Digital Media Data and Market Intelligence Management for International Business

MA Media and Business

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Preface

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1 Introduction

Over the last decades, companies have experienced many transformations regarding their strategies for digital media use in marketing. Marketing service providers who started by managing relationships with the customers are now facing competition over improving the overall customer experience under the escalating complexity of technologies (Spies, Hesse, & Loesch, 1997). Big data management has gradually become even more necessary for digital corporate communication, which aims to have a far-reaching impact on reaching the consumers and driven strategizing. As Letouze (2012) note, data-driven strategies add more value to the decision-making process and ultimately can direct marketing activities. Companies can use it to develop strategies across a wide range of aspects such as employing dynamic pricing or improving product to outperform its competitors (Erellves et al., 2015; Van Riel et al., 2013).

Only in the past few decades have digital media platforms such as social media emerged to offer consumers room to express their opinion about business, and they can easily become value destroyers instead of value creators (Leeflang et al., 2014), for example, by leaving a negative product review. This can trigger a reputation crisis for any established business. This calls for marketers to model the digital media environment effectively through quantitative analytics of digital data. This can be either structured or unstructured data, such as textual posts of customers that do not easily fit in quantitative analytical paradigms. Marketers can thus enlarge their ability to judge the direction of trends in the digital domain (Leeflang et al., 2014); in particular, those who promote the products or brands via one or more forms of electronic media are or should be adaptive to the changes in the medium and the market in order to retrieve market insights.

Most strategists around the globe are eager to acquire this knowledge from big data: 91% of marketers and 100% of Chief Marketing Officers (CMO) believe that data-driven strategy is one of the milestones of marketing success (Rogers & Sexton, 2012; Kumar et al., 2013). In recent years many private companies that seek solutions to the big data challenge primarily engage in the development of analytics (Strong, Lee & Wang, 1997). However, strategically employing big data analytics for digital marketing is still a relatively new practice that companies are experimenting with, which incurs mistakes that make corporate data management inconsistent and incomplete (Van Dijk & Poell, 2015; Strong, Lee & Wang, 1997). Mistakes that occur in analytics are largely neglected since they are often not found to be detrimental, even though the management of data theoretically requires accuracy (Neamtu et al., 2014). For example, many marketers start to work on data even when it is not completed - 29% of marketing leaders report that they lack sufficient consumer data to accomplish their ambition in making conclusions from the data (Rogers & Sexton, 2012; Kumar et al., 2013). Companies rarely manage to find the appropriate solution for big data, and it is now even more challenging since big data seems to be everlastingly expanding along with "data exhaust" (the vast trail left by various online behavior) (Walton, 2016).

Subsequently, the future of big data consumer analytics in the competitive market has been a heavily debated topic from many angles. International business historically took up an important place in the Dutch digital media landscape. However, the way international business is structured in the Netherlands is slightly complex. It is first of pivotal to have sufficient physical, human, organization and capital resources for operation (Barney, 1991). Many companies conduct marketing research and strategizing based on limited knowledge and unlimited ignorance (unknown about what is unknown) in an attempt to achieve their goals and remain competitive (Erevelles et al., 2015). Thus, companies need to enhance their existing, adaptive, and dynamic capabilities in order to maintain their competitive advantage in response to the changes in the market (Day, 2011, 2014; Kozlenkova et al., 2014). However, Erevelles et al., (2015) argue that partial ignorance in addition to adaptive capability not only better motivates the desire for new information, but also encourage investigation into hidden insights that can be retrieved from market phenomena. All of the topics above lead to the main research question of this project:

> How do companies in the Netherlands retrieve market insights from digital media data and use it to develop data-driven marketing strategy?

1.1 Societal and Academic Relevance

This question is both socially and academically relevant for several reasons. First of all, seeing reach and social engagement as public values brings an interesting discussion into the debate of data driven strategies. In the era of information overload, the audience lacks the capability to address the rising complexity of online information and efficiency. There has been a recent call for business to assist in addressing the complexity by offering personalized and thus more relevant information, which incurs new challenges and reveals the existing technical issues (Vuokko & Karsten, 2007). Understanding how businesses conduct their digital data management and strategizing can offer a window to how businesses are addressing these issues.

Along with the fact that data analytics appears to be inadequately employed by digital marketing strategies, there are very a limited number of research studies that have focused on big data strategies devised for corporate communications (Vuokko & Karsten, 2007; Kaghan & Bowker, 2001). Among which are outdated focus on industrial production and industrial relations combined with the difficulties of conducting studies on sociotechnical innovation in the information age (Kaghan & Bowker, 2001). Many scholars call for research in the areas of digital data and urges researchers to investigate the rich data originating from social network sites (Hinz et al., 2011; Libai et al., 2010; Blazevic et al., 2013, Kumar et al., 2013). Mulhern (2009, p.98) asserts the importance of developing a strategic framework for digital media marketing to confront the challenge of big data, stating that "there is a direct need for a theoretical framework for the emerging world of digital media and digital services that is emerging."

While there has been much research done about measuring the performance of digital marketing strategies, the synergies and complementarities between strategic and tactical measures are worthy of examination and therefore are important to integrate into the performance dashboard[1] (Kumar et al., 2013). It is consequently fascinating to look at how technical products can be developed to better assist the digital media marketing activities. However, no studies as of yet have aimed to take an in-depth look at how business perform in big data analytics for digital media operations. To fill in this gap, this thesis mainly focuses on the decision-making process for future directions of each company regarding big data analytics. It mainly investigates the best-demonstrated practices of big data management in the digital marketing domain of the

[1] an easy to read, often single page, real-time user interface, showing a graphical presentation of the current status (snapshot) and historical trends of an organization's or computer appliance's key performance indicators of marketing performance to enable instantaneous and informed decisions to be made at a glance.

Netherlands. The study explores the specific approaches of corporate big data management across the procedures of data collection, extraction, and enhancement.

By constructing and analyzing several Dutch company profiles and analyzing each maturity level, this research unveils how digital marketing managers have become adaptive towards this change in acting for various business. The analysis aims to contribute to a deeper understanding of managing data across media and propose a framework to structure and assess data management for operational implications. At the outset, the author should briefly describe the key concepts mentioned in the research questions, and these definitions will specify the scope of this study.

1.2 Key Concepts and Definitions

Digital marketing is defined as "the promotion of products or brands via one or more forms of electronic media" according to Business Dictionary (2016). For example, advertising mediums that might be used as part of the digital marketing strategy of a business could include promotional efforts made via the Internet, social media, mobile phones and electronic billboards, as well as via other digital channels such as television and radio channels. *Digital data* is "the data produced through human interaction with services provided by the Internet (e.g. search and clickstream data), and human interaction with others on the internet (e.g. data from social media, blogs, community forums, and incentivized referrals)" (Kumar et al., 2013, p.334). Considering the relevance of the processed datasets - which is a product of analyzed regular data and data exhaust, are thus also included in the definition of digital data in this study.

To retrieve *market insights*, one needs to start by accessing community data, which is data generated by different online sites by users who aspire to amplify their personal impact through online behaviors. This data can be further distilled to infer user profile by categorizing different characteristics and interpreting meanings (George et al., 2014). After carrying out an appropriate analytical and interpreting process, companies with sufficient industry knowledge have the potential to retrieve useful insights that reveal trends in the market and then combine the findings into an actionable marketing strategy.

1.3 Thesis Outline

This study concentrates on the strategic perspective used to examine each business's performance in big data and its prospect for growth. Many corporate uses of data managing strategies are not commonly evidenced by reports, especially if they have not yet structured or very competitive in this practice. Taking this into consideration, using 15 semi-structured interviews with decision-makers who work in marketing, media, and business areas, this thesis sheds light on the most recent insights of the analytics on digital media and data-driven strategizing in the Netherlands.

Data analysis of this study was conducted through across case and within case analysis to compare and contrast the differences and maturity of each practice, and overall to generate referable benchmark models for future use by practitioners and strategists. To do that, this study employed computer-mediated analytical tools of semantic network analysis, which entails a structured, quantitatively analytical approach of concepts to further validate the findings. Key findings and discussion are constructed after those sections and concluded with a summarization of the primary results to encourage further discussions. Limitations and future implication in research will be discussed in the end.

2 Theoretical Framework

To understand and evaluate the effectiveness of data strategies for international business, it is first necessary to clarify the relationships between various aspects that relate to this research. First of all, the unique interactions between company and audience via digital media channels needs to be analyzed theoretically, to understand how the current service providers are operating, since they are usually limited by resources and skillsets to use and process big data efficiently. Second, related to this general concept of limited resources, companies have the option to adapt their operational environment and enhance their capabilities of managing big data. Last but not least, the development of data analytics is discussed in context of the digital media market where people engage with each other with traces of their online footprint and and the incorporation of these ever-changing insights into data-driven marketing. The specifics of the elements and concepts are considered in the context of the research question in order to explain the current operational condition of big data management among Dutch digital marketers and to further guide the direction of the interviews and the data analysis.

2.1 An Overview of Engagement and Digital Media

2.1.1 Customer relationship management

There is no doubt that new technologies are influencing the relationship between companies and consumers. Nowadays, service can be personalized through information technology, particularly by the use of packaged CRM (customer relationship management) software implemented across various marketing channels, such as the Internet, databases, mobile apps, analytics, and search engines (Maklan, Peppard, & Klaus, 2014). Service providers tend to use a diversified approach in achieving customer satisfaction with consideration of various dimensions, such as network reliability, coverage, care, provisioning, and billing, all of which have an effect on the customer's perception of their service provider (Spies et al., 1997). This direct effect on company image leads to a global competition of big data management, which underpins the pursuit toward workflow efficiency, innovation and consumer surplus (Manyika et al., 2011). Marketers are expected to acquire the knowledge of a complex and adaptive operational system for effective planning and execution to develop customer-oriented strategies (Mulhern, 2009). The elements of this system include the connections, patterns of media pieces and content and ads that consumers share (Mulhern, 2009).

Equally important, the most prominent type of platform for audience engagement and participation, though, is digital media which plays a prominent role in marketing as well. Through changes in the media environment in terms of structure and technology, multichannel design is a deliberate process that controls the "go to market" decisions (Van Bruggen et al., 2010). Management of customer relationship happens around multi-platforms including blogs, wikis, and social networks to encourage social participation (Mulhern, 2009), of which the various types and services will be discussed extensively in the next section.

2.1.2 Digital media environment

Compared to other traditional channels, digital marketing channels incur the largest volume of data, lowest cost, and best performance, which contributes to the conversion of visiting customers into buyers (McClure, 2007). Therefore, it is of importance to focus on channel optimization across paid, owned or earned media, and online social networks (Mattern et al., 2012). Paid media are purchased spaces such as website interactive banner, social media ads, paid content promotion, etc. (Mattern et al., 2012); Owned media are media involved in the retail activities of a company in which the corporate communications and transactions occur, such as companies' websites and mobile apps (Mattern et al., 2012). Earned media indicates those unpaid spaces which are developed and contributed by those branding professionals outside the company, such as PR managers and digital journalists who regularly accept press releases from PR firms (Mattern et al., 2012). Online social networks, and especially social media platforms, from a firm's perspective, are platforms where two-way communications occur actively between digital marketers and online audiences, such as the brand's official Facebook page (Mattern et al., 2012).

Various social media platforms are now available and allow for interaction between companies and their consumers and online content audiences (e.g., Facebook, Twitter, and YouTube and more). These platforms are also characterized as "collaborative projects, blogs, content communities, social networking sites, virtual game worlds, and virtual social worlds" (Kaplan & Haenlein, 2010, p.60). They have been highlighted overall as a zero cost channel for brand exposure by drawing in public attention and is one that outperforms the traditional earned channels, such as editorial coverage on TV or press (Mattern et al., 2012). Their importance is significantly present throughout each stage of the value chain and the knowledge of this particular market can benefit companies in devising data driven strategies across stages of product development, marketing, brand building and so forth.

Social media not only shifts more power of communication to users but also turns the communication manager's work (i.e., branding, campaigning, and marketing) into a paradox – the brand is no longer defined by brand managers but by the public (Maklan et al., 2014). Online social networks not only enable users to engage with the world socially but also offer them the opportunity to interact with different members of their own networks (Weeks & Holbert, 2013, as cited in Wagler & Cannon, 2015). It redistributes the power of communication evenly to various end users in the social networks. The behavior of consumers in a network is affected by others, especially by those having more social impact, no matter whether it is in the context of a brand or not (Gandomi & Haider, 2015; Jenkins, 2006).

2.1.3 Data-driven marketing

The environment of social media contributes to a set of increasingly heterogeneous data sources, which continues to impose a wide range of technical challenges in the stage of extraction and integration (Neamtu et al., 2014). Companies who understand this evolution have gradually shifted their marketing operations while reconsidering the priorities and allocation of finances in digital marketing, along with transforming the workflow and development of essential skillsets (Edelman, 2010). They are directing their attention toward data-driven marketing, which is information technology enabled marketing and is one of the products of managing big data. Many companies thus have started to acquire developers and data scientists in order to learn from their target customer group to enhance the relevancy of their offerings.

While it is considered the cost of doing business, many critics argue that data-driven marketing often insufficiently meets the ever-rising expectations with respect to providing enough useful insights and creating returns (Downling, 2002). To demonstrate that gap, digital media has fundamentally transformed strategies of marketing and services across the stages for planning, targeting, engaging and maintenance of consumers and partners, and pricing (Mulhern, 2009). To elaborate, marketing communication planning entails the combining and evaluating of the strategic roles of different communication disciplines in order to obtain the clarity, consistency and greater impact of a marketing strategy in its accomplishing its short or long-term goals in corporate communication, which is time-consuming (Schultz, 1993; Saeed, Sub, Layyah, Bilal, & Naz, 2013).

Aspects of opportunities and room for growth in big data operations for digital marketing have been addressed in literature (Mulhern, 2009; Carr, 2008; Reubel, 2008; Kastidou & Cohen, 2006). The important elements include social and other kinds of interactivity, customer demand considerations, and useful metrics (Mulhern, 2009). To illustrate, the strategy of digital marketing needs to include considerations of the social network where consumers share their opinions with one other, including the notion of message senders and receivers, which manifests as the interpersonal connection and information on digital media (Plummer et al., 2007; Jenkins, 2006). Naturally, the changes in the network among consumers and the network's potential to grow in the social media landscape also have serious implications on the interactions between organizations and consumers (i.e. interactivity) included (Reubel, 2008; Kastidou & Cohen, 2006). The strategy should also involve both the innovation and aggregation of digital empowerment that satisfy consumer demands and needs (Carr, 2008; Mulhern, 2009). Mulhern (2009) emphasized that many metrics in use can focus on the varied personal experiences in digital media and its operating costs.

Now that corporations' development in this data-driven marketing and strategy has been discussed, the existing technology-mediated digital marketing activities are next presented in the following section.

2.2 Digital data analytics

2.2.1 Big data definition & formats

Even though the concept of big data predates the arrival of machine intelligence, the definition has changed considerably along with the advances of information technology. In comparison to the very earliest kinds of data employed in data analytics for decision and executive support in the 1970s, the data strategists now use much larger data sets, labeled "big data" to support decisions, discovery, and production (Davenport, 2014). To summarize recent discussions of big data definition, the notion of "3Vs" has been used to characterize big data. "Big data is high-*volume*, high-*velocity* and high-*variety* information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making" (Gartner IT Glossary, n.d., p.1).

When discussing big data, *volume* simply indicates a large amount of data. It is most frequently mentioned, as there has been an excessive amount of data produced with a sharp increase in the last few decades. The magnitude of the data for some data repositories is on the order of petabytes, which is "equivalent to 20 million traditional filing cabinets of text" (Erevelles et al., 2015, p. 898). There is a large amounts of data that are generated through the process of online interactions with consumers, such as transactions involving governmental organizations and private firms (George et al., 2014).

The notion of data *velocity* indicates the fast speed in data transactions with regard to the speed at which data is produced, arrives (e.g., real time), or is gathered; it also connotes the processing time involved in data transfer, i.e. uploading and downloading (Zwitter, 2014). This velocity has been accelerated in the last decade, making fast trend prediction (one of the big data activities now) even more difficult. For example, every second, there are numerous user-generated data across different social media data.

Variety refers to the diverse genres of data, including videos, audio, text documents, email, images, and so forth. It also refers to big data consisting of diverse categories of information, namely, public data (including online community data), private data, data exhaust, and self-quantification data (George et al., 2014). Community data, a genre of unstructured data that illustrates the *variety*, are generated by users who contribute to different forms of data that contain their intention of communication, enlarging their effect on an online community (George et al., 2014). These channels in which people perceive, think, and operate the data are what George, Haas, and Pentland (2014, p. 321) referred to as "information sources." They define big data as the datasets that consist of a plurality of information sources, including "Internet clicks, mobile transactions, user-generated content, and social media as well as purposefully generated content through sensor networks or business transactions such as sales queries and purchase transactions" (George et al., 2014, p. 321).

Recently, practitioners and scholars have expanded the key concepts of big data into the "5Vs" (Marr, 2015; Ularu, Velicanu, Puican, & Apostu, 2012), adding *veracity* and *value*. *Veracity* refers to "the degree in which a leader [or anyone for that matter] trusts the information in order to take decision" (Ularu et al., 2012, p. 4). The last V refers *value* and refers to deriving value, profitable or beneficial in any way, from the other "V's" (Marr, 2015).

Although there is always some degree of innovation in the definition of big data, we should not come to view it as something completely new without knowing these essential "V's." These concepts that have been recently established in the discipline of big data have registered strong growth in the past decades. Therefore, they are closely intertwined with this study and investigating corporations' activities relating to the

"5V's." Next to these major concepts, the format of big data has also been widely-recognized as another major characterization of big data and thus will be introduced in the next section.

