Promises and Perils on the Frontier of Big Data Usage

How the Perception of Big Data Changes Managerial Decision-Making in Marketing

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Christoph Wortmann

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Prof. Dr. Sven Reinecke

and

Prof. Dr. Christian Belz

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I dedicate my dissertation to my deceased grandparents Heinrich and Margaretha Wortmann.

Zurich, July 2019

Christoph Wortmann

Vorwort

Die vorliegende Dissertation steht für den Abschluss eines intensiven, herausfordernden Abschnitts meines Lebens, der zugleich auch eine wunderschöne Zeit voller neuer Erfahrungen war. Gerne möchte ich mich an dieser Stelle bei allen Personen, die mich auf meinem Weg zur Doktorwürde begleiteten und unterstützten, sehr herzlich bedanken.

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Christoph Wortmann

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Abstract

This research investigates how the perception of Big Data changes executives' managerial decision processes in marketing. As researchers and practitioners utilize increasingly sophisticated statistical models to exploit the potential of Big Data, research on how managers react to it and how their reactions change decision-making processes is surprisingly scarce. While we do not doubt the value of Big Data, the current research is the first investigation to examine whether, when, and why managers may use Big Data in a potentially misleading way. Five studies with 773 experienced executives consistently demonstrate that, potentially because of its great value, top managers become less cautious and less defensive in the presence of Big Data. First, managers perceive Big Data as a new information source, thus greatly relying on its recommendations for action – even in a domain where this might be misleading (e.g., innovation management). Interestingly, this relationship is found to be particularly evident for top managers, and it might be driven by the fact that executives attribute to Big Data a higher credibility level compared to other information sources (e.g., market research, practical experience, etc.). Second, we show that Big Data activates executives' situational promotion focus, leading them to become more risk-seeking and egocentric. In other words, they become less cautious and defensive concerning their decision-making processes. Finally, it turns out that a deactivation of top managers' inherent lay belief "the more, the better" tends to reduce the incidence of erroneous perceptions of Big Data leading to less cautious decision-making.

Zusammenfassung

Die vorliegende Dissertation untersucht, wie die Wahrnehmung von Big Data Prozesse im Entscheidungsverhalten von Führungskräften im Marketing verändert. Obschon Wissenschaft und Praxis immer anspruchsvollere statistische Modelle entwickeln, um das volle Potential von Big Data zu nutzen, sind Forschungsarbeiten über die psychologische Perzeptionswirkung von Big Data bei Führungskräften, und die damit einhergehenden Änderungen im Verhalten, überraschenderweise Mangelware. Hier setzt die vorliegende Arbeit an. Es wird erstmalig untersucht, inwieweit die Wahrnehmung von Big Data den Entscheidungsfindungsprozess von Top-Managern im Marketing beeinflusst und welche negativen Konsequenzen sich daraus ergeben können. Anhand von 5 unterschiedlichen Studien mit insgesamt 773 erfahrenen Führungskräften im Marketing konnte konsistent gezeigt werden, dass die Wahrnehmung von Big Data zu einem weniger vorsichtigen und weniger defensiven Entscheidungsverhalten von Top-Managern führt. Dies ist vor allem der Tatsache geschuldet, dass Exekutives Big Data als eine neue und gewinnbringende Informationsquelle wahrnehmen und entsprechenden Handlungsempfehlungen überwiegend Folge leisten – auch in Bereichen, wo ein Fokus auf Daten in der Entscheidungsfindung irreführend sein kann (z.B. Innovationsmanagement). Interessanterweise ist dieser Zusammenhang bei Top-Managern stärker ausgeprägt, als bei Managern im unteren Management. Die Studienergebnisse zeigen, dass Exekutives Big Data eine stärkere Glaubwürdigkeit zuschreiben, v.a. im Vergleich zu anderen Informationsquellen (z.B. Marktforschung oder praktisches Erfahrungswissen), was den oben beschriebenen Zusammenhang erklärt. Des Weiteren konnte gezeigt werden, dass die Wahrnehmung von Big Data den situativen Promotionsfokus von Top-Managern aktiviert, was zu einer höheren Risikobereitschaft und einem höheren Mass an Egozentrismus bei Entscheidungsprozessen führt. Die beschriebenen potenziell negativen Auswirkungen der Wahrnehmung von Big Data bei Top-Managern lassen sich durch eine bewusste Deaktivierung des Alltagsglaubens «je mehr, desto besser» abfedern.

1 Introduction

1.1 Problem Statement and Relevance Description

"Market research is unrealistic and unreliable. Thus, executives use only those kind of results that are beneficial for their own work and career. They want to convince their colleagues in the organisation by using respective facts and figures and they seek for confirmation subsequently" (Belz, 2018, p. 45).

The above quotation from Christian Belz, emeritus professor of management with special focus on marketing at the University of St. Gallen, stems from observations that the usage of market research information and marketing metrics in general does not always serve the purpose of increasing firm performance. Sometimes executives use facts and figures selectively, to avoid blame from colleagues (e.g., playing safe, justification, etc.). This phenomenon, called "defensive behaviour", is well documented (Ashforth & Lee, 1990; Gigerenzer, 2014). Related to this, there is a major research line questioning the promises of an exclusive data focus by demonstrating the superiority of human intuition and easy rules of thumb, called heuristics, for instance (Wübben & von Wangenheim, 2008; Gigerenzer & Gaissmaier, 2011; de Langhe, 2016). The crucial need now is to investigate how managers react and behave when more and more data become available. This is the starting point of our research.

There has been a tremendous data growth in recent years, accelerated by the proliferation of the internet, social networks, and the increasing digitalization of business processes. As a result, huge amounts of unstructured and structured data – called Big Data – have become available in real-time. To illustrate, Google "processes 20 petabytes of information a day" and Facebook users "share 2.5 million pieces of content each minute" (Wedel & Kannan, 2016, p. 102). A recent comment by Eric Schmidt, former Google CEO, gets right to the point: "There were 5 exabytes of information created between the dawn of civilization through 2003, but that much information is now created every 2 days" (World Economic Forum, 2015). Recognizing the huge potential, practitioners embrace these developments, especially as a recent study conducted by the International Data Corporation (2017) projects a double-digit growth for the worldwide

Big Data market through 2020, resulting in total revenues of $210 billion. Not for nothing, Davenport and Patil (2012) already claimed several years ago that data scientist will become the sexiest job of the 21st century. Thus, the hype around Big Data is ubiquitous, and more and more executives tend to use Big Data and Data Analytics when it comes to decision-making (KPMG, 2016) in order to derive sound marketing activities, optimize the buying process, and target customers more individually, for example (Trusov, Ma, & Jamal, 2016). McAfee and Brynjolfsson (2012) have scientifically proven the meaningfulness of data-driven decision-making, concluding that companies are, on average, “5% more productive and 6% more profitable than their competitors” (p. 64) when pursuing such an approach. Referring to these findings, it seems that supply-chain performance particularly benefits from investments in Big Data (Gunasekaran et al., 2017). Additionally, a brand-new study conducted by Müller, Fay, and vom Brocke (2018) further supports the above-mentioned effects of Big Data by demonstrating that its implementation is positively associated with firm performance.

In this context, it is important to give a brief glimpse into how academia as well as practice defines Big Data in order to distinguish it from market research. Big Data can be characterized in terms of “3 Vs”: *variety*, *volume,* and *velocity* (Gunasekaran et al., 2017). To start with the first criterion (*variety*), Big Data subsumes multiple different data sources as well as data formats including structured, semi-structured, and unstructured data (e.g., text data, physical data, etc.). In contrast to this, market research is solely focused on structured data from quantitative surveys and/or qualitative research designs. Furthermore, organisations are confronted with huge data masses (*volume*) that lead from terabytes to petabytes, “whose size is beyond the ability of typical database software tools to capture, store, manage, and analyse” (Manyika et al., 2011). Such dimensions are inconceivable when dealing with market research data. Finally, the last criterion, *velocity,* is generally understood to mean that huge amounts of different data sources have to be analysed in real-time, which is in fact a big difference from market research because it involves much longer time frames (Schroeck et al., 2012; Kuss, Wildner, & Kreis, 2014; Duan & Xiong, 2015). Taking these definitions into consideration, there are justified doubts as to whether top management is aware of these differentiating characteristics. With reference to this, Ariely (2013) stated: “Big Data is like teenage sex: everybody talks about it, nobody really knows how to do it, everyone thinks everyone else is doing it, so everyone claims they are doing it."

While both practitioners and researchers are fascinated by the possibilities of Big Data and data-driven decision-making, research on how managers psychologically react to Big Data and how this might change decision processes remains scarce. This is somewhat surprising as the famous and honourable Marketing Science Institute already noted in 2014 that more research is needed on how organisations can leverage the massive amounts of available data and ultimately improve their decision-making (Marketing Science Institute, 2014). Along these lines, Moorman and Day (2016, p. 16) concur that more "insights into how metrics use influences individual marketing decision-making" are indispensable in order to achieve marketing excellence. We believe that the rise of Big Data further intensifies this need. Interestingly, there is very little research on Big Data in marketing. To be more precise, between 2015 and 2018 there was no substantial contribution concerning this topic in the four top-tier marketing outlets (*Journal of Marketing, Journal of Marketing Research, Journal of Consumer Research,* and *Marketing Science*), except a special issue about the integration of marketing, statistics, and computer science published by *Marketing Science* (Chintagunta, Hanssens, & Hauser, 2016). Existing literature deals primarily with the value-added potential of Big Data without having any focus on managerial decision-making and underlying psychological processes. Older literature primarily investigated how decision-makers utilize market research information (e.g., Deshpande & Zaltman, 1984), how decision-support systems improve decision-making (e.g., van Bruggen, Smidts, & Wierenga, 1998), and which influencing factors foster the use of (marketing) metrics in organisations (Mintz & Currim, 2013).

Thus, the current investigation aims to address this research gap by examining how the perception of Big Data influences the decision-making process of executives and marketing managers. Indications for their reactions can be found in prior research on algorithm aversion (Dietvorst, Simmons, & Massey, 2015), which suggests that executives may be easily threatened by this new information source (algorithms). On the other hand, research on algorithm appreciation (Logg, Minson, & Moore, 2018) suggests that especially top management might perceive Big Data as a powerful new tool for making decisions and could therefore begin greatly relying on it. Further assumptions regarding underlying psychological mechanisms are derived from the theory of technology dominance (Arnold & Sutton, 1998) and the regulatory focus theory (Higgins, 1997). As this is the first investigation to analyse managerial outcomes and behaviours triggered by Big Data, we specifically analyse whether, when, and why executives and marketing managers use Big Data in their decision-making processes. Additionally, we launch a discussion about how to avoid potentially negative managerial outcomes and behaviours resulting from indiscriminate use of Big Data. To realize this aspiration, the present thesis is thus aimed at answering the following research question:

How does the perception of Big Data change managerial decision-making behaviour in marketing?

It is important to stress that we do not aim to investigate how the actual implementation of Big Data changes managerial decision-making, since only the "Big Five" (Amazon, Apple, Microsoft, Facebook, and Alphabet) actively utilize Big Data in their daily business. The vast majority of companies have a significantly lower degree of maturity in this arena. Nonetheless, a recent survey fielded by KPMG showed that 68% of surveyed executives in Germany consider using Big Data in the future (KPMG, 2016). Thus, we believe that it is reasonable to investigate how decision-makers react to the term "Big Data" and its associated conceptualizations, assuming its widespread use in the near future.

Across five studies with 773 experienced marketing executives, this research makes the following three contributions. First (1), marketing executives do perceive Big Data as a new information source when it comes to decision-making. They have a greater tendency to rely on recommendations for action based on Big Data compared to recommendations derived from other (traditional) information sources (such as market research or practical experience). Interestingly, this stance is especially evident among those in top management. We find support for this in two studies, independent of both self-rated and trained quantitative skills. These findings are in line with Belz' observation that "executives' expectations of data analysis results often remain inflated or naïve" (Belz, 2018, p. 44). Second (2), building on regulatory focus theory (Higgins, 1997), we detect that top managers' displayed behaviour is due to their activated promotion focus, making them less cautious and less defensive in their decisions by taking less advice from employees, for instance. In a way, Big Data makes top managers feel invincible and able to ignore employee voices. This is in line with existing research stating that individuals who feel powerful have a greater tendency to ignore advice and help from others (Tost, Gino, & Larrick, 2012). Consequently, Big Data might impair working conditions, employee motivation, and managerial effectiveness (Hirschman, 1970; Zapata-Phelan, Colquitt, Scott, & Livingston, 2009; Morrison, 2011), which may lead to a bad firm performance in the end. Furthermore, the aversion of top managers to joint decision-making might explain why middle managers do not rely on Big Data that much: They might feel threatened due to the possibility of being substituted in the decision-making process. Third (3), we find evidence that top managers' lay belief "the more, the better" causes them to become less cautious in the presence of Big Data. Thus, an active questioning of this lay belief might prevent top managers' lofty evaluation of the concept of Big Data from being associated with the aforementioned consequences for decision-making. Thus, we are of the opinion that the mere perception of Big Data potentially changes traditional decision-making processes substantially.

1.2 Research Design

We make use of a multi-method research approach in order to answer the research question. First we run four controlled experiments with 614 experienced marketing managers (online as well as paper-and-pencil) to study cause-effect relations implied by the perception of Big Data. As this is one of the first studies to investigate managerial outcomes and psychological behaviours generated by Big Data, we aim to achieve a high degree of internal validity resulting from the fact that controlled experiments allow participants to act in uncontaminated conditions (Kerlinger & Lee, 2000). Three out of the four controlled experiments in this research are online experiments. The reason for that is straightforward: It is nearly impossible to convince top executives to participate in laboratory experiments due to time and location restrictions. Undoubtedly, online or internet experiments carry many advantages. Most importantly, there is no experimenter bias, meaning that the participants can exclusively focus on the experiments without feeling disturbed or embarrassed by an attendant. In addition, the respondents can complete the experiments in a convenient and familiar situation, eliminating another important confounding effect in paper-and-pencil experiments (Rosenthal & Fode, 1963; Reips, 2002). Nevertheless, we also have one controlled paper-and-pencil experiment with 94 managers in order to replicate the findings of one of the online experiments, resulting in greater robustness of the results.

In contrast to this, we also make use of survey research in order to increase external validity of our overall results and findings (Winer, 1999). To be more precise, we conduct one field study with 159 top marketing and sales executives to revalidate the experimental findings and to provide a more realistic scenario (greater reference to the participant's own organisation). In doing so, we try to consider the importance of internal as well as external validity in our research.

Apart from this, our research further contributes to the application-oriented research in three ways (Ulrich, 1981). One important aspect is the so-called *Entdeckungszusammenhang*. Thus, we aim to detect potential new problems associated with the rise of Big Data in managerial decision-making that have not yet been recognized. The *Erklärungszusammenhang* is another major dimension in Ulrich's concept. With reference to this, we strive to gain insights into how Big Data changes existing decision-making processes of marketing executives in a potentially misleading way. Finally, we consider the so-called *Anwendungszusammenhang* by addressing concrete activities one should avoid when working with Big Data.

1.3 Dissertation Outline

Figure 1 summarizes the structure of the present dissertation that consists of eight main chapters. The first chapter serves as the introduction, including the above-outlined description of the problem and its relevance for research and practice, the presentation of the research question, as well as the following overview of the dissertation.

