed 'trustworthy' or 'misleading' by human fact checkers. For instance, the sample source for real news articles was selected from Business Insider's report of 'most trusted and least trusted' news outlets (Engel, 2014) and included well-established news outlets with no intent to mislead their audience. Fake news articles were sourced from Zimdars' (2016) list of misleading news sources which have had at least one news article identified as false on the fact-checking website snopes.com.

Step 2 of the data collection process involved randomly selecting 75 news articles from each source group – real news and fabricated news – for a total of 150 articles. Only “hard” news articles have been included in the data set, whereas editorials or opinion pieces were excluded.

Data analysis

The unit of analysis encompassed the written text in the body and titles of the two types of news articles (fake and real). Following suggestions in the literature, the body and titles of fake and real news communications were analysed separately. Data analysis in paper E encompassed subjecting each record to the AI application ‘Watson’, a software which had been used in other academic research, for example, to extract personality profiles from written text (Majumder et al., 2017; Mostafa et al., 2016) or to understand the sentiment portrayed in a body of text (Cambria, Schuller, Xia, & Havasi, 2013; Pitt, Kietzmann, et al., 2018). Artificial intelligence applications had also been utilized to perform linguistic analyses in the context of fake news (Chen et al., 2015; Horne & Adali, 2017; Potthast et al., 2017; Rubin et al., 2016).

Following the ‘Watson’ analysis, the second step in the data analysis included further analysing the emotion and sentiment scores using the content analysis software DICTION (Pitt et al., 2017; Short et al., 2018) for descriptive statistics. In addition, the statistical software package SPSS 25 was employed to perform hypothesis testing for differences between fake news (titles and article body) and real news (titles and article body).

3.4.5 Research method paper E

Paper E answers RQ 5: What are the contributions of artificial intelligence and human resources to different activities in creating market knowledge from big data? Paper E utilizes a mixed method research approach, including human coding by the researchers and automated content analysis via the AI application ‘IBM Watson’. The combination of human and AI analysis methods in paper E is termed ‘hybrid’ analysis.

The research context for paper E was to investigate themes around consumption restraint behavior, more specifically Buy Nothing Day

(BND). In BND, individuals commit to buying nothing on the most popular shopping holiday of the year: ‘Black Friday’.

Sample and data collection

Three years of Twitter data were collected during the Black Friday shopping seasons in 2016, 2017, and 2018. The data set for each year included all tweets containing the term ‘Buy Nothing Day’ or the hashtag ‘#BuyNothingDay’ within a ten-day time period surrounding the actual BND date (November 24th in 2016; 23rd in 2017, and 22nd in 2018). A ten-day time period was chosen to include the related shopping holiday Cyber Monday and any pre-BND anticipation and post-BND reflection. Although the time period covered the span of 10 days, each year roughly 70 % of the tweets have been sent on BND itself. In each year of data, the full data set of tweets containing the term ‘Buy Nothing Day’ or #BuyNothingDay was cleaned to remove duplicate tweets, i.e., retweets. In addition, as this research focuses on individuals, all tweets originating from a corporate account, a brand, or an organization have been eliminated. Lastly, all non-English tweets were eliminated due to the language limitations of the researchers.

Data analysis

The unit of analysis in paper E encompassed individual tweets during the ten-day time period described above. Data analysis involved manual coding as well as automated content analysis using the AI application IBM ‘Watson’. The manual content analysis has been modelled based on that of Robson et al. (2015) and encompassed three steps. Step 1 involved two researchers independently reading one hundred and fifty randomly selected tweets and coding these tweets into the categories of motivations for participating in BND developed from the literature. In step 2, the researchers together reviewed and deliberated each coding decision until consensus is reached. Following this, in the third step, the researchers discussed and compared the coding categories that were identified and extracted commonalities between them. From these commonalities the list of initial coding categories was revised, and associated definitions and examples were developed for each coding category of motivation.

All of the remaining tweets were then coded using the coding categories developed in step 3. This procedure was repeated for each year of data. In 2017 and 2018, new categories of consumer motivations emerged and were added to the coding categories. A random selection of one hundred and fifty tweets from the previous year were re-evaluated to determine if these new codes had been present (but overlooked) in coding. No such evidence was found.

The automated content analysis using AI follows analysis techniques modeled based on the extant literature. The AI application 'Watson' was deemed appropriate as it had been used in other studies to analyse unstructured text data on social media sites (Pitt, Kietzmann, et al., 2018; Pitt, Mulvey, et al., 2018). In addition, 'Watson' is particularly well suited to analyze Twitter data (Biondi et al., 2017) due to its algorithms being trained on large data sets of text data from social media sites. The latter is important as the language used in social media posts often lacks proper structure and employs informal language (Cvijikj & Michahelles, 2011; Yassine & Haij, 2010), making the use of automated content analysis techniques more complex.

The literature suggests analyzing large data sets (Cvijikj & Michahelles, 2011; Yassine & Haij, 2010), which is why the entire Twitter data sets were subjected to content analysis, instead of only a sample of each year's data set. The qualitative information derived from the manual and AI content analyses was then quantified by manually calculating additional statistical analyses, including descriptive and frequency calculations (Fakis et al., 2014) to develop further understanding of the motivations and human values expressed in the tweets. Table 12 summarizes the research methodology utilized in this thesis.

Table 12: Summary of research methodology

Paper / Study	Research approach	Research method
Study A	Conceptual	Literature review
Paper B	Conceptual	Literature review
Study C	Qualitative	Empirical, using semi-structured interviews
Paper D	Qualitative	Empirical, using automated content analysis via AI, subsequent hypothesis testing
Paper E	Qualitative	Empirical, using hybrid content analysis (human and AI analysis)

3.5 Research quality

As part of methodological considerations, a researcher needs to take steps to establish research quality. There are two basic properties of empirical measurements that ascertain research quality: reliability and validity (Carmines & Zeller, 1979). First, one can examine the reliability of a measurement. In quantitative research, reliability is concerned with the extent to which a measurement, test or procedure produces the same result if repeated with comparable methods (Carmines & Zeller, 1979; Golafshani, 2003; Hair et al., 2011). While the term 'reliability' is typically used for evaluating the quality of quantitative research, the idea is also used in qualitative research (Golafshani, 2003), albeit it may be referred to with different terminology. In qualitative research, consistency is an essential criterion for research quality (Golafshani, 2003) and encompasses the degree to which different researchers assign consistent themes or patterns or the same researcher arrives at coherent interpretations over repeated measuring (Hair et al., 2011).

The second quality criteria of empirical measurements is validity (Carmines & Zeller, 1979) which, in quantitative research, refers to the degree to which a measurement, construct or conclusion measures what it is supposed to measure (Hair et al., 2011; Pallant, 2013). For qualitative research, credible, trustworthy and defensible measurements or results capture the analogue of the validity idea (Golafshani, 2003).

For content analysis in particular, which is used in paper D and paper E in this thesis, Krippendorff (2004) establishes three forms of validity: (i) face validity, i.e., whether the research findings make sense, are plausible and believable without being given detailed reasoning; (ii) social validity, i.e., whether the findings have relevance and meaning beyond an academic audience, and (iii) empirical validity, i.e., whether the findings are supported by previous evidence and established theory. In designing and executing the methods in these articles, a number of steps were taken to establish reliability (consistency) and validity (credibility) and are described in detail below.

Research quality of study A and paper B

Because study A and paper B were conceptual in nature, the concepts of reliability and validity do not apply. No empirical methodology was required, and data were gathered from academic databases to access the existing literature.

Research quality of study C

Study C used a qualitative research approach employing semi-structured interviews. To establish consistency (reliability) and credibility, trustworthiness and defensible measures (validity), a number of steps were taken in study C. Regarding data collection, best practice is verbatim transcription (Flick, 2018). For study C, all interviews were audio-recorded and then transcribed into MS-Word by a professional transcription service. In addition, one researcher reviewed a sample transcription, compared it with the original audio data, and concluded that the MS-Word files represented an accurate representation of the audio files.