Strategists are faced with dealing with very large and fast-moving data that can be either structured or unstructured (Davenport, 2014). Both of these data types can be particularly useful and valuable for marketers and strategists, enabling them to set up the evaluative environment regarding their performance of targeting audiences (Bendle & Wang, 2016). However, the corporate practice of big data lacks a formal and coherent definition leading researchers to evolve in inconsistent and multiple directions (De Mauro, Grimaldi, & Greco, 2015). These directions can affect the operations surrounding big data collection, use and management. Thus, many scholars have thus attempted to present a better understanding using different approaches to examine the form of big data. Traditionally, structured data are often managed in large relational databases and are accessed largely through SQL, the programming language created for querying data (Hashem et al. 2015). Numbers, words, names, short phrases (such as addresses), and dates are all often considered structured data. Bendle and Wang (2016) state that structured data is characterized by a defined form and can also include direct measurements, such as star ratings, survey responses (e.g., binary yes/no questions), and tabular data organized in complex, relational ways in traditional databases. Unstructured data are data that do not follow a specific format, according to Hashem et al. (2015). This kind of data refers to with "human-created text and a litany of file types" (Data Gravity, 2014, p. 2), which includes text documents and multimedia objects. Many business-related documents such as strategy reports and white papers are often considered and treated as unstructured.

With the arrival of the digital media, digital marketing data has become an important component of marketing data analytics incurring the need to incorporate data from multiple sources: search queries, clickstreams (i.e. trail of a user's clicking behavior on a website), social media, blogs, community forums, and data from first-hand reach approaches, including online surveys and experiments, transactions, online behavior observations, and product reviews (Kumar et al., 2013, p. 334). Based on the aforementioned definitions, the author characterizes and constrains *big data* as kinds of digital data relevant to the RQ, data that has a focus on different digital communities of business where brand advocates or target audiences assemble and from where data can be acquired. Despite this focus, the complexities surrounding the different, aforementioned dimensions of big data are ever-present in digital marketing and market strategizing.

2.2.2 Data sources for market inferences

As discussed, a new set of data sources and accompanying tools and measurements are at the root of changes in digital marketing, allowing companies to innovate and continuously strive to optimize this process (Edelman & Singer, 2015). In the past, companies have collected marketing data via qualitative research approaches such as focus groups, surveys and so forth (Kumar et al., 2013). Kumar et al., (2013, p. 334) specify some of the latest digital user-generated data and examples of their respective measurements in Table 2.2.

Table 2.2: Data source, measurements, and metrics for digital data management

Data source	**Measurement**	**Metrics**
Search queries	Web sources	Web traffic breakdown Website traffic breakdown Volume Valence of posts Volume and valence Membership size Web traffic breakdown Visual attention Emotional valence
Clickstream	Website page clicks	
Social media	Size of brand mentions	
Blogs	Positive, neutral, negative	
Community forums	Conversations	
Incentivized referrals[2]	Membership increase	

Today, there is a wide range of digital tools available, which enables marketers to investigate customer online behaviors across multiple channels, some of which are digital versions of the traditional methods. Thus, the availability of data tools and sources yields a wide range of metrics and complex key performance indicators (KPIs) focusing on consumer activities such as purchasing (Kumar et al., 2015). Many analysts access the KIPs and analytics through interfaces - marketing dashboards, which is a “detailed compilation of all of the pertinent data about a company's marketing efforts” (Wise Geek, 2016, p. 1). It combines different digital marketing activities into one

[2] Customers voluntarily recommend other people to purchase or experience the products and services.

platform, bringing key metrics together for analysis and visualization (Kumar et al., 2015). This enhances the efficiency of performance monitoring and analytics

As already implied, a common theme that has recurred throughout the literature is from where and how digital marketing data can be aggregated and analyzed (e.g., the aforementioned marketing dashboard), given its varied sources and formats. This discussion has also come to be focused on one crucial element, which is the understanding of the customers and their behavior and the developing of customer-centric strategy. The next section will primarily focus on this strategic approach of how marketers look at digital media data, in particular user-generated data, and the relevant techniques.

2.2.3 Conceptual framework of the customer journey

Companies are pressured to adapt to the digital media market by acquiring the knowledge of the environment and to reposition themselves accordingly to the changes. In this context, conceptual tools such as the customer journey give companies the capacity to draw more conclusions about the market by learning how consumers behave. Customer journey is “a reflection what does a customer experience during orienting, purchase and use of a product or service” (Flow Resulting, 2016, p. 1). The concept includes several components: 1) a consideration of the stages through which the customer interacts with the company and its different brands by experiencing the products and services, 2) customers’ receiving recommendations from other customers, 3) marketing initiatives enacted by the company to build customers’ awareness; and 4) their being exposed to the marketing initiatives (Doogan et al., 2010; Edelman & Singer, 2015). These elements apply to all the audiences who gather on various digital media where company-consumer interactions happen.

Customer journey not only depicts the process, starting with a customer’s noticing the brand to the action of purchase, but also more advanced tracking of customers’ behavior, e.g., the myriad of behaviors and measurements enumerated in Table 2.2. This perspective or conceptual tool allows marketers to obtain market insights and thus enhance the relationship between the company and consumers by, for example, improving its products and services. Thus, data organized, analyzed, and understood according to the stages of customer journey provide companies with more detailed understanding of a customer's preferred channels and thus they facilitate optimal prioritization of services and product offerings. An understanding of the customer journey enhances the development of audience-oriented strategies and helps companies achieve their marketing objectives (Van Bruggen et al., 2010).

Furthermore, many marketers argue that a marketing strategy should always focus on certain moments of the consumer's behavior—the touch points. This phrase refers to the contexts or moments when consumers are most likely to be influenced, typically because they feel more comfortable with the company in terms of the experience from using its products or services (Court et al., 2009). For example, when a mother who watched one of P&G's successful videos which portrays the scenario of moms taking care of their kids from their childhood until witnessing moments of some achievement, e.g., an athletic champion, this mother embedded in a similar context is likely to be touched and thus influenced to purchase the products of P&G. Similarly, the viewer may be emotionally attached to this promotional material (and consequently may also unconsciously choose the brand) because of past familiarity with the portrayed situation. These captured points have been interpreted as different stages in a "funnel," where consumers start to consider multiple brands and then marketing methodically directs consumers to minimize the number of brands and leave one last brand to purchase (Court et al., 2009).

Therefore, efficient tracking of the customer journey is a key requirement for optimized budgeting and marketing campaigns (Leeflang et al., 2014). Although the navigation of digital media marketing in association with the customer journey is still an open question in literature in practice and academia, there are concepts and practices unveiling the bridge between knowledge of the pipeline surrounding the customer journey and the data-driven marketing. This level of understanding the customer can be acquired through different activities of marketing communication, such as social listening from online reviews and discussions on social networks, which underpins each consumer-centric service and product development (Doogan et al., 2010).

2.2.4 Engineering strategy to reap market insights

Although big data is becoming undoubtedly ubiquitous, scholars and practitioners reveal that only few truly valuable market insights have emerged from the analytics process. Therefore, it is necessary for companies to change and improve their way of doing analytics. Within this climate, many scholars have expressed the value of employing analytical strategies, which have already been used in the communication industry, with an emphasis on data mining, data analytics, and future prediction (Maklan et al., 2014; Wagler & Cannon, 2015; Weeks & Holbert, 2013). Labrinidis and Jagadish (2012) offers an outline of steps for generating insights from big data from data management and analytics (Figure 2.3).

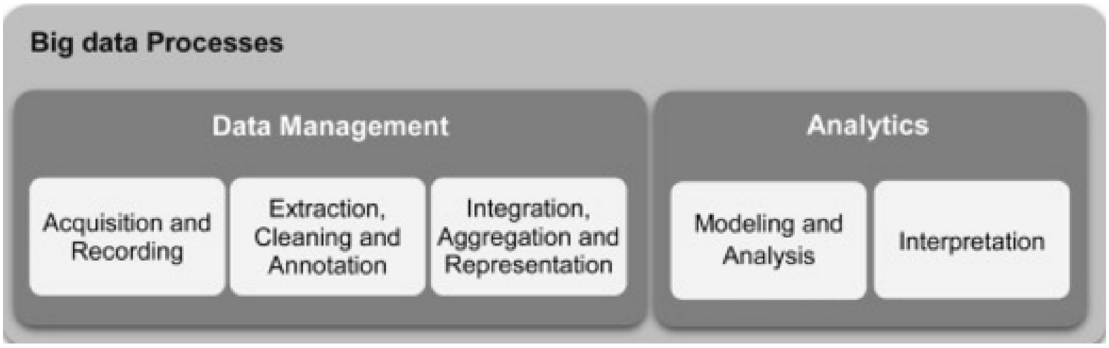

Figure 2.3: Processes for extracting insights from big data (Gandomi & Haider, 2015).

An example of applying this approach for handling big data would be the mining of considerable volumes of semi-structured data for enterprises to improve their services and product recommendation systems regarding optimal website design (Gandomi & Haider, 2015). In this case, dependence on any single performance measurement is not adequate to examine the achievement of big data goals. Mahr (2010) emphasizes that it is important to have a hybrid strategy for a complex issue such as big data challenges. He argues that this strategy should include consideration of measurements derived from various existing academic sources and scientific frameworks for the purposes of exploration and exploitation of performance appraisal (Mahr, 2010).

The necessity to gain deeper insights on advanced forms of data analytics is thus underlined by companies who endeavor to develop data driven strategies. Within this climate, IBM has developed a framework for digital media industries to measure their capability and development in dealing with considerable amount of digital information.

The extent to which progress towards building this capability has been made and how much there exists room for growth is standardized in this framework. The framework is a conceptual tool that contains a set of elements and their relations with different advanced levels in big data operation and has slightly different foci than the steps of Gandomi and Haider, enumerated earlier in Fig 2.4. IBM has summarized this process as: 1) accessing data, 2) performing basic analysis, 3) predicting and reacting to consumer behavior and 4) converting data into actionable insights delivered in real time" (Figure 2.4; IBM White Paper, 2016, p. 9, in order of decreasing complexity).

Figure 2.4: Big data maturity process (IBM White Paper, 2016, p.10).

Using the above theoretical foundation, this thesis now has some foundation for analyzing how the industry is performing regarding data-driven marketing and strategy. But, to perform such a high-level analysis, the larger strategic context and operational environment for international business should be discussed and is introduced in the next section. This will help with defining the complex position businesses have in a competitive media market in which big data analytics are essential for learning more about the audience from multiple digital platforms and channels.

2.3 Operational Analysis

How the elements of big data acquisition, management, analytics, and strategic exploitation are operationalized within the corporate environment continues to be explored in the literature. This section discusses further some operational approaches in companies' systems and infrastructure of data-driven marketing (IBM White Paper, 2016). This section discusses reasoning approaches in the context of big data, adaptive capability, and assessment of resources.

2.3.1 From reasoning approaches to insights

To access the knowledge of big data, there are mainly two approaches: deductive reasoning and inductive reasoning. Inductive reasoning assumes that scientific inquiry starts from "observing a phenomenon before forming hypotheses derived from existing theory" (Erevelles et al., 2015, p. 890). In line with this, technology and algorithms allow researchers to mathematically identify patterns without formulating hypotheses, also referred to as data mining (Anderson, 2008; Erevelles et al., 2015; Lyceet, 2013). In contrast, many scholars reveal that deductive reasoning approaches (i.e. formulating hypotheses based on theory) expose limitations of big data, even though it is a common approach for scientific inquiry (King et al., 2004; Lawson, 2005). As Letouze (2012) states, many analytical practices (research or otherwise) start from "experience and intuition," which contrasts with the nature of big data analytics. Still, the chosen analytical reasoning approach for the purposes of gaining knowledge about the digital market needs to be adjusted according to the constraints of digital media and technology. In other words, both approaches are valuable and thus indispensable to big data practice.

Digital media data contain many behavioral indicators, many of which are unobtrusively obtained unlike much of traditional data-gathering approaches (Mulhern, 2009). These behavioral findings offer insight to improve the capacity to tackle big data and leverage the strength in data-driven marketing planning (Mulhern, 2009). Both the mass and unobtrusive nature of big marketing data are amenable to the host of available algorithms companies use to investigate the data and retrieve insights.

In this context, Mulhern (2009) argues that these insights can only be revealed by machine and then followed by additional processes of analysts' interpretation. This raises the question of how companies are using human intelligence and machine intelligence to solve the puzzle brought by big data – the market insights. Machine intelligence enables a transformation of data, from automated discovery of patterns, to insights to decision maker (Gupta, Mann, Singh, Carlsson & Lum, 2016). Furthermore, data driven marketing services require companies to consider fact-based decision-making (Kumar et al., 2013). In other words, the authors argue that not only the automatic decision-making process brought by machine intelligence matters, but also the decision makers, the human intelligence which ought to have some role in devising data driven strategy.

All in all, these two approaches of reasoning, inductive and deductive, are both indispensable for the growth of digital marketing and theory. Moreover, the use of human intelligence and machine intelligence are thus considered in this research. To what extent that the approaches for reasoning process and capability enhancement are feasible remains to be seen yet also remains relevant, as these competencies are essential for companies, as is discussed in the next section.

2.3.2 Adaptive Capability

Today, companies have to respond quickly to the changes in the market with skills, knowledge, and resources within the company to create new value (Day, 2014). Adaptive capability is acquired from consumer insight and are derived from big data that facilitate the value creation process in a wide range of marketing activities (Ambrosini & Bowman, 2009; Day, 2011; Ma, Yao, & Xi, 2009). The created value can be temporarily competitive or sustainable (Ambrosini & Bowman, 2009; Erevelles et al., 2015). When this exploitation succeeds, companies are exposed to opportunities to strengthen their adaptive capability (Erevelles et al., 2015).

This exploitation is clearly distinguishable from the knowledge of the consumers, who consider online reviews made by others before they make further purchasing decisions. As such, a negative review would easily trigger a backlash for the brand reputation and image. In the course of finding the right paths and means for influencing the consumer, many companies set up fast responsive mechanisms, if any negative interactions on social network sites emerge. Royal Dutch Airlines KLM has fairly well-developed customer service provided on Twitter. Thus, the official global account of KLM reads as a dynamic banner, also indicating its response time. This real-time feedback bridges the relationship between customer and brand. To achieve this level of near real-time analytics, from a technical point of view, the tasks require intensive labor that includes, to name a few, data mining, unification, transformation, and so forth as well as visualization as a part of data analytics (Neamtu et al., 2014).

Firms should proactively respond to these changes in the external environment by capturing the signals from consumers in order to forecast the future (Day, 2011, 2014). These market insights can further their practice into transformed data-driven marketing targeting the consumers in a more effective way. To achieve the complex levels mentioned above, operational environments need to be adjusted, and basic infrastructure of big data needs to be in place before the possibility of successful data management activities.

2.3.3 Assessment of resources

In today's increasingly competitive environment of business, firms need to reconfigure their resources to develop a sustainable competitive advantage (Day, 2011; Kozlenkova et al., 2014). Company resources of big data, both tangible (i.e., computer) and intangible (i.e., tacit knowledge), determine the level of performance, especially when these resources are rare, imperfectly imitable, and exploitable by the company (Erevelles et al., 2015; Lee & Grewal, 2004). While Barney (1991) identified a resource-based model that illustrates the strengths and weaknesses of a company and the environmental models of competitive advantage regarding opportunity and threats for both internal and external environments, he omitted consideration of the complexity of digital media environment and the ways in which these forms may come into revolutionized. Erevelles et al. (2015, p. 898) highlighted that corporate resources are valuable when "a company's bottom line is improved or when the resources generate something valuable to the customers that competitors cannot achieve."

To summarize the complex context of resources and, to help focus the analysis of a firm's environment regarding its operation of big data, the author examined Barney's (1991) theory on important resources of companies' physical, human, and organizational capital resources in the context of big data. First, the firm needs to establish software or a platform in which data are collected, analyzed, and stored – the *data warehouse*. In recent years, more advanced data management platforms, which may be referred to as such data warehouses, have been correspondingly developed (Agrawal, Das, & Abbadi, 2012). These are regarded as affordable infrastructures, such as cloud computing and cloud accelerators that allow for increased accessibility, rapid content delivery, and storage space for the effective use of big data platforms (Agrawal et al., 2012). There has been a rising use of systems, which are known as marketing decision support systems, to facilitate marketing operations, which coordinate the data collection, systems, tools, and techniques into an environment for marketing action (Kumar et al., 2013, p. 332).

Second, it is of pivotal to have the latest *knowledge* of big data analytics. Big data enables studies on the masses. Marketers analysts strategize using insights and knowledge gained from several key genres of big data: tracking data (such as geographic or web-sphere locations, or transactions, data exhaust, clickstream, etc.), and other online behaviors and content (e.g., social media) (Hilbert, 2016). These tracking enables marketers to have sufficient and accurate understanding towards the market, retrieving market insights, in order to devise data driven marketing strategies. Insights can be acquired through *knowledge* of analytical approaches such as A/B testing, cluster analysis, data fusion and integration, data mining, genetic algorithms, machine learning, natural language processing, neural networks, network analysis, signal processing, spatial analysis, simulation, time series analysis, and visualization (George et al., 2014). In the past, big data analytics relied on the knowledge of statistics to identify the effectiveness of data management and the value added by big data. Nowadays, the high-volume and high-variety nature may contribute to a shift in data management. As indicated earlier in this literature review, many digital marketers and analysts are now dealing with qualitative and unstructured data that that may not be the right fit for those traditional statistical models and require the use of more advanced methods.