In chapter 2, we focus on the theoretical development of the dissertation by considering different interdisciplinary research streams. Based on selected theories and an extensive literature review, we derive five hypotheses that we aim to validate in the empirical section. As this is one of the first investigations to analyse managerial outcomes and behaviours generated by Big Data, the question of how marketing executives make use of marketing metrics in their decision-making process is of special importance in order to derive assumptions about the utilization of Big Data (cf. section 2.1). Interestingly, existing research solely focuses on certain characteristics fostering the usage of market research, decision support models, or marketing metrics, as well as on respective organisational framework conditions (Wierenga, 2011). Quantitative and psychological research on how marketing executives precisely react to data has remained surprisingly scarce. We agree with demands for more elaborated (psychological) insights regarding top management's utilization of marketing metrics and the related influence on decision-making processes (Moorman & Day, 2016). We believe that the theory of technology dominance (Arnold & Sutton, 1998) serves as a reasonable theoretical foundation to explain marketing managers' reaction to Big Data (cf. section 2.2). On the one hand, this theory focuses on the utilization of technology and decision aids; and on the other hand, it explains specific (psychological) influencing factors that determine the likelihood that decision-makers rely on the technology. Referring to the basic message of the theory of technology dominance, we further believe that top- and lower-level management will behave differently when faced with Big Data Analytics. Our assumption that top management in particular has a greater tendency to make use of Big Data is discussed in section 2.3. In order to identify an explanatory mechanism for such decision-related behaviour, we supplement the original theory of technology dominance with an additional influencing factor – called perceived credibility. We consequently believe that the ubiquitously postulated superiority of Big Data (e.g., McAfee & Brynjolfsson,

2012) leads to a higher perceived credibility of Big Data that might explain top management's decision-making behaviour (cf. section 2.4). However, we are aware that top managers' perceived credibility may be an intuitive explanation for why they will have a greater tendency to rely on Big Data. Thus, we try to detect additional (underlying) psychological mechanisms that explain its utilization in the decision-making process. With reference to this, we propose that executives' regulatory focus plays an important role in the way that the perception of Big Data activates either a (situational) prevention or promotion focus that leads top managers to rely on the recommended actions that stem from their particular regulatory focus. Thus, they become either more or less cautious and defensive in their decision-making process (cf. section 2.5). Recent research shows that regulatory focus theory has a huge impact on organisational behaviour and work-related constructs (e.g., Higgins & Cornwell, 2016), underlining its suitability as an explanatory factor in this context. Finally, we aim to identify a possible debiasing mechanism to avoid the potentially negative consequences of Big Data (cf. section 2.6). We believe that top managers' inherent lay belief "the more, the better" influences how the perception of Big Data activates an individual promotion focus that might lead to a less cautious decision-making behaviour.

In chapters 3, 4, 5, 6, and 7, we present five empirical studies with 773 experienced marketing executives in order to test our various hypotheses. Table 1 gives an initial overview of the conducted empirical studies by summarizing the main findings and showing how they relate to each other. More specifically, a first online experiment with executives in an innovation-management setting provides initial evidence that Big Data causes them to accept resulting recommendations for action (cf. chapter 3), compared to other important information sources such as practical experience and/or market research. Interestingly, this tendency is particularly strong for top executives (e.g., CEO, CMO, or Head of Sales). In contrast to this, lower-level marketing managers (e.g., marketing, sales, or communication managers) refuse to accept such recommendations. This relationship is found to be independent of their subjective individual skills in quantitative analytics. We used an innovation-management context to demonstrate that an exclusive reliance on Big Data might backfire when it comes to decision-making, since it is nearly impossible to develop disruptive innovations out of Big Data (Martin & Golsby-Smith, 2017).

Demonstrating the robustness of the effect, we replicate the above-mentioned findings by using a controlled paper-and-pencil experimental setting with 94 marketing managers (cf. section 4). All received a comprehensive training in statistics and analytics in a four-day executive education program in order to make sure that their objective quantitative skills are on a similar level. We used such an approach to address the fact that top managers might overrate their quantitative skills since existing research shows that they are prone to overconfidence (e.g., Mahajan, 1992). We found that top managers' reliance on Big Data is driven by the fact that it possesses a higher perceived credibility – compared to practical experience or market research.

In chapter 5, we demonstrate that top managers' reliance on Big Data is caused not only by its perceived credibility but also by an overly confident and less cautious/defensive decision-making behaviour. More precisely, the results of a correlational study – exclusively conducted with top managers – demonstrate that the (perceived) maturity level of Big Data in organisations activates top managers' individual (and situational) promotion focus, leading to a more risk-seeking and egocentric decision behaviour.

In chapter 6, we revalidate and replicate these findings through experimentation and moderation (Spencer, Zanna, & Fong, 2005), showing that an activated (situational) prevention focus deactivates the effects of Big Data on becoming less cautious and less defensive. To the contrary, we can also demonstrate that the perception of Big Data activates top managers' situational promotion focus, leading them to become risk-seeking when it comes to important decisions regarding firm performance. Additionally, we find first indications that this particular outcome is driven by managers' inherent lay belief "the more, the better".

Finally, we offer further evidence for this assumption in chapter 7. It seems that the individual and inherent lay belief "the more, the better" drives the aforementioned relationship such that the experimental deactivation of this lay belief avoids the situational activation of top executives' promotion focus triggered by their perception of Big Data (in their organisations) and, consequently, no effects on the individual decision behaviour can be observed. The detection of a potential debiasing mechanism enables the avoidance of negative effects caused by Big Data on managers' individual decision behaviour since an activation of managers' prevention focus leads to procrastination or status quo biases (Ariely & Wertenbroch, 2002).

A conclusion and general discussion of our research findings constitute the last chapter of the present dissertation. We further elaborate on several theoretical implications in order to contribute to existing research, as well as on several practical implications for managers. Finally, we outline methodological limitations of our work and discuss suggestions for future research.

Figure 1: Overview of the dissertation

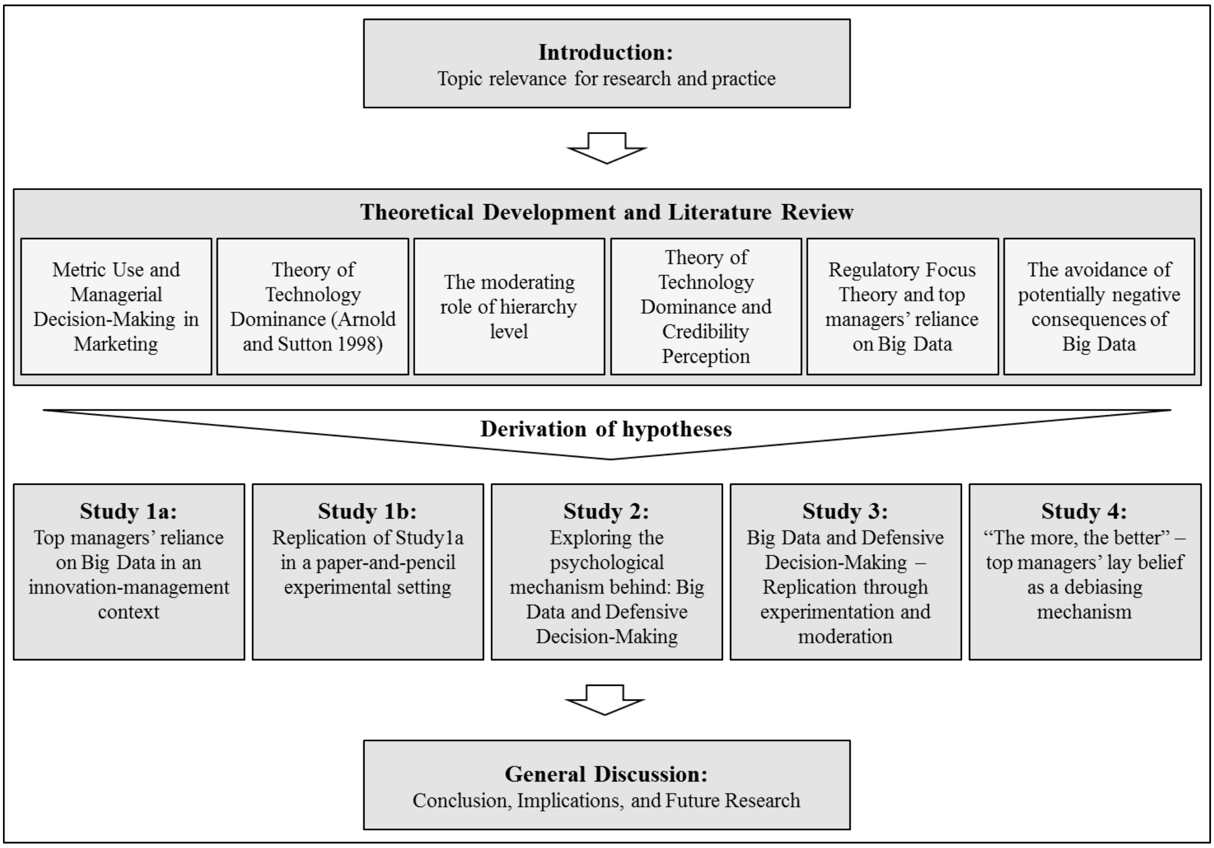


Table 1: Overview of the empirical studies

Study	Subjects	Main Findings
Study 1a (Online experiment)	**N = 274** managers	• Managers have a greater tendency to accept recommendations for action derived from Big Data (compared to other information sources, such as market research and practical experience). • This effect seems to be particularly evident for top managers. • The results are independent of the self-rated skills in quantitative analytics.
Study 1b (Paper-and-pencil experiment)	**N = 94** managers	• Replication of the results found in Study 1a. The results are independent of top executives' objective skills in quantitative analytics. • Big Data has a higher perceived credibility (compared to market research and practical experience), leading to a higher tendency to accept its recommendations for action.
Study 2 (Field study)	**N = 159** managers	• Top managers' reliance on Big Data is also caused by an overly confident and less defensive and cautious decision-making behaviour. • The perceived maturity level of Big Data activates top managers' situational promotion focus, leading to a less defensive and cautious decision-making behaviour.
Study 3 (Online experiment)	**N = 121** managers	• Replication of results found in Study 2 through experimentation and moderation analysis. • Detection of first indications that this relationship is driven by top managers' inherent lay belief that "the more, the better".
Study 4 (Online experiment)	**N = 125** managers	• Clear identification of a potential debiasing mechanism (lay belief "the more, the better").

2 Theoretical Background, Literature Review, and Derivation of Hypotheses

2.1 Metric Use and Managerial Decision-Making in Marketing

Even though managerial decision-making has been labelled the “single most determining factor for the success of marketing management” (Wierenga, 2011, p. 89), it has not been extensively investigated in marketing research so far. This is somewhat surprising, as the famous social scientist Herbert A. Simon already remarked in 1955 that the vision of a human decision-maker equipped with complete information and full rationality is unrealistic. He further insisted that, consequently, more insights are needed on how decisions are made in order to get a realistic view concerning decision-making practices of human beings. This includes a deeper understanding of potential cognitive limitations and biases as well as consideration of the particular context/environment of a decision-making process (Simon, 1955). Surprisingly, Simon’s demand has more or less faded away due to the fact that marketing research overwhelmingly concentrates on consumer behaviour instead of analysing the roots of managerial decision-making (Wierenga, 2011).

The scarce literature on this topic is predominantly outdated and makes managers’ perception and utilization of market research information the subject of discussion. More precisely, researchers tried to identify important influencing factors that explain the respective usage of market research information. In terms of identifying influencing factors, one can distinguish three different units of analysis: individual, interaction, and organisational/formal. Basically, decision-makers’ individual characteristics are less important in this context; however, existing research identifies two important variables to keep in mind. First, prior beliefs affect the evaluation and utilization of market research information such that decision-makers are more likely to use research information when it confirms their prior beliefs. In contrast to this, research that is contrary to prior beliefs has a significantly lower likelihood of being taken into account by decision-makers; and furthermore, it is considered to be of a lower overall quality too (Hanjoon, Acito, & Day, 1987). Second, the individual experience level of managers also affects decision-making processes and information usage – especially when the decision at hand is less programmed and formalized (e.g., new-product development). More experienced managers consider the existing information more carefully, prefer more and diverse information, and generally make on average more conservative decisions than less experienced managers (Perkins & Rao, 1990).

Apart from this, Moorman, Zaltman, and Deshpande (1992) emphasize the importance of the interaction dimension between market research users and researchers. They found that managers' trust in market researchers positively affects the usage of market research information. However, it is astonishing that there is only an indirect effect of trust, meaning that it affects research utilization through other important variables, such as quality of interaction and the involvement level of the market researcher. Thus, a high level of trust between managers (users of market research information) and researchers fosters the establishment of these relationship processes.

Of greatest importance when it comes to the identification of influencing factors facilitating the use of market research information are organisational and more formal variables. According to Deshpande and Zaltman (1982), the organisational structure of a firm constitutes the main lever regarding the information utilization. Decentralized and less formalized firms have a greater tendency to make use of market research information compared to companies with a different organisational structure. The authors justify this finding by the fact that the decentralized organisational structure allows managers more freedom when it comes to market research activities. Besides, marketing managers in decentralized companies perceive greater flexibility to fulfil their working task in general, resulting in a higher tendency to make use of market research information (Deshpande, 1982).

In addition, existing research demonstrates that marketing managers consider market research information in their decision-making processes more often when there is a high exploratory purpose of the research, as well as a high technical quality of the results. Whereas the latter point belongs to common sense and needs no further explanation, the findings regarding the exploratory purpose are somewhat surprising because exploratory research is generally associated with high uncertainty, assuming the possibility of marketing managers' rejection (Deshpande & Zaltman, 1987). Over and above that, the degree of implementable recommendations generated from market research, as well as the political acceptability of the results, are positively associated with the use of market research information too. However, both influencing factors are difficult to specify because external market researchers are not generally informed about whether the market research results are transformed into quantifiable marketing activities, and besides, the results can be presented in different ways depending on the target group (Deshpande & Zaltman, 1982, 1984).

Lastly, marketing managers make frequent use of market research when there is less surprise information given. This finding is consistent across different industries (e.g., consumer products and industrial products). More precisely, marketing managers show tendencies of a confirmation bias or escalation of commitment when research indicates that their pet product is not performing well, meaning that they try to defend their own decisions and offensively criticise market research information instead of questioning their own product/decisions (Deshpande & Zaltman, 1982, 1984). Interestingly, the individual involvement level with the initial decision does not cause such an escalation of commitment bias – recent research shows that the initial positive beliefs and the later interplay with (negative) new information are more important in this context (Biyalogorsky, Boulding, & Stealin, 2006). Nevertheless, there are no further insights available regarding how organisations can avoid this kind of confirmation bias when marketing managers are confronted with surprising results, resulting in a continuous acceptance problem of market research in organisations.

Apart from the investigation into how marketing managers make use of market research information, another body of literature elaborates on marketing managers' perception and usage of decision support models (computer simulations, for instance). According to van Bruggen, Smidts, and Wierenga (1998), decision support models generally improve the effectiveness and quality of the decision-making performance – especially in complex environments with a variety of different information. One reason for this observation is that decision support models provide continuous feedback to the decision-maker, enabling a better feeling for the market and its associated interdependencies. This reduces the tendency of decision-makers to be prone to anchoring or adjustment heuristics/bias, leading to a better decision-making performance. However, research shows that decision support models facilitating an intuitively appealing strategy might lead to a bad decision-making performance in the end. In contrast, it makes more sense to use a decision support model that considers an intuitive strategy and simultaneously enriches it by considering a mechanical approach (e.g., computerized database of historical cases). The utilization of such decision support models is especially expedient in less predictable environments (Hoch & Schkade, 1996). In addition to that, research investigates whether managers' individual characteristics influence their usage of decision support models. In this context, managers' analytical predispositions play an important role such that managers at a high analytical level outperform those at a lower analytical level because the variable selection for the decision support model is much easier for them. Thus, one might expect that managers with high analytical abilities are more attached to using decision support models. However, other influencing factors are also worth mentioning. Managers' individual risk aversion, cognitive differentiation, and involvement level all determine the usage of such models too. Interestingly, the extensive utilization of decision support models leads in turn to a higher user satisfaction (Zinkhan, Joachimsthaler, & Kinnear, 1987). Table 2 summarizes the related empirical studies in terms of setting, key finding(s), and managerial implications.