Regarding data analysis for study C, most transcripts were reviewed a minimum of two times. Each transcript was systematically reviewed by one researcher and initial, first order codes that were informant-centric were developed. The aim then was to generate codes that were subsequently collated into themes; constant comparison of these labels allowed higher-order labels to be extracted. This iterative process led to the identification of core categories, which were then utilized in the next stage of coding: axial coding (Strauss & Corbin, 1997) in which the relationships, similarities and differences were analysed. One researcher coded independently; the results were subsequently discussed with other researchers not involved in the coding to ensure credibility.

Finally, results of the analysis were examined using negative case analysis to enhance the rigor of the investigation. This involved re-examination of each interview after the analysis was completed in order to determine whether the emergent themes were indeed applicable. This process revealed no disconfirming evidence. The final review substantiated that the themes reflected the meanings evident in the dataset as a whole.

Research quality of paper D

The empirical research in paper D used automated content analysis of 150 news articles, and following recommendations by Hair et al. (2011), the communication narratives were analysed in a systematic way. Here, the AI application IBM 'Watson' was selected as this tool has been previously used in social sciences research (Dabirian, Kietzmann, & Diba, 2017; Pitt, Kietzmann, Botha, & Wallström, 2018; Pitt, Mulvey, & Kietzmann, 2018). Moreover, the AI application 'Watson' was built on Plutchik's (2001) theory of basic human emotions in the literature. Specifically, 'Watson' uses the classifications of emotions including joy, sadness, anger, fear and disgust which have received substantial consideration in the literature and are considered valid measures for the AI analysis.

Paper D used an independent samples t-test which is based on a mathematical formula that does not require researcher interpretation and is thus not subject to researcher bias. In addition, the dataset in paper D had been employed in previous research on fake news identification and was thus deemed appropriate by other researchers (Horne & Adali, 2017).

Regarding validity, the findings in paper D were consistent with the evidence from previous studies on the sentiment contained in fake news articles (Horne & Adali, 2017; Horne, Dron, Khedr, & Adali, 2018). Moreover, the findings are supported by the literature on message framing, specifically with respect to the role of emotional appeals in marketing communications. This suggests that the analysis and findings display a high degree of empirical validity.

Furthermore, the prevalence and growth of fake news and their impact on businesses and societies is a widely debated topic among scholars, practitioners, and policymakers, and calls for systemic and pragmatic solutions to tackle the fake news crisis are increasing. This suggests that the analysis and findings have a high degree of social validity. In addition, paper D drew conclusions using an independent samples t-test on a large dataset, which may pose the risk of a Type I error (false-positive). To address this limitation and establish validity, the paper reported the effect size for each test performed.

The findings in paper D were discussed with other researchers, including my supervisors and other marketing scholars. Moreover, two anonymous reviewers provided feedback on the manuscript during the review process with the *Journal of Product and Brand Management*. This is known as engaging in peer-review in research and is suggested to facilitate trustworthiness and credibility (Creswell & Miller, 2000).

Research quality of paper E

Paper E used manual content analysis via human coders and automated content analysis via AI. In manual content analysis, reliability, i.e., consistency, is assessed by the degree to which "researchers agree on what they are talking about. Here, then, reliability is the degree to which members of a designated community concur on the readings, interpretations, responses to or uses of given texts or data" (Krippendorff, 2004, p. 277). Accordingly, to establish consistency, the manual content analysis in paper E was modelled based on previous research which used human coding in content analysis (Robson et al., 2015).

Two researchers independently reviewed and coded a randomly selected sub-sample of 150 tweets. The two researchers then deliberated each coding decision until consensus was reached. Following this, the two researchers identified and extracted commonalities between the codes and developed associated definitions and examples for each code before coding the remainder of the dataset.

The automated content analysis in paper E followed again a systematic approach as suggested by Hair et al. (2011) using the AI application 'Watson'. Automated content analysis methods typically have high reliability (Su et al., 2017), since human biases or subjective judgements do not apply here. Moreover, regarding validity of the automated content analysis, the AI application 'Watson' was built using Schwartz' theory of human values which is a well-established model in the literature to classify value-dimensions (Schwartz, 2012). This suggests that the automated content analysis exhibits a high degree of validity.

In addition, regarding empirical validity, the findings in paper E were consistent with established evidence and literature on consumption restraint, thus suggesting a high-level of empirical validity. The findings were discussed with other scholars, including co-authors, my supervisors and other marketing scholars. Moreover, two anonymous reviewers provided feedback on the manuscript during the review process with the *European Journal of Marketing*. This peer-review process facilitates trustworthiness and credibility (Creswell & Miller, 2000).

3.6 Chapter Summary

This chapter presented the research methodology that was chosen to investigate the research problem. This chapter began with a presentation of the research paradigm, research approach and research design and how these are applied to the research problem in this thesis. Next, the discussion explained the methods employed in each of the three papers and two studies, followed by an explanation of the research quality considerations.

Chapter 4: Findings and contributions

This chapter provides the findings from the studies and papers in response to each research question posed in this thesis, discusses this thesis' contribution to theory, managerial implications and suggestions for future research. It first reviews the key findings from each study and paper respectively and discusses the relevance of the findings with respect to each research question. The chapter then moves to discussing the contributions of this thesis to theory and the body of knowledge, in addition to outlining managerial implications. The chapter closes with suggestions for future research opportunities.

4.1 Overview of findings for each paper or study

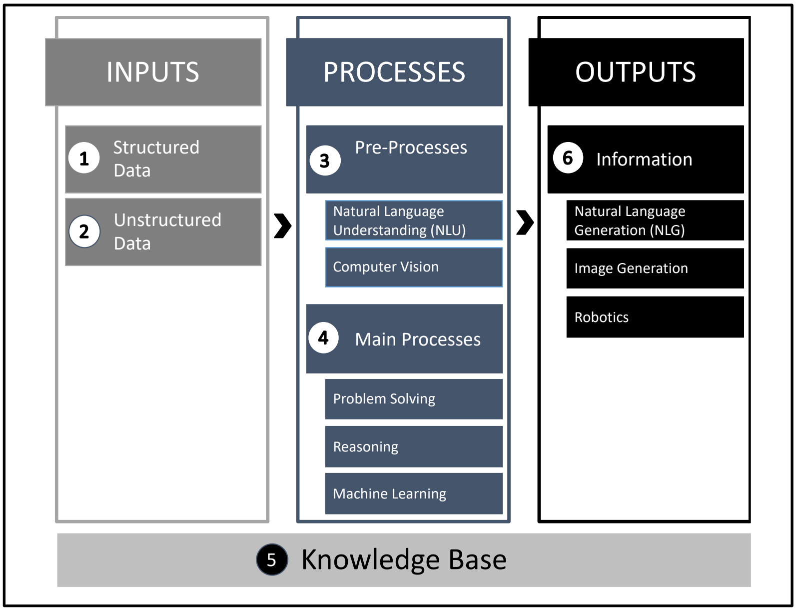
Section 4.1 provides an overview of the findings in response to the research question addressed in each of the papers or studies.

4.1.1 Study A: How does artificial intelligence contribute to creating market knowledge from big data?

As outlined in chapter 2.7, the research objectives of study A are to explain 'what AI is and how it works' in non-technical terms, thus addressing a research opportunity identified in the literature (Duan et al., 2019; Martínez-López & Casillas, 2013; Moreira Nascimento et al., 2018). The second research objective of study A is to tie understanding of AI to the marketing literature, specifically to the literature on market knowledge. To achieve this second objective, study A conceptually explores how AI contributes to creating market knowledge.

Study A explains AI viewed through an input-process-output lens and introduces a framework by which to describe AI according to six foundational elements. These elements are termed 'building blocks'. In addition to defining each building block in non-technical terms, study A explains how each building block works and clarifies the relationships between the different building blocks. The explanations are further illustrated by means of a graphical representation (see Figure 4).

Figure 4: Artificial intelligence - building blocks and their interrelationships



The six building blocks encompass: (1) structured data and (2) unstructured data, (3) pre-processes (i.e., natural language understanding and computer vision), (4) main processes (problem solving, reasoning, and machine learning) (5) knowledge base, and (6) information (i.e., natural language generation, image generation, and robotics).

Building block #1: Structured data
Structured data are data that are standardized and organized according to predefined schema and encompass one of the two types of inputs for AI.

Building block #2: Unstructured data
Unstructured data are not standardized or organized according to a pre-defined schema (Balducci & Marinova, 2018) and encompass the second type of inputs for AI.