Third, it is important to equip to corporation with the skills by bringing in *data strategists and scientists* on board or outsourcing this need. Many practitioners have indicated their concern regarding the lack of suitable talent— people who have the skills and know-how to capture relevant data from consumer activities and effectively transform data into valuable insights leading to value-adding strategy. In other words, the analytical talents profile for big data management can comprise data scientists with marketing intelligence skill or marketing specialists with data science background. Many suitable skills, comparable to those of statisticians, mathematicians, and econometricians, are often represented in data analytic personnel. However, many companies revealed that data scientists seem to lack a strong background in marketing which can result in a disconnect between marketing and analytics (Leeflang et al., 2014). Zoher Karu, the vice president of global customer optimization and data at eBay, emphasized the importance of matching the fittest talents with data analytics. Her remarks reveal the difficulties of finding the right talent (Buluswar et al., 2016, p. 1): “We cannot have people with singular skills…I look for people with a major and a minor.

[For example,] you can major in analytics but you can minor in marketing strategy…to make sound business decisions, based on analytics that can scale." It is also common for companies to outsource their data analytics tasks to digital media agencies that specialize in both data analytics and marketing to partnership as strategic alliances (Leeflang et al., 2014).

Furthermore, there must be appropriate *organizational structure* that facilitates corporate big data management and analytics' efficiently transforming data findings from insights into action (Sorli & Stokic, 2009). Many businesses nowadays are making intuitive decisions in developing transformative organizational structure and talents for data practice. Many scholars criticize that companies sometimes are too rooted in traditional organizing principles and rely too much on past experiences regarding how things work out, which all may hinder changes in the organizational structure when changes are necessary in order to respond to shifts in the market (Teece et al., 1997; Zhou & Li, 2010; Erevelles et al., 2015). Whether or not an innovative or transforming model for digital data management fits the existing business model is of pivotal consideration. As Sorli and Stokic (2009) argues, the transformed structure "offers the potential for economic growth within the company" (ibid, p. 258). This can also be evident in the fact that many under-performers who are incompetent in digital data analytics also critically review their organizational structure and comment that it is "troublesome" in the context of data management, and hence it is even more challenging to perform their tasks (Brown & Gottlieb, 2016). Although it is not easy to validate such statements in this context, such assertions demand some reflection on the relations of the corporate governance environment and data management rewards.

One of the prime examples of shifts in organizational structure under the challenge of digital media is that of Golin (Garcia, 2011). Under the G4 model (Figure 2.5), employees are divided into four groups: (1) strategists, who use data and research to serve as business analysts; (2) creators, who are the idea generators and storytellers; (3) connectors, who function as the channel experts, reaching audiences via more than a dozen 'touch points;' and (4) catalysts, who use best practices, partnerships, and other methods to keep clients ahead of the curve. In this structure, traditional titles like vice president (VP) are changed into community managers and within different groups, staffers are titled as social media specialists. Even though in Golin's case the practice of the roles remains the same as traditionally labeled ones, the function of each role is clearly defined and everyone's values are aggregated on a less hierarchical environment.

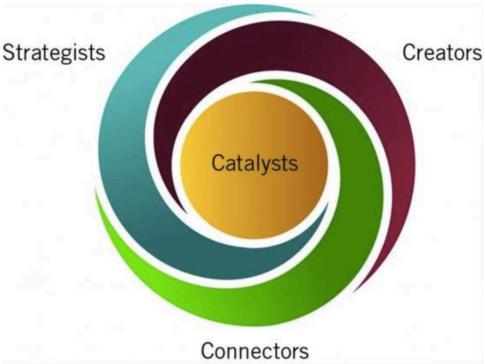

Figure 2.5: G4 Model[3]

In the context of digital media data management for a marketing strategy, whether there should be team or an individual who is responsible for linking big data to marketing insights is not yet primary concern. Still, some examples such as G4 model in the industry demonstrate the organizational shift demanded by the ever-changing environment of digital media and the big data that it incurs and reveal the potential evolution of the data management infrastructure. The emergence of leadership in corporate data management and the capability to find and retain the right talent for this function have become less likely to be favored in a condition where there is a lack of support for the enactment of strategies for data-driven marketing (Brown & Gottlieb, 2016).

2.4 Summary

Previous academic and industry findings show that big data practices vary across firms and industries based on types of big data metrics employed, the reported initiatives, and the communication channels utilized in data-driven marketing. International businesses can use big data by implementing metrics and conceptual and analytical frameworks and tools to retrieve insights from the market. They can treat these as resources for enhancing their practices to outperform their competitors or

[3] www.golinharris.com

other industries. They can also actively engage with audiences in appropriate ways through multiple channels to implement and validate their big data analytics outcomes. Important to note though is that the existing structure of organizations often has to adapt to the organizational transformation demanded by the effective exploitation of digital media data. How strategically companies are dealing with these issues in the Netherlands is the main research focus of this thesis.

3 Method

To test the aforementioned hypotheses, this empirical research examined how digital media data have been analyzed and translated into market insights and transformed into digital media strategies. In this section, the methodologies are justified, the data analysis process is clarified, and the ethical considerations are documented.

3.1 Research Design and Rationale

This study employs a mixed methods design – it uses both qualitative and quantitative approaches: collecting data by semi-structured interview, and analyzing them by using semantic network analysis and qualitatively interpret the results based on within and across case analysis. Gilbert (2008) notes that qualitatively and quantitatively probing the research subject has the potential of offering more than twice the value of the results from a single method. The following graph illustrates the method structure of this study (see Figure 3.1).

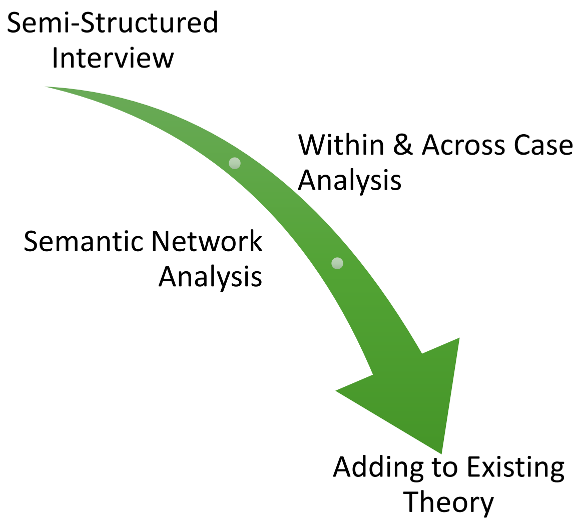

Figure 3.1 Method Structure of this Study

With this design in place, it becomes more feasible to examine corporate performance in big data marketing strategy regarding each development and implementation stage, which can be difficult to be obtained public domain sources. Although many positivists perceive the exploratory study that involves the process of consulting practitioners to be unscientific (Gilbert, 2008), the author takes a constructivist stance towards the research data. The focus of this research is human knowledge (e.g. explicit knowledge, tacit knowledge and empirical know-how), that plays a pivotal part of corporate assets, rarely accounted for in the balance sheet (Hujsak, 2015).

Also, semantic network analysis is used as a primary method of analysis; it is an approach to retrieve the hidden meaning in text corpora. Unlike linguistic researchers who regard specific characteristics of language as the objects of analysis, the author follows the sociological tradition, by focusing on the human experience that appears to be prominent in the text (Tesch, 1990). This method facilitates the extraction of tacit knowledge possessed by strategy directors who propose, innovate and make decisions on big data strategy, and constantly interact with corporate marketing practitioners and data professionals.

3.2 Sampling

Sampling of interviewees (i.e. the research units) was necessary as it is infeasible to interview a much larger group of subjects. Sampling is the process of selecting a small number of relevant subjects to set up the estimation of unknown knowledge, situation of a large group (Kumar, 2014). The sampling population in this thesis is then digital strategy directors in the Netherlands. Purposive sampling was first used as an effective sampling approach for this study to select strategy directors in the field of digital media. It is a non-random approach to obtain a predetermined number of people who are positioned to provide the needed information for this study (Kumar, 2014). This design is particularly useful in this field of corporate data analytics for digital marketing in which only a little is known.

The selection criterion for selection of digital strategy directors was as follows. The interviewees needed to be able to contribute to this research based on their background in strategy, understanding in corporate big data analytics and knowledge of how it is related to digital marketing. By interviewing those key players, the relevance of both organizational, industrial, and whether certain emphasis in big data practice for corporate communication (e.g. techniques, innovative initiatives towards “5V”) will emerge.

Being confronted with the challenge of big data, organizations are reconstructed under the managerial and technological elites as intermediaries, which maintain a large sociotechnical network (Kaphan & Bowker, 2001). With a considerable budget, many corporate communication departments have taken the lead in handling the complexities of unstructured data problem while many have outsourced it to strategic alliances for market insights. Thus, in addition to in-house marketing managers, analytic service providers are included as interviewees due to their contribution in this field.

This study examines the interview transcripts from 15 interviewees; this group is composed of women (N=2) and men (N=13) participants between the ages of 25-35 (N=3) and above the age of 36 (N=12). Among which, there are five analytic service providers, and ten strategy directors. Below a table with the company, personal details and position, interview approach is included (see Table 3.2). Some of the participants wished their names to remain anonymous.

Table 3.2: Interviewees[4]

Company	Interviewee	Company	Approach
Jack Van De Burger	Strategy Director	Wecanbeheroes	F-t-F[5]
Man Yong Toh	Founder of Advertising Agency	Moore	Telephone
Sander van den Born	Vice President in Marketing,	CGI	F-t-F
Maarten Cleeren	**Strategy Director**	**Elsevier**	**F-t-F**
Gerard Loosschilder	Brand Manager Consultant	Acer	F-t-F
Participate A	**Consumer Marketing Manager**	**A FMCG brand**	**Telephone**
Justin Sandee	Manager Digital Strategy B2b	SBS	F-t-F
Pim Stouten	**Strategy Director**	**LexisNexis**	**Telephone**
Tjibbe Renkema	Strategy Director	TBWA	Telephone
Participant M	**Business Intelligence Manager**	**A FMCG brand**	**F-t-F**
Tim Geenen	Director of Strategy & Innovation	Bannerconnect	Skype

[4] This is the final sample (N=10) for data analysis. The omission of other data corpus will be discussed in limitations.
[5] F-t-F means face to face.

One issue of interviewing key figures is the difficulty of gaining access to them, as Laurila (1997) reveals. Many challenges exist for interviewing elites (Mikecz, 2012). This happened in this research; in two cases the author was invited to make the appointment with the director's assistant instead of the director under an excuse such as "she knows my schedule".

This study then employed snowballing sampling while there was no sufficient list to use as a frame of sample (Gilbert, 2008); the sample is selected by using networks, a few professionals are selected and interviewed; furthermore, they are asked to identify other suitable interviewees within their network (Kumar, 2014).

Also, the researcher posted recruitment notification on LinkedIn, and few personal contacts further shared this post. Although the direct impact of this post is hard to evidence, there was a sharp increase in the number of readership of this post within a week. The process of sampling continued until some saturation point was reached (Kumar, 2014) such that no new information was perceived to be available from added research units (Gilbert, 2008). In this study, this saturation is evidenced in the coverage of competencies. This sample should be appropriate due to the variety of industries and the most appropriate position examined in the current stage of corporate development on big data management.

In the end, three interviewees who participated stem from author's personal network, two from participants' recommendation and ten directors are selected based on purposive sampling via LinkedIn.

3.2.1 Semi-structured Interviews

Some of research data relevant to this thesis' topic is generated or can be gathered from external stakeholders (advertising agencies, Google, data agencies). This information may not exist in published materials and rather reside in corporate confidential files. Thus, this study employed semi-structured interviews with current practitioners. This allow for the acquisition of the most up-to-date knowledge encompassing the latest data-driven marketing strategies.

Interviewing refers to a process of information collection through interactions – commonly face-to-face verbal interchange between interviewers and interviewees, which allows interviewers to elicit information, opinion from another person (Kumar, 2014). Having a semi-structured format ensured a structural and unstructured process. Major questions were asked in the same way each time with not fixed sequence and freedom for follow-up questions based on the answers (Gilbert, 2008; Kumar, 2014). The researcher benefited from the uniform questions which generates comparable data (Kumar, 2014), contributing to a holistic understanding towards the marketing strategies. This study takes an exploratory and explanatory investigation towards the field of big data in digital marketing, and thus more relevant questions were allowed in this semi-structured approach.

3.2.1.1 Face-To-Face & Telephone Interviews

In face-to-face interviews, the physical context can affect how interviewers and participants behave and present their contributions to the interview (Miller 1995; Kendall 1999, as cited in Kazmer & Xie, 2008). In this study, many directors perceived their office as the most comfortable place to participate in this study and thus five interviews were conducted in their offices. The face-to-face context enables researcher to capture many non-verbal communication (e.g., laugh), and other hidden emotions that matter (e.g., resistance) by perceiving the participants' negative changes of voice in interviews (Kazmer & Xie, 2008). Even though noting of these elements is more labor-intensive, engaging in this additional interview task yields a greater extent of valuable information. Also, relevant follow-up questions were more freely constructed in this conversational context compared to telephone interviews.

A telephone interview is effective and a more economical approach of data collection for the researcher, and it is also ideally suited to those professional respondents who have tight schedules (Kazmer & Xie, 2008). This method is also useful as participants are geographically dispersed (i.e. Amsterdam, Rotterdam and other locations in the Netherlands) (Kazmer & Xie, 2008).

3.3 Data Collection

To acquire interviewees, invitations to participate in interviews were emailed to each key figure via LinkedIn and a personal contact list. The reason for choosing LinkedIn is that this platform has become popular as a source for the professional exchange of commercial ideas where the key players of big data may participate to discuss industry-relevant topics (Smith, 2001). Those who use this social platform actively and regularly contribute to this social engagement and discourse of ideas, and people tend to rely on network like LinkedIn mostly for professional use (Wagler & Cannon, 2015). In other words, people may be willing to be contacted through this professional channel on matters that relate to their job.

Also, LinkedIn's easy accessibility facilitated the purposive sampling process and allowed the difficulties in contacting key players in media and business to be overcome. Therefore, a key player's complete profile (picture, work experience, description of responsibilities, and education) on LinkedIn and their LinkedIn network of over 500 connections are suggestive of their active status and regular usage of LinkedIn. This also indicates that the key player is more likely to respond via LinkedIn and also be responsive to inquiries from strangers and short notice solicitations, as evidenced by their initial prompt acceptance of the researcher's request for establishing a LinkedIn "connection" (a necessary precursor to sending an interview invitation).

As discussed, the advancement of data management is also likely to be outsourced to external data insight or analytic service providers (constituting a strategic alliance), due to the lack of suitable big data analysts within the company, depending on the level of practice of in-house team and of specialized consulting firm and different objectives of data management. Thus, a wide range of titles was employed in searching for relevant research units within LinkedIn: Digital Strategy Directors, MarCom Managers, and Strategy Director at media agencies, global corporations, and creative agencies in the Netherlands and within the domain of media, marketing and advertising.

Many LinkedIn invites (to establish a LinkedIn social connections) were sent, followed by 65 invitation emails to those accounts who accepted the invite. The interview invitation email contains the description of this study in addition to the probes written in the consent form. This form is devised from the template "Informed Consent Form" from Erasmus University Rotterdam Erasmus School of History, Culture and Communication (see Appendix A).

Regarding the level of anonymity, the author respected any decisions made by participants and informed their rights beforehand by sending out the consent form before the interview, and participants had the chance to confirm their status of anonymity before their interview. The author provided four options regarding the anonymity level by sending out an invitation follow-up thank you email. The email contained the introduction of analytical methods and informed them that each interviewee (and consequently their company and its competency) would be the research unit. Also, the researcher specified four ways in which interviewee may be referred to in the thesis (using the name of this thesis' author as an example): 1) the strategy director from EUR (or some more description), Rosa; 2) Participant A from Company A; 3) Rosa from a global FMCG brand; 4) fully anonymous. In the last condition, it is ensured that there is no way to identify the interviewee and company in the paper.

Interviewees once again received verbal introduction and confirmation about their rights of confidentiality during the interview ("Would you mind that I record this interview and quote you by name?"). The researcher also brought the consent form to remind the interviewees of their fundamental rights and the academic usage of interview data. For those who not yet confirmed a positive answer to this question, the researcher sent a follow-up email to confirm.

The researcher had suggested a quiet area to allow for better quality of interview recordings, a location that was also have to be decided by the availability of interviewees. 15 interviews in total were conducted in English, and each interview lasted approximately 40-60 minutes depending on the availability of interviewees. All interviews were recorded and transcribed verbatim. Interview questions (see Appendix B) were developed primarily based on the theoretical framework discussed above, and the interviewers also deviated from the prepared questions if needed (e.g. "What makes you say that?" "What do you mean by that?").

3.3.1 Operationalization and Topic List

The interview is divided into four sections: consumer insights, data-driven marketing planning, cross-media integration and communications to multiple stakeholders, based on Mulhern's (2009) discussion of how marketing activities are formed in the digital era as integrated marketing communication. Correspondingly, there are sub-topics around those topics for interviews such as big data definition & strategies; digital media strategy; market insight - data mining, data analytics, and future prediction; communications to multiple stakeholders. The situations where the text "Key Points", "Topic Guide", "Purpose of the interview" was described on the interview protocol, was designed to be the probes of this research (see Appendix B). The researcher referred to them to keep consistency in defining key terms for interviewees, standardizing the key topics of this study. The research questions are examined accordingly.

To measure the operational performance of a corporation regarding to its big data strategy, this study considers several indicators of key performance in big data management. These contain the company's reaction to the challenges brought by and the strategy towards dealing with different data sources and types, and the techniques of big data management. This thesis also focuses on how the companies deal with data of consumer interactions from different channels (including those that are owned, paid, earned as well as social media channels); these data comprise both unstructured and structured data. Meanwhile, there are several interview probes and topics used in soliciting more relevant data to the research questions that appear to be less present in previous literature (but judged to be important by the researcher): value of human interpretation, integrated data analysis warehouse, advances of big data management and the existence of big data strategic framework.

Given the context that the majority of marketing communication practice may not have an advanced mechanism for big data analysis, the change in digital media marketing brought by big data was considered to be high relevant to this research and included as one of the interview topics. This design has a potential to identify the corporate trends of the practice on a regional and industrial level in the Netherlands.