Table 2: Empirical studies on market research and decision support systems in managerial decision-making

Author(s)	Research Question(s)	Method	Major Results	Journal	Category
Deshpande (1982)	Why do some consumer product companies have a higher tendency to use market research than other ones?	Structured interviews with managers from large firms (Fortune 500 sample; n=16); correlational mail survey with product/brand and marketing managers (n=92).	• Managers operating in decentralized and less formalized firms have a higher tendency to make use of market research information. • This finding is independent of the individual work experience. • Participation in decision-making (adoption, modification, or deletion) is positively associated with market research information use.	*Journal of Marketing Research*	Market Research/ Managerial Decision-Making
Deshpande and Zaltman (1982)	Which factors affect marketing managers' attention and use of market research information?	Two-stage process: 1) personal interviews in 7 large firms (n=16); 2) correlational survey with marketing managers (n=176).	• Organisation structure (formalization/centralization), technical quality, surprise, actionability, and researcher-manager are the most important variables regarding the use of market research information. • Organisation structure is by far the most important factor.	*Journal of Marketing Research*	Market Research/ Managerial Decision-Making

Author(s)	Research Question(s)	Method	Major Results	Journal	Category
Deshpande and Zaltman (1984)	Which factors foster the usage of market research in consumer goods and services firms?	Correlational survey with managers and researchers in consumer goods and services firms (n=90).	• With regards to the usage of market research in consumer goods and service firms, the most important factors are interaction, political acceptability of research results, the technical quality of research, as well as the exploratory purpose of research. • However, there are differences between researchers and managers. For researchers, most important is the interaction with managers followed by political acceptability of the recommendations and the exploratory purpose of research. • In contrast to this, managers perceive the formalization of their own company as well as the technical quality of the final research as most important.	*Journal of Marketing Research*	Market Research/ Managerial Decision-Making
Deshpande and Zaltman (1987)	Which factors affect the use of marketing information in consumer and industrial firms?	Correlational telephone survey with industrial marketing managers (n=201).	• In comparison to consumer business, marketing managers in industrial firms use marketing information more often when there is a greater exploratory objective in information collection, a greater degree of formalization in terms of organisational structure, and when there is less surprise information given.	*Journal of Marketing Research*	Market Research/ Managerial Decision-Making
Hanjoon, Acito, and Day (1987)	How do decision makers assess and utilize marketing research information?	Experimental (laboratory) study with MBA students who have some statistical knowledge and business experience (n=170).	• Prior beliefs are positively associated with the evaluation and utilization of market research information. • However, there are no differences between qualitative and quantitative market research when it comes to usage.	*Journal of Marketing Research*	Market Research/ Managerial Decision-Making

Author(s)	Research Question(s)	Method	Major Results	Journal	Category
Zinkhan, Joachimsthaler, and Kinnear (1987)	What are important influencing factors that positively affect the use and satisfaction with a decision support system (e.g., computer simulation)?	Laboratory experiment with n=165 respondents (MBA students from a major university); second convenience sample with n=41 nonstudent managers.	• The authors found that individual involvement, manager's risk aversion, and cognitive differentiation are important levers for the usage of decision support systems. • The associated user satisfaction depends on age and the extent of information search; however, age does not affect the latter variable (e.g., decision support system).	*Journal of Marketing Research*	Decision Support Systems/ Managerial Decision-Making
Perkins and Rao (1990)	How does the individual experience of managers affect decision-making?	Semi-structured interviews with brand managers of a major Fortune 500 corporation (n=15).	• Managerial experience and decision programmability interact in decision-making. • More specifically, experience affects information usage such that more experienced managers rated more information as useful when it comes to decision-making. • Furthermore, more experienced managers made decisions that are more conservative on average.	*Journal of Marketing Research*	Information Usage/ Managerial Decision-Making
Moorman, Zaltman, and Deshpande (1992)	How does trust between market research users and researchers influence the usage of market research information and relationship processes?	Correlational survey with market research information users (n=779).	• The perceived quality of interaction and trust are most significantly associated with market research usage. • Trust affects market research utilization through indirect effects (for instance, researcher involvement). • Besides, user-researcher interactions are a critical variable when it comes to relationship processes.	*Journal of Marketing Research*	Market Research/ Managerial Decision-Making

Author(s)	Research Question(s)	Method	Major Results	Journal	Category
Hoch and Schkade (1996)	How should a decision support system be designed in order to capitalize on the strengths and compensate for the weaknesses of a decision-maker?	Laboratory experiment with n=119 graduate and undergraduate students from the University of Chicago.	• Decision support systems perform best and improve decision-making when an intuitive approach (e.g., simple linear model) and a mechanical approach (e.g., computerized database of historical cases) are combined.	*Management Science*	Decision Support Systems/ Managerial Decision-Making
van Bruggen, Smidts, and Wierenga (1998)	How does a marketing decision support system influence individual decision-making process?	Laboratory experiment with n=80 students enrolled in a business administration/economics master program.	• (Marketing) decision support systems positively affect the individual decision-making performance of the participants (especially in data-rich environments). • Decision-makers are better able to understand the market and its interdependencies due to the continuous feedback provided by such models. To be precise, they can easily select the right variables for a marketing decision support model. • The utilization of marketing decision support systems avoids the implementation of human decision biases (anchoring and/or adjustment bias). • The individual cognitive style influences how much a decision-maker benefits from a decision support system. Highly analytical decision-makers outperform less analytical decision-makers in this context.	*Management Science*	Decision Support Systems/ Managerial Decision-Making

More recent research overcomes the sole focus on managers' utilization of market research information and (marketing) decision support systems by focusing on individual (marketing) metric use in general. According to Mintz and Currim (2013), marketing-mix performance and metric use are positively correlated, underlining the meaningfulness of such a broader approach. Furthermore, these authors demonstrate that personal characteristics of managers (e.g., experience and quantitative background) are less important in explaining metric use by investigating 1287 different marketing-mix activities from various companies and industries. In contrast to this, organisational variables – such as firm strategy and metric orientation environmental characteristics (e.g., market turbulence) – facilitate metric use. This emphasis on organisational aspects is in line with existing research regarding the use of market research information (e.g., Deshpande & Zaltman, 1982). Concerning the actual use of metrics, Mintz and Currim (2013) show that marketing metrics (e.g., awareness, market share, etc.) are more important than financial metrics. The superiority of marketing metrics over financial ones when it comes to the actual usage in firms is not uncontroversial in existing literature. For instance, Ambler, Kokkinaki, and Puntoni (2004) demonstrate that there is a high consideration of account metrics and, simultaneously, little consideration of sales and profitability metrics across marketing managers.

Other research investigates specific types of marketing metrics. In this context, one important aspect is the usage of customer satisfaction metrics, which play a major role in decisions associated with customer service and account management. However, customer satisfaction metrics are not used in other key functional areas, and managers make use of such metrics on a tactical rather than strategic level, resulting in a lower degree of efficiency for decision-making (Morgan, Anderson, & Mittal, 2005). Furthermore, Bucklin and Gupta (1999) investigated the actual usage of scanner data in firms. Interestingly, most firms perceive those kinds of data as an investment that is associated with costs because the improvement of existing marketing decisions is not guaranteed. There can be no doubt that such points of view inhibit the efficacy of marketing metrics for decision-making in general.

The above-mentioned positive relationship between (marketing) metric use and firm performance might be caused by the fact that the usage of metrics (by means of marketing decision support systems, for instance) improves the effectiveness of managerial decision-making in general (van Bruggen, Smidts, & Wierenga, 1998). Table 3 summarizes the relevant empirical studies in terms of setting, key finding(s), and managerial implications.

Table 3: Empirical studies on (marketing) metrics usage in managerial decision-making

Author(s)	Research Question(s)	Method	Major Results	Journal	Category
Bucklin and Gupta (1999)	What is the role of UPC scanner data for consumer packing firms in the US?	Two-stage process: 1) personal interviews with n=41 managers; 2) enriched by the results of survey-based study conducted by Davidson and Stacey (1997).	• Executives are sceptical when it comes to the actual usage of UPC scanner data. • The utilization is perceived as an investment associated with costs, and the value-added potential for better decision-making performance is generally questioned. • Generally, firms prefer cheaper solutions than the collection and usage of scanner data.	*Marketing Science*	Metrics Usage/ Managerial Decision-Making
Ambler, Kokkinaki, and Puntoni (2004)	What are important factors when it comes to the usage of marketing metrics in the UK?	Two different studies: 1) correlational survey with marketing and finance executives in the UK (n=531); 2) correlational telephone survey with marketing and finance executives in the UK (n=231).	• Accounting metrics are of special importance for marketing metrics. • There is little consideration of sales and profitability metrics. • Brand equity is widely measured, but there is no formal integration into a related assessment system.	*Journal of Marketing Management*	Metrics Usage/ Managerial Decision-Making

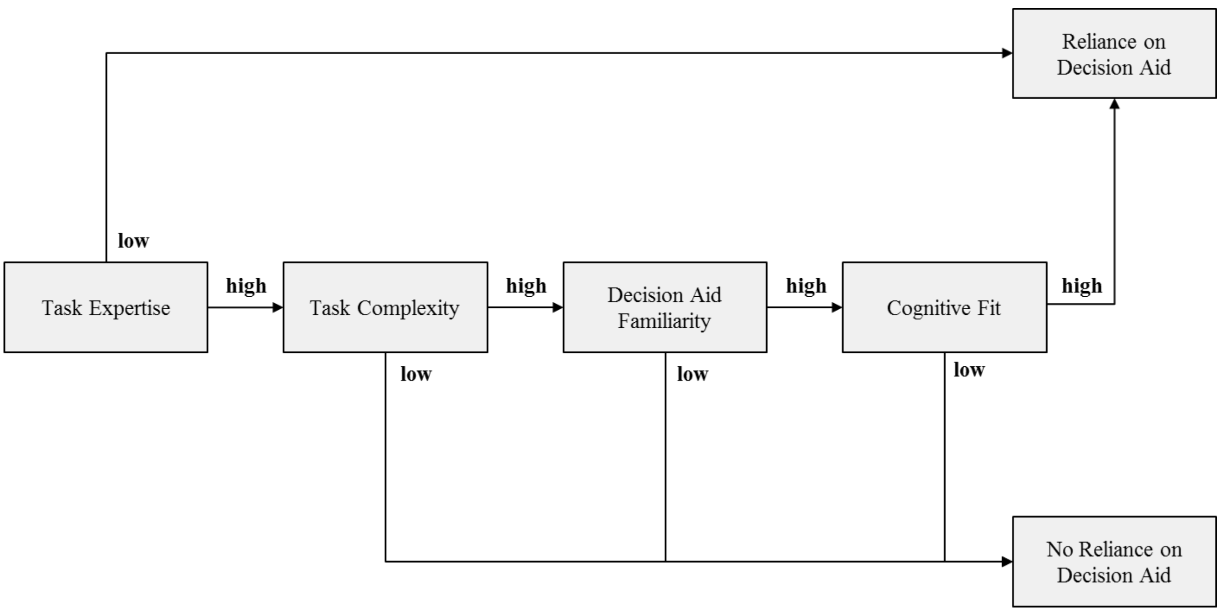
Author(s)	Research Question(s)	Method	Major Results	Journal	Category
Morgan, Anderson, and Mittal (2005)	Does the utilization of customer satisfaction metrics lead to a competitive advantage? Which company-wide processes should include the usage of customer satisfaction metrics?	Three-stage process: 1) literature analysis and desk research; 2) in-depth interview with 142 managers in 37 firms; 3) focus-group setting with 12 managers from seven different firms.	• The utilization of customer satisfaction metrics is widespread. The main application areas are customer service and account management, which seems intuitively reasonable. • There is a very narrow approach existing when it comes to the usage of customer satisfaction metrics, meaning a lack of usage in key functional areas. • Besides, those metrics are used on a tactical rather than strategic level.	*Journal of Marketing*	Metrics Usage/ Managerial Decision-Making
Mintz and Currim (2013)	What are the drivers of marketing and financial metrics usage in a managerial marketing-mix decision context? Does metric usage lead to a better performance of marketing-mix decisions?	Correlational survey with managers from different industries (n=439).	• The usage of metrics (marketing and financial) depends on firm-specific variables (for instance, firm strategy and metric orientation) instead of personal characteristics. • Interestingly, managers use metrics especially for product development and internet advertising. • Metrics use affects marketing-mix performance in a positive way.	*Journal of Marketing*	Metrics Usage/ Managerial Decision-Making

Apart from these research findings concerning the usage of market research information, decision support systems, and marketing/financial metrics, quantitative and psychological research on how marketing executives precisely react to data remains surprisingly scarce (Hattula, Herzog, Dahl, & Reinecke, 2015). The rise of Big Data further increases the importance of associated research, and studies on how marketing executives respond to the enormous potential of huge amounts of various data sources may be as necessary as the actual advancements in data science. Consequently, Moorman and Day (2016, p. 19) claim that "we need insight into how metrics use influences individual marketing decision making, including the decision-making processes activated and trade-offs manifested when marketers use different types of metrics." Indications for marketing managers' reactions to Big Data can be found in the theory of technology dominance (Arnold & Sutton, 1998), which is discussed in greater detail in the following section.

2.2 Theory of Technology Dominance

The theory of technology dominance is an extension of the well-known technology acceptance model (Davis, 1989), and it explains specific influencing factors that determine the likelihood that decision-makers rely on an available (technological) decision aid. It was developed to elaborate on why decision aids had such limited success in the audit domain, and how such aids should be defined to increase the likelihood of use (Arnold & Sutton, 1998; Arnold, Collier, Leech, & Sutton, 2004). A decision-maker relies on a specific decision aid when two baseline conditions are fulfilled: acceptance and influence. This means that the user of the decision aid has to integrate the aid in the decision-making process (acceptance) and that it acts as a crucial part of the judgment formulation (influence). As a result, the decision aid takes dominant control of the individual decision-making process. Concerning the identification of the factors leading to reliance, Arnold and Sutton (1998) solidified the results of prior studies in this field. Figure 2 displays the influencing factors leading to reliance on a decision aid or vice versa.

Figure 2: Theory of technology dominance – Influencing factors leading to decision aid reliance (Arnold & Sutton, 1998)



The first factor is called *Task Expertise,* meaning that someone relies on a specific decision aid when there is no ability to carry out the specific task on his own. Thus, it can be assumed that inexperienced users with no working experience will rely on a decision aid (Arnold et al., 2004). Providing that a certain level of expertise is ensured, three other influencing factors come into play: *Task Complexity, Decision Aid Familiarity,* and *Cognitive Fit*. Regarding the first-mentioned influencing factor, decision-makers simply seek help from a relevant decision aid when the complexity level of the task is high. For instance, Chau and Hu (2001) show that medical professionals rely on technology aids in their decision-making process only when they lead to a significant simplification of problems (with simultaneously easy handling of the respective decision aids). The explanation of the factor *Decision Aid Familiarity* is straightforward: A user should have previously used a specific aid in order to be familiar with it. Again, there is empirical evidence for this assumption. Mackay and Elam (1992) observed that usage patterns of decision aids were positively associated with familiarity with the aid. Lastly, *Cognitive Fit* refers to the "congruence in the cognitive decision processes and prompted cognitive reasoning between the aid and the user" (Arnold & Sutton, 1998, p. 180). In fact, the cognitive processes used when working with a specific decision aid to solve a task should match the normal cognitive processes (e.g., for daily tasks) of the decision-maker (Hampton, 2005).