Building block #3: Pre-processes

Pre-processes include cleaning, normalization, transformation and feature extraction of data. The goal of these pre-processing activities is to generate high-quality structured data, which can then be analysed in AI's main processes (building block 4). Depending on the type of unstructured data inputs, these pre-processes include natural language understanding and computer vision.

Natural language understanding

Artificial intelligence uses natural language understanding (NLU) to assign meaning to human language embodied in text (written language) and acoustic signals (spoken language). NLU assigns meaning to text by analysing the syntax (i.e. the structure of sentences), semantics (i.e., the relationship between words, phrases and symbols) and pragmatics (i.e., the context in which words or phrases are used in natural language (Gill, 2017). Artificial intelligence thereby gives meaning to unstructured data; this has been difficult to impossible to achieve with previous information technologies which required structured data as inputs.

Computer vision

Computer vision transforms visual images in the physical world into representations which can subsequently be processed by other AI building blocks. Computer vision provides the algorithmic backend to recognize patterns in and extract meaning from pixels.

Building block #4: Main processes

Artificial intelligence's building block 4 is 'main processes', and encompasses problem solving, reasoning, and machine learning.

Problem-solving

Problem-solving involves choosing the best solution from a range of alternatives for reaching a goal. Divergent problem solving implies generating and evaluating a number of alternative solutions for a given problem. In divergent problem solving, no single best solution exists – a host of alternatives can be equally valuable. Convergent problem solving is concerned with narrowing down alternatives to find an optimal answer to a problem. However, this does not mean that AI problem-solving always explores all options to arrive at the optimal solution. Instead, AI often relies on heuristics to generate solutions that are sufficient for the problem at hand (Tecuci, 2012).

Reasoning

Reasoning refers to applying logic to generate conclusions from available data. While problem-solving was about finding solutions for problems, reasoning is concerned with the type of logic underlying these processes. Here, two kinds of reasoning exist. Deductive reasoning combines premises, i.e., logical statements that are believed to be true to obtain new conclusions. Accordingly, if the premises are true, so is the conclusion. Inductive reasoning, also known as bottom–up reasoning, does not use rules but instead attempts to generate hypotheses from specific observations. In inductive reasoning, AI tries to detect patterns and develop rules that would not only be conclusive for the data at hand, but that can also be applied to future problems or situations.

Machine learning

Machine learning (ML) encompasses computational techniques that let computers learn from experience, i.e., progressively improve their performance on their own. In supervised machine learning methods, input training data are provided along with correct outputs from which the computer learns the patterns and develops the rules to be applied to future instances of the same problem. Unsupervised machine learning methods encompass techniques where computers are given training data sets but no correct labels. Unsupervised learning aims at finding structure and relationships in these input data. Reinforcement learning tries to teach agents to learn intelligent behavior from their own past experience. In other words, AI systems learn from various sources not only from the structured and unstructured input data, but also from their own processes.

Building block #5: Knowledge base

A knowledge base stores digital representations of aspects of the real world in which these representations operate, for later access. For AI's knowledge base, these representations can be data or information from pre-processing, but also information about relationships between objects or events, rules or actions (Hayes-Roth et al., 1983).

Building block #6: Information

Information, the sixth building block of AI, results from data being processed in value-creating ways and being placed into a formative context so that meaning emerges. Information represent the outputs of AI processing. The information resulting from AI processing can then be used to support human decision-making or in tasks performed by computers. The information resulting from AI main processes can be used in natural language generation, image generation, and robotics.

Natural language generation (NLG)

While natural language understanding (NLU) focuses on identifying the meaning of written text, natural language generation (NLG) performs the complimentary task: producing written narratives in conversational language as output. Natural language processing (NLP) is the umbrella term that encompasses NLG and NLU. The written narratives created through NLG can also take the form of an auditory response delivered back to humans; this is referred to as speech generation, for instance in chatbots that can converse with humans or non-human actors. In addition, AI applications just recently managed to accurately mimic an individual's voice after learning which sounds go with text as well as learning about the idiosyncrasies of how one talks.

Image generation

Image generation is the reverse of image recognition: when the AI system is fed an image, even with missing data, it can create complete images as output. In addition, AI can generate images from text descriptions, in practice often referred to as drawing bots. Image generation has recently become more sophisticated due to advancements in AI's main processing building blocks, so much so that concerns about the authenticity of images are increasingly raised (Kietzmann et al., 2019).

Robotics

Robotics refers to the use of AI in machines that physically interact with and alter their environment, for example in environments where work by humans would be too expensive, too dangerous or sheer impossible, such as disaster relief. Another application of robotics is conversation agents, such as chatbots. The application of chatbots ranges from responding to frequently asked questions or holding more complex dialogues, such as booking appointments on behalf of clients.

In summary, AI uses structured and unstructured data (building blocks #1 and #2) as inputs and pre-processes these data via natural language understanding and computer vision (building block #3). These pre-processed data can then be further transformed in value-creating ways via its main processes (building block #4). AI's knowledge base (building block #5) provides effective storage for the results from the pre-processing and main processing activities, for future use in AI's pre- or main processing. The final AI building block introduced in the framework (building block #6) encompasses outputs, i.e., AI's post-processing interface with its environment. These outputs, in the form of information, can support human decision making or become inputs into other computers or information technologies. Furthermore, where applicable for each building block, study A clarifies commonly used technical terms, such as deep learning or artificial neural networks in a non-technical way for a marketing practitioner audience.

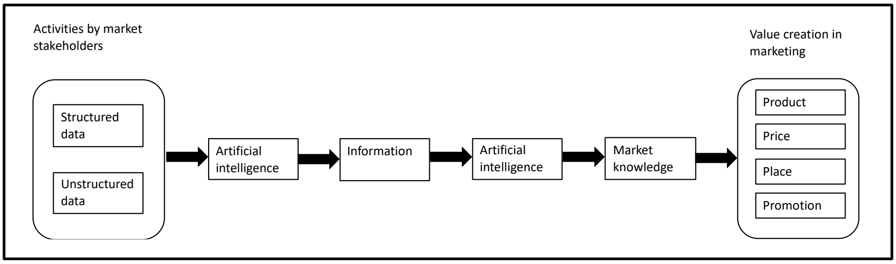
One contribution of study A is to explain to marketing professionals in non-technical terms 'what AI is and how it works'. Given the profound impact that AI is expected to have on marketing and the increasing interest among scholars and practitioners, understanding of AI, its elements and how it works is a first important step before being able to assess its impact. Here, study A introduces a framework of AI consisting of six building blocks, provides a definition and explanation of each building block and explains the interrelationships of these building blocks, along with current use cases to illustrate the discussion.

Artificial intelligence can be used in a combination of any or all of these building blocks to help marketers create market knowledge. A core argument in study A is that the input-process-output transformations and the use of different AI building blocks enables the transformations of vast amounts of data, particularly unstructured data, into information and ultimately knowledge. This is explained below.

Contributions of AI to market knowledge

A second contribution of study A is the introduction of a conceptual framework and the discussion of how AI contributes to the creation of market knowledge (see Figure 5).

Figure 5: Creating market knowledge from big data using artificial intelligence



Artificial intelligence, as information technology that acts intelligently, can be used to help B2B marketers analyse big data created by market stakeholders, i.e., customers, competitors and other, external market stakeholders. Through the use of AI and its building blocks, these data are processed, categorized and given meaning, so that information results from these analyses. For instance, AI can process structured and unstructured data inputs, such as customers' recency, size, frequency and the type of past purchases, web browsing behavior, psychographic and demographic characteristics and interactions with the firm and identify characteristics of current customers.

In addition, AI can analyse data of written and non-written user-generated content on social media platforms which can provide information about customer needs, preferences, attitudes and behaviours (Martínez et al., 2016). The AI application 'IBM Watson', for example, can identify sentiment, emotions, values, and attitudes expressed in a piece of text (Biondi et al., 2017; IBM, 2018). These psychographic characteristics can be valuable information for innovation and new product development efforts. In addition, AI can be used to identify themes and patterns in individuals' posts about their use of a product, which can reveal information about the user experience and point to areas to enhance this experience. This discussion suggests that the contribution by AI to market knowledge is by assigning meaning to data, e.g., by identifying patterns or relationships. This transforms data into information.