As mentioned, this study looks at the strategy side of the digital marketing analytics. The relevant elements of sociotechnical innovation remain relatively stable, as it is constituted of organizational structures, material technologies, and tacit knowledge in the development. During the stage of qualitative analysis, accessing the 'pragmatic knowledge' is important for research which means established principles, rules that guides the actions of analysis process during different stages (Schilling, 2006). Although the established principles are rare and the relevant theories are not yet tested by enough empirical verifications, the author constructed a topic list to examine the practice (see Table 3.3). These topics, that largely follow the argumentation in the theoretical framework, guide the semi-structured interview. The construction of thematic topics in the results section is mainly derived from these areas.

Table 3.3: Overview of Interview Topics and Probes

Topics	Probes
Big Data Understanding & Transitions And Progress	Definition, from “3V” To “5V”, Volume, Variety, Velocity, Veracity, Value, Structured vs. Unstructured Data
Outcomes from and Areas Involving Data Analytics	Consumer Insights, Data-Driven Marketing Planning, Cross-Media Integration, Communications To Multiple Stakeholders
Analytical Tools, Measurements, and Metrics in Use	Web Site Traffic Breakdown Volume, Emotional Valence of Posts, Community Membership, Visual Attention, Size of Brand Mentions, Conversations
Data Sources	Search Queries, Clickstream, Social Media, Blogs Community Forums, Incentivized Referrals
Operational Personnel	Data Scientists, Leaders, Strategists, Others
In-House Resources	Data, Data Warehouse, Tools, Skills, Knowledge
Strategic Framework	Social, Demand-Based, Interactivity, Metrics, Customer Journey, Intuition to Insights through Algorithms
Analytical Competency	Maturity Level: Accessing Data, Performing Basic Analytics, Predicting And Reacting to Consumer Behavior, Converting Data Into Actionable Insights in Real Time
Scientific Inquiry	Deductive Reasoning & Inductive Reasoning

3.4 Validity & Reliability

Qualitative research appears to have high validity, because interview participants are required to actively provide answers rather than passive acceptance (Silverman, 2015). In this study, the participated strategy directors contributed respective tacit knowledge acquired in distinct organizational environment and in certain stage of the maturity regarding data analytic competency.

Meanwhile, the elements of validity as discussed by Silverman (2015) seem to be largely aligned in this study. First, the impact of the researcher on research setting is tremendous - each research stage has been carefully designed and developed by the researcher (Silverman, 2015). Secondly, the researcher is perceived to have contribution towards data generation in the process of qualitative data collection, as it is perceived as a collaboration between the researchers and participants with regard to co-constructing the interview data. Thirdly, a respondent’s account regarding the practice of big data strategy is more commonly to be truthful as they are granted with the choice of anonymous participation.

Additionally, respondent’s validation was initially carried out right after each interview, by confirming the key arguments and findings with the interviewee by interview notes. Then, three directors were invited for a follow up interview with analyzed findings. As such, the author ensures the validity of this finding to some extent by reaching out the subjects again after the launch of interviews in order to acquire more analysis confidence by their reviewing and feedback of the findings.

The analysis of the interview data employed both qualitative and quantitative analytical approaches from which conclusions were drawn. The process was assisted by computer-mediated tools and the researcher's having subject-related background to enhance the reliability in the interpretation.

Also, the study examines the practice of big data among a wide range of industries across the industry sectors of retail, technology, finance, luxury, health, and consumer goods. One may argue that big data management varies across the companies, let alone the scale of industries. Taylor (2007, p.1) asserts the importance of learning other competitors in the market regarding how they run the business to make real change: "If we want to create a sense of urgency around innovation, we have to learn from industries that move much faster than this field." This diversity in datasets contributes to a high reliability.

In this study, the biases brought by of snowballing sampling may not as detrimental as being used in survey, since this research used interviews, which was examined qualitatively. A small sample can provide a reasonably good estimation of population characteristics and as long as the population is relatively homogenous (Kumar, 2014) in terms of the positions of the people and goals of their businesses. Also, the sample size in qualitative research does not play a significant role because of the objective of studying a spread of diversity rather than magnitude (Kumar, 2014).

Moreover, several steps were taken to ensure a highly reliable interview approach: pre-testing of the interview questions and interviewer training (Silverman, 2015) in order to produce a concrete interpretation of data and minimize the subjective interpretation in the reporting (Seale, 1999).

3.5 Data Analysis

The thesis employs a combined, mixed methods strategy for data analysis, in contrast to many designs that only supplement qualitative analysis with quantitative approaches. (Schilling, 2006). The hybrid approach ensures some reliability and a typicality check of the selected material (Lunt & Livingstone, 1996). The following figure illustrates the design of data analysis for this study.

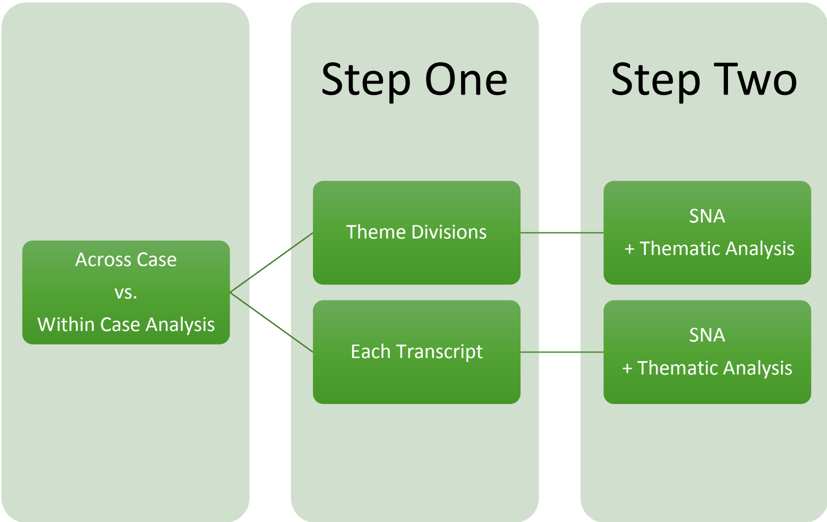

Figure 3.1: Analysis Design Overview

The following paragraphs will briefly exemplify the analysis employed in this study, the details are going to be further elaborated on later in relevant section.

3.5.1 Semantic Network Analysis

The interview transcripts were first subjected to a Semantic Network Analysis (SNA[6], also known as Relational Content Analysis according to van Atteveldt (2008) which is a computer-aided text analysis process. It is one of the "text mining techniques [that] are used for automated information retrieval from textual data sources" (Drieger, 2013, p.1). SNA is used as this method is advantageous when the data is unstructured such as the verbal texts of transcriptions of interviews; it derives useful, structured information from many unstructured text documents (McKee, 2011). A network depiction of the *concepts* (words and word phrases) and their semantic relations, drawn from one or multiple text sources, enables the researcher to uncover areas of meaning and focus in the text, both distinct and overlapping from multiple source; these inferences are not easily detectable through traditional qualitative approaches (van Atteveldt, 2008). Further justification for the method is provided below.

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[6] The abbreviation sometimes also known as social network analysis. However, one must keep in mind that the appearance of SNA in this thesis all refers to Semantic network analysis.

Furthermore, Semantic Network Analysis represents the text content as a network of objects (or concepts) and structures the relations among these objects (van Atteveldt, 2008). The knowledge extraction from a network representation can be used to answer the research question, because all relevant concepts revealed by the research units are present in the extracted network (van Atteveldt, 2008). In this study, all interviews are conducted based on key topics identified from the literature (see Operationalization and Topic List), and this method is thus useful in analyzing this particular set of interview response data to answer the research question.

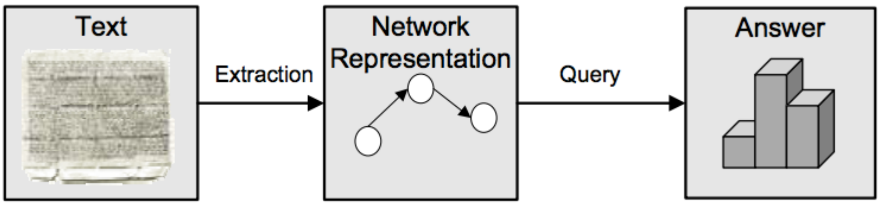

Figure 3.2[7]: Semantic Network Analyais (van Atteveldt, 2008, p.4).

The network (also called a graph) is generated computationally (i.e. automatically) under a set of parameters and consists of labeled nodes (i.e. the concepts) and edges (i.e. their semantic relations based on collocation) (Helbig, 2006; Drieger, 2013). The reason for visualizing the textual data is to be able to accurately interpret the key concepts and themes and their relations which constitute a cognitive map, indicating how one concept, category, or theme interconnects and affects others (Kazmer & Xie, 2008) within the mind of each individual (or across individuals). By focusing on structural properties and employing a rich spectrum of metrics, the SNA approach offers many advantages in visual exploration and analysis (Drieger, 2013). SNA can also reveal the decision-making process of each director based on their reflection of big data practice in their company.

This research employed the SNA tool VOSviewer, which identifies the most relevant noun phrases (i.e. the concepts referred to as '*terms*' in the tool's literature) maps these in a semantic network through collocation within a paragraph, identifies clusters these terms indicating a theme, and visualizes the map and the clusters (van Eck & Waltman, 2015).

[7] Figure 3.2 shows a schematic representation of Semantic Network Analysis (van Atteveldt, 2008, p.4).

However, there exists some frameworks and empirical studies to evidence how the abstract concepts are highly relating to one and another theoretically (van Atteveldt, 2008). Many linguistic scholars support the approaches for interpretation of network (Harley, 2014; Smith and Medin, 1981), saying “the meaning of a word is given by how it is embedded within a network of other meanings” (Harley, 2014). Schank (1972, 1975) argued that the meaning of each unit of analysis could be represented by the conceptual dependencies between the semantic primitives underlying the words within the unit (Harley, 2014). They are not merely associations that represent co-occurrence, but they themselves have a semantic value (Harley, 2014). According to decompositional theory, the meanings of individual words are broken down into their component features in the network, also called as “semantic markers” by Katz and Fodor (Harley, 2014). For instance, the word “big data” was simply the sum of all associations to the word, meaning that isolated by itself it is not powerful enough to capture all the meanings.

Smith and Medin’s (1981) identify the essential defining features of the concepts in capturing a relationship between concepts. They point out the procedures of identification involves recognizing the instances of the concepts. In this study, these instances are reflected in the context of each interview.

Apart from having a basic understanding towards SNA algorithm and linguistics, graph theory also provides metrics and statistical properties for graph interpretation. The analysis started by understanding basic concepts from graph theory and the immersion of the statistical properties that this study used to describe the semantics structure (Steyvers & Tenenbaum, 2005). A semantic network consists of a set of codes/ vertices and edges that join pairs of nodes (Steyvers & Tenenbaum, 2005) with the following implications as summarized by Drieger (2013, p.6). “Nodes” simply means a word or multi-word phrase, aka an n-gram, that constitutes a discrete concept, such as “big data”. Investigating nodes[8] in the context of clusters (subgraph or subgroups) reveals how concepts may be connected to one another within a common, potential

[8] The number of nodes in the network is denoted by n.

theme (Drieger, 2013). In this study, an edge is an undirected[9] link between two nodes, and a graph in which the edges remain are undirected (Steyvers & Tenenbaum, 2005). This edge signifies some relation between coded concepts.

Clusters highlight the subsets of nodes and edges, which are strongly interrelated; and reveal potentially prominent themes and discussions. These clusters may be bridged through key concepts (Drieger, 2013). Smaller clusters, such as a fully connected group of three nodes, which is called "closed triad", is sometimes worthy of attention and investigation, (Simmel, 1977, as cited by Tsvetovat, 2011). A nuclear family is a suitable example that illustrates the equivalent ties in between three parts.

The density of the network or a cluster, which can be described as sparse or dense, indicates the prominent structure under the main network system (Drieger, 2013). Sparseness indicates reduced coherency on a unit (such as a cluster or whole network), while a dense network indicates a higher level of coherency among words (Drieger, 2013). Moreover, hubs represent nodes with high activity (or, put formally, high degree centrality) due to many semantic relations (Drieger, 2013). For instance, the degree centrality measure assesses the extent to which a word or multi-word concept or node collocates with other words or concepts.

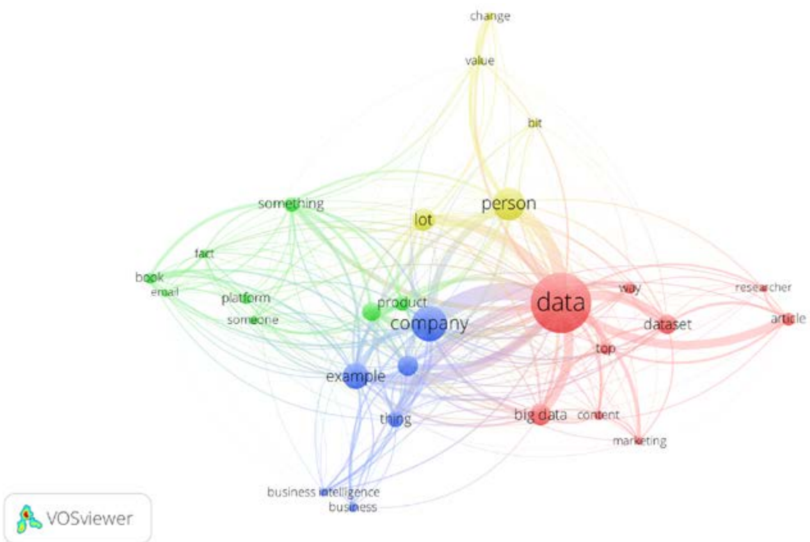

Figure 3.3: Sample graph for Collocation Relations among Concepts

[9] Technically, it means there is no causal or other relational directionality in the edge. This is commonly employed in SNA (Drieger, 2013).

3.5.1.1 Summary of Network Analysis and Its Algorithm

By adjusting the parameters of the layout in VOSviewer, a network is generated automatically. It is important to note that VOSviewer distinguishes clusters of concepts that are structurally and topically similar by color, using a stochastic statistical algorithm called probabilistic latent semantic indexing (Van Eck & Walkman, 2015). The tool also places nodes using a force-directed algorithm such that concepts having common linkages are placed near one another.

The algorithms of layouts and clusterings in VOSviewer are formalized as mathematical functions known as "quality measures" (Noack, 2008). These quality measures divide the representations of networks into layouts and clusterings. Layouts assign the vertices to positions in a metric space, and clusterings partition the vertex set into disjoint subsets (Noack, 2008). Both representations can group closely connected vertices, by placing them in the same cluster adjacent with each other (Noack, 2008). In contrast, they can separate sparsely connected vertices, by placing them at positions that are far away from each other in different clusters (Noack, 2008). As such, the network produced by VOSviewer can naturally reflect the community structures of the the population of concepts.

Thick, strong edges indicate high levels of co-occurrence and highlight the most prominent semantic relations in each network examined. In the within-case analysis, which will be addressed as follows, the author identified and focused on the top three high performers of big data in order to benchmark the best practices for the industry.

As this research aims to obtain specific knowledge on how international business employs big data analytics and the challenges they face, the relations among prominent concepts that appear in the visualized network were examined by categorization and clustering in order to expand the author's knowledge gained from the interviews and previous literature.

3.5.1.2 Within-Case & Across-Case Analysis

The case study approaches of within-case and across-case analysis were conducted to achieve the research objectives. These together have been proven to be effective for critical reflection on the identified themes (Ayres, Kavanaugh & Knafl, 2003). This strategy also minimized the loss of valuable data, contributing to a more comprehensive view towards the topic. Both analytical approaches illustrate the decisions made for interpretative and analytical procedure (Ayres et al., 2003), and thus were employed independently to achieve a diversification in results.

Within-case comparisons for each informant's account on the theme of big data could reveal advances each made in big data development; these were tagged with * during the interview process. Moreover, as Ayres, Kavanaugh and Knafl (2003) assert, it is necessary to take in the individual's account within their own context but also capture and compare the varied experiences across different individuals.

In this study's within-case analysis, corporate competence in data-driven marketing are highlighted respectively among top three performers. For example, to acquire the knowledge of the "best practices", the sample for this analysis consists of the players who "substantially outperform industry peers", as LaValle et.al (2011, p.22) emphasize. Interviewing those key players, the similarities and differences of comparing with each big data practice for corporate communication emerged.

Across-case strategy compares the experiences of interviewees in order to identify significant, cross-case-cutting categories within a larger amount of data, which is employed based on the premise that probing on a single case would not reveal prominent overlapping themes and categories (Ayres et al., 2003) that is, revealing commonalities across different cases. The data were separated into qualitative meaning units through coding and sorting (Ayres et al., 2003).

During the initial stage, each respondent's transcript is reviewed to reveal the most important propositions to produce a collection of significant and relevant sentences (Ayres et al., 2003), based on the theoretical background and empirical findings. Regarding SNA results, while multiple prominent clusters were observed, the analysis focuses on those that are theoretically relevant.

As this researcher is interested in the emerging themes that reveals directors' concerns and new direction towards managing big data for digital media, thematic analysis was used for the across-case analysis. Thematic analysis allows patterns to emerge and to be recognized (Fereday & Muir- Cochrane, 2006), and thus this method is suitable for this study. All the transcripts were aggregated to one file (over 40000 words) and divided according to themes. This study coded and classified a sample of ten interview transcripts into text fragments (sentences or paragraphs).

Segments of answers from these interviewees are given a label, which represents the primary topic of the segment, and further merged into sub-themes (Boeije, 2010).