To summarize, the theory of technology dominance postulates that an experienced decision-maker relies on a specific aid when task complexity is high, the aid has previously been used, and there is a congruency of the cognitive fit between the aid and the user. The predictions of this theory have been empirically tested by Hampton (2005), who found support for the overall model even though there was no effect regarding the factor *Decision Aid Familiarity*. However, this might have something to do with the related unsuccessful manipulation in the work of Hampton (2005; confounding variables such as user interface could have influenced the results). Even though this model was developed for an accounting setting, the transfer to the marketing context seems suitable – especially as data-driven decision-making becomes more and more important in marketing, allowing the utilization of technological decision aids (Trusov, Ma, & Jamal, 2016). Thus, the theory of technology dominance can serve as a conceptual framework in our effort to understand decision-making in marketing.

Coming back to the above-mentioned baseline conditions of this theory (acceptance and influence), we believe that these conditions are met when working with Big Data, and we suggest that executives perceive Big Data as a powerful new information source, thus greatly relying on it in their decision-making process. Existing research in this field supports this assumption, since results from six different experiments show that people have a greater tendency to believe in recommendations and advice when it comes from algorithms than from a human being (Logg, Minson, & Moore, 2018). We expect this phenomenon to be more apparent when it comes to Big Data due to its ubiquitously lauded superiority (McAfee & Brynjolfsson, 2012). However, there is also evidence for a contradictory prediction. Recent research shows that people are generally averse to statistical algorithms and prefer a human forecaster when facing the challenge of making forecasts and predictions. This so-called algorithm aversion can be explained by the fact that people quickly lose confidence in statistical algorithms after seeing the resulting performance and noticing that these approaches can lead to the same mistakes a human forecaster would make (Dietvorst, Simmons, & Massey, 2015). Thus, we also suggest that marketing executives might feel easily threatened by Big Data, resulting in a lower tendency to use it. With reference to these two contrasting predictions, we therefore formulate the following two hypotheses:

H_{1a}: Marketing managers have a greater tendency to accept recommendations for action derived from Big Data compared to recommendations derived from market research or practical experience.

H_{1b}: Marketing managers have a lower tendency to accept recommendations for action derived from Big Data compared to recommendations derived from market research or practical experience.

2.3 The Moderating Role of Hierarchy Level

On a related front, we further propose that top managers (i.e., CEO, CMO and/or Head of Sales) have a greater tendency to accept recommendations for action derived from Big Data compared to lower-level managers (i.e., marketing and communication managers). First and foremost, top- and lower-level managers do have divergent goals that influence metric use. Top management is responsible for the overall performance of the company and for long-term organisational purposes, visioning, and strategies. Thus, executives should be more inclined to use Big Data due to its purported superiority and value-added potential (Manyika et al., 2011; McAfee & Brynjolfsson, 2012). In contrast to this, research shows that lower-level managers select metrics that can improve their own decisions, and besides, they are responsible for the definition and execution of concrete plans (Lehmann & Reibstein, 2006; Finkelstein, Hambrick, & Cannella, 2009), not abstract strategy. Thus, we believe that Big Data might be too vague for them in terms of improving their own decisions. We also believe that the definition and execution of plans need a concrete examination and questioning of broader concepts (in this case, Big Data). Most companies have not implemented any Big Data solution yet and to do so is associated with a huge investment. Thus, it seems reasonable that lower-level managers are more sceptical when it comes to the utilization of recommendations generated from Big Data Analytics.

In addition to that, Perkins and Rao (1990) determined that experienced managers appreciate more information when it comes to decision-making. According to Wedel and Kannan (2016), "volume" (meaning huge amounts of data that can no longer be processed with traditional methods) is one main characteristic of Big Data, and most executives are aware of that. Therefore, we expect that top managers are more inclined to use Big Data. Moreover, time pressure is – amongst other things – one of the most salient problems managers face in their daily business (e.g., Mintzberg, 1973). In the end, it impedes a complete processing of information, resulting in a higher probability of making irrational decisions (Simon, 1955). This situation is further complicated by the fact that most organisations lack statistical expertise (Barton & Court, 2012), and top executives in particular usually have limited time and resources to critically reflect on Big Data. Lastly, existing research shows that experienced executives are more prone to systematic biases that stem from overconfidence (Mahajan, 1992). Consequently, top managers might perceive Big Data as an impressive new tool giving them the opportunity to make powerful decisions independent of the advice of lower-level management. In contrast to this, lower-level managers might feel more threatened if top management listens less to them (Fast, Burris, & Bartel, 2014), thus feeling challenged by Big Data. Considering all the above-mentioned points, we hypothesize:

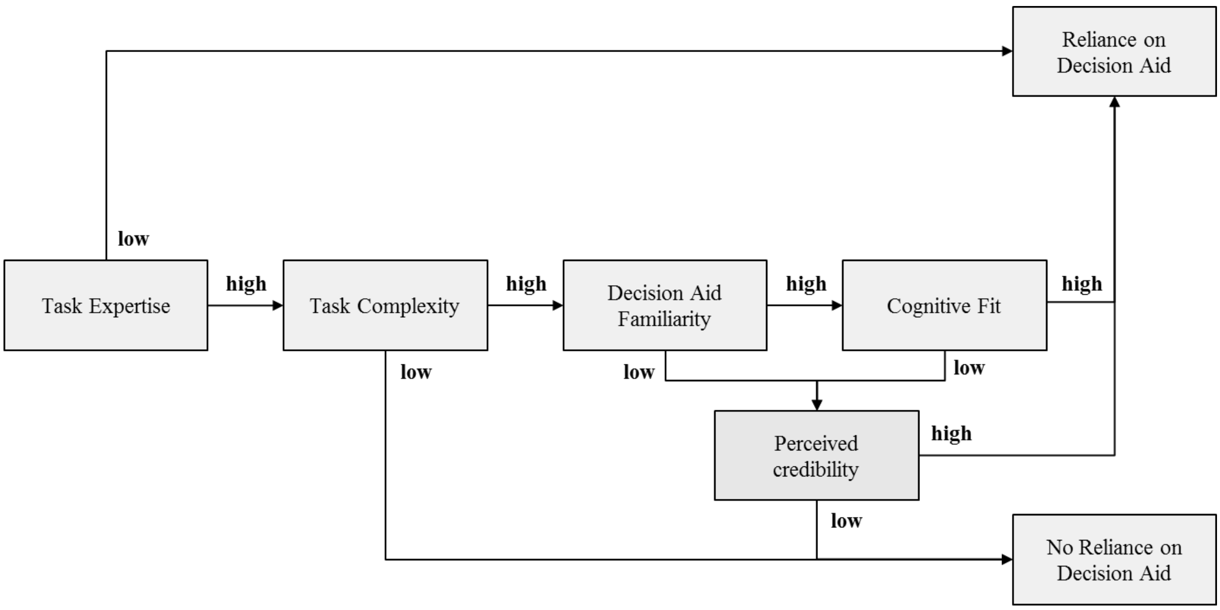
H_2: Top managers have a greater tendency to accept recommendations for action derived from Big Data than do lower-level managers.

2.4 Theory of Technology Dominance and Credibility Perception

In relation to the above-mentioned theory of technology dominance, an international survey with 607 executives showed that 58% of the participants make use of Big Data for decision-making support and that 29% even use it for automated decision-making (Capgemini, 2012). Thus, there can be no doubt that Big Data can be classified as a (technological) decision aid. One possibility that we have already hypothesized is that a strong emphasis on Big Data may direct (top) managers to believe in the associated recommendations for action and make less use of their intuitive and creative potential. As a consequence, (top) executives may show indications of data faith without any critical questioning of the results delivered by Big Data. We believe that the interdisciplinary theory of technology dominance forms a reasonable theoretical foundation to outline how decision-makers reach decisions when presented with technology-derived advice.

A potential reliance on Big Data and its recommendations for action (compared to other information sources, such as market research and/or practical experience) might be caused by the oft-repeated superiority of Big Data (McAfee & Brynjolfsson, 2012). But it is still unclear what drives (top) managers to this reliance. We believe that the postulated superiority of Big Data induces a higher perceived credibility that leads to a kind of data faith and a negligence of managers' own intuition and creativity. Considering the theory of technology dominance, it may make sense to supplement the original model with the influencing factor *perceived credibility* (see Figure 3).

Figure 3: Theory of technology dominance – Supplemented by the influencing factor perceived credibility (own illustration, based on Arnold & Sutton, 1998)



Nonetheless, the interpretation and argumentation of this adjusted model do not differ very much from the original one. More precisely, the factors *Task Expertise* and *Task Complexity* are not affected through the integration of the new influencing factor *Perceived Credibility,* because a decision-maker will still automatically rely on a specific aid (regardless of the associated perceived credibility) if he or she lacks the ability to deal with the task alone. Furthermore, the perceived credibility of a decision aid (in this case Big Data) should not have any influence on the task complexity. In contrast to this, it is reasonable to assume that the individual familiarity with Big Data (as a decision aid) as well as the individual cognitive fit are both on a relatively low level due to the high degree of novelty of this information source. Actually, decision-makers with a low decision aid familiarity and/or cognitive fit should not rely on the respective aid – at least if you follow the premises of the original model. However, the ubiquitously repeated superiority of Big Data (McAfee & Brynjolfsson, 2012) should increase its perceived credibility as an information source and decision aid. As a consequence, decision-makers should attribute to Big Data a high level of credibility, resulting in a greater tendency to rely on it when it comes to an actual decision-making situation, and even if the familiarity and cognitive fit with it are on a relatively low level. Thus, the perceived credibility should play an important role in the individual decision-making process of top executives. Recent research from psychology and neuroscience further supports this assumption. According to Weisberg, Keil, Goodstein, and Gray (2008), people show a higher tendency to believe in explanations of psychological phenomena when neuroscience references are invoked. This effect is called "the seductive allure of neuroscience". Additional research further demonstrates that people attribute a higher level of credibility to that kind of information (Im, Varma, & Varma, 2017). Considering these factors, it seems that both neuroscience references and Big Data can be treated as anchor-words in their respective disciplines, associated with a high level of credibility driving individual actions. From this it follows that top managers' greater tendency to accept recommendations for action derived from Big Data is driven by the higher perceived credibility. This leads us to the following hypothesis:

H_3: Facts and figures derived from Big Data Analytics should have a higher perceived credibility for top managers – compared to lower-level managers – inducing a higher tendency to accept the recommendations for action made.

2.5 Regulatory Focus Theory and Top Managers' Reliance on Big Data

While the perceived credibility of Big Data may be an intuitive explanation for why top managers will have a greater tendency to resort to Big Data, we aim to further identify underlying individual psychological processes that determine the utilization in order to derive managerial implications that are closer to reality. We strive to close the research gap on how managers psychologically react to data in their decision-making processes.

There can be no doubt that the impact of theories from social psychology on marketing has become stronger in recent years – especially in consumer behaviour. The application of social psychology theories allows the detection of underlying psychological mechanisms of marketing phenomena. A key example is the self-affirmation theory (Steele, 1988) because it offers a reasonable explanation for why consumers choose highly aesthetic products, for instance (Townsend & Sood, 2012). There are several other social psychology theories that have a huge impact on marketing, such as self-assessment or self-awareness theory (e.g., Duval & Wicklund, 1972; Sedikides, 1993). All of the above theories can be subsumed under the so-called self-categorization theory (Turner et al., 1987) since it focuses on the dualism of personal and social identity. With reference to this, the famous regulatory focus theory addresses aspects of people's personal identity in its discussion of individual psychological predispositions that drive motivational needs (Higgins, 1997). Other research shows that individuals' regulatory focus is strongly associated with self-assessment and self-esteem (Leonardelli, Lakin, & Arkin, 2007; Gorman et al., 2012), underlining its importance in the constitution of a personal identity. In contrast to the other above-mentioned personal-identity theories (e.g., self-affirmation, etc.) that are almost exclusively used to explain consumer behaviour, the regulatory focus theory has a strong influence on organisational behaviour as well as management activities (e.g., Higgins & Cornwell, 2016). Thus, we believe that this theory is particularly suitable to explain the underlying psychological mechanism governing why top managers should have a tendency to believe in recommendations for action derived from Big Data.

Regulatory focus theory is based on the notion that human beings try to achieve pleasure and avoid pain, and it suggests strategies for how these needs can be satisfied by distinguishing two different self-regulatory systems: promotion versus prevention focus (Higgins, 1997, 1998). A promotion focus is characterized by advancement and achievement, and individuals focus on maximizing goals in order to achieve these needs. Regarding an organisational-behaviour setting, individuals strive to exceed and advance beyond the existing status quo to achieve growth and nurturance (Higgins & Cornwell, 2016; see Table 4). In contrast to this, a prevention focus is associated with safety and security as individuals focus on minimizing losses (Chernev, 2004). Consequently, they strive to maintain or even restore the status quo in order to fulfil duties and avoid unnecessary risks (Higgins & Cornwell, 2016; see Table 4). Both self-regulatory systems ultimately aim to achieve a desired end-state – even though different characteristics lie at their core. Either a promotion or a prevention focus can be considered as a psychological predisposition, meaning that individuals have a specific disposition that is determined by socialization processes, for instance (Higgins, 1997). However, research shows that both foci are independent of each other and can co-exist in one individual. As a result, they can be shaped by environmental as well as situational cues (e.g., Crowe & Higgins, 1997; Higgins & Cornwell, 2016; Johnson et al., 2017).

Table 4: Differences: prevention/promotion focus (Higgins & Cornwell, 2016, p. 57)

Component	**Prevention focus**	**Promotion focus**
Primary concerns	Safety and security	Nurturance and growth
Primary goals	Oughts, duties, and obligations	Ideals, hopes, and aspirations
Success	Non-loss (0)	Gain (+1)
Failure	Loss (-1)	Non-gain (0)
Preferred strategy	*Vigilant strategies:* maintaining or restoring status quo	*Eager strategies:* exceeding/ advancing beyond status quo

Linking this notion to top managers' reactions to Big Data, we see that two opposing effects might occur. One, if Big Data impresses top managers, their reliance on it might be a consequence of getting either more cautious or more euphoric in their decision-making process. In many organisations, defensive motives and guiding principles are indeed widespread, meaning that executives have a tendency to pursue actions that are self-protective. Thus, they avoid risky decisions and cover their back by relying on joint decision-making, for instance (Ashforth & Lee, 1990; Gigerenzer, 2014). Given this propensity together with the glowing reputation of Big Data, there is the possibility that the availability of Big Data further activates top executives' prevention focus, thus leading them to become more defensive and cautious by using Big Data as a safe option to justify wrong decisions. There are multiple reasons that support this latter anticipated decision behaviour. For example, research shows that individuals with an activated prevention focus favour the status quo as a desirable end-state and disparage advancements, resulting in an active avoidance of risky decisions (Crowe & Higgins, 1997; Boldero & Higgins, 2011; Higgins & Cornwell, 2016). In line with this argument, Gino and Margolis (2011) found that a prevention focus is associated with a lower likelihood of unethical behaviour and a greater appreciation of moral standards. Literature from consumer behaviour further suggests that prevention-focused consumers have a smaller consideration set concerning choice alternatives. Thus, we might expect top executives to favour a cautious and defensive decision-making due to a smaller choice-alternatives consideration set, resulting in adherence to the status quo (Pham & Chang, 2010). Lastly, research demonstrates that individuals with an activated prevention focus prefer an accuracy strategy (and refuse fast progress) when it comes to decision-making (Wan, Hong, & Sternthal, 2009). Thus, top executives with an activated prevention focus should have a greater tendency to behave more defensively and cautiously in their decision-making processes.