Using machine learning, this information can then be applied to predict which prospects, for instance, are likely to convert. Data, information, and the results from machine learning are stored in AI's knowledge base for future analysis, just like a human memory would store previous experiences, information, and knowledge. In summary, through machine learning and AI's knowledge base, information is combined with other information and knowledge in a specific context, thus resulting in the creation of (new) market knowledge.

Hence, the above discussion suggests that AI impacts the creation of market knowledge through enabling enhanced information quality and quantity from big data, and through applying information in a specific business context, combining it with other information and data so that knowledge emerges. The results from study A and the framework depicted in Figure 5 above suggests that AI mediates the relationship between data and information and between information and market knowledge.

4.1.2 Paper B: How does artificial intelligence impact the creation of market knowledge from big data and what are the implications for human resources?

Paper B addresses RQ 2 in the context of the B2B sales process. Paper B has two research objectives: First, to explore how AI changes the B2B sales process which traditionally has been human-centric (Syam & Sharma, 2018); this is termed the 'AI-enabled sales process'. The second research objective is to explicate the implications for human resources at each stage of the AI-enabled sales process.

To achieve these objectives and answer RQ 2, the conceptual paper B reviews the relevant literature on sales, specifically focusing on the sales process, also known as the sales funnel (Syam & Sharma, 2018). It should be noted that, while traditionally the model has been referred to as the sales funnel, more recent studies suggest that especially in the early stages of the funnel, the marketing and sales functions are highly integrated, thus calling for a conceptualization that includes both marketing and sales tasks (Järvinen & Taiminen, 2016; Syam & Sharma, 2018). In line with this recent view, paper B discusses marketing tasks as they apply to different stages of the sales funnel, in addition to sales tasks.

Paper B explicates the value-add contributions that AI can bring at each step of the sales process, and how it changes the tasks that were traditionally performed by humans at each stage of the sales process. Building on the building blocks of AI discussed in study A, paper B examines the AI building blocks and their implications for different stages of the sales process. The AI building blocks discussed in more detail in paper B include unstructured data (building block #2), natural language understanding and computer vision (building block#3), machine learning (building block#4) and natural language generation and robotics (building block #6).

The paper proposes that these building blocks impact critical sales tasks that were traditionally performed by humans, which is termed the 'AI-enabled sales process'. The paper then clarifies the roles that human resources play at each stage of the AI-enabled sales process. Table 13 summarizes the traditional tasks along each stage of the sales process, the value-add contributions AI can bring to each tasks and how human resources add value at each stage of the AI-enables sales process.

Table 13: Artificial intelligence and human contributions for value creation in B2B sales

Stage of the B2B marketing / sales funnel	Traditional marketing and sales tasks	AI Value-Add to traditional marketing and sales tasks	Human Value-Add to AI-enabled marketing and sales task
(1) Prospecting	Lead generation: Finding potential customers Lead qualification: Evaluating prospects' propensity to buy	Build rich prospect profiles (structured and unstructured data) Predictive lead qualification Update lead generation and and lead qualification models via machine learning	Interpret prospect lists and explain inconsistencies Verify lead qualification and put into business context
(2) Pre-approach and (3) Approach	Lead Nurturing: Acquiring more information about leads and making contact	Ad targeting and re-targeting: Personalized and customized communication messages and channel Content curation Making contact via digital agents (e.g., chatbots)	Monitor ad targeting, re-targeting and content curation Take over from or delegate to AI-digital agents during contact.
(4) Presentation	Communicating the problem-solving characteristics of the offering (e.g., prototype, use cases, simulation)	AI-enabled prototyping Emotion AI	Build rapport, trust and credibility Address questions in-person Interpret emotions and respond effectively
(5) Overcoming objections and (6) Closing	Negotiating sale and overcoming objections	Curate competitive intelligence (e.g., for sales battlecards) Dynamic pricing	Communicate product benefits Build rapport, trust and credibility Interpret emotions and respond effectively Persuasive communication
(7) Follow-up	Fulfilling the current order Follow up beyond the current order Upsell, cross-sell	Automate work flows Automate post order service (e.g., chatbots) Build rich customer profiles (structured and unstructured data) to uncover new needs	Oversee order processing and fulfilment Strengthening exchange relationship Personal post-service follow-up Interpret new needs and explain inconsistencies

Paper B provides a number of contributions to the literature. First, paper B addresses the call for more research put forward by scholars to investigate AI and human resources (Duan et al., 2019; Singh et al., 2019; Syam & Sharma, 2018), and how AI impacts the creation of market knowledge (Balducci & Marinova, 2018; Berger et al., 2019; Davenport et al., 2019; Martínez-López & Casillas, 2013; Metaxiotis et al., 2003; Wedel & Kannan, 2016). Paper B proposes value-add contributions that AI can bring at each stage of the sales process. Artificial intelligence can effectively and efficiently process and analyse large and complex data, particularly unstructured data, into information. Here, AI is a tool that helps find hidden patterns in big data.

Human resources, specifically, intuition, business experience, and detailed knowledge about the business and industry are necessary to deal with contradictory or uncertain information, to verify AI-generated information and to create knowledge from information. In addition, human resources are required to derive the 'so what', i.e., the implications of the AI-enabled information for business decision making. For instance, sales professionals decide on the appropriate course of action using AI information. In addition, the relationship building aspects are paramount in B2B sales, and this is an area where human contributions outperform AI.

In summary, paper B posits that AI and human contributions can be complementary. AI is effective and efficient at analytical tasks in B2B sales, such as data analysis, predictive lead qualification, or prospect profiling. In addition, AI can also replace repeatable mechanical tasks in B2B sales, such as scheduling or responding to inquiries. Human resources outperform AI when it comes to interpersonal and creative tasks in B2B sales. The potential for combining AI and human contributions for value creation throughout the B2B sales funnel is significant. Human resources continue to play an important role in all stages of the sales process. Intuition, deriving implications from AI output information, and relationship building are some of the key resources that humans bring to the AI-enables sales process.

Another contribution of paper B lies in providing seven managerial considerations for maximizing the value from using AI and human contributions. These managerial considerations can help managers not only understand some of the critical issues they may face when integrating AI into their sales process, but also offer guidelines on how to address these issues. Table 14 summarizes the managerial considerations suggested in paper B.

Table 14: Managerial considerations for maximizing collaborative intelligence

Managerial consideration	Explanation
(1) Training is essential	Training of sales professionals and support staff in using AI and interpreting AI-generated information is essential.
(2) Link AI to enterprise knowledge management strategies and tactics	AI is a key enabler for customer knowledge management, by capturing, organizing and sharing customer information.
(3) Leave insights and social-emotional tasks to human intelligence	Human resources are critical in deriving insights and implications from AI-generated information and deciding on an appropriate course of action. Social and emotional intelligence from human resources remains critical.
(4) Support customers through the transition	Acknowledge and support customers through the changes brought about by AI at each stage of the sales process.
(5) Expect resistance	Change management can support sales professionals through the AI-enabled sales process and overcome resistance.
(6) Information security is paramount	As more data is collected, stored and analysed using AI, information security and customer privacy considerations are critical
(7) Build a sales force structure and processes supportive of AI	New organizational or department structures, in addition to different processes and workflows in sales may be required to maximize the value from collaborative intelligence.

4.1.3 Study C: How do artificial intelligence and human resources interact in creating market knowledge from big data?

The research presented in study C explores the interaction of AI and human resources in creating market knowledge about competitors (in the literature termed competitive intelligence, but termed competitor knowledge or knowledge about competitors in this thesis). Study C provides empirical evidence that market knowledge about competitors is heavily co-created by human (i.e., sales professionals and sales enablement professionals) and non-human actors (i.e., AI) through activities and integrating resources. The AI is classified as an economic actor due to its potential for agency, i.e., due to its potential to influence human actors' decisions and behaviours. This is explained below.

Actors (who?) in creating competitor knowledge

The empirical findings pointed to three different actors with different roles in creating competitor knowledge: These are the 'bot', the 'curators', and the 'consumers. The bot refers to the data gathering and analysis software including AI, specifically natural language understanding and machine learning. The curators are individuals who provide data and information management, interpret the AI-output and create content for use by the third group of actors, the consumers. The consumers are the end users of the content created by the curators.