The sub-themes within the ten topics (see Table 3.5) were then analyzed by SNA to unveil the semantic structure within each theme group. Across-case analysis was conducted by this thematic analysis by using a constant-comparative method (Lindlof & Taylor, 2011). Apart from the parameters documented under each graph, there are words which seem to be industry-related (such as “music”) and example related (“barbeque”) were deselected in the across-case thematic analysis in order to focus more on the practices. In each of the within-case and across-case analyses, three prominent cases or SNA networks (respectively) were selected, according to how well the networks portray rich clusters that address the research question.

3.5.1.3 Operationalization and Data Analytics

Table 3.5. Operationalization of Thematic Division

Themes	Operationalization	Example
Big data Definition	What big data means to the interviewee	“I think big data is data mining that you can combine all data sources to each other.”
Challenges and opportunities	Obstacles to implementing their companies’ practices, according to the intervieww	“Change, cost and sometimes is very difficult.
Corporate data management	Data that shows the characteristics of corporate strategy of big data management	“We so far manage everything centrally, so at the very beginning we made a decision to what can be centralized, it means that we have a big data centrum data platform, we have the robust architecture to do these reporting and campaigning…”
Owned data analytics	Data analytics that the company performs in-house	“And that also includes for example the customers service piece that we have, so when customers contact us, why do they contact us, what is the reason behind it, can we ultimate that, can we make sure the information that they are finding on our website doesn’t require them to ask us a question.”
Data driven strategy	How datasets are processed, interpreted, and transformed into actions or customer-centric plans	“… we don't always have the luxury of face to face relationship and therefore we need to reach out the digital touch points and then data is the key to realize, so everything we do is there to increase the engagement of our prospect customers, but obviously also increasing the customer value, so that is we deliver the right things to them.”
Digital Media Strategy	How and what insights are retrieved from data across different platforms	“I would say across the paid own, and earned media channels, it specifically has sharpened the way we plan our media, and also based on affinity of customers throughout different media channels we know what to choose, and we have an idea what works, and what doesn't work, so we shift media budgets along the different touch points, and

		hopefully via earned [media], we can generate the most conversion instead of only going after paid, because that is highly costly, so based on that on the entail, we try to move the budgets along the different media touch points”
Future Directions	Suggestions for future directions and advice to other companies	“So data provenance is a big issue. So a big issue for big data is that you need to know where your data comes from in order for it is to be reliable or not.”
Map metrics and measurement	The specific approaches and measures used across different companies	“… if you see a lift by the frequency of the product, or if you see the buying of more products in the same bucket, these are the things we measure during a period of two years, because these are the things that sometimes they can get out of business, or changing location etc.”
Relevancy and personalizatio n	Understanding and use of relevant, retrieved data	“To listen carefully for the response, so you should only send the right things to the right consumer customer prospect, if they are open for that, before you reach out to them, firstly you need to really carefully understand if that really meets their needs, so if you are wrong sometimes, you need to adjust…”
Transition and progress made	The answers under the question how has digital media changed your work and big data analytics	“The data model is prepared for that, we just rolling out new technologies across the countries, and then we are better able to formulate, implement our strategy, then we are much abler to do so. In the past we couldn't, because it was fragmented, but we are not really started to collect the search behavior within our owned environment.”

In the analysis stage, the corpus[10] contains only the interviewees’ answers; interview questions were deleted in the procedure of data cleaning, so only the essential and relevant follow-up responses of the researcher were included in the datasets.

Technically, this study chose paragraphs as the analysis unit. The primary reason for this was that many interviewees were very enthusiastic about the topic and thus many of the statements were not precisely grammatically structured, which made sentence-level partitioning difficult. Secondly, other measure units such as words and sentences are not appropriate. Due to the complex and conceptual nature of this topic, many interviewees’ answers to the probes tend to involve multiple, relevant topics within one paragraph. Even though the VOSviewer’s window size is automatically fixed

[10] The processed dataset is called corpus that contains large set of text data or documents, which plural from is known as corpora (pl.), which means sets of sets (McKee, 2011).

to a certain unit, it is not affected much in this project because the representation of rich semantics within a paragraph window is robust enough to address the RQ.

Overall, the SNA mainly focuses on the clusters of meaning within the large corpora of interview transcripts; these refer to distinct and common themes in interviewees experience with data management strategy including decision making, actors, the process of strategy development, and other topics discussed by the interviewee that all underpin the central interview question. These dimensions highlight the elements of network structure, including edges, paths, nodes, and hubs.

A codebook for mapping some adjoining concepts into key noun phrases was generated through Automap and Gephi (Lee, 2016). It was then applied in the SNA produced by VOSviewer in order to capture important n-gram concepts such as "big data" or "customer journey" rather than being shown in isolation (Lee, 2016). The table below shows a portion of the codebook applied in SNA ranked by frequency. Specific steps taken to generate the codebook were documented step-by-step in the SNA Codebook Application Manual (see Appendix C).

Table 3.6. Codebook

label	**replace by**
big data	big_data
digital media	digital_media
historical data	historical_data
customer journey	customer_journey
quantitative data	quantitative_data
social media	social_media
touch points	touch_points
data sources	data_sources
qualitative data	qualitative_data
mobile phone	mobile_phone
unstructured data	unstructured_data
target audience	target_audience
new insights	new_insights
real time	real_time
business model	business_model

During the process of configuration in VOSviewer, the decisions made on the minimal co-occurrence word's criteria are crucial as they largely decide the patterns and appearance of the graph. The decision of threshold has not been fully theoretically explored in the literature but there exist some guidelines. Under typical SNA approaches, words with frequency counts below 2 or 3 were omitted from the semantic network (Drieger 2013). While VOSviewer filters for highly "relevant" terms (concept noun phrases) through an entropy calculation, for this thesis, the highest number of relevant term was selected (100% relevance retrieval). The researcher also identified many irrelevant terms that each interviewee used regularly that were also being captured in the statistical selection process. These terms such as "the other hand" and "in fact" were deselected in the final configuration stage in this project.

In the analysis section, the graph is accompanied by the following information on basic network statistics and VOSviewer parameters: 1) Number of words (W), 2) Number of Nodes (N), 3) Number of Edges, and 4) Configuration: Minimal Threshold, 5) Relevant Terms[11] (RT) to inform future readers of the thesis on how these results are created.

[11] The differences in number of RT and N is because some differently defined concepts for example "something", "thing" are taken out, while highly relevant concept such as "data" are included in the final version of the dataset (Lee, 2016).

4 Results

The following figures present a network generated by the transcripts of three interviewees representing each strategy. The design of within-case analysis and across-case analysis allow the researcher to understand the maturity of digital data used in each business. In the interview transcript, the existence of knowledge and expert coalitions in big data strategy and use can be identified. This study sought to discover how generating this big data has been executed, processed, and analyzed to adjust the digital media strategy. Therefore, within-case and across-case analysis mainly focused on three best practices that show a comparatively more advanced practice in this field.

4.1 Within Case Analysis

The data visualization tool, VOSviewer reveals insights from the interview text under the automated network generation process. The statistical content analysis process results in a distinct focus of digital media data strategy. Nodes are sized based on the number of total co-occurrences and colored to highlight clustering. Edges are sized and colored based on the number of co-occurrences between each mentioned concept within a paragraph window.

Network analysis of semantic network offers a perspective of the interview data that qualitative content analysis may not reveal. For example, dyads and triads that span multiple question answers immediately reveal sets of relationships among concepts that may not have necessarily coded together under typical qualitative analysis.

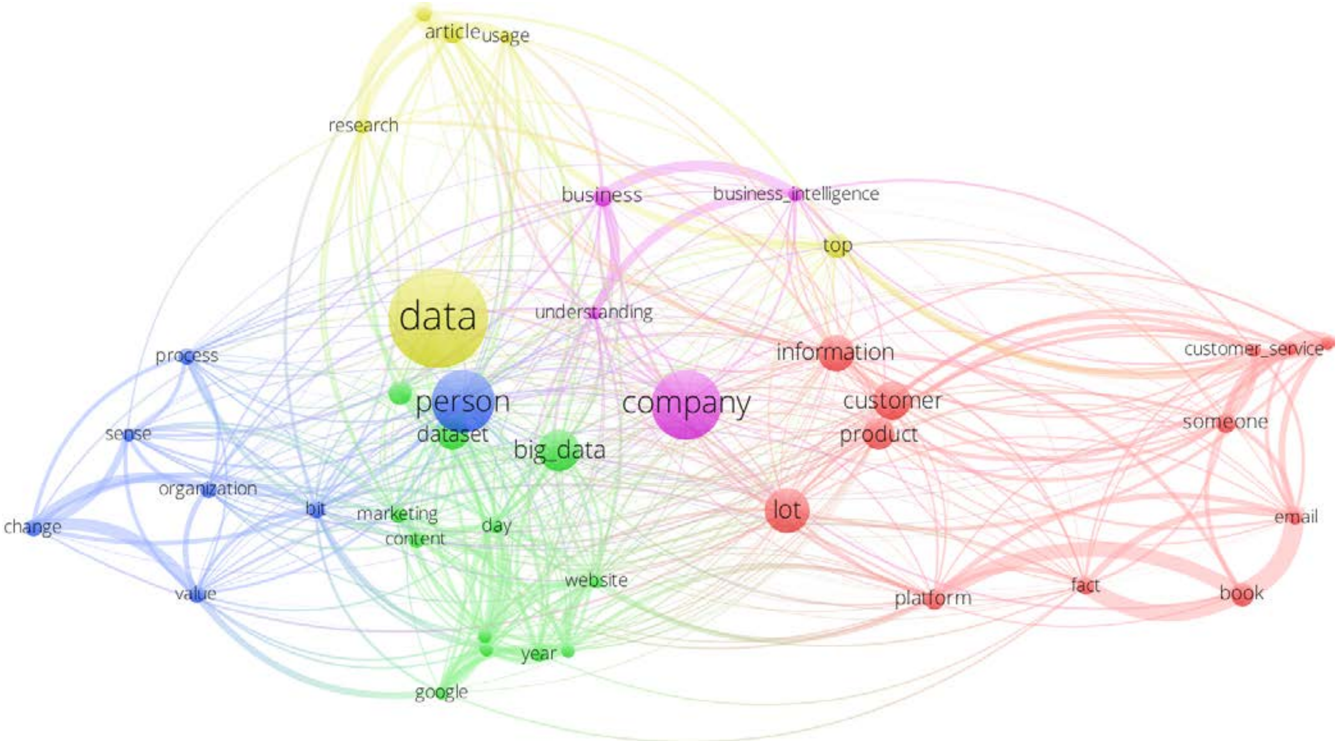

Figure 4.1: Maarten, Elsevier (Interviewee, Company), Number of words (W) = 5097, Number of Nodes (N) = 38, Number of Edges (E) = 575, Configuration: Minimal Threshold (MT) = 4, Relevant Terms (RT) = 42

The semantic network of interview data from Maarten of Elsevier visualizes the importance of each node, as seen in Figure 4.1, as well as the prominent themes (colored clusters). Maarten's discussion reveals three main themes: "data", "person", and "company"[12]. Among which, person seems to be an interesting finding which relates to the controversy that who should be the person responsible for doing what task in big data management in the company. As the interview data itself reveals, there is a "person" who contributes to the dataset, data and the big data development and management 'process' within the 'company' or 'organization' (thematic of the blue cluster). As Maarten discussed in the interview, there is a "data governance organ" at Elsevier, which makes decisions on how data can be used. He also mentions that the datasets shall be available across different departments by any means such as reporting or different accessibilities of data by department and level of power in the company. This

[12] One must keep in mind that organization in the context of interview is defined different from company. From the perspective of internal analysis and external analysis respectively. The reason why organization is coded independently is considering Maarten referred organization as "data governance organization" many times.

shows an advanced managerial environment that a team is assigned to monitor the development and utilizing owned data sources for operation.

The distinction of 'big data' and 'data' arises from discussion focus on 'big data' as opposed to generic 'data'. Maarten describes Elsevier as a "big data producer" and grossly defines big data as "just a lot of data". Thus, 'data' is strongly connect with Elsevier's specific data services, highlighted by the yellow cluster (with the nodes 'research', 'article', and 'usage'). The word "top" is emphasized several times in the interview - "on top of the data, we…", revealing that Elsevier proactively analyzes and retrieves insights from the dataset of academic articles and their producers and their usage.

This indicates a high maturity level of big data management. He gives an example regarding the workflow: "So that data is coming into us by from the front end, and then we are producing dataset that has been used in other big data research for example a production of pharmaceuticals productions of medicines, which are extracts from something like gene bank that we match together with the datasets that we generate on top of the journal articles that we produced."

This graph shows data and person are closely related with each other; *information*, *customer*, and *product* are within the same cluster with more highlights. Also, they have moderately strong linkages (co-occurrences) among them, highlighting their strong associations. This points to Elsevier's maturity in data managing strategy that information in the interview are the scientific articles produced by customers (researchers), and how they act on the Elsevier website are very much impacting on its product development in terms of how it is represented and to be searched by algorithms.

As Maarten claims that "We are a big data producer in a sense we produce a lot of data. That production processes are mostly honed towards customers and we then use big data internally for our own business processes. For example, we are using big data now to predict for users of our content, what content they might also be interested in. So, it is a suggestion. It is all that suggest service. That also allows us to understand in all of the customers that we serve, what the trends are, let's say in what people are looking at, and how people wanna engage with our content, what emerging fields of research there are. That of course allows us again to produce better results internally, and to create new solutions that target specially those goods." This response illustrates how the *information* are use from the *customer* and for the *customer* to develop and offer more relevant *product[s]*.

It is not surprising that *company* are isolated from these two density clusters (data, person and information customer product) which may indicate the position of the company is also trying to find out a solution for these topics even though these functions seem to be adequately developed. "We produce data as a company in a way is much more advanced than how we actually use big data internally to make our business process better." says Maarten.

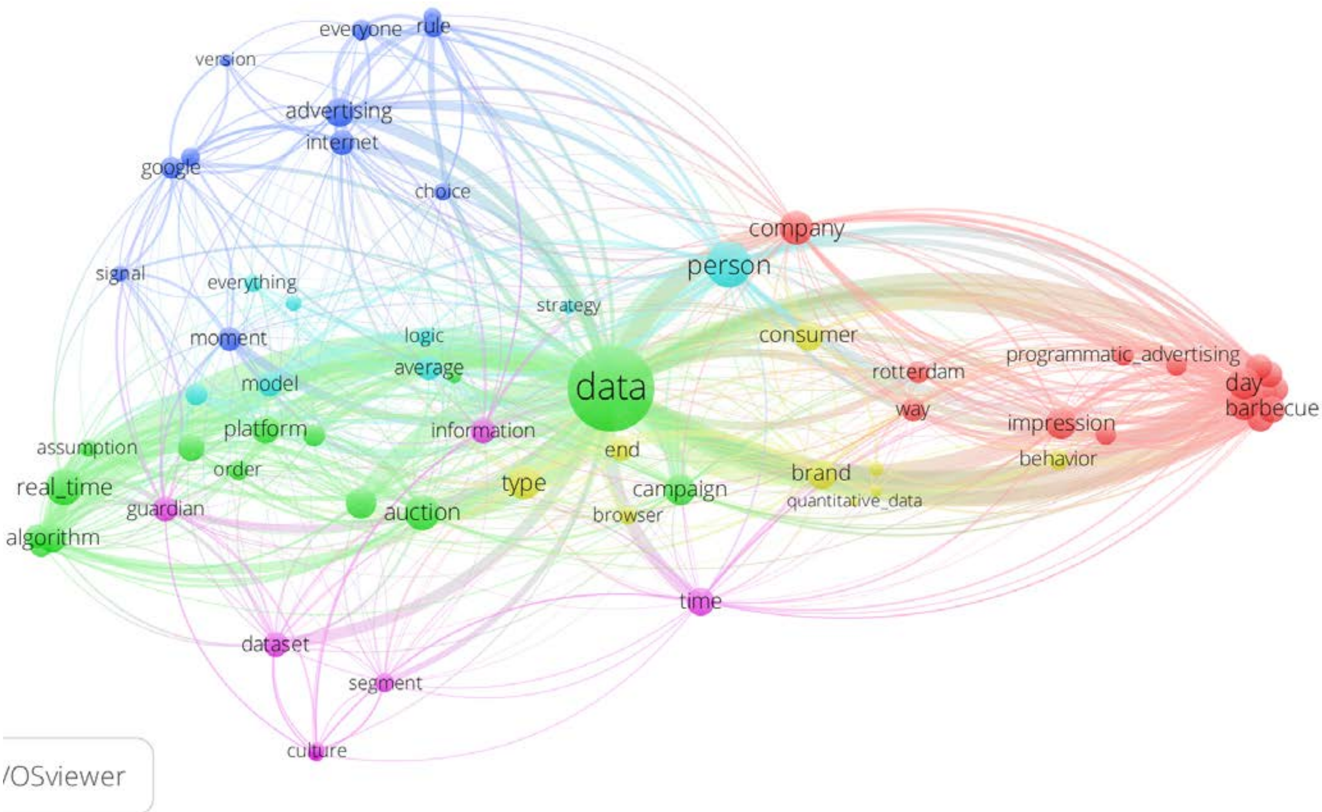

Figure 4.2: Tim Geenen, Banner Connect (Interviewee, Company), W = 3362, N = 68, E = 756, MT = 2, RT = 70

In the semantic network of Tim's interview, the green cluster indicates a high-end competency in big data, with algorithms in place that enhances the monitoring and analytics capability into nearly real time; according to the interviewer, there is only as short as two-hour delay in updates. This development is shared across digital media platforms where advertising auctions take place. Though having this level of advanced development, Tim says: "I actually want to have that in real time because I want to influence that auction, maybe because I have different data point, for example, DSB multi platform and it uses a bidder, it uses real time bidding technology and it is based on algorithms, and if I have more or better on you, I could influence the algorithm in real time, I could only do that if I also have real time data, so in order to have that, you need to stream data, or you need to have the algorithm or decision tree that you can execute in real time.” This finding illustrates a close to real time monitoring and analytics competence are developed across advertising bidding platforms, which informs in-house marketers to make their decisions on whether or not to continue or abort certain investment in advertisement on digital media spaces.