On the contrary, the opposing effect can arise when the reputed potential of Big Data itself equally well activates top managers' situational promotion focus, thus making them less defensive and less cautious by perceiving Big Data as a new and powerful tool to become more successful. There can be no doubt that power is one important variable favouring confidence that leads individuals to make risky decisions in the end (Anderson & Galinsky, 2006). Furthermore, discounting of advice occurs when decision-makers overvalue their own opinions and simultaneously disparage other people's opinions (Krueger, 2003). Interestingly, individuals even reject advice from experts when they feel empowered (Tost, Gino, & Larrick, 2012). We believe that this might be exactly the case when decision-makers deal with Big Data due to its continuously heralded superiority and value-added potential (McAfee & Brynjolfsson, 2012). In line with this argument, research finds that promotion-oriented individuals strive to achieve maximal performance by taking risks and valuing change – especially when they believe that a new alternative (in this case, a new tool for decision-making) outperforms the original one (Liberman, Idson, Camacho, & Higgins, 1999; Gino & Margolis, 2011). This is a potential outcome when Big Data comes into play regarding the individual decision-making process. Over and above that, promotion-oriented individuals want to avoid maintaining the status quo, as this is perceived as an undesirable end-state (Higgins & Cornwell, 2016), and individuals with an activated promotion focus show a clear preference for risky economic reforms. Additionally, this regulatory system is characterized by a tendency for unethical behaviour (Gino & Margolis, 2011) and the favouring of rapid progress when it comes to decision-making (Wan, Hong, & Sternthal, 2009) – decision outcomes that might occur when perceiving Big Data as a new and powerful tool to derive more efficient and successful decisions in the end. Lastly, Markovits, Ullrich, van Dick, and Davis (2008) demonstrated that promotion-oriented individuals are more emotionally attached to an organisation, resulting in more risk and selfish decisions due to the high degree of emotionality. Tables 5 and 6 summarize the relevant empirical studies in terms of setting, key finding(s), and managerial implications.

Table 5: Empirical studies on regulatory focus theory and decision-making & behaviour

Author(s)	Research Question(s)	Method	Major Results	Journal	Category
Liberman, Idson, Camacho, and Higgins (1999)	Are strategic decisions concerning stability and change being influenced by regulatory focus theory?	Two experimental studies with n=130 respondents (undergraduate students from Columbia University) and four battery studies with n=270 respondents (same sample).	• Prevention-focused individuals tend to prefer strategic decisions that favour stability over change and are more conservative. • Promotion-focused individuals tend to prefer strategic decisions that favour change over stability and are more risky.	*Journal of Personality and Social Psychology*	Regulatory Focus/ Decision-Making & Behaviour
Markovits et al. (2008)	What is the relationship between employees' individual regulatory focus and organisational commitment?	Correlational survey with n=520 employees from private and public-sector organisations.	• Promotion-focused employees have a stronger affective (emotional) commitment to an organisation than do prevention-focused employees, who have a stronger continuance (focused on naked cost-benefit ratio). • In addition to that, both prevention- and promotion-focused employees show a normative commitment (feel an obligation to the firm).	*Journal of Vocational Behaviour*	Regulatory Focus/ Decision-Making & Behaviour

Author(s)	Research Question(s)	Method	Major Results	Journal	Category
Wan, Hong, and Sternthal (2009)	What is the influence of consumers' regulatory orientation and decision strategy (information processing) on their brand judgments?	Four laboratory experiments with n=333 respondents (students from the University of Hong Kong and Northwestern University).	• Prevention-focused consumers evaluate their brand choice in a positive way when the underlying decision strategy is characterized by accuracy rather than fast progress. The opposite applies for promotion-focused consumers. • This relationship is mediated by a feeling of confidence for prevention-focused consumers only.	*Journal of Consumer Research*	Regulatory Focus/ Decision-Making & Behaviour
Pham and Chang (2010)	How does a promotion and/or prevention regulatory focus influence the search for information about alternatives?	Three laboratory experiments with n=354 students.	• Promotion- as well as prevention-focused consumers make use of different information-search strategies. While promotion-focused consumers research more in a global manner, the opposite (local manner) applies to prevention-focused consumers. • Promotion-focused consumers have a larger consideration set, meaning that they consider more alternatives when making a choice.	*Journal of Consumer Research*	Regulatory Focus/ Decision-Making & Behaviour
Boldero and Higgins (2011)	How does a promotion/prevention focus affect risky (conservative) decision-making in politics?	Two laboratory experiments with n=424 respondents (students enrolled in a second-year psychology course).	• Promotion-focused respondents used eager strategies (in the political domain) in order to be enthusiastic and to maximize the individual outcome. Generally, those individuals are more prone to risky decisions. • Prevention-focused respondents used vigilant strategies (in the political domain) in order to be careful and to do what is necessary. Generally, those individuals are more prone to conservative decisions.	*Political Psychology*	Regulatory Focus/ Decision-Making & Behaviour

Author(s)	Research Question(s)	Method	Major Results	Journal	Category
Gino and Margolis (2011)	How do regulatory focus and risk preference influence (un)ethical behaviour in organisations?	Four laboratory experiments with n=371 respondents (undergraduate, graduate, college, and MBA students at a university in the USA).	• The main finding is that the situational regulatory focus of individuals affects the likelihood of (un)ethical behaviour and risk perception. • A promotion focus is associated with unethical behaviour, whereas a prevention focus induces ethical behaviour. • This relationship is mediated by the respective risk perception. Promotion-focused individuals are more prone to risk-seeking behaviours. In contrast to this, prevention-focused individuals are more prone to risk avoidance instead.	*Organisational Behaviour and Human Decision Processes*	Regulatory Focus/ Decision-Making & Behaviour

Table 6: Empirical studies on power (perception) and decision-making & behaviour

Author(s)	Research Question(s)	Method	Major Results	Journal	Category
Anderson and Galinsky (2006)	How does the possession of power affect risk perceptions and risk-taking behaviour?	Five experimental studies with n=268 respondents (mostly undergraduate students at Northwestern University).	• A heightened sense of power is positively associated with individual (optimistic) risk perception and the engagement in risky behaviour. • Individuals' positive and optimistic perception of their own risk estimates is a strong mediator of the relationship between power and risky behaviour. • Furthermore, there are some indications that the above-mentioned relationship might be moderated by expressions of responsibility.	*European Journal of Social Psychology*	Power Perception/ Decision-Making & Behaviour
Tost, Gino, and Larrick (2012)	How does a decision maker's subjective sense of power affect the related decision-making?	Four laboratory experiments with n=460 respondents (students from a private university in the eastern USA; college and graduate students from a local university; and adults).	• A feeling of empowerment is associated with a lower tendency to make use of advice from others and to generally downgrade expertise from experts. • The behaviour of discounting advice from others is mediated by feelings of competitiveness and confidence. • This relationship can be eliminated by inducing a feeling of cooperation with the advisor among individuals.	*Organisational Behaviour and Human Decision Processes*	Power Perception/ Decision-Making & Behaviour

This discussion leads to the conclusion that the activation of opposing self-regulatory systems could lead top managers to increasingly rely on Big Data and thus explains the very same decision behaviour. To pinpoint the psychological mechanism, we contrast the following two hypotheses:

H_{4a}: Top managers resort to a reliance on Big Data because it activates their prevention focus, thus making them more defensive and cautious in their decision behaviour.

H_{4b}: Top managers resort to a reliance on Big Data because it activates their promotion focus, thus making them less defensive and less cautious in their decision behaviour.

2.6 The Avoidance of Potentially Negative Consequences of Big Data

According to recent research in management and information systems, Big Data can be defined by three different keywords: *volume*, *variety,* and *velocity* (Buhl, Röglinger, Moser, & Heidemann, 2013; Gunasekaran et al., 2017). The first-mentioned definition criterion (*volume*) is of special importance, as it is the primary characteristic perceived by decision-makers (Gandomi & Haider, 2015). But what do we actually mean by *volume*? Manyika et al. (2011, p. 1) define the *volume* criterion as follows: "Big Data refers to datasets whose size is beyond the ability of typical database software tools to capture, store, manage and analyse". Apart from this very technical definition, there is an existing common wisdom that having more of something is always good and aspirational (Kyung, Thomas, & Krishna, 2017). However, recent research – particularly in organisational behaviour and social psychology – indicates that this assumption might be misleading in some contexts (cf. "less-is-more-effect"; Gigerenzer & Gaissmaier, 2011). According to Wübben and von Wangenheim (2008), easy rules of thumb (heuristics) sometimes outperform sophisticated analytical methods in some contexts, leading to a questioning of the general "the more, the better" assumption. With reference to this, we believe that the overrepresentation of the *volume* dimension in the minds of the executives triggers the common wisdom or lay belief "the more, the better" when perceiving

Big Data as a new information source for making decisions. Lay beliefs are people's naïve assumptions about reality (Dweck, 2000), and research demonstrates that they affect people's interpretation of their social environment (Wyer, 2004), meaning that they can alter general cognitive structures that influence the perception of the world (Molden & Dweck, 2006). Ultimately, this might lead to a different information intake and processing. Interestingly, lay beliefs are malleable – so they can be influenced by external factors that induce individual learning processes (Levy, Chi-Yue, & Ying-Yi, 2006), resulting in important managerial implications. Apart from altering perception, lay beliefs have the potential to actively influence preferences and change behaviours. According to Wang, Keh, and Bolton (2010), lay theories of medicine (e.g., health remedies, etc.) affect consumer preferences relating to a healthy lifestyle. These results are indeed not limited to the consumer behaviour/health context. Research shows that organisational or group-level lay beliefs change people's cognition and behaviour too (Murphy & Dweck, 2010). Putting all these factors together, we propose that executives' inherent lay belief "the more, the better" might activate their individual promotion focus, resulting in a less defensive and less cautious decision-making behaviour when perceiving Big Data. Consequently, we finally hypothesize:

H_5: Top executives' lay belief "the more, the better" causes the activation of their promotion focus when presented with Big Data, leading to a less defensive and less cautious decision-making behaviour in the end.

From this it follows that a deactivation of the lay belief "the more, the better" should avoid potentially negative managerial decision behaviours generated by Big Data due to the fact that top executives' individual promotion focus should no longer be activated.

3 Study 1a: Top Managers' Reliance on Big Data in an Innovation-management Context[1]

3.1 Overview

In Study 1a, we analyse whether the perception of Big Data, compared to other information sources, leads to a higher reliance on its recommendations for action among marketing managers. Even though we aim to work out the differences between Big Data and market research, it is also necessary to consider managerial intuition in terms of practical experience as an additional information source (e.g., Hoch & Schkade, 1996; Gigerenzer, 2014; de Langhe, 2016) because research shows that managerial intuition outperforms data-driven approaches in some contexts (Wübben & von Wangenheim, 2008; Dane, Rockmann, & Pratt, 2011). Beyond that, we also investigate potential differences in the response behaviour of top- and lower-level managers. We chose an innovation-management context in order to increase the practical relevance of the results. According to Martin and Golsby-Smith (2017), a sole reliance on data-driven decision-making might hurt the innovativeness of companies since new product and disruptive innovations cannot be evolved by analysing historical data (Gigerenzer, 2014). Thus, a strong reliance on Big Data might have harmful consequences for the competitiveness of a company. The scenario of this study is described in the following section.

3.2 Participants

A total of 274 marketing managers, recruited via email from both a large alumni pool of a mid-European business school and the membership roster of a national marketing association, completed the study (76.6% male, $M_{age} = 46.91$ years, $SD = 9.58$). Respondents could participate in a raffle for three bottles of champagne to ensure incentive compatibility. We included a suspicion-probe question at the end of the questionnaire in order to test whether the participants were aware of the purpose of the study. No participant was able to detect the true goal of the investigation.

[1] This study was presented in a modified form at the European Marketing Conference 2018 in Glasgow.

3.3 Procedure

Participants were asked to assume the role of the CMO of a fictitious tea company called "Montrix". In this position, they had to evaluate the company's latest innovation idea, specifically, art tea boxes that play music targeted to the tea bag's type and also serve as a timer for tea preparation (length of music piece equals tea preparation time). We chose tea for the target product as we believe that it represents a category everybody is at least somewhat involved and familiar with. In line with this argument, participants showed an acceptable level of familiarity ($M = 3.84$, $SD = 1.66$, $\alpha = .912$; 7-point Likert scale from Machleit, Allen, & Madden, 1993; 7 = high familiarity) and involvement ($M = 5.30$, $SD = 1.41$, $\alpha = .923$; 7-point Likert scale from Mantel & Kardes, 1999; 7 = high involvement). Participants were told that the idea had been either developed by practical experience (condition 1), market research (condition 2), or Big Data (condition 3), and they were randomly assigned to these three conditions. These different information sources serve as the independent variable in this study. The respective scenarios for each condition are provided in Figures 4–6.

Figure 4: Study 1a (Scenario: Practical experience)

You are the marketing director of a well-known consumer goods manufacturer called Montrix, which has approximately 50,000 employees in 25 countries and generates annual sales of approximately $16 billion. In this position, you are among other things responsible for product management and product development. During a meeting of the marketing department, a new concept for the product "Quinteassential" will be discussed. This concept was previously developed in several internal meetings by the marketing, communications, and R&D departments and is based solely on the many years of experience and the sense of customer preferences of the respective managers involved.

<u>Product description:</u>
"Quinteassential" are very special tea boxes. Not only do these look beautiful, they also keep the tea fresh for longer, thanks to the functionality of the form and the materials used. On the front, the boxes are decorated with artwork by Alberto Seveso.

The artist has created his own design for each tea mixture using ink and a special water technology, which, through the colors and the special shape, should represent the taste and intensity of the tea. On the back of the package is a QR code. If you scan it, you will be forwarded to a song, which again is matched to the tea blend. At the same time, the music is used as a timer because the song has the same length as the brewing time of the tea. The tea is ready when the song is over.

Figure 5: Study 1a (Scenario: Market research)

You are the marketing director of a well-known consumer goods manufacturer called Montrix, which has approximately 50,000 employees in 25 countries and generates annual sales of approximately $16 billion. In this position, you are among other things responsible for product management and product development. During a meeting of the marketing department, a new concept for the product "Quinteassential" will be discussed. This concept is based on the customer preferences of your core target group, which have been previously identified by your market research department through customer surveys, in-depth interviews, and focus groups. Based on this market research data, the development of a new product design was carried out.

Product description:
Equivalent to the scenario in Figure 4.

Figure 6: Study 1a (Scenario: Big Data)

You are the marketing director of a well-known consumer goods manufacturer called Montrix, which has approximately 50,000 employees in 25 countries and generates annual sales of approximately $16 billion. In this position, you are among other things responsible for product management and product development. During a meeting of the marketing department, a new concept for the product "Quinteassential" will be discussed. This concept is based on the customer preferences of your core target group, which have been identified by Big Data Analytics. In this regard, internally available structured data sources (including scanner data, customer movement profiles from initial test markets, and data on the buying history of existing customers) were combined with unstructured external data sources (including social media data, consumer reviews of competing products, and geo-data). The resulting extensive database was evaluated using complex data-mining algorithms.