The bot collects data from a number of publicly available sources, company and news websites, blogs, social media, court filings, patents and public financial reports, and also from internal sources such as data and information logged in customer relationship management systems. Duplicates are removed, the data is organized and scored on relevancy by the bot, using machine learning. This provides a first level of analysis by the bot which adds usefulness and purpose to the data. The result of this first level of analysis by the bot is information.

This information is reviewed by the curators, who apply their existing expertise and knowledge to verify, review and interpret the AI-information in the context of their specific business needs. The results from study C suggest that it is the knowledge and expertise of the curators that enables information to be turned into knowledge. Curators also make the knowledge explicit for use by other actors, mainly consumers. This ‘making explicit’ encompasses creating communications, such as battle cards, sales messages, or newsletters, using visual and written tools. The content produced by the curators is utilized by the consumers, another important actor. The consumer’s role largely includes the ‘consumption’ of content, i.e., retrieving it and applying it during the sales process.

Activities in creating competitor knowledge (how?) and resources (what?)

The creation of competitor knowledge begins with collecting data from varied sources. The effectiveness of the data collection relies on both human and AI resources. As part of data collection, human resources are necessary to identify relevant competitors and type of data required, specifically industry and business expertise. Using natural language understanding, AI identifies relevant data, categorizes, removes duplicates and subsequently improves the relevance of its data inputs and using machine learning.

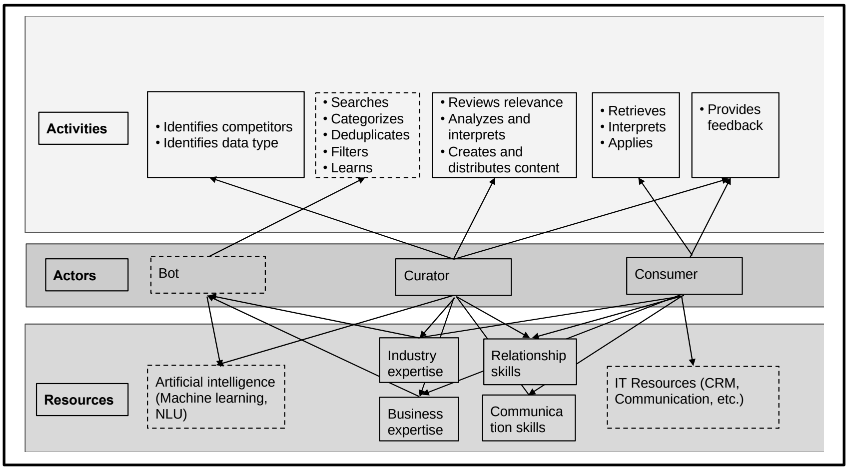
Subsequent activities include reviewing the AI-generated information, determining its relevance, providing deeper level analysis by interpreting it, and contextualizing. These activities are key tasks performed by humans, primarily curators, using their industry and business expertise. The ‘review’ and ‘relevance’ activities are performed by sales enablement professionals and improve the performance of the data collection via AI. For example, when an employee marks something as important or unimportant, AI updates its machine learning building block and progressively becomes better during data collection.

Providing deeper level analysis, synthesizing various pieces of AI-generated information, interpreting and contextualizing the AI-information are key activities performed by sales enablement. These activities create competitor knowledge which the curators then make explicit and transferrable by generating content (written and visual). This requires communication skills. In addition, the review and relevance activities also provide feedback to AI, i.e., act as inputs to the AI technology, specifically to machine learning.

As described above, the content created by sales enablement professionals (curators) are distributed to the sales staff, which are the consumers of the competitor knowledge. One key resource here is digital tools that consumers are familiar with and use regularly, such as CRM tools. Consumers retrieve, utilize and further interpret the content, which may result in (new) knowledge creation. Sales professionals also provide feedback to sales enablement or ask follow-up questions. The results from the interview suggest that relationship building skills are an important resource for these activities.

The discussion above suggests that market knowledge about competitors results from the interaction and combination of AI and human resources. In fact, a key contribution of study C is a deeper understanding of the structure of interactions and the nature of human resources in creating competitor knowledge. Figure 7 depicts the structure of interactions graphically.

Figure 6: Interactions of AI and human resources in creating market knowledge: Activities, actors and resources



4.1.4 Paper D: What are the mutual contributions of artificial intelligence and human resources in creating market knowledge from big data?

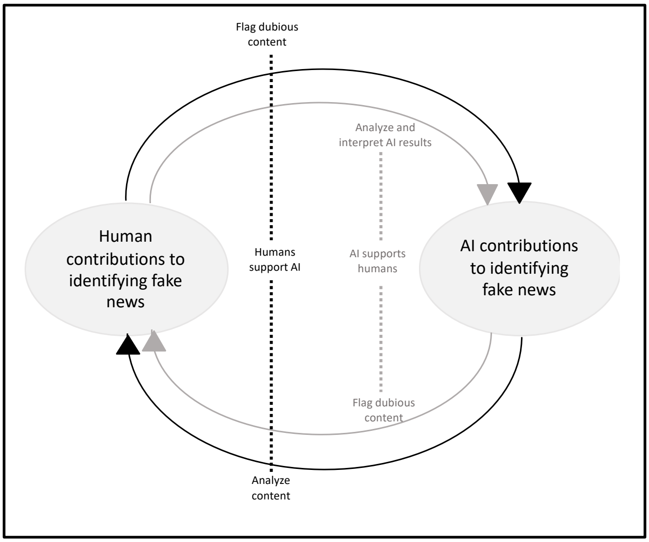
The research presented in paper D examines AI and human resources in the context of professionally-generated big data in text form (as opposed to user-generated text data in paper E). The research in paper D responds to calls for more research on the computational methods of using AI to analysing unstructured data in marketing (Balducci & Marinova, 2018; Berger et al., 2019; Davenport et al., 2019; Wedel & Kannan, 2016).

The literature suggests that the combination of AI and human contributions can help organizations effectively analyse big data in text form, for example to identify fake news (Pitt & Berthon, 2018), which is the context for paper D. In addition, media organizations are increasingly making use of AI and human inputs for fake news screening. At the time of conducting the empirical research in paper D, Facebook had just announced its plans to expand its team of content specialists, in addition to relying on AI to screen for fake news (Hern, 2018; Wakefield, 2019).

Paper D provides a methodological contribution by demonstrating the mutual contributions of AI and human resources in creating knowledge from big data. Artificial intelligence is an important enabler to transforming data into information. Specifically, the paper reveals that the building blocks of unstructured data, natural language understanding, machine learning, and natural language generation play particularly important roles in the transformation of data into information. The use of AI makes the coding of large unstructured text data more efficient and substantially less time-consuming than manual coding. The output information generated by AI can then be used by the researcher for further analyses and interpretation. Specifically, the output information from the AI processing was then subjected to further quantitative analysis via hypothesis testing. Effective use of hypothesis testing relied on the researcher's knowledge about and experience with this form of statistical analysis. Thus, an important finding with respect to RQ 4 is that the relationship between AI and human resources is complementary: Artificial intelligence transforms data into information, and that knowledge results from human contributions, specifically, expertise about the what and how of statistical analyses and an understanding of the literature and previous research.

Moreover, paper D introduces a framework by which to describe the complementary relationship between human and AI contributions (see Figure 7). The framework suggests that human contributions support AI, using their existing knowledge to interpret and flag news content. Here, trained observers further analyse, verify, and interpret the information produced by AI, thus creating knowledge. Artificial intelligence also supports humans, for instance by 'doing the heavy lifting' in transforming large data sets into information. Thus, the findings suggest that AI and human contributions can be complementary in creating market knowledge.

Figure 7: Human and artificial intelligence (AI) contributions in fake news identification



4.1.5 Paper E: What are the contributions of artificial intelligence and human resources to different activities in creating market knowledge from big data?