Another indication is the red cluster that location data, “Rotterdam”, weather data and activity data (barbecue) are now closely related to the company’s big data trainee programme “Programmatic Advertising[13]”. It is pioneering the way in which advertising can be revolutionized by programming languages and the performance of promotional project can be analyzed and monitored more scientifically. Tim indicates that the timing of external corporate activities can be optimized by combining different datasets: “…the time you start [to] advertise your company, so you take environmental data, like weather or economical data or use data to influence your campaign, another one is in the summer, a lot of people go barbecue, so on a date, it is good weather or on a most specific location, that is a good weather that day, actually start to targeting people with barbecue sauces with or barbecue supplies[14], so you mix the data from the programmatic advertising and the advertising ecosystem, and the environmental data.” This shows an advance in using additional data in order to gather the insights regarding customer conversion that at what point in future they might purchase. He asserts that by proactively acting on these insights, adjusting the offerings both the product itself but also the way of presenting online to encourage customers to take the action no matter whether or not they had the intention in mind.

Even though the semantic graph above condenses many codes together, the graph indicates the agency directors are dealing with big data through compressed time

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[13] Programmatic media buying, marketing and advertising is the algorithmic purchase and sale of advertising space in real time. During this process, software is used to automate the buying, placement, and optimization of media inventory via a bidding system (O’Sullivan, 2015).

[14] An example we discussed which largely relates to the company he is serving for as advertising service provider, typically FMCG companies.

granularity - on an analytical unit of day or even shorter (as discussed two hours). According to Tim "we purchase a few hundred million impressions [online performance of projects] and advertising impressions per day in an auction model, of all those single impression, we have data, so let's say we process a terabyte per day, I would consider that very scalable big data, but the volume is huge, when we do research and analysis, you can go so many different ways, because you are dealing with actual people behind the data, you cannot really predict their behavior and never really know if you are gonna click on that ad, I never gonna know if you are gonna purchase something after you saw an ad, but with the scale of the data, this big, you can actually start to make predictions, not so much on the individual user level, but in general consideration yes you can."

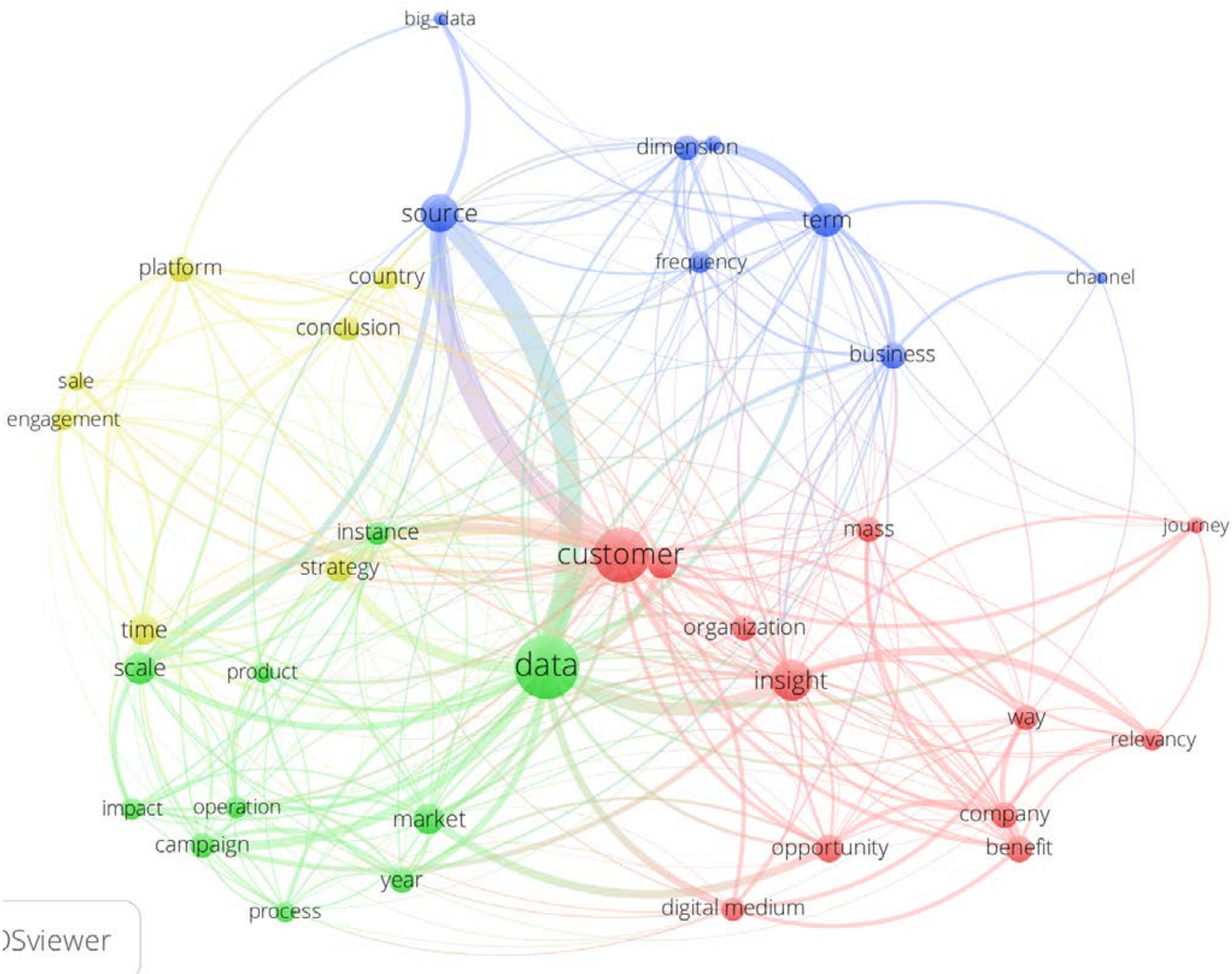

Figure 4.3: Participant M, A FMCG Company (Interviewee, Company), W = 4630, N = 42, E = 310, MT = 4, RT = 42

As the Figure 4.3 indicates the strong edge between data and source, customer and country. Besides, many codes are presented on a chain: journey, customer and scale; relevancy, insight, data, and scale; opportunity, market, operation and campaign. These relational network reveals first customer journey concepts are well performed in fast consumption brands that analytical process are very much combined with the knowledge of through the journey. Second, the company is trying to enhance its relevancy in offerings in response to customers' preferences which data contains market insights and this process has a potential to scale across different branches.

These two key points are addressed in the interview: "To listen carefully for the response, so you should only send the right things to the right consumer customer prospect, if they are open for that, before you reach out to them, firstly you need to really carefully understand if that really meets their needs, so if you are wrong sometimes, you need to adjust, if you are good in it, you need to scale, so relevancy is all about continuous testing and monitoring, so you have to have your dashboard in place, you need to have your performance code in place that you measure around every step over the journey. So basically act on your insights, so basically some insights would only come per week or per month, the most static ones, but those which you can monitor on an instant way, you need to use it...That will show it, if you have the relevancy." So far, even such level of interactivity between companies and consumers are hardly empirically studied – the instant expansion of data exhaust can be addressed by proactive experimenting on consumers to impact on the data, and also, use reduced datasets to meet short-term goals of analytics.

Third, the director perceives all these challenges positively as opportunity within the respect across market, operation and campaign – "So manageable that we have identified that sources that we generate insights from, and we have agreements about how frequently the data moving into our data central hub, so in that sense, it is quite predictable, according to agreements, so that is why I refer to as manageable, so we basically can plot all data architecture and also identify the frequency and accuracy of the data…"

Based on the SNA algorithm, those nodes of customer, data, organization and insight happen to be clustered together which indicates its semantic relationship and evidences the fast consumption industry are mainly rely on the data generated by the customer to bring insights for the organization. These can be explained according to the interview text, the data gathering procedures that reflects customer life including data source from “purchase behavior” to “click stream behavior”: “There is indeed different approaches to analyze online click stream data as well as purchase data, and we have tools to analyze different behavior with the focus of customer in mind.” according to the interview participant.

Another one of the prominent sets are the time and scale which form up a heated cluster, this shows the concerns even from those top performers that it is not the time yet that those practices can be sufficiently scale across the branches within the business around the world “It is still very important that you are measuring things right, to use the right KPI for instance, to show a wider organization that this can work, and it can scale, so small tasks, learn from it, adapt, modify, and see the results if it is okay, and scale it wider that these are really important steps so start very small, get some prove, adjust and scale.”

These results are generated through qualitative interpretation on quantitative treatment and visualization of the text data. One must keep in mind that the notion of data here is used and defined differently across interviews, some means data sources and some represents the source of information. The inferences thus far are based on structural features observed in the visualization.

This analysis suggested that such a representation might be a result of strategic mindset, structural environment and knowledge with regard to data management and digital media strategy development.

Although these properties hold reliably for these graphs which the analyst produces by using software, which ensures contains randomized statistical process, they do not hold for many other semantic networks. This is due to the fact that statistical representation process in VOSviewer allows graph to be structured with certain colors and layout. That is to say, the results are systematically produced based on the criteria recorded above and also relevancy with the subject. Irrelevant terms are taken in the configuration stage; this procedure has been done through by the researchers’ knowledge in the interview context. For instance, fact, course, are commonly part of the phrase in fact and of course, and others regular phrases that different interviewees use to a great extent and thus being captured in the statistical procedure. However, these examples illustrate how semantics are connected under the same statistical parameter criteria. Researchers who immerge themselves all the interview transcripts and the research objectives would be able to generate the same result.

4.2 Across Case Analysis

The following discussion mainly focuses on the maturity level of big data practice across business. As discussed, this theoretical model contains several different performance indicators that classify the different levels of practices into these aspects: accessing data, performing basic analytics, predicting and reacting to consumer behavior, converting data into actionable insights in real time (IBM White Paper, 2016; see Figure 2.4). As expected, these three strategists acknowledged the ownership of the data that data are acquired for granted by owned digital media channels. Whether or not there are collaborations with partners for data acquisition to achieve a diversification in datasets largely depends on specific objectives and incentives such as truly being able to access to the knowledge.

All interviewees discuss how data is gathered from online and offline channels to predict the next actions that customers might take. Analytical activities are carried out to achieve the objective of improving each offering in the market. Even though the ownership of big data is an enabler of more advanced practice, many businesses enrich their datasets by purchasing from third parties. Regarding communications to multiple stakeholders (Mulhern, 2009), all companies had a neutral to positive attitude towards other data owners such as Google and Facebook. The bigger the scale of the company is, the more open-minded the directors are towards the collaboration, especially focusing on the value exchange. The following shows the mixed emotions with both the reliance on those data companies and the opinion of having distinctively owned datasets.

> "We would like to work with the network, so the more we tap into, the better results we get, so we are very open…it is always a win-win, because it is always we have something for them and they have something for us." – Participant M, FCMG Company.

> "We work together with Google, so they are more partners than threat...But I would imagine that there will be more difficult to not integrate with their tools, because they have got such a massive amount of data, but they don't have everything right." – Toh, Moore

> "We also have data out of Google, because we do our own campaigns, we know what traffic derives from them. We also have Facebook analytics, Twitter

analytics etc. In that part we do work with those parities, we don't share... We don't have their knowledge and we use their knowledge". – Justin, SBS

Six out of ten participants revealed to have basic infrastructure of big data, this shows more than half of the business seem to have their team and skill set in place – in the maturity level of "standing" accessing data (IBM White Paper, 2016). The second stage "walking", means performing basic analytics also includes the capability of testing small campaigns (IBM White Paper, 2016). Consumer brands show more capacity of market testing and the techniques are varied according to objectives. The methods mainly include A/B testing and scenario testing. Only two out of ten companies confirmed having this level of advancement.

> "With the data that we generate by doing A/B testing on whether or not [we should use a click bottom for conversions], or download button should be red or green for example." – Maarten, Elsevier

> "I think there is not a measurement of one, so it means when you measure, you have to place into several four or five or even six different scenarios, depending on how much members are going to validate your position". –Tjibbe, TBWA

Businesses which operate consumer brands tend to show a stronger focus on Metrics and KPI as well as the tracking of data exhaust because these results largely affect the improvements of products in terms of pricing, features, and design that determines the market position of the business and its interactivity with the consumers. Participant M reflected on the criteria of setting up KPI for its market performance, stating: "First one, clearly about engagement; secondly about sales".

Next to that, preserving and maintaining the basic statistical process is the stepping stone of big data analytics even though real actionable insights are still rare to find. The primary data modelling approaches contain predictive analytics, prescriptive analytics, and descriptive analytics[15]. Descriptive analytics shows the current status, which contains information about the customer base. Information about age and wages are retrieved and analyzed using different statistical analysis techniques such as standard deviation. Prescriptive analytics was revealed to have an impact on project management, especially how one interference has an impact on certain line management. Probability models is used in addition to achieve an optimized resource allocation, improvements as well as providing addition information to the customers.

> "We use some standard probability models, like logistic regression to understand the propensity of buying or certain scale of certain product for every customer, and this is quite interesting for us, because it the attained goal is to come up with personalized communications, personalized offers to each one of our customers based on the data scale. So for that, we basically use standardized probability models to come up with the probability or the likelihood of buying certain scale for each of our customers so that we are gonna target all those parts that most interesting certain scales and for other excuse, we target others". – Participant M, FCMG Company.

This aligns with the stage of "jogging" which represents the capability to predict and react to consumer behavior (IBM White Paper, 2016). This level largely remains on the activities related to purchasing, such as sales prediction and the possible steps that the consumers are going to take. There is not sufficient evidence to show business to business companies are in this stage now.

"Running" represents converting data into actionable insights in real time (IBM White Paper, 2016). The competence of real-time ROI measuring and actionable insights is hardly developed. Real-time measuring only appears in the advertising industry, where bidding activities are carried out. Though real time contains 2-hour delay, there is evident progress that monitoring activities are close to "real time". In this stage of value transformation, many businesses seem to be less capable of adapting.

Regarding the research question of how data-driven marketing is enhanced by digital data analytics that reveal market insights, few interviews exemplified their current stage of development.

> "so the voice of the customers would be a very good example, we are generating information from the customers' data we are getting. and we are generating that from a specific team, the data analysts and they source that then through applications and through reports to people within product groups that can use the data to improve our renewals, increase our product availability by improving our products and also create more efficiency by renew customer services pipeline by identifying pinpoints across the customer experience". – Maarten, Elsevier

Besides, many interviewees show their awareness of acquiring market knowledge in the process of data analytics, however, there is not enough evidence to show that conceptual tools are used together with the quantitative analytics process.

Those conceptual tools, especially customer journey, are widely implemented among agencies who retrieve market insights directly by first-hand research. Those agencies also commonly employ a wide magnitude of concepts and framework to acquire market knowledge of the products and services they are offering.

> "It is important to know who your target audience in the funnel is where they are in the customer journey". – Jack, Wecanbeheros

> "You have to understand the business way and the industry as well, only looking into quantify sets of data with numbers will not bring you the light, if you truly want to spot the opportunities, you need to truly understand the market as well." – Participant M, FCMG Company.

Moreover, what is shared in common among those performers who seem to have better development is that they have multiple strategic alliances, and four stages of maturity are more or less achieved by outsourcing to different partners who have the specific expertise.

> "We are not particularly using big data to generate insights from ourselves from the parities [the responsible team], we asking companies to do that for us. We are not internally doing everything with big data, we are also sending it off or within our venders do that for us, use them on third parties". – Maarten, Elsevier.

> "If it is paid media so for instance banners or paid search, that is something you can manage, so you basically reach out to your media agency to do a further analysis" – Participant M, FMCG Company

It is also evident that there is a premised divergence between market insight and data insight practices. Many directors revealed that they have several departments and roles are working on this. In CGI for example, the main digital marketing activities are all moderated by marketing dashboards built by the in-house team which shows its level of owned data analytics. However, the specific accounts of analyzing for marketing purposes are proposed to the board and controlled by different departments belonging to a different main division altogether – the marketing department and IT department.

Overall, both within case analysis and across case analysis implies there are sufficient internal resources within companies. The attitude is positive towards outsourcing and collaboration with other specialized parties for exchanging value in terms of knowledge which can be acquired by accessing the data and skills. The metrics and strategic framework employed are verified across businesses.

4.3 Thematic Analysis

4.3.1 Thematic Segments

All the thematic segments were analyzed in SNA and hereby presents three key findings. The selection criterion for themes to report is this: they are currently under-developed subjects for which empirical studies are especially needed; the graphs comparatively contain richer results concerning the theme.