<u>Product description:</u>
Equivalent to the scenario in Figure 4.

Having read the information, participants were given the following three options: (1) rejecting the innovation, (2) accepting the innovation with adjustments, or (3) accepting the innovation. Participants' strategic choice served as the dependent variable (M = 2.20, SD = .728). Lastly, they had to indicate how familiar they are with quantitative analysis methods (M = 3.78, SD = 1.61; 7 = high familiarity). Across all studies, we measured age and gender and could not find any influence on the overall results. Therefore, we will not discuss these variables. Table 7 contains information regarding the target measures, scale, and corresponding items.

Table 7: Study 1a – measures

Measure	***Scale***	***Items***
Familiarity (from Machleit, Allen, & Madden, 1993)	7-point Likert scale (1 = I totally disagree, 7 = I totally agree)	The product category is familiar to me.
		I feel experienced regarding utilization of the product category.
		I am very knowledgeable about the product category.
Involvement (from Mantel & Kardes, 1999)	7-point Likert scale (1 = I totally disagree, 7 = I totally agree)	The selection of the right kind of tea is very relevant for me.
		The selection of the right kind of tea is very important for me.
		Choosing the right type of tea means a lot to me.
Participants' strategic choice	Ordinal scale (1 = I reject the product concept, 2 = I accept the product concept, but I have change requests, 3 = I accept the product concept)	To what extent do you accept the presented product concept for "Quinteassential"?
Participants' quantitative background	7-point Likert scale (1 = I am not familiar at all, 7 = I am very familiar)	How familiar are you with quantitative analysis methods (e.g., regression analyses)?

3.4 Results

Since the independent as well as the dependent variables have an ordinal scale level, we tested $H_{1a/1b}$ by conducting an ordinal $\chi 2$-Independence Test between participants' strategic choice and the respective information source. The analysis revealed a significant dependence between variables ($\gamma = .250$, $p = .003$). As can be seen from Table 8, executives in the Big Data condition tend to believe the derived recommendations for action more compared to participants in the other conditions.

Table 8: Contingency table: Information sources and agreement with product proposal

		Agreement with product proposal			Total
		No agreement	Agreement with adjust-ments	Full agreement	
Information source	Practical Experience	20	30	24	74
	Market Research	19	48	33	100
	Big Data	11	40	49	100
Total		50	118	106	274

We further calculated odds ratios in order to evaluate the direction as well as the concrete strength of the dependence. The codomain of an odds ratio lies between zero and +∞, whereby a value of one indicates no interdependencies between two variables (Backhaus, Erichson, Plinke, & Weiber, 2015). For the example at hand, we used the two different formulas (Marascuilo & Serlin, 1990) for calculating odds ratios:

$$\text{Odds ratio}_{\text{\_AgreementBigData}} = 1 - \frac{\text{N (Agreement}-\text{Big Data)/ N (Big Data)}}{\text{N (Agreement}-\text{Other Conditions)/ N (Other Conditions)}}$$

$$\text{Odds ratio}_{\text{\_RejectingOtherConditions}} = 1 - \frac{\text{N (Rejecting}-\text{Other Conditions)/ N (Other Conditions)}}{\text{N (Rejecting}-\text{Big Data)/ N (Big Data)}}$$

Participants assigned to the Big Data experimental condition were found to be approximately 50% more likely to fully agree with the recommendation for action compared to participants assigned to the other two conditions. In contrast to this, participants in either the practical experience or market research experimental condition were approximately 104% more likely to reject the innovative idea compared to participants in the Big Data condition. In addition, the individual quantitative skills of the executives might influence the results such that highly experienced managers are more likely to accept the product proposal. Thus, we have to control for this influence factor. In doing so, we ran an ordinal logistic regression with participants' strategic choice as the dependent variable and the information source as the independent variable. We included the individual (self-assessed) quantitative skills as a covariate. We therefore estimated the following regression model:

$$\text{Agreement} = \beta_0 + \beta_1\text{ExperimentalCondition} + \beta_2\text{QuantitativeSkills} + \varepsilon$$

where ExperimentalCondition = 3 if participants have been assigned to the Big Data condition (2 = market research, 1 = practical experience). The variable QuantitativeSkills is metrically scaled, and the variable ε denotes corresponding regression residuals. We conducted one ordinal logistic regression (Winship & Mare, 1984; Ronning & Kukuk, 1996) due to the fact that the dependent variable Agreement is ordinally scaled (1 = I reject the product concept, 2 = I accept the product concept with changes, 3 = I accept the product concept). The analysis demonstrated a significant impact of the information source on agreement with the innovative idea. More precisely, participants assigned to the market research condition showed a lower agreement level with the idea – compared to the Big Data condition ($\beta = -.649$, Wald = 5.79, $p = .016$). Additionally, the same pattern can be observed when comparing participants in the practical experience condition to participants in the Big Data condition ($\beta = -.849$, Wald = 8.43, $p = .004$). There is no statistically significant impact of the (self-reported) quantitative skills ($\beta = -.063$, Wald = .779, $p = .377$) on the dependent variable. Thus, the results were independent of these skills.

We further split our sample into two groups in order to evaluate potential differences between top- and lower-level management (H_2). With reference to this, 58.8% of the participants can be classified as top-level management (e.g., CEO, CMO and/or Head of Sales) and 41.2% as lower-level management (e.g., communication and/or marketing manager). Once again, we conducted an ordinal $\chi 2$-Independence Test demonstrating a significant dependence between the independent and dependent variables for top-level managers ($\gamma = .287$, $p = .008$). In other words, executives at the top level have a higher tendency to accept the recommendations for action generated from Big Data compared to lower-level managers (cf. Table 9). In contrast to this, no significant dependence can be found when analysing lower-level executives (γ = .200, p = .131, cf. Table 10).

Table 9: Contingency table: Information sources and agreement with product proposal (top-level management)

		Agreement with product proposal			Total
		No agreement	Agreement with adjust-ments	Full agreement	
Information source	Practical Experience	13	14	13	40
	Market Research	13	29	22	64
	Big Data	7	20	30	57
Total		33	63	65	161

Table 10: Contingency table: Information sources and agreement with product proposal (lower-level management)

		Agreement with product proposal			Total
		No agreement	Agreement with adjust-ments	Full agreement	
Information source	Practical Experience	7	16	11	34
	Market Research	6	19	11	36
	Big Data	4	20	19	43
Total		17	55	41	113

The odds ratios for top executives fully agreeing with the innovative product idea show a positive effect, indicating that they are 56% more likely to accept the idea when assigned to the Big Data experimental condition. In comparison to the Big Data condition, top executives are 104% more likely to reject the innovative idea when assigned to either the practical experience or market research experimental condition.[2] Again, we ran an ordinal logistic regression in order to control for the self-rated quantitative skills of the top managers. The related regression model remains unchanged:

$$\text{Agreement} = \beta_0 + \beta_1\text{ExperimentalCondition} + \beta_2\text{QuantitativeSkills} + \varepsilon$$

The analysis revealed a significant dependence between the independent and dependent variables. Compared to participants in the Big Data condition, top executives in the market research condition show a lower tendency to agree with the innovative idea (β = -.673, Wald = 3.73, p = .053). In addition, top executives assigned to the practical experience condition showed a lower approval rate too (β = -1.059, Wald = 7.19, p = .007). Similar to the analysis of the overall sample, there is no significant influence of the individual quantitative skills (β = -.130, Wald = 2.01, p = .156).

3.5 Discussion

This study finds evidence for our contention that managers have a greater tendency to accept recommendations for action derived from Big Data compared to recommendations derived from market research or practical experience (H_{1a}). Two different statistical methods demonstrate exactly the same results, underlining the robustness of the findings. The results remain unchanged even if we control for managers' (self-rated) quantitative skills, resulting in an exclusion of this potential confound. The results also support our second hypothesis stating that top managers have a greater tendency to accept recommendations for action derived from Big Data compared to lower-level managers (H_2). Once again, we used two different statistical methods showing the same results. From this it follows that (top) managers do perceive Big Data as a new and different

[2] The respective formulas for calculating the odds ratios remain unchanged as well.

information source, changing existing behaviour patterns in decision-making. To provide further evidence for this implication and the results of Study 1a, we arranged a controlled paper-and-pencil experiment with marketing executives. In this way we address the limitation of using managers' self-rated quantitative skills as a control variable because all participants received a comprehensive training in statistics and marketing intelligence in a 4-day seminar, ensuring that the objective quantitative skills are at the same level.

4 Study 1b: Replication of Study 1a (Paper-and-Pencil Experimental Setting)[3]

4.1 Overview

In Study 1b, we aimed to replicate the results found in Study 1a in order to achieve greater robustness. According to Wierenga (2011, p. 11), one major challenge in research on managerial decision-making is "to get real marketing decision makers in the lab." We took this demand into account by choosing a paper-and-pencil experimental setting. Paper-and-pencil experiments are especially suited to investigate cause-and-effect relationships since they allow a better control of potential confounding variables (e.g., noise, presence of other people, etc.). Besides, participants should have a higher tendency to take the experiment seriously, as the experimenter may walk around (Patzer, 1996). However, such experiments are time-consuming in terms of recruiting a sufficient number of participants. Online experiments can reach a high number of people very quickly. Thus, they are most frequently chosen in social science nowadays (Baum & Spann, 2011), underlining the uniqueness of the present study.

4.2 Participants

We recruited 94 marketing managers from an executive education program of a mid-European business school to participate in a controlled paper-and-pencil experiment (77.7% male, M_{age} = 41.24 years, SD = 8.28) with the same setting as in Study 1a. Once again, the possibility of winning three bottles of champagne served as the main incentive to participate. We also included a suspicion-probe question at the end of the questionnaire in order to test whether participants were aware of the purpose of the study. An examination of the responses revealed that no participant was able to detect the true goal of the investigation.

[3] This study was presented in a modified form at the European Marketing Conference 2016 in Oslo, at the European Marketing Conference 2017 in Groningen and at the European Marketing Conference 2018 in Glasgow.

4.3 Procedure

As already mentioned, the experimental setting was the same as in Study 1a. Once again, participants had to assume the role of the CMO of a fictitious tea company called "Montrix". In line with the results of the previous study, participants were familiar with the chosen product ($M = 4.31$, $SD = 1.51$, $\alpha = .926$; 7-point Likert scale from Machleit, Allen, & Madden, 1993; 7 = high familiarity) and showed a high involvement level ($M = 5.43$, $SD = 1.27$, $\alpha = .944$; 7-point Likert scale from Mantel & Kardes, 1999; 7 = high involvement) regarding the product category of tea. Participants' strategic choice (agreement with the innovative product idea) was the dependent variable. The different information sources (Big Data, market research, and practical experience) served as the independent variable. Executives also evaluated the perceived credibility of the different information sources ($M = 4.97$, $SD = 1.00$, $\alpha = .842$; 7-point Likert scale from Williams & Drolet, 2005), as we believe that this might explain the performance of Big Data (compared to market research and practical experience) in Study 1a. Finally, participants indicated their familiarity with quantitative analysis ($M = 3.56$, $SD = 1.56$; 7 = high familiarity). In contrast to Study 1a, we did not include executives' (self-rated) quantitative skills in the main analyses of this study due to the fact that all participants received an intensive training in statistics and marketing intelligence during a 4-day seminar, ensuring an equal level of objective quantitative skills among them. Table 11 shows the corresponding items, measures, and scales.

Table 11: Study 1b – measures

Measure	***Scale***	***Items***
Familiarity (from Machleit, Allen, & Madden, 1993)	7-point Likert scale (1 = I totally disagree, 7 = I totally agree)	The product category is familiar to me.
		I feel experienced regarding utilization of the product category.
		I am very knowledgeable about the product category.
Involvement (from Mantel & Kardes, 1999)	7-point Likert scale (1 = I totally disagree, 7 = I totally agree)	The selection of the right kind of tea is very relevant for me.
		The selection of the right kind of tea is very important for me.
		Choosing the right type of tea means a lot to me.
Participants' strategic choice	Ordinal scale (1 = I reject the product concept, 2 = I accept the product concept, but I have change requests, 3 = I accept the product concept)	To what extent do you accept the presented product concept for "Quinteassential"?
Participants' quantitative background	7-point Likert scale (1 = I am not familiar at all, 7 = I am very familiar)	How familiar are you with quantitative analysis methods (e.g., regression analyses)?
Perceived credibility (from Williams & Drolet, 2005)	7-point Likert scale (1 = I totally disagree, 7 = I totally agree)	The product category is trustworthy.
		The product category is reliable.
		The product category is honest.

4.4 Results

We again found empirical support both for H_{1a} and for H_2, enhancing the robustness of the results found in Study 1a. An ordinal $\chi 2$-Independence Test with the respective information source and participants' strategic choice showed a significant dependence between the variables ($\gamma = .324$, $p = .036$). According to Table 12, marketing executives in the Big Data condition have a higher tendency to accept the derived recommendations for action – compared to market research and practical experience.

Table 12: Contingency table: Information sources and agreement with product proposal

		Agreement with product proposal			Total
		No agreement	Agreement with adjustments	Full agreement	
Information source	Practical Experience	6	22	2	30
	Market Research	6	22	5	33
	Big Data	2	23	6	31
Total		14	67	13	94

We further calculated odds ratios, which indicated the supposed direction of this relationship. Marketing managers in our sample were approximately 74% more likely to accept the product innovation when they were assigned to the Big Data condition versus not. In contrast to this, executives in the market research or practical experience condition were found to be approximately 195% more likely to reject the innovative idea.

In order to verify H_2, we further split the sample in two different groups consisting of 55.3% lower-level management (e.g., communication and/or marketing manager) and 44.7% top-level management (e.g., CEO, CMO and/or Head of Sales). The ordinal $\chi 2$-Independence Test demonstrated a significant dependence between the independent and dependent variable for top managers (γ = .519, *p* = .003, cf. Table 13) but not for lower-level managers (γ = .027, *p* = .920, cf. Table 14).