The research presented in paper E responds to calls for more research on the computational methods of using AI to analysing unstructured data in marketing (Balducci & Marinova, 2018; Berger et al., 2019; Davenport et al., 2019; Wedel & Kannan, 2016), and specifically on hybrid content analysis (Lewis et al., 2013; Su et al., 2017). It demonstrates a research methodology in which automated content analysis (via AI) and manual analysis (via human coders) can effectively be used to analyse Twitter data. This combined analysis is termed ‘hybrid analysis’ in paper E.

The findings from the empirical analysis in paper E provide a number of contributions to the literature. First, paper E contributes to the literature on content analysis in marketing as the findings reiterate the usefulness of combining manual (human) and automated (AI) content analysis techniques into a hybrid method. The findings from paper E suggest that AI and human resources offer different contributions for different activities of the market knowledge creation process. These benefits are summarized in Table 15 and explained below:

Table 15: Artificial intelligence, human resources and market knowledge creation processes

Market knowledge creation activity	Artificial intelligence	Human resources
Collecting data	• Knowledge base to store data	• Human expertise required to identify type of data based on research questions
Analysing data (data → information)	• Efficiency (speed) • High reliability due to o Removal of human bias o Low risk for errors in analysis • High validity due to o Natural language understanding and machine learning building blocks being able to identify semantic representation of text, including syntax, pragmatics and semantics • Knowledge base to store information	• Considers non-text symbols during analysis (e.g., emojis, gif's, etc.)
Interpreting information (information → knowledge)	• Information applied to a specific business context, using previous information and experience through machine learning • Knowledge base to store knowledge and machine learning results	• Interpret AI-generated information using domain-specific knowledge • Explaining counter-intuitive or contradictory information • Derive implications for marketing decision making ("So what?")

For data collection, human knowledge is necessary to identify the type of data to be collected based on the research questions and research objectives. Specifically, in paper E, the researcher consulted the existing research on consumption restraint, and used their research skills and expertise to identify the type of data needed based to effectively answer the research questions. Once collected, AI provided efficient storage of the data via its knowledge base (AI building block #5).

For data analysis, AI provides a number of benefits in analyzing the data in a meaningful way to derive information. One benefit is efficiency. Artificial intelligence is capable of analyzing large volumes of data faster than humans. This is one advantage where AI outperforms human analysis; the latter is labor-intensive and more prone to mistakes as coders' ability to concentrate decreases with increasing data volumes.

Another potential benefit is the high reliability of the AI analysis due to the removal of human bias in the content analysis process and a lower risk for errors. Moreover, using natural language understanding and machine learning (AI building blocks #3 and #4), AI can identify the underlying meaning of text, which was very difficult to impossible with previous automated tools that relied on a built-in dictionary. Specifically, AI is able to analyse the including syntax, pragmatics and semantics of text written in everyday language, just as human coders would. Thus, AI analysis may achieve high validity and not face the same validity concerns as other automated analysis tools that were outlined earlier. Human coding, on the other hand, while less efficient, and more prone to researcher subjectivity and errors, can consider non-text content, such as symbols, during the coding process to derive meaning. These symbols, including emojis or gifs, can provide meaning about the underlying sentiment or meaning expressed in the tweets.

In terms of transforming the information into knowledge, both, AI and human resources provide a variety of contributions for these activities. With respect to AI contributions, machine learning updates AI's processes based on previous experience and its application in a specific business context. For example, if characteristics of current customers are applied by AI to predict future customer purchases, machine learning updates from this application in a specific business context and improves its performance based on this experience. Thus, AI interprets and learns based on previous information and experience. Artificial intelligence's knowledge base provides effective storage of this knowledge.

With respect to human contributions to the different knowledge creation activities, humans interpret the AI-generated information using their domain-specific knowledge. For instance, the AI-scores on the prevalence of human values in the tweets was interpreted by the researchers, using their existing knowledge from the literature and based on their research backgrounds. Moreover, human expertise is required to explain and clarify the AI outputs, particularly for results that are counter-intuitive or even contradictory, as is the case in paper E's discussion of the seemingly contrary findings regarding one of the human value dimensions expressed in tweets. Finally, human knowledge is required to derive the implications of the information generated by AI for marketing researchers and practitioners.

In summary, the results from paper E suggests that AI and human resources provide different benefits at different stages of the market knowledge creation process. While AI is effective at extracting information from large volumes of text data, human skills are needed to turn this information into knowledge, such as the implications for managerial decision making. In this regard, AI can do the 'heavy lifting' by processing large datasets, for instance via its natural language understanding and its machine learning building blocks. Thus, the value that AI can bring is primarily of analytical nature, i.e., data analysis and processing. The value-add contributions from humans lie primarily in interpreting the AI-generated information and deriving insights and implications for marketing decision making. In addition, humans explaining the automated results is critical, particularly when the results are counter-intuitive or even contradictory.

Thus, AI as one specific automated content analysis application can complement human capabilities (Jarrahi, 2018), an approach that has recently been termed "collaborative intelligence" (Wilson & Daugherty, 2018). Indeed, the use of AI may be particularly useful when it comes to extracting information about consumers' underlying psychological attributes or processes, such as values from large volumes of data. AI algorithms, with their ability to analyse large volumes of text, can derive information more efficiently than humans would. In addition, by analysing content voluntarily created by consumers themselves, marketers may obtain information that otherwise would be difficult to gain with more traditional consumer research approaches, such as interviews or surveys, where participants may be reluctant or incapable to offer the required information. Here, the research in paper E provides a methodological contribution by demonstrating a methodology of understanding human values whereby the limitations of response bias, lacking self-awareness, socially desired responses and the time and effort required from consumers completing a value survey can be minimized. Thus, AI has the potential to enhance the effectiveness and efficiency of human approaches to deriving market knowledge (Jarrahi, 2018).

4.2 Contributions to theory

This thesis contributes to the body of knowledge in marketing, specifically on the methods to deriving market knowledge from unstructured data using AI which is an identified gap in the marketing literature (Balducci & Marinova, 2018; Berger et al., 2019; Davenport et al., 2019; Wedel & Kannan, 2016) and practice (Marketing Science Institute, 2018). In addition, this thesis contributes to theory, specifically RBT which is the theoretical lens underpinning this thesis. This section discusses the contributions to knowledge and theory. In doing so, the current chapter first discusses AI as a resource, followed by a discussion of human capabilities. In addition, a conceptual model is proposed along with a number of propositions to advance further scholarly understanding on AI and human resources in creating market knowledge from big data.

4.2.1 Creating market knowledge from big data: The role of artificial intelligence as a resource

Today, social media and the IoT have turned the market into an incessant generator of big data (Erevelles et al., 2016). Due to the five V's of big data, traditional information technologies are ill-equipped to effectively deal with these data. Moreover, the limited capacity of humans poses difficulties in processing these data into information and create market knowledge.

Artificial intelligence is a resource that marketers can use in creating market knowledge. In terms of the RBT criteria, AI meets the criterion 'valuable' as it improves the effectiveness and efficiency of creating information from data. Artificial intelligence, via its natural language understanding and computer vision building blocks, can analyse unstructured data in written, auditory or visual form which other information technologies are unable to do. These analyses provide structure and meaning to data, for example, by identifying patterns, relationships or frequency of occurrence. Thus, these analyses transform data into information. Information is an antecedent to creating market knowledge which in turn allows marketers to provide better value to customers.

The second RBT criterion is a 'rare' resource, i.e., a resource that is not abundant or possessed by a large number of other organizations. The underlying assumption of RBT with respect to rarity is that a firm can only gain an edge over competitors by having or doing something that competitors cannot have or do. Intuitively, one may suggest that AI does not meet the criteria of a rare resource as it is available to and affordable by many marketers. However, AI has the potential to become a rare resource through its use. Machine learning, one of AI's most important building blocks, progressively improves based on previous experience. As a result, AI may be able to solve a wider range of problems, increase the accuracy with which problems are solved, or increase its processing speed. However, with machine learning, AI learns from various sources, not only from the data inputs, but also from its own processes, and becomes progressively more targeted to a focal organization. These – data inputs or processes – are unique to a focal organization and not available to other organizations. In addition, the human capabilities required for the effective use of AI may create a barrier to entry for other firms that do not possess these human capabilities. Thus, it is suggested that AI meets the 'rare' criteria of RBT resource.