4.3.1.1 Relevancy and Personalization

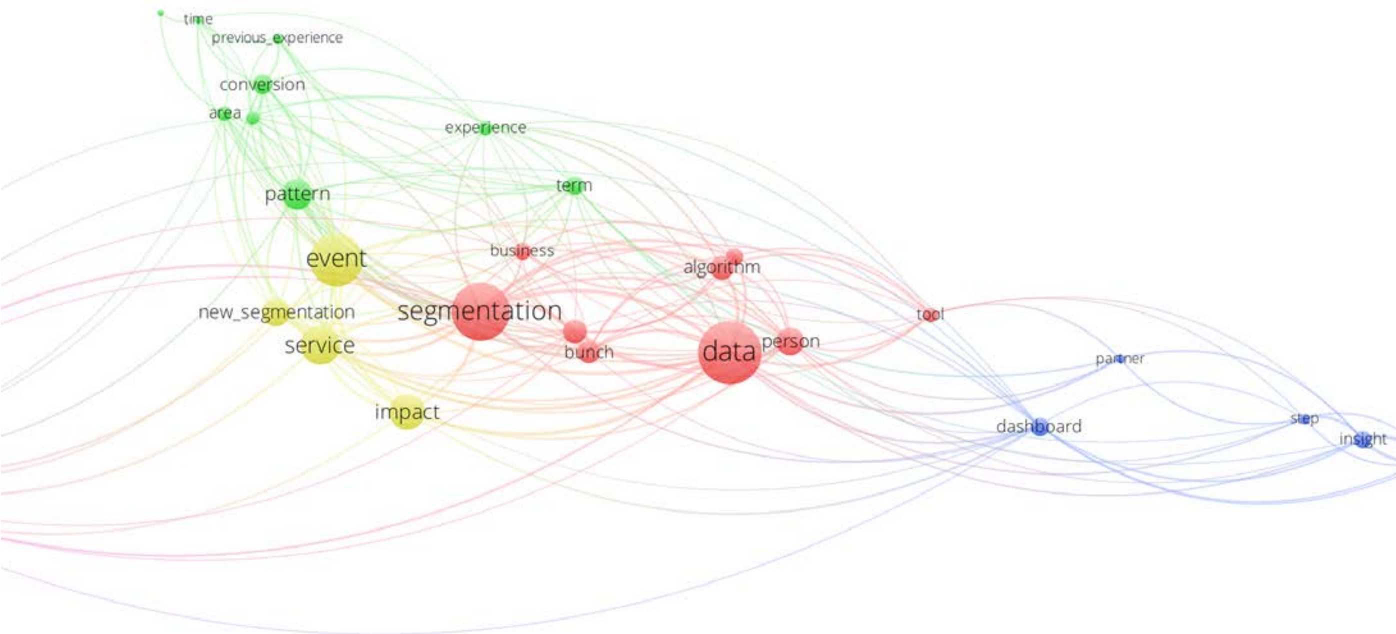

Figure 4.4: Relevancy and Personalization, W = 1445, N = 31, E = 193, MT = 2, RT = 38

The theme of this graph is "relevancy and personalization". In the central cluster, "segmentation", "data", and "algorithm" shows its relationship as a closed triad. Also, it must be noted that they belong to the same cluster, which means that they are closely related vertices (Noack, 2008). This has been evidenced in interview context as media agencies thrive on developing analytic automation tools and algorithms based on social and consumer behavior in response to the constant changes in the market, especially in the context of event management and outperforming other rivals to gain a competitive advantage. Contrary to the mainstream definition of segmentation which largely relates to the divisions of the target group, the segmentation here in the interview context is "value segmentation", which evidences the fairly specialized service offerings from the digital media consultancies. The segmentations of a specific target group are concluded based on matching data in which it shows high correlation. Algorithm analysis also enables businesses to benchmark when a decision-making process is required.

The blue cluster shows the current practice of having a “dashboard” to facilitate the engagement activities delivered to the customers. Different steps in the concept of customer journey are taken either from partnering with expertise or analyzing in dashboards, which direct analytics to insights. Many data giants such as Google and Facebook are considered to be “difficult to maneuver [data activities] without”. The node “partner” is inspired in the opposite to “threat” by the interview probe, showing high co-occurrence with other concepts within this cluster. This shows not only a positive but also a critical attitude towards this relationship among strategy directors.

4.3.1.2 Metrics and Measurement

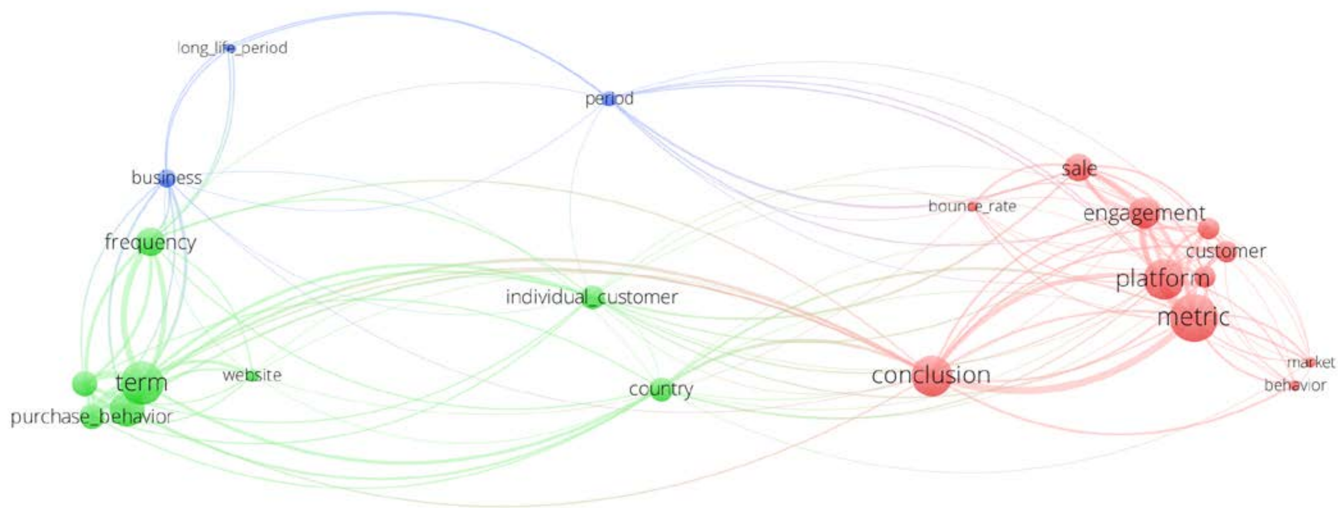

Figure 4.5: Metrics and Measurement, W = 942, N = 22, E = 129, MT = 2, RT = 27

The parameters are optimized for the best results. This is particularly significant in the SNA analysis for the theme “metrics and measurements”. It is noted that this corpus is particularly scattered that the lowest number of minimal number of co-occurrence words “1” is selected and the higher relevant terms are presented here. However, if MT =1, more than two-thirds of the terms cannot be captured within the interface size of VOSviewer. That is to say, the metrics and measurement that are currently in use seem to be diversified and far from being homogeneous. Perhaps they are varied by different industries and analytical objectives.

As can be concluded from the graph, “frequency” is a key measurement that is often related to “purchase behaviors” and thus sales information where it can be gathered on platforms such as “websites”. The behavior data is considered as the key to insights. Key measures, including “frequency”, volume, recency [urgency], were discussed in the interviews, even though the latter two are not clearly visible in the graph. This data that reveals “intentions” drives practitioners to have an in-depth understanding of customers on a unit of each individual. Different dimensions are combined for the analytics, and frequency often relates to “monetary models”.

The metrics implication seems to be shared across companies as it is also evident in another chain relationship. The red cluster shows several strong coalitions: “conclusion”, “metric”, “engagement”. In the interview context, this illustrates many conclusions are derived from the analysis conducted by different metrics, and from where engagement takes place. The level of engagement from each individual customer is monitored and analyzed under the criteria of interactive span and interactive frequency. It thus presents an important theoretical indication that digital media marketing concepts are sufficiently used in practice that intertwines with analytical metrics in the corpus of metrics and measurement.

Apart from that, two other sets of relations reveal the advance in combining conceptual framework and metrics, strong edges are shown between “engagement” and “metric”; “engagement” and “platform”.

4.3.1.3 Future Directions and Indication

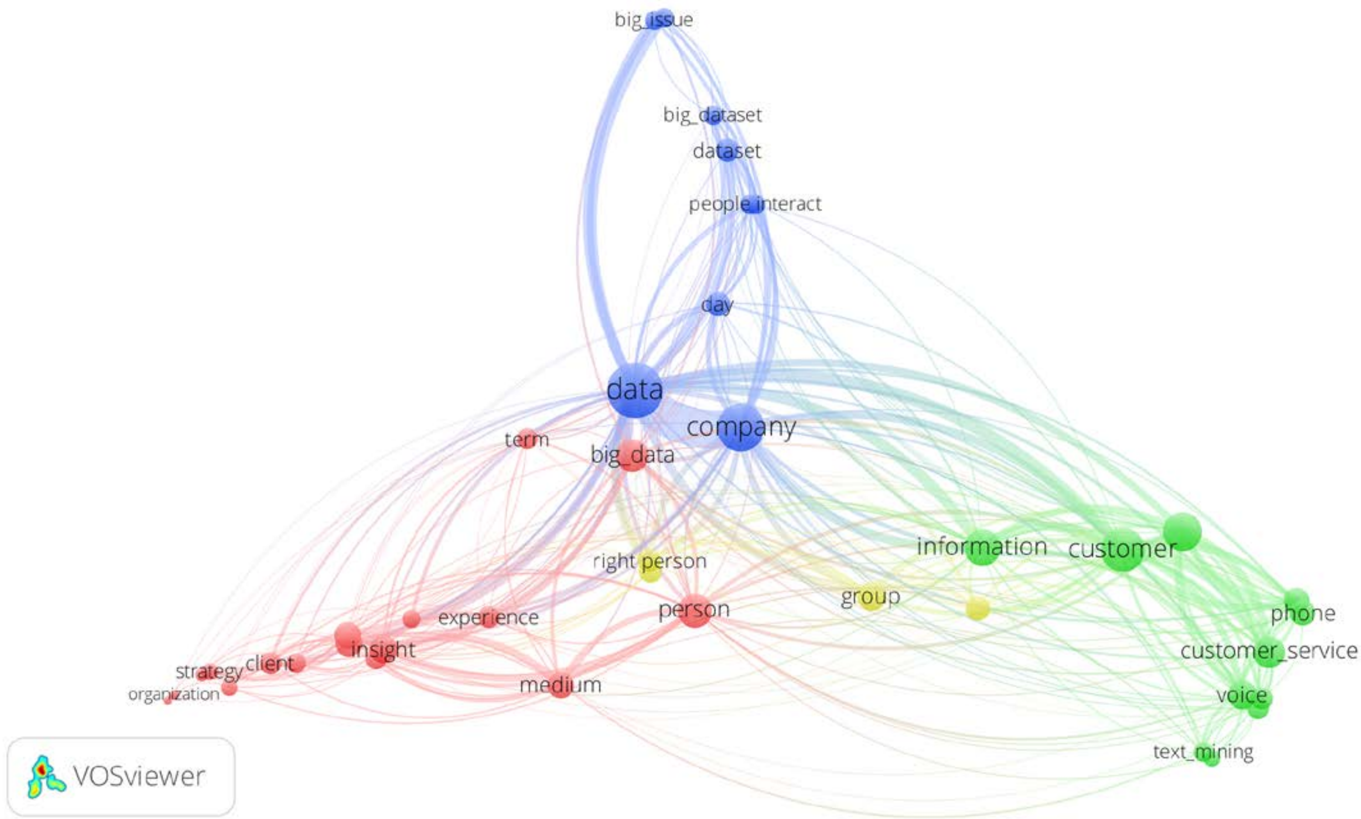

Figure 4.6: Future directions and indication, W = 1884, N = 51, E = 341, MT = 2, RT = 53

This graph of the theme "future directions and indication", compared with the previous two, shows an equally spreading out layout. As Noack (2008) explains, the semantic representation separates sparsely connected vertices, by placing them at positions that are far away from each other in different clusters. This seems to reveal a diversification in the directions of the future development of this field. However, these nodes shown in Figure 4.6 compared with the above two, appear to have a homogenous corpus. It repetitively shows the essential elements of company, consumer, and data with each relevant cluster.

Strong edges can easily be identified between the key node "data" and other concepts such as "company", "customer", "information", and so forth. However, there are not many theoretical implications of this finding, as the cluster consists of a wide magnitude of generic concepts that are relevant to this study, especially those key nodes and strong edges. Given the context that these three themes comparatively offer rich data, not all SNA graphs are worthy of analytics. It may indicate that practitioners have not yet reached a consensus regarding the future of digital data. It is not surprising in the environment where there does not seem to be a "one size fits all" strategic framework for digital media analytics.

4.3.2 Theoretical Discussions

4.3.2.1 Value of Human Interpretation

From the perspective of the interviewees, the main advantage of human as opposed to machine in big data practice is the flexibility in applying conceptual tools which enables the integration of market knowledge into data analysis and giving them meaning based on this complementary process as Gerard, Marketing Advisor at Acer, asserts. He states that data is valuable only when it is properly processed and interpreted in order to achieve the objectives in business: "It is just like a bucket of ingredients, and like preparing a dish, sometimes you need peace, sometimes you need beans, you know, but they are all in your bucket, all in your groceries, so big data is like a bag of groceries to create receipts, you don't need anything, you need to pull something that is in there." From the interviews, it seems clear that the data interpreter plays an important part in digital data management.

Also, the unlimited possibility of accessing a wide range of strategic indication to adjust the digital media strategy based on the results are more important than focusing on details in technical improvements. Among the interviewees, six of them mentioned that those who understand the market predominantly make the data valuable, ready for use rather than the algorithms in machine. As Toh, the owner of Moore, a leading branding consultancy in Amsterdam, says: "Often times I think creative work is more important than how you execute digital media. Digital media is more often like hey how can we amplify it; how can we optimize in a way that possible? At the end, often times that we overlooked it - how can we go from considerations to conversions? I think that is more important than how do we optimize the DSN [Data Source Name]".

Another dilemma of human and machine contribution is if the level of compatibility between machine and data are high (i.e. structured data), the work automated by machine with self learning potentials, to address the challenge of big data in which human brain cannot solve. Nevertheless, human brain plays an integral role in understanding the machine language and operates the process of analytics. As participant M says "if there are standard data models, that you could basically taking care of by a machine, then we will do it, so it is more or less structured machine learning than is done by automation. Machine learning can also mean that things we cannot come up with ourselves, so there is a big variety that refers to your big data that human brain cannot consume. So I think we are entering into an era that is more important, but also it starts with, okay the non stroke, the machine starts with the so-called structured and unstructured data, it needs to feed with some boundaries, some criteria some definitions; otherwise, you put abokedabou [a phrase that indicates obscure and meaningless nature of big data] in and abokedabou out, you need to get some logic and that come from human brain as well."

4.3.2.2 Integrated Data Analysis Warehouse

Opinion towards whether or not having a warehouse in which data sources and analytical activities are combined, seem to be largely affected by the practice in the company. That is to say, their view appears to be biased towards how they are analyzing. Director Tjibbe, the marketing analysis director from MEC, who have experience with adobe marketing campaigning tool, asserts the advantages of using one platform for analysis as creating more integrated solutions. "It is like a socket, so you put all kind of different datasets into a kind of data management platform and what I said about all those different silos, that is how businesses are created, different parts are responsible for different parts of the business, and the beauty I guess is everything come together, so this is the total budget for brand, this is for sales, promotions, and then you have all the data."

Companies operating with incomplete data analytics across platforms can enter the market efficiently and exploit external resources better. As Marteen states "There is a lot of value in understanding how people interact, and also very aware of the fact that. Especially with a large technology companies like Google and Facebook starting to engage more with the way that people interact by starting combine datasets from different products."

4.3.2.3 Strategy of Outsourcing and Horizontal Integration

Implementations of digital strategies at all levels within holding companies seem to have more potential in leveraging the strength to handle big data among its network. Those who own data own the power. The agency operation model facilitates the acquisition of data from various sources. They are gathered from different regions, offices and agencies brands and their clients. Digital behaviors are thus all accessed for granted in a less constrained way than SMEs and independently agencies that operates on its own. As Tjibbe says "you do see that within the industry we approach on silo level, but WPP, Ogilvy, they are pretty far of creating a meta overview, so that we do not only measure or analyze within a certain closed environment, instead, a total overview, that is the power of an agency network." Another participant reflected his motivation of establishing data analysis hub as an approach of horizontal technique acquisition: "I am focusing more on the value exchanges… to deal with it in a principled way."

Two respondents indicated the decision of outsourcing often relates to the scale of the company and also the maturity of the business. Successful big data analytics requires basic infrastructure for that operation including people and finance. As Jack commented "While smaller companies does not have their resources, and money and person to mine that data collect the data, to work with it. So they outsource it to agencies…If you are a small company, and if you have small clients, it is not lucrative to set up this business."

4.3.2.4 Ways of Successful Implementation of Big Data Practices

Moreover, eight out of ten participants believe that the analysis strategy starts from asking the right questions. Jack explains the best practices the complementation of market insight with digital data. "By knowing that these people are personally very interested, we can raise our offer to present them a banner on a suitable time. And if person is not in the market by far, we are not going to present him this banner, or not pay so much for this content with him. By working with data party, and also with the police plant, we as a media agency could be very efficient in communication with this prospect, because we know how much he is interested in and how much you were into leasing a car, so that helps us to spend the media money more efficiently."

Several interviewees point out the possibilities of richer opportunities in the market, if the model of customer journey is sufficiently used for enriching the market knowledge in collaborating with the analysis. "…at least you need to understand what kind of information that people had before, what kind of steps they take to get that information or the demands are really high, based on what [and so forth]" says Tjibbe.

4.3.2.5 Main Obstacles to the Implementation of Big Data Practices

According to interviewees, the main obstacle to the implementation of big data are data quality. Lack of understanding objectives renders the data acquisition process imprecise and hence lead to inadequate analytics. One participant shed doubts on the effectiveness of using significant findings as a supportive evidence for strategies and commented it as "more about the confidence level in statistics" …she further explains that "you are looking for Iphone [owners] and I gave you data about '95% of the consumers are using tablets', [apparently] the relevance is low." Also, Tjibbe has given an example regarding the veracity. He exhibited doubts on the truthfulness of a wide array of online behaviors specially on platforms like Facebook profiles.

Despite the fact that people are "faking" their live online, he is in favor of the potentials of machine to address this issue. He believes that machine monitoring of online behaviors comparatively brings more value to the big data analytics "Machine can find out what people are truly behaving which potentially increases the quality of the data compared with survey, which people believe how they behave or they want others to understand a certain way how they behave."