Table 13: Contingency table: Information sources and agreement with product proposal (top-level management)

		Agreement with product proposal			Total
		No agreement	Agreement with adjustments	Full agreement	
Information source	Practical Experience	3	11	1	15
	Market Research	4	7	3	14
	Big Data	0	7	6	13
Total		7	25	10	42

Table 14: Contingency table: Information sources and agreement with product proposal (lower-level management)

		Agreement with product proposal			Total
		No agreement	Agreement with adjustments	Full agreement	
Information source	Practical Experience	3	11	1	15
	Market Research	2	15	2	19
	Big Data	2	16	0	18
Total		7	42	3	52

The analysis of the respective odds ratios showed that top managers in the Big Data experimental condition were approximately 235% more likely to accept the product idea compared to participants in the other experimental conditions. As all participants received a 4-day training in statistics and marketing intelligence, the results were independent of executives' objective quantitative skills. We ran two ordinal logistic regressions (for lower-level and top-level management) with the respective information source as independent variable, participants' strategic choice as dependent variable, and the individual (self-assessed) quantitative skills as covariate to revalidate this interdependence. Thus, we formulated the following regression models:

$$\text{Agreement}_{\text{LLmanagement}} = \beta_0 + \beta_1\text{ExperimentalCondition} + \beta_2\text{QuantitativeSkills} + \varepsilon$$

$$\text{Agreement}_{\text{TLmanagement}} = \beta_0 + \beta_1\text{ExperimentalCondition} + \beta_2\text{QuantitativeSkills} + \varepsilon$$

In line with the results of Study 1a, the ordinal logistic regression model revealed a significant dependence between the information source and agreement with the product idea for top managers. Participants in the market research experimental condition were more likely to reject the product proposal compared to participants in the Big Data condition ($\beta = -1.84$, Wald = 4.80, $p = .028$). The same applies for those in the practical experience condition ($\beta = -1.99$, Wald = 5.61, $p = .018$). Additionally, the self-reported quantitative skills had no statistically significant impact on the dependent variable ($\beta = -.072$, Wald = .359, $p = .549$). When analysing lower-level management, there is no statistical dependence for the market research condition ($\beta = .683$, Wald = .611, $p = .434$) or for the practical experience condition ($\beta = -.175$, Wald = .039, $p = .843$). Once again, the self-reported quantitative skills of the lower-level executives had no significant impact on the dependent variable ($\beta = .029$, Wald = .060, $p = .806$). The results of Study 1b were independent of the self-rated as well as the objective quantitative skills, resulting in a replication of the results found in Study 1a as well as a verification of H_{1a} and H_2. Thus, we found further empirical evidence that Big Data is perceived as a new data source – even though we did not detect a psychological mechanism that can explain the individual response behaviour of the top executives.

We assume that the main effect of having a greater tendency to accept recommendations for action derived from Big Data (compared to other information sources, such as market research or practical experience) might be explained by the ubiquitously repeated superiority of Big Data (e.g., McAfee & Brynjolfsson, 2012), resulting in a higher perceived credibility (H_3). Subsequently, we performed a univariate analysis of variance (UNIANOVA) in order to investigate whether the information sources differ in terms of their perceived credibility. The results are displayed in Table 15.

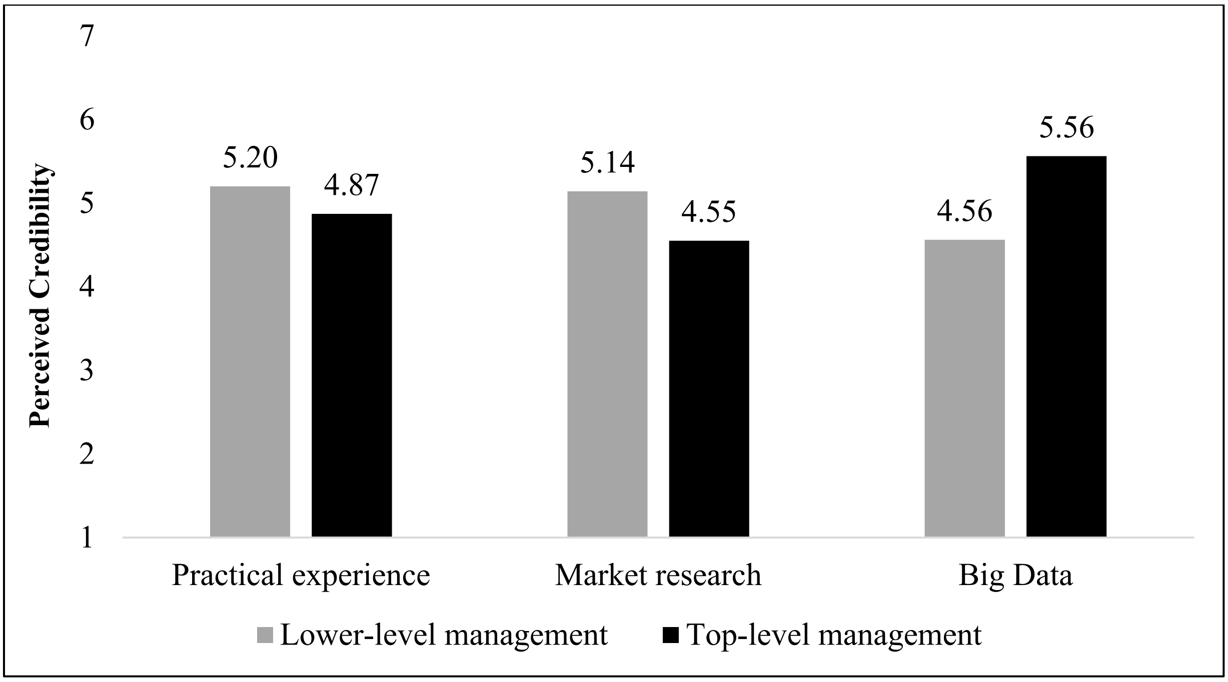
Table 15: Univariate analysis of variance – results of study 1b

	df	F-Value	*p*-Value
Information source	2	.468	.628
Hierarchy level	1	.019	.891
Information source x hierarchy level	2	6.09	.003

Adjusted R^2 = .075
Dependent variable: Perceived credibility

The analysis revealed no significant main effects for information source (F(2, 91) = .468, *p* = .628) or hierarchy level (F(1, 92) = .019, *p* = .891). In contrast to this, the respective interaction term was statistically significant (F(2, 91) = 6.09, *p* = .003), accounting for the main effects. Interestingly, the results did not change substantially when controlling for the individual self-rated quantitative skills and degree of maturity concerning Big Data in organisations. We further calculated simple contrasts to show the exact differences between the information sources when measuring the respective perceived credibility.

Figure 7: Simple contrasts of study 1b – perceived credibility



A close inspection of Figure 7 reveals that top-level executives attribute a higher credibility to facts and figures derived from Big Data (M = 5.56; on a 7-point Likert scale) than do lower-level executives (M = 4.56; on a 7-point Likert scale). This difference is statistically significant ($F(1, 92) = 8.242$, $p = .005$, Credibility – Big Data$_{\text{_Top Level}}$ = 5.56; Credibility – Big Data$_{\text{_Low Level}}$ = 4.56). In addition to that, top-level executives consider Big Data to have by far the highest credibility – compared to insights generated from market research and/or practical experience.[4]

Even though we found that the credibility assessment depends on the respective information source (experimental condition), we did not yet specifically test whether the perceived credibility also influences participants' strategic choice. Hence, we tested for a

[4] Interestingly, there is a reverse effect when assessing the credibility of facts and figures generated from market research, meaning that lower-level executives attribute to market research a higher credibility than top-level executives do ($F(1, 92) = 3.040$, $p = .085$, Credibility – Market research$_{\text{_Top Level}}$ = 4.55; Credibility – Market research$_{\text{_Low Level}}$ = 5.14).

mediated moderation in order to investigate this assumed relationship. Following Muller, Judd, and Yzerbyt (2005), we estimated the following two regression models[5]:

$$\text{(1) Agreement} = \beta_0 + \beta_1\text{ExperimentalCondition} + \beta_2\text{Hierarchy} + \beta_3\text{ExperimentalCondition x Hierarchy} + \beta_4\text{QuantitativeSkills} + \varepsilon$$

$$\text{(2) Agreement} = \gamma_0 + \gamma_1\text{ExperimentalCondition} + \gamma_2\text{Hierarchy} + \gamma_3\text{ExperimentalCondition x Hierarchy} + \gamma_4\text{Credibility} + \gamma_5\text{Credibility x Hierarchy} + \gamma_6\text{QuantitativeSkills} + \zeta$$

where ExperimentalCondition = 3 if participants have been assigned to the Big Data condition (2 = market research, 1 = practical experience) and Hierarchy = 1 if participants are top executives. Credibility and QuantitativeSkills are metrically scaled (cf. Table 16). The variables ε and ζ denote corresponding regression residuals. We conducted two ordinal logistic regressions (Winship & Mare, 1984; Ronning & Kukuk, 1996) due to the fact that the dependent variable is ordinally scaled (1 = I reject the product concept, 2 = I accept the product concept with changes, 3 = I accept the product concept; cf. Table 16). The results of the two ordinal logistic regressions are shown in Table 16.

[5] The estimation of a third regression (with perceived credibility as dependent variable) is not necessary due to the above conducted UNIANOVA. It has been shown that the interaction term of information source (experimental condition) and executive hierarchy level is statistically significant (see Table 15; even when we control for the individual self-rated quantitative skills).

Table 16: Mediated moderation analysis – results of study 1b

	Model (1)			Model (2)		
	β	Wald	*p*-Value	γ	Wald	*p*-Value
ExperimentalCondition	.025	.004	.950	.282	.408	.523
Hierarchy	-1.67	1.82	.178	-3.49	1.61	.204
ExperimentalCondition x Hierarchy	1.21	4.25	.039	.645	1.03	.311
Credibility				.842	5.01	.025
Credibility x Hierarchy				.599	1.48	.223
Quantitative Skills	-.041	.073	.787	-.002	.000	.989
Nagelkerkes R^2		.134			.361	

For the first regression (model 1), the main effects of both experimental condition and hierarchy are not statistically significant (β_1 = .025, Wald = .004, p = .950; β_2 = -1.67, Wald = 1.82, p = .178). A significant interaction term (β_3 = 1.21, Wald = 4.25, p = .039) accounts for the main effects. The second ordinal logistic regression (model 2) helps to verify whether the interaction effect β_3 on the dependent variable (Agreement) is mediated by the individual perceived credibility. According to Muller, Judd, and Yzerbyt (2005), a full mediated moderation can be confirmed when the interaction effect of the individual perceived credibility of the information source and the respective hierarchy on participants' strategic choice (in this case, agreement with the product proposal) is insignificant. Furthermore, the direct effect of the credibility variable on the dependent variable has to be significant, and lastly, the interaction effect consisting of the experimental condition and executives' hierarchy level has to be insignificant – compared to the first regression model. Closer inspection of Table 16 reveals that γ_5 is not statistically significant (γ_5 = .599, Wald = 1.48, p = .223), resulting in fulfilment of the first requirement of a fully mediated moderation. In addition, there is a direct effect of the individual perceived credibility on executives' strategic choice (γ_4 = .842, Wald = 5.01, p = .025), meaning that a high perceived credibility of a particular data source leads automatically to a higher tendency to accept the respective product proposal. In contrast to this, there is no statistically significant interaction effect consisting of the respective information source and executives' hierarchy level on the dependent variable (γ_3 = .645, Wald = 1.03, p = .311). Thus, the other two requirements for having a fully mediated moderation model are met as well. This means that the interaction effect β_3 on Agreement is fully mediated by the individual perceived credibility of the information source. To put it in a nutshell: Compared to other information sources, the higher perceived credibility of facts and figures generated from Big Data Analytics leads to a higher tendency to accept the respective recommendations for action among top executives.

4.5 Discussion

In this study, we chose a paper-and-pencil experimental setting to replicate the findings of Study 1a concluding that facts and figures generated by Big Data Analytics influence managerial decision-making such that executives have a greater tendency to rely on the respective recommendations for action (compared to other information sources) – even in a domain where this might be misleading. These results were independent of executives' objective as well as self-rated quantitative skills. Similar to Study 1a, we found this relationship to be particularly evident for top executives, leading to a final verification of H_{1a} and H_2. Interestingly, we found that the strategic decision behaviour of (top) executives is not influenced by the individual information source only. The associated perceived credibility determines top managers' individual decision-making too. Thus, we found an important lever that influences the relationship between the information source and the decision outcome. However, we did not yet detect a psychological mechanism that can explain the individual response behaviour.

5 Study 2: Exploring the Psychological Mechanism behind Big Data and Defensive Decision-Making[6]

5.1 Overview

The purpose of Study 2 was to detect the psychological mechanism behind the effects found in Studies 1a and 1b. We elaborate on two competing and less intuitive mechanisms: Top executives may rely on Big Data either because it makes them more cautious and defensive in their decisions or, conversely, because it leads them to become more euphoric and less cautious. Thus, we aimed to falsify one of our contrasting hypotheses, H_{4a} or H_{4b}. Defensive and cautious decision-making is an important topic in organisational research (Ashforth & Lee, 1990; Morrison & Milliken, 2000); however, there is no existing literature regarding the empirical validation of this construct. With reference to this, we aimed to develop a scale measuring the extent of defensive and cautious decision-making in organisations. In doing so, we chose an exploratory online survey (correlational) study design.

5.2 Participants

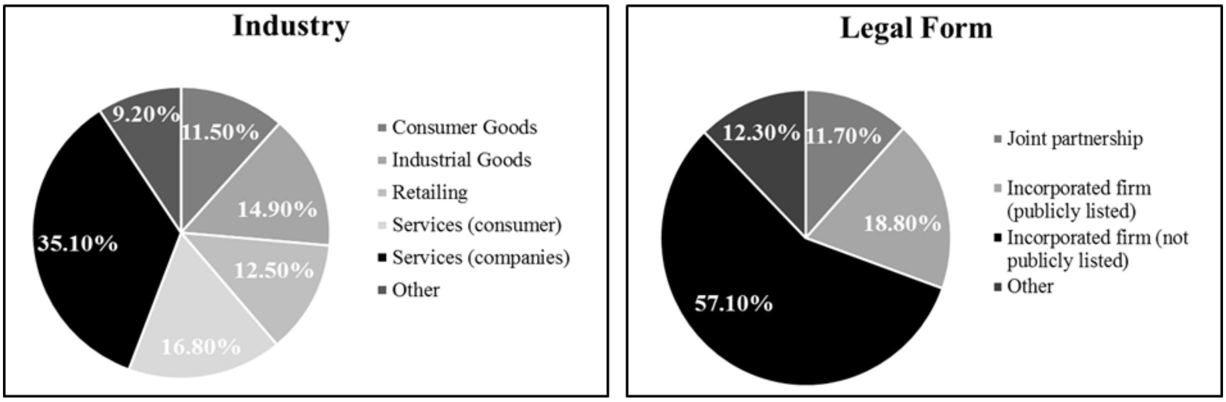
For this purpose, we recruited 159 top executives to take part in an online survey, all of them being CEO, CMO, or Head of Sales (87.3% male, $M_{age} = 48.12$ years, $SD = 8.91$), from both the large alumni pool of a mid-European business school and the membership roster of a national marketing association. Participants had a chance to win three bottles of champagne and relevant management literature.

Figure 8 provides further information regarding the sample of this correlational study. The majority of participants work for companies that provide services for organisations (35.1%). Affiliation with the other industries is more or less equally distributed. In contrast to this, the imbalance of the sample is far higher when specifying the legal form,

[6] This study was presented in a modified form at the European Marketing Conference 2017 in Groningen and 2018 in Glasgow.

meaning that 57.1% of the top executives represent incorporated firms that are not publicly listed. Considering these things, we are aware that our sample lacks representativeness concerning the distribution of industries and legal forms in Switzerland. Nevertheless, we are of the opinion that it will not affect the identification of potential psychological mechanisms explaining the results found in previous studies.