With respect to the third RBT criterion, this thesis posits that AI meets the 'imperfectly imitable' criteria, as it is not easy to imitate by competitors. Similar to the argument in the previous paragraph, competitors may be able to acquire AI technology, however, certain building blocks, such as machine learning and knowledge base are unique to a focal firm and not easily copied by other organizations due to machine learning, problem solving, and reasoning building blocks. Lastly, the RBT criterion of 'organization' refers to organizational procedures and activities to exploit a resource. Here, this thesis suggests that AI is embedded and integrated within organizational activities and other resources, and that marketers organize to use AI in creating market knowledge, for instance by identifying the type of data, data sources, and incorporating AI-enabled information into marketing activities. Thus, AI meets the 'organization' criteria of resource.

The role of AI as an RBT resource occurs primarily in the transformation of data into information and also in the transformation of information into knowledge. In terms of the former, i.e., transforming data into information, AI processes big data, particularly unstructured data inputs, and effectively and efficiently analyses these data and transforms them into information. For instance, unstructured text data can be effectively processed via the natural language understanding building block, while the reasoning, problem-solving building and machine learning blocks turn these data into information, for instance by extracting sentiment, emotions, human values, themes, or other information of interest from the data.

In terms of the latter, i.e., transforming information into knowledge, AI is also a key resource that marketers can use. As discussed previously, knowledge is information that has been combined with experience, context, and interpretation (Davenport & Prusak, 1998). Artificial intelligence's machine learning building block enables its learning from its own experience, without being explicitly re-programmed to do so. In machine learning, AI learns from its data inputs and also from its problem solving and reasoning processing. Machine learning also updates data and information stored in the knowledge base and refines its problem solving and reasoning processes by combining information with experience and context – which is essential to the notion of knowledge as described earlier.

In summary, AI is an RBT resource in creating market knowledge through transforming data into information and information into knowledge. Through transforming data into information, AI is primarily a resource of analytical nature. This analytical nature encompasses AI's ability to process data and information to perform tasks or solve problems and learn from its experience (Huang & Rust, 2018). For instance, AI learns and adapts using its problem solving, reasoning and machine learning building blocks, and updates its processes and knowledge base with this learning. The analytical role of AI's is well suited for complex, yet systematic and well-defined tasks in market knowledge creation; for example, those that require finding patterns, identifying relationships or frequency of occurrence of phenomena in data.

4.2.2 The role of human capabilities in creating market knowledge from big data

Human resources are an important capability in creating market knowledge enabled by AI. According to RBT, capabilities are a subset of a firm's resources that improve the productivity of other resources (Kozlenkova et al., 2014; Srivastava et al., 2001). Human capabilities improve the productivity of AI as a resource in creating market knowledge. For instance, domain-specific expertise, e.g., business and industry knowledge, are essential in identifying what type data is relevant for AI to use an input, given a certain question to be answered or type of market knowledge to be created. In addition, human contributions are essential in verifying, interpreting, and deriving implications from AI outputs. Specifically, human capabilities make sense of AI-created outputs, conduct further analyses or apply the AI outputs in marketing and sales tasks.

Here, the role of human capabilities is primarily of intuitive nature. This intuitive role encompasses the ability of humans to think creatively, create insights and adjust to new situations (Huang & Rust, 2018) using creative problem solving, expertise, and intuition. For example, interpreting the AI-enabled information outputs, making business-sense

of this information and using the resulting knowledge in interactions with a customer is a capability where humans outperform AI.
In addition to the intuitive roles, the role of human capabilities in market knowledge creation enabled by AI can be of empathetic nature. This is related to the intuitive role discussed above, as the human ability to make sense of AI outputs also encompass sense-making and decision making from a social, interpersonal, or emotional perspective. This encompasses an awareness of one's owns emotional state, empathy, the ability to build relationships and responding in an emotionally appropriate way in marketing or sales situations. While AI technologies increasingly become more sophisticated to recognize, interpret, and even respond to emotions, human capabilities still play an important role in these tasks. For instance, and as discussed in paper D, while AI may identify a customer's emotions in a sales situation, sales professionals are still paramount in responding appropriately emotionally, and influence others' emotions.

4.2.3 The nature of contributions by artificial intelligence and human capabilities

This chapter so far discusses the role of AI as a resource and the role of humans as an important capability in creating market knowledge. The discussion also suggests that the nature of contributions provided by AI as a resource and human capabilities differ. Specifically, AI resources provide contributions that are primarily of analytical nature, while the nature of human capabilities are primarily of intuitive and empathetic nature. These findings are summarized in Table 16.

Table 16: The nature of AI and human contributions in market knowledge creation

	Artificial intelligence	Human resources
Analytical - process data and information to solve problems in a specific context and learn from it. Complex, systematic well-defined activities in creating market knowledge.	√√	√
Intuitive – creative problem-solving, verifying, interpreting AI outputs.	√	√√
Empathetic – interpreting AI outputs for interpersonal decisions in marketing.	√	√√

4.2.4 Artificial intelligence, human capabilities and resource-based theory

The discussion in this thesis argues that AI and human capabilities influence the creation of market knowledge. The discussion also suggests that AI and human contributions play different, yet complementary roles in the creation of market knowledge. The current section discusses the findings from the perspective of RBT. It discusses how the three key constructs – AI, human capabilities and market knowledge – are related, develops propositions about their relationships and a conceptual model about these relationships.

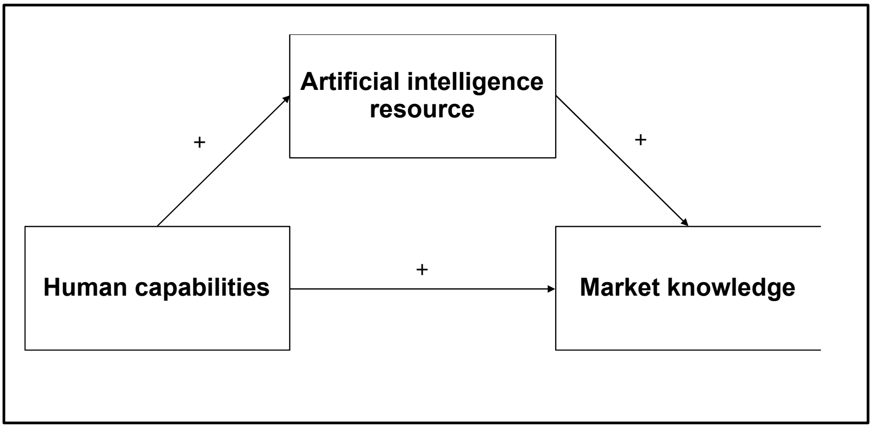
The value of AI as a resource in creating market knowledge is not built-in to the AI information technology per se. Rather, the value of AI as a resource stems from how it is combined with other resources, specifically human capabilities. This reflects the view proposed by Penrose (1959) suggesting that simply having access to a resource does not necessarily provide an advantage to firms. Rather, it is the way in which resources are used in combination with other resources, that results in value creation for firms. “Strictly speaking, it is never the resources themselves that are the “inputs” into the production process, but only the services that the resources can render. The services yielded by resources are a function of the way in which they are used – exactly the same resources when used for different purposes or in different ways and in a combination with different types or amounts of other resources provides a different service or set of services." (Penrose, 1959, p. 25). Following this line of argument by Penrose, it is relevant to consider the interplay of AI information technology with other resources for creating market knowledge.

The research in this thesis provides empirical evidence that the value from AI emerges in combination with human capabilities. Human capabilities play an important role in realizing the value creation potential from AI for creating market knowledge. One way in which human capabilities impact the potential from AI is regarding the type of data and information to be collected and analysed. For instance, human expertise, such as industry, business knowledge or other domain-specific expertise, is important to identify the type of data required, data sources or the type of analysis to be conducted as suggested by the results from study C, paper D and paper E. Moreover, the value creation potential from AI is impacted by individuals' skills to interpret and communicate the AI output, thus making the resulting knowledge explicit. For example, the results from study C suggest that curators create knowledge using AI-enabled information, and make this knowledge explicit in various forms, including battle cards, newsletters, or other communications.