Additional problems can be raised by the lack of suitable operational environment within the organization. Three participants revealed corporate environment as a constraint in the development of maturity model, in many cases there requires a persuasive analyst who is also good at internal lobbies to make the change more likely to happen. Gerard, the marketing intelligence advisor for Acer describes: "Most companies are super tankers, like oil tankers, like big ships, they move in a certain direction, they don't steer left or right or if they do it is not like they often move. They just keep going for a long time." Moreover, several respondents indicated the inaccessibility of data within the companies incur more difficulties for digital media strategy development. Few interviewees assert that the internal lobbying for improvements in competency is confronted with challenges "So it is very difficult if you are implementing this type of change to have the organization understand where the value is without actually doing it."

4.3.2.6 Knowledge Sharing Network & Leadership

To deliver a substantial competitive advantage, knowledge and expertise are combined based on several strategies of internal and external acquisition of talents and leaders.

This is particularly evident among those business who want to quickly develop and market or require additional expertise and assistance for further development. The functional structure of digital data analysis is also discussed in the interview with Sander, the Head of CGI marketing describes who he works with "Yeah, if you get that various organizations which I closely collaborate with…we have different leaders in our organizations that run different product portfolios so I closely work with them to understand what consult to the markets, I closely work with our CTO, so that is mainly on the technology, architecture, data processing type side. I engage with large clients directly to understand what the market wants beyond the existing technology, and I engage with the academic world to understand what would be the next thing that comes to data technology." This quote evidences that my interviewees are driven to adapt to the changes in digital media by learning from different sources that are available to them.

Marteen, business director at Elsevier, indicated the interactions within the functional network in companies regarding knowledge sharing: "data analysts, and they source that then through applications and through reports to people within product groups that can use the data to improve our renewals, increase our product availability by improving our products and also create more efficiency by renew customer services pipeline by identifying pinpoints across the customer experience." This response also shows the boundaries between departments regarding accessing to key data analytics findings, as the word "within" illustrates how these assets are possessed in isolation across functions.

In line with this, regarding to the controversies regarding who shall be responsible for big data management, Justin, the Marketing Manager of SBS, one of the most influential media companies in the Netherlands, gave the following answer. "Often you also got an insight department, the research department, what you now see is that the data is getting from the digital department into the research or the insights department and that lies under the strategic department." Such descriptions of which groups of employees are responsible for this practice and how the tasks are distributed across the departments shows that internal resources are in place. This sounds a semi-centralized structure of team within the companies.

In addition, Toh reveals the problematic emphasis on advancing technology without considering its application among the people. "The availability of the data is massive and we only grow extensively with more sensitive technology to make the work. I think it is more about finding the right people to do the right analysis…allow data to grow to a leadership positions in the companies." This quote supports the functional network and it shows directors' awareness towards the gap between having potential leaders and placing them at the suitable positions.

5 Conclusion

5.1 Discussion and Conclusion

The research question for this study was "How do companies in the Netherlands retrieve market insights from digital media data and use it to develop data-driven marketing strategy?" In sum, the interviewed professionals conclude that their best practices ought to commence with digital media data analysis focusing on the questions regarding the objectives needed to achieve. Their practice considers combining datasets from applicable channels and sources, and filtering the relevant portions for the analytics and statistical processing. This is followed by their drawing of conclusions in conjunction with market understanding, all the while maintaining their desire to incur minimal resources in terms of talents, time, knowledge, and operational structure.

Many interviewees reveal that having accurate market insights matters most, while recognizing the importance of optimizing their practice for finding insights relevant to digital marketing. In most of the cases examined, the interviewees revealed their focus on primarily data analytics, and less focus on converting results and insights into executive strategies for business. Thus, what seems to continue to be missing is the translation of data into insights, despite the fidelity of digital media data due to its commonly being unobtrusively collected customer opinions, intentions, and behavior (Mulhern 2009). While the interviewed directors all aim to make their contribution to digital data management, the retrieval of real insights of customer behavior from big data seems to remain limited. This capability has, however, become increasingly crucial for a business to maintain its competitive position in the market (Day, 2011; Ambrosini & Bowman, 2009).

In this regard, it is not surprising that the majority of interviewees consider that the value of digital data management relies more on the strategist/analyst rather than the machine, as the results, having potential market value, continue to require correct interpretation via human intelligence. Furthermore, human and machine intelligence are intertwined with each other. As Letouze (2012) criticizes, all big data practice starts from intuition and experience, which contradicts with its scientific nature. This study's finding challenges the extant scholarship that the deductive reasoning process, starting from intuition and experience, enhances its reliability.

The stages of combining data analytics with in-depth understanding towards the market and interpreting the analytical results in the context of the "customer journey" is affirmed to be of special importance. This is in line with Edelman and Singer's (2015) argument that analyzing and interpreting data throughout different stages adds more value to consumers and brands and enhances the competitive advantage through development and application of different strategies pertaining to this journey. It is evident that the notion of customer journey, and the accompanying touch points where customer's can be activated for conversion into behaviors such as purchasing or subscribing, is a strong focus among businesses, especially business to customer firms and media consultancies.

Moreover, many practitioners consider first-hand consumer research data, such as surveys, continue to enhance the value and validity of the pool of big data. This kind of data also has potential in producing actionable insights no matter if it is combined or not with the conceptual framework of customer journey. For example, data on actors' social networks (real-life or online) may not necessarily be captured through the customer journey framework, yet retain high potential for valuable insights for data-driven marketing. Albert and Barabasi (2002) discusses the centrality of the independent decision makers gives way to social clusters that make purchase decisions and effectively constitute the target audiences. In line with this, only few cases show consideration for both quantitative and qualitative procedures in an attempt to create the generic "customer profiles" and segmentations. These findings indicate one thing, however, that better understanding of the market through multiple paradigms, data channels, and collection techniques, the more likelihood that big data can be turned into "value".

5.1.1 Operational Structure

The current landscape of digital media platforms is indeed multi-faceted. Concepts ranging from data analytics, digital marketing, and digital strategy all influence and are relevant to business. All these stages are proven to have high correlations with the divisions in the functional structure of the company, and thus also have relations to the activities surrounding its products and services. The study finds that strategic and technical functions are not adequately collaborating together to address the issues of data overload, scattered data sources, biases from managerial functions, low accountability, and transparency, just as Kumar et al., (2015) identified.

Still, it is crucial that such a suitable operational model be in place (Brown & Gottlieb, 2016). The results show that companies have few resources and not enough sufficient support from the technical team in order to focus on managing data for marketing. The data scientists unsurprisingly remain responsible for the collection and analytics of data that the companies own or govern, even though they do not have marketing background and knowledge. Certainly, it meets the interests of multiple roles in the organizations, which are largely considered and divided as separate practices in organizations.

Another emergent finding regarding effective data strategy execution is the critical roles of team and leaders. The leader role in the process is not evident in the results; only two of out ten interviewees seem to be confident about their impact on the practice. Although whom the directors collaborate and interact with varied, they all show high awareness towards the subject of leadership, but the majority of them do not consider themselves as prominent data-driven strategizing leaders in the field.

5.1.2 Implication of Data Analytics and Data Services Across Industries in the Netherlands

During the process of advancing digital data analytics, tensions and competition emerge in the move towards ecosystems of channel optimization (Van Bruggen, et al, 2010). It is important to acknowledge that those top performers tend to show a more positive attitude with regard to the challenges brought by big data as they see them as opportunities. The results show that true actionable insights are hard to reap even among the best performers. However, there is an established knowledge-sharing network among strategists on a global level, where solutions and innovations are shared to scale within the organizational network. It can perhaps be a motivation for growth and continuous progress.

The corporations which have activities surrounding fast-moving consumer goods show a comparatively stronger adaptive capability (Day, 2011; Ambrosini & Bowman, 2009) that represent sophisticated analytical designs which involve varied data models. This capability enhances the company’s competitive data-driven decision-making and can yield a sustainable advantage in its offerings to the market (Ambrosini & Bowman, 2009; Erevelles et al, 2015). Thus, these performers are more likely (than those in other organizations) to be able to transform their advanced analytics and adaptive capabilities into true “value”. Their operational structure appears much more developed and tasks are assigned clearly with objectives.

This research also shows that digital media agencies and digital marketing service providers all have very specialized services that make a distinct contribution towards corporate data management. Many started from traditional marketing analytics and hence the capability of dealing with large datasets that contain market insights are high. For those who specialized in digital media services, the awareness of the challenge was mostly put into initiatives in actively acquiring competence with partners in an attempt to continuously outperform the market and thus reap more opportunities and collaborations with various business.

Results further show that many large-scale companies, especially those business-to-business firms, are presently only prepared for optimizing digital media strategies as part of their wider digital marketing communications strategy, instead of considering it as priority or as an important source to enhance its marketing activities based on analytics.

As van Bruggen et al., (2010) assert, the functionalities of diverse channels need to be improved simultaneously rather than one at a time in order to provide consumers with tailored products at the right time and place. Otherwise, channel management becomes ineffective. Also, this argument is applicable to all industries; it is especially pivotal for businesses that largely rely on content creation or work as a content platform provider. It seems that many traditional media brands such as public broadcasters have not yet fully adapted their focus onto the opportunities and value brought by real-time monitoring across multi digital media channel analytics (van Bruggen et al., 2010).

That being said, this does not mean that interviewees did not express a clear awareness that they are operating in an appropriate way leading to a higher maturity level. Eight out of ten interviewees revealed having tools, platforms, and basic tracking, essential resources for operation (Barney, 1991). Many revealed having multiple departments working on the analytics and insights, contributing to an assembly line for the “value” creation. This shows many companies have come to be aware of the importance of transforming organizational structure in response to the changes in the digital market (Teece et al., 1997; Zhou & Li, 2010; Erevelles et al., 2015). The internal sharing of these assets seems to be less emphasized across non-technical departments such as the business development department. Instead, managers and other leadership roles are discussing solutions with their counterparts within the organizational network even across the the broader.

5.1.3 Unstructured Data as Milestone in Big Data Sophistication

Contrary to expectations and scholarship of George et als' (2014) who concludes that many companies now show advances in unstructured data, this research finds that the practice in Holland is not being developed. Unstructured data across multiple media platforms is far from being systematically explored in the field of digital marketing, let alone being utilized for generating more value to the business. Only traditional marketing research activities involve this form of data via first-hand research approaches such as focus groups and surveys.

There is no evidence from the interviewees that shows there exist talents let alone a team who manages the unstructured data scattered across digital media. Perhaps there are not enough resources regarding talents, knowledge, and tools prepared, and many express being satisfied with their status quo about their development. Many quotes evidence this: "Everything is now manageable", "Regarding the unstructured data, I am not yet scared"; "Well, we have to do that [work on big data] step by step"; "yeah, everyone is now...more or less on the same page." This omission of the intention of managing unstructured data only illustrates the subject's characterization as a non-technical leader. The consequence of these viewpoints is that the actual unstructured data management and its innovation has not been fully appreciated or understood, thereby also leading to biased discussions about big data management towards structured data.

5.1.4 Summary

More often than not, a person new to a particular field needs to become acquainted with the existing practices and executive frameworks. The study mainly focuses on enhancing data-driven marketing across digital platforms and therefore studying relevant frameworks becomes significant for this study. For the field of data analytics in digital marketing, marketers have to consider analytics-mediated communication management across multiple media as fragmented landscapes where many people share their ideas that can impact sales performance. At least, it has become clear that there is not yet one universal way in which businesses structure their market insights department towards the use of big data analytics.

Nonetheless, working with such data remains challenging, not in the least, because of the difficulties in acquiring market knowledge. Thus, achieving accurate results that indicate real insights of the market are not easily obtained by solely using conventional applications. These findings reveal that companies are operating based on sufficient knowledge and resources towards structured data (i.e., numbers) and ignorance towards the real market insights. Companies should enhance relevance in public offerings, and develop metrics and measurements according to analytics objectives. Last but not least, technicians, marketers, and decision makers from large companies who target global audiences have to act fast to react to the changes in the online consumption market with available resources of skills and finance to deal with digital data.

This thesis has found supporting signs to the premise of high involvement of “humans” (i.e. market intelligent analysts) in analytics as well as the interpretation stage, in addition to the assistance of technology and analytical software - the “machines” - in increasing efficiency and accuracy of the analytic and interpretation processes. Themes pertaining to strategy and current challenges confronting the media and business landscape in the Netherlands have also been identified. This thesis hopes to contribute a combined viewpoint worthy of further inspection to the current studies.

5.2 Limitations

The research aims to fill the gap between the measures for tactical and strategic operations regarding big data and marketing as Kumar et al., (2013) mentions. It was thus more often than not the case that the interviewees were not solely responsible for digital strategy for marketing, but also the digital solutions for business, or even a larger influence scope. This sample can thus be criticized as being not fully comprehensive and under-representing the full scope of individuals involved in the data-driven marketing and strategizing process.

Furthermore, companies of specialized services can be explored and captured in the interview sample. For instance, those that deal with unstructured data solutions through various techniques: topological data analysis (i.e. Ayasdi, Quid, Palantir), social (i.e. Crimson Hexagon, SM2, Sysomos, Radian6, Talkwalker) (Spanjaard, 2016), channel marketing (i.e. Adobe Analytics). These data solution companies are pioneering distinct analytics to facilitate digital marketing activities and optimize marketing performance.

Among which, the topological and social analytical perspectives are particularly relevant to advancing this study, as the analysis of a network structure borne directly of digital data (aside from the SNA) can provide deeper insights.

There are several limitations in interviews. One of them is the language preference. Even though English may be considered a second native language to interviewees, many directors may have felt more comfortable to contribute in Dutch. Consequently, some interviews were found to have a less valuable content for this study and hence were not included in the analysis stage.

Some interviews were interrupted by other unexpected interventions; this led to a few shorter interviews. The question trajectory also influenced some quality of the interviews. To achieve a standard of validity, the interview method requires all participants interpret the interview questions in the same way, and articulated expressions are not allowed to have any room for uncertainty (Silverman, 2015). However, maintaining some flexibility in asking follow-up questions in the semi-structured interviews enables the researcher to follow an intuitive structure, which is mostly different from the original questioning sequence proposed in the interview protocol. So, the variations in the questioning trajectories yielded some divergence in answers. Though the influence of each word and sentence in use and to what extent it can influence the results of the study are hard to demonstrate, this indeed can raise some doubts. However, this flexibility also enhances the research value to a great extent that is worth discussion.

Regarding SNA analysis, the author is aware of the fact that there are there are many other SNA tools that can be used for additional text analysis and semantic network visualization (e.g. AutoMap, ConText, Gephi according to Columbus et al., 2010; Diesner, 2014; Bastlan, Jacomy & Heymann, 2009). After having constructed the dataset with interviewees for this study, semantic networks within the transcripts were extracted using the software tool VOSviewer, although other tools such as AutoMap (Columbus et al., 2010) and ConText (Diesner, 2014) offer different SNA features. (The alternative methods of SNA were explored, however, due to time constraints and not having the compatible operation system for some of the tools, additional analytics were not conducted.

A comprehensive inclusion of all existing semantic analysis models is beyond the scope of this thesis. However, there are some other configurations that can be done to enhance the reliability of this study. For instance, "term-frequency/inverse document-frequency" (TF-IDF) metric found in several text analysis tools can be a useful criterion to assess the importance of a word or phrase and is worthy of future consideration (Wu et al., 2008). Moreover, the author is aware of the fact that thematic analysis graphs contain a few noise words, which can either be merged into another concept in the codebook or be cleaned by the deselection function in the last step of VOSviewer configuration.

However, the impact of this drawback has been minimized by focusing on real insights even though some connections among concepts are relatively strong. For instance, Figure 4.6 resents a strong edge between "data" and "big issue". This has been technically highlighted as having a strong relation, but theoretically there is not much implication as the interviewee repeated the phrase "big issue" in different parts of the interview.

Besides, to compensate VOSviewer's drawback that only noun phrases are extracted, the research could have used ConText's summarization features to extract relevant concepts of other parts of speech (such as adjectives and verbs) that were not captured in this thesis' SNA (Diesner, 2014).

One limitation relates to the codebook application. Considering the controversial procedure of manually adjusting the codebook, the author did not apply any further actions towards the software produced codebook as opposed to operationalization. Phrases like "big data" and "data" can sometimes be combined into one; however, participants may use big data and data to indicate same or different concept freely. That is why the researcher finds value in discussing them as separate concepts in the results, but future researchers should take this into account and give a more reasonable indication and also evidence as to what extent certain indication should be penalized.

5.3 Future Research

More precise semantic network analysis may be derived from examining the directional nature of associations among concepts. As Creswell (2008) has identified, in the context organizational technology studies, the ordering of words and concepts within the relational structure, which this thesis ignored, can expose priority and potentially causal relations.

Social media has transformed the relationship between corporations and the public from a buyer-seller relationship into that of among and within virtual communities (Maklan et al., 2014). Social media not only allows users to engage with the world socially but also offer them the opportunity to interact with different members of their own networks freely (Wagler & Cannon, 2015). Active users have more social capital and can distribute content efficiently in order to enable more conversations among users (Wagler & Cannon, 2015). Thus, future research should focus on social media analytics pertaining to corporate digital marketing activities, given that relevant unstructured data from social media is wealthy and expanding overwhelmingly with each second. The rich data originating from social networking sites is especially promising in which there is lack of research (Kumar et al., 2013), particularly in the context of digital marketing and strategy. More research is thus needed to understand particularly when service managers should start to focus on these areas.

The author identified that there is a lack of the capability to handle unstructured data among business. It is of utmost importance for service management. This raises the question to what extent companies are operating its data analytics to cover unstructured data and the extent of their awareness of how much capability they have in handling this kind of data and how much value it can provide. It is thus interesting to focus on the relationship between knowledge and ignorance of their operations regarding unstructured data. Erevelles et als' (2015) resource-based theory argues that companies are largely running its activities on limited knowledge and unlimited ignorance.

Future inquiry should look further into how industry players develop a strategy in terms of how social media platforms play a role in strategy development as well as the specifics of how information about the customer's profile/persona informs strategy.

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