4.2.5 A conceptual model about the relationship between human capabilities, artificial intelligence and market knowledge

The findings in this thesis suggest that the creation of market knowledge relies on AI and human capabilities and that human capabilities positively influence the creation of market knowledge (direct effect) and that this relationship is mediated by AI (indirect effect). A key contribution from this thesis is the formulation of a conceptual model (shown in Figure 8) and a number of propositions regarding the relationship between AI as a resource, human capabilities and market knowledge. This is discussed in the current section.

Figure 8: A conceptual model on the relationship between human capabilities, artificial intelligence and market knowledge



With respect to the direct effect, human capabilities are positively related to the creation of market knowledge from big data. The research in this thesis suggests that humans' pre-existing knowledge, for example about the industry, business, or other domain-specific knowledge is with respect to their ability to interpret information in a specific business context and make sense of it given a specific marketing problem, thus creating new market knowledge. Humans' communication skills make this new knowledge explicit and enable others to use it for specific marketing tasks. Thus, proposition 1 suggests that human capabilities are positively related to the creation of market knowledge.

Proposition 1: Human capabilities are positively associated with market knowledge.

With respect to the indirect effect, the findings in this thesis also suggest that human capabilities may not be able to create market knowledge from big data per se, but rather that the positive effect is mediated by AI resources. This thesis posits that human capabilities positively impact the effectiveness of AI resources. Human expertise is important to identify what type of data or information should be collected and analysed, given a specific marketing problem. In addition, human knowledge is relevant for identifying relevant data and data sources for AI to use as inputs. The research in this thesis suggests that these human capabilities can positively impact the effectiveness of AI which is summarized in proposition 2:

Proposition 2: Human capabilities are positively associated with the effectiveness of AI resources.

In addition, the research in this thesis suggests that AI has a positive impact on the creation of market knowledge. Artificial intelligence enables enhanced information quality and quantity through its ability to analyse and process vast amounts of data accurately and effectively. Artificial intelligence can be used to reduce cost and time for analysing big data, hence increasing the efficiency of generating market knowledge. Artificial intelligence resources can do much of the heavy lifting related to analysing large, unstructured, complex and continuously updating data sets, by finding patterns, themes and relationships in big data and transforming this data into information. Artificial intelligence can also be used to improve the effectiveness of market knowledge, for example through enhanced customer profiling or more accurate predictions about customer behaviours. Through machine learning, AI also updates its problem solving and reasoning algorithms which is then stored in its knowledge base, thus continuously improving the efficiency and effectiveness of market knowledge creation. Thus, proposition 3 suggests that AI resources are positively linked with market knowledge.

Proposition 3: Artificial intelligence resources are positively associated with market knowledge.

Two sub-propositions are suggested that concern the direct effect of AI resources on market knowledge effectiveness and efficiency as follows:

Proposition 3a: Artificial intelligence resources are positively associated with the effectiveness of market knowledge.

Proposition 3b: Artificial intelligence resources are positively associated with the efficiency of market knowledge.

In summary, the conceptual model shown in Figure 8 and the propositions suggest that human capabilities are positively related to the creation of market knowledge and that this relationship is mediated by AI as a resource.

4.3 Implications for managers

This thesis provides a number of implications for managers. First, it clarifies the technological phenomenon AI by explaining its building blocks in non-technical terms and illustrating the relationships between the different building blocks. For marketers to be able to assess the implications of AI properly, they need to understand what AI is, how it works, and how the different building blocks contribute to creating market knowledge. This thesis provides an easily digestible framework, introduced in study A, that managers can use to understand the different building blocks of AI and their relationships.

Another important contribution for managers from this research lies in providing a structured discussion on the implications of AI for managing market knowledge. Specifically, this thesis provides evidence that AI facilitates knowledge management processes by transforming data, and particularly big data, into information and information into knowledge. In today's marketplace, big data is discussed as a new form of capital, however, many firms fail to realize its value potential (Balducci & Marinova, 2018; Erevelles et al., 2016). To create value from this new form of capital, firms must allocate appropriate physical and human resources, and AI is an important resource in this regard.

A further implication for managers resulting from this research is an understanding of the role of human capabilities when utilizing AI for creating market knowledge. Specifically, this thesis suggests that human contributions are an important capability that enhances the productivity of AI as a resource. This is important for managers to understand to inform their marketing decision making.

Lastly, this thesis provides an understanding for managers with respect to the nature of contributions provided by AI and humans in creating market knowledge. This understanding is important for managers as it enables them to devise and implement knowledge management strategies and tactics in marketing and allocate resources appropriately. Specifically, this thesis provides evidence that AI is primarily a resource of analytical nature, through transforming data into information and information into knowledge. The analytical nature of AI's role is well suited for complex, yet systematic and well-known tasks in creating market knowledge; for example, those that require finding patterns and synthesizing large amounts of data and information and learn from them. Human capabilities, on the other hand, are primarily intuitive and empathetic in nature. While the intuitive nature encompasses the ability of humans to think creatively and adjust to new situations using creative problem solving, expertise, and intuition when using AI, the empathic nature entails managerial decision making from a social, interpersonal, or emotional perspective.

4.4 Limitations and future research

This thesis investigated how marketers create market knowledge from big data using AI and human resources. As outlined in the previous sections, this thesis provides important contributions to theory and managerial implications. However, this research is not without limitations which will be discussed below, in addition to future research avenues.

The empirical work in this thesis focused on text data which is one particular form of unstructured data. The empirical analysis of this textual data relied heavily on natural language understanding as a pre-processing building block of AI. Other pre-processing building blocks, such as computer vision or speech recognition, were not utilized, as no image or speech data was utilized. This presents opportunities for future research, whereby scholars could employ other forms of unstructured data. In particular, analysis of speech and image data using AI building blocks has been identified as a fruitful area for future research in the literature (Balducci & Marinova, 2018).

This thesis focused on understanding AI and how this information technology, combined with human resources, creates market knowledge. Yet, like all technologies AI has its own limitations and there may be situations in which the use of AI detracts value more than it adds value. Future research should explore the 'downsides' of AI for market knowledge creation, including issues related to consumer or employee privacy, consumer or employee misperceptions of AI, or failures of AI to extract meaningful information from data. Research on these and other downsides would be beneficial for academics and practitioners alike.

Another area that would benefit from better understanding is that of the isolated contributions of the different building blocks of AI to market knowledge creation. This thesis identifies that the building blocks of AI have roles that are specific to different activities in the creation of market knowledge. Future research could focus on enhanced understanding of the roles that individual building blocks of AI, rather than AI more generally, have for creating market knowledge. To accomplish such an understanding, case studies of organizations that use AI for creating market knowledge would be beneficial.

In addition, the conceptual model and the propositions put forward could be empirically investigated. Such empirical studies could be performed in different industries or organizational environments. This would allow for a more nuanced understanding of AI resources, capabilities and the relationships between these key constructs and the respective roles in market knowledge creation.

Research on AI in marketing is limited, and the research presented herein focused on AI in the context of market knowledge creation. Yet, AI has potential to contribute value to other aspects of the marketing function; future research could thus explore the use of AI in marketing outside of the realm of market knowledge. For example, the use of AI in promotional activities or as part of omni-channel retailing experiences could be explored. Such investigations could shed light on the full spectrum of AI's potential to create value for marketers.

4.5 Chapter summary

With the increasing interest and adoption of AI among marketing professionals, the research in this thesis contributes to an increased understanding of the role of AI and human capabilities in creating market knowledge. This research conceptually and empirically investigates the contributions, interactions and activities in creating market knowledge from big data using AI and humans. In doing so, it makes three key contributions to the scholarly literature which are discussed in detail in this chapter. First, it provides a non-technical understanding of what AI is, how it works and its implications for creating market knowledge, thus addressing an identified gap in the marketing literature. Second, it provides an understanding of the nature of contributions by AI and humans to creating market knowledge from big data. Third, it proposes a conceptual model and offers five propositions about the relationships between AI as a resource and human capabilities in creating market knowledge. Research on AI in marketing is currently limited and growing, and this thesis provides a contribution to the increasing scholarly interest on the AI phenomenon.

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Chapter 5: Appended papers and studies

The three research papers and two studies in this thesis explore different aspects of the market knowledge creation process and outcomes using AI and human resources. Each paper and study is answering one research question in this thesis. Chapter 5 includes the papers and studies in full-length form and their publication status, where applicable.