Figure 8: Sample of the correlational study



5.3 Procedure and Measures

We first measured top executives' perceived maturity of Big Data in their firms by asking them to answer an adapted version of the 3-item Customer Analytics Scale by Germann, Lilien, Fiedler, and Kraus (2014). In doing this, we replaced the term "customer analytics" by the term "Big Data" ($M = 2.67$, $SD = 1.57$, $\alpha = .910$; 7-point Likert scale, 7 = high perceived maturity level of Big Data). This measure is used as the independent variable in our analysis. In order to ensure a common understanding of Big Data, we told the respondents that it can be understood as the storage and mostly automated analysis of large amounts of data from multiple sources. To explore our two competing mechanisms (H_{4a} vs. H_{4b}), we next asked participants to indicate their current regulatory focus on a 3-item semantic differential scale ($M = 2.15$, $SD = .919$, $\alpha = .568$; semantic differential scale adapted from Pham & Avnet, 2004; 1 = high situational prevention focus, 7 = high situational promotion focus). This measure served as our mediator variable. We further asked participants to provide information regarding their individual decision behaviour. As there is no established scale available measuring cautious and defensive decision-making, we developed our own scale referring to previous literature on defensive behaviour in organisations (Ashforth & Lee, 1990). In doing so, we first derived five items measuring the extent of how defensive and cautious top executives are in their managerial decision behaviour. We then ran an exploratory factor analysis (EFA) using principal components analysis with a varimax rotation in order to further aggregate the items. This procedure revealed that all items loaded strongly on a single factor capturing top executives' defensive and cautious decision-making behaviour[7] (M = 3.70, SD = .904, α = .539[8]; 7-point Likert scale, 7 = high level of cautious and defensive decision behaviour). Thus, we came up with the following items:

I like to share risk through joint decision-making.

I take great efforts not to offend anyone.

I go along with the majority.

I primarily take actions that have a high probability of success.

I tend to make conservative estimates of future performance.

This measure was the dependent variable in our analysis. Beyond that, we raised various control questions such as gender, age, industry, legal form, and individual quantitative skills. Table 17 shows the corresponding items, measures, and scales.

[7] The single factor had an eigenvalue of 1.787, and there is a visible kink in the Scree plot after the first factor.

[8] A reliability score (Cronbach's Alpha) above 0.50 is considered appropriate given the circumstance of such an exploratory measure (Hinton, Brownlow, McMurray, & Cozens, 2004).

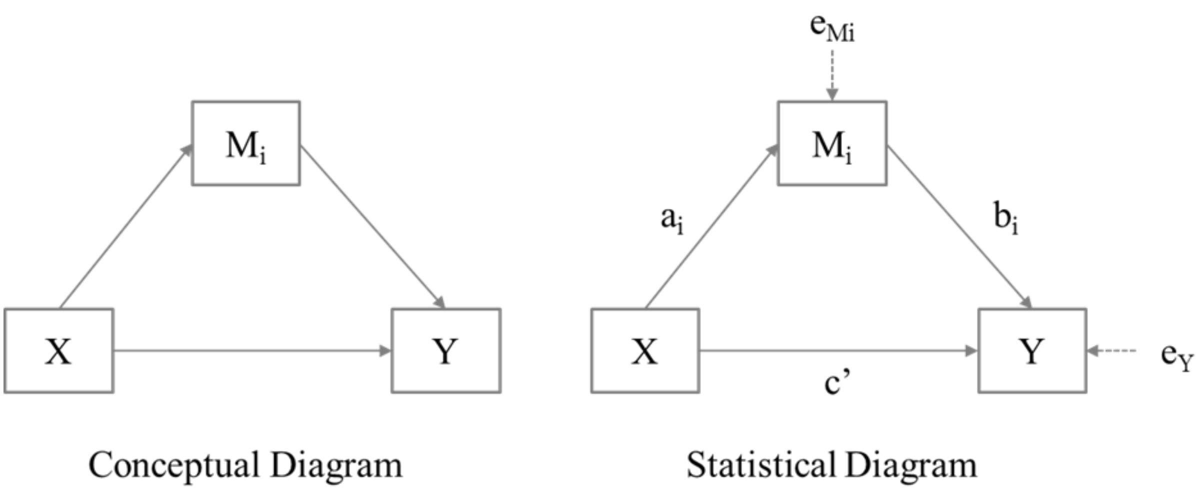
Table 17: Study 2 – measures

Measure	*Scale*	*Items*
Perceived maturity of Big Data (from Germann et al., 2014)	7-point Likert scale (1 = I totally disagree, 7 = I totally agree)	In our firm/business unit, we extensively use Big Data.
		Virtually everyone in our firm/business unit uses Big Data-based insights to support decisions.
		When making decisions, we back arguments with Big Data-based facts.
Current regulatory focus (adapted from Pham & Avnet, 2004)	Semantic differential scale	I would do … what is right (= 1) vs. whatever I want (= 7).
		I would … pay back my loans (= 1) vs. take a trip around the world (= 7).
		I would … do whatever it takes to keep my promises (= 1) vs. go wherever my heart takes me (= 7).
Defensive and cautious decision behaviour (new scale)	7-point Likert scale (1 = I totally disagree, 7 = I totally agree)	I like to share risk through joint decision-making.
		I take great efforts not to offend anyone.
		I go along with the majority.
		I primarily take actions that have a high probability of success.
		I tend to make conservative estimates of future performance.

5.4 Results

We utilized a bootstrapped mediation model (Hayes, 2009) with perceived maturity of Big Data in organisations as independent variable, the individual (current) regulatory focus as mediator, and the five-item measure of top managers' defensive and cautious decision behaviour as dependent variable in order to test our contrasting hypotheses H_{4a} and H_{4b}. We transformed the mediator variable (current regulatory focus) by logarithmizing its respective values, since the Kolmogorov-Smirnov test has revealed that the residuals are not normally distributed (Massey, 1951). According to Preacher and Hayes (2008), we sampled 10,000 bootstrap samples while performing the bootstrapped mediation. We set $\alpha = .95$ as confidence level. We also inserted some control variables (e.g., industries the top executives are working in, legal form, and individual quantitative skills) in order to address endogeneity. This often occurs in non-experimental research (e.g., surveys or field studies) due to a potential omitted-variable bias (Marais & Wecker, 1998). Since it is nearly impossible to control for each important variable in a field study/survey setting, the resulting non-consideration of some variables might influence statements regarding the statistical significance of the results (van Heerde, Dekimpe, & Putsis, 2005). Over and above that, Figure 9 displays the statistical and conceptual foundations of a simple (or parallel) multiple mediator model (Hayes, 2009).

Figure 9: Conceptual and statistical foundations of a mediator model



A close inspection of Figure 9 shows that a simple multiple mediator model estimates the direct and indirect effect(s) of X on Y through one or more mediators (M). A full mediation is given when the indirect effect(s) of X (in this case, top executives' perceived maturity of Big Data in their own organisation) on Y (in this case, top executives' extent of defensive and cautious decision-making) through M (in this case, participants' current regulatory focus) is statistically significant, and simultaneously, the direct effect of X on Y is not (Hayes, 2009).

In order to test a bootstrapped mediator model, we used model 4 in Hayes' PROCESS macro (2012), and simultaneous regression analyses revealed that top executives' perceived degree of maturity of Big Data activates their current (situational) promotion focus ($a_i(\beta) = .052$, $t = 2.52$, $p = .013$). Ultimately, this leads to a less defensive and cautious decision behaviour ($b_i(\beta) = -.408$, $t = -2.22$, $p = .028$), which is in line with H_{4b}. In addition, the indirect effect through regulatory focus (promotion orientation) was significant too ($a_ib_i(\beta) = -.021$, SE = .0135; 95% CI [-.0523, -.0003]).[9] Since the direct effect between the perceived degree of maturity of Big Data and top managers' defensive and cautious decision behaviour was not statistically significant ($c'(\beta) = -.065$, $t = -1.38$, $p = .169$), we found evidence for a full mediation.

As already mentioned, we calculated a different bootstrapped mediation by inserting some additional company- and industry-specific variables (e.g., company size, legal form, etc.) in order to address endogeneity.[10] Interestingly, we found the same results as in the baseline model. At first, the direct effect between the independent and dependent variable was again not statistically significant ($c'(\beta) = -.069$, $t = -1.43$, $p = .155$). In contrast to this, the indirect effect via regulatory focus was significant because the respective confidence interval did not contain the value zero ($a_ib_i(\beta) = -.023$, SE = .0139; 95% CI [-.0549, -.0012]). This means that the perceived degree of maturity of Big Data in organisations activates top executives' situational promotion focus ($a_i(\beta) = .054$, $t = 2.52$, $p = .013$), leading to a less defensive and less cautious decision behaviour ($b_i(\beta) = -.423$, $t = -2.29$, $p = .023$). Thus, we once again found evidence for a full mediation.

[9] The confidence interval does not contain zero, indicating statistical significance.
[10] We once again had to transform the mediator variable because the residuals are not normally distributed.

5.5 Discussion

To put it in a nutshell, Study 2 shows that Big Data changes traditional managerial decision-making on a behavioural level. Following up on Studies 1a and 1b, we detail why top managers have a higher tendency to accept recommendations for action generated from Big Data. In this context, we have analysed two competing explanations: Top executives may rely on Big Data either because it makes them more cautious in their decisions (e.g., Big Data as a scapegoat) or, conversely, because it leads them to become more euphoric (e.g., Big Data as a powerful tool to make ultimate decisions). In doing so, we created a measure for defensive decision-making and investigated whether the perceived maturity of Big Data in organisations influences the decision behaviour of top executives via regulatory focus. In support of H_{4b}, findings reveal that respondents' perceived maturity of Big Data activates their situational promotion orientation, which in turn leads them to behave less defensively and less cautiously.

In order to revalidate these empirical findings, we aim to replicate them in Study 3 through experimentation and to demonstrate the detected process through moderation (Spencer, Zanna, & Fong, 2005). Furthermore, if the results prove to be robust, simply activating top executives' prevention focus to reduce non-defensive decision-making may be neither practical nor effective, as it may lead to other negative consequences such as procrastination or status quo biases (Ariely & Wertenbroch, 2002). Consequently, it might be more beneficial to lead top managers to critically reflect on Big Data by, for example, encouraging them to question the common lay belief "the more, the better".

6 Study 3: Big Data and Defensive Decision-Making – Replication through Experimentation and Moderation[11]

6.1 Overview

The main goal of Study 3 was to replicate the results found in Study 2 by using an experimental setting. Our empirical results are thus not influenced by any endogeneity problems because the experimental randomization eliminates all occurring systematic biases as well as potential correlations between omitted variables and independent ones. From this it follows that we do not have to consider any omitted-variable bias that might influence the results of the experiment at hand (e.g., Rubin, 1974; Schafer & Kang, 2008). In particular, we aimed to gain additional empirical evidence that the perception of Big Data (as an information source) activates top managers' promotion focus, thus influencing strategic decisions (H_{4b}) such that the individuals become more egocentric and euphoric. In order to be coherent with the previous studies, we just investigated top executives, even though the analysis of the behaviour of the lower-level management would be interesting too. Additionally, we did not further consider top managers' practical experience as an experimental condition since we aim to investigate, amongst other things, whether Big Data is perceived differently from market research, thereby resulting in a new information source for top managers. We also made initial investigations of whether top executives' lay belief "the more, the better" might influence the activation of the individual promotion focus induced by the perception of Big Data. The participant-selection process and specific scenario of this study are described in the following sections.

6.2 Participants

For this purpose, we recruited 121 top executives (82.6% male, M_{age} = 45.08 years, SD = 8.91) to take part in an online experiment, all of them being CEO, CMO, or Head of Sales, from both the alumni pool of a mid-European business school and the membership roster of a national marketing association. The executives were give a chance to

[11] This study was presented in a modified form at the European Marketing Conference 2018 in Glasgow.

participate in a raffle for three bottles of champagne and relevant management literature in order to ensure a certain degree of incentive compatibility. We included a suspicion-probe question at the end of the questionnaire to determine whether participants were aware of the purpose of the study. Similar to the prior experiments, no participant was able to detect the true goal of the investigation.

6.3 Procedure

Participants were asked to assume the role of the CEO of a fictitious company operating amusement parks in the US – called "Amazing Adventures". They were provided with some general information (e.g., different locations and states where Amazing Adventures is operating its parks, etc.) as well as important information regarding firm performance (e.g., average size of the existing parks, average number of visitors per park, annual turnover, etc.). Participants were then randomly assigned to either a Big Data or a market research condition, meaning that they were told that the customer targeting of Amazing Adventures is based on either sophisticated algorithms and data mining or on quantitative and qualitative market research techniques. The respective scenarios for each condition are provided in Figures 10 and 11.

Figure 10: Study 3 (Scenario: Big Data)

In order to improve its understanding of customers as well as its success on the market, Amazing Adventures successfully established a cloud-based Big Data system in recent years. For example, visitor data and waiting times per attraction are not only recorded in real time, they are also combined with external data such as weather and holiday time as well as entries and comments on their own (i.e., the Facebook page of Amazing Adventures) and third-party social media platforms.

Amazing Adventures collects real-time information about consumer behaviour across all operated amusement parks primarily via the Entrance Pass, which is not only an entry ticket – it also serves as a room key for the affiliated hotels and as a shopping card for the shops and restaurants, as well as for access to Fast Lanes. The Entrance Pass is also equipped with a GPS-enabled chip.

Figure 11: Study 3 (Scenario: Market research)

In order to improve its understanding of customers as well as its success on the market, Amazing Adventures regularly conducts traditional market research. For example, the company conducts about a dozen focus groups on a yearly basis, each one with 8–12 selected customers. Among other things, these focus groups are supposed to analyse underlying reasons for park visits in more detail.

In addition, Amazing Adventures' market research team conducted a representative customer survey across all parks this year; in each park, nearly 200 visitors participated. For the completion of the survey's standardized questionnaire, participants were willing to spend about 15 minutes on average.

Following presentation of the scenario, we manipulated top executives' situational prevention focus by telling a randomly chosen half of the participants that Amazing Adventures aims to avoid unnecessary investments and thus pursues a careful corporate policy. The other half of the participants did not get this information. Then top executives were told that the top management of Amazing Adventures is currently considering building a new amusement park in Portland, Oregon. With reference to this, participants had to make a judgment regarding the number of future visitors to the new park in the first year in order to prepare this decision. Thus, top executives' estimate served as the dependent variable in this study (M = 12.8 million, SD = 56.7). In sum, we established a 2x2 between-subjects design with Big Data vs. market research manipulation and prevention prime vs. control condition as factors (independent variables). Afterwards, we asked participants to indicate their current regulatory focus on a 3-item semantic differential scale (M = 2.21, SD = 1.03, α = .701; semantic differential scale adapted from Pham & Avnet, 2004; 1 = high situational prevention focus, 7 = high situational promotion focus). We then asked executives whether they believe that more and diverse data sources always lead to better individual decision-making. In doing so, we used a 3-item scale that has been validated in a prior pretest via Amazon MTurk (M = 4.72, SD = 132, α = .702; 7-point Likert scale, 7 = full agreement that more and diverse data sources lead to better decision-making). This variable aims to measure top executives' inherent lay belief that "the more, the better" – adjusted to the decision-making context. Finally, participants indicated their age, gender, quantitative skills, and position in the organisation. Table 18 shows the corresponding items, measures, and scales.

Table 18: Study 3 – measures

Measure	***Scale***	***Items***
Estimation of future visitor numbers to the new park	Open question	How many visitors do you expect in the opening year of the new park?
Current regulatory focus (adapted from Pham & Avnet, 2004)	Semantic differential scale	I would do … what is right (= 1) vs. whatever I want (= 7).
		I would … pay back my loans (= 1) vs. take a trip around the world (= 7).
		I would … do whatever it takes to keep my promises (= 1) vs. go wherever my heart takes me (= 7).
Lay-belief scale (new scale)	7-point Likert scale (1 = I totally disagree, 7 = I totally agree)	If more data are available, decision-making becomes much easier.
		The quality of decision-making processes increases with a higher availability of data.
		Miscellaneous data sources facilitate decision-making processes.

6.4 Results

The manipulation of the situational regulatory focus was successful. An analysis of variance (ANOVA) with the prevention-focus manipulation versus control group predicting the individual situational regulatory focus demonstrated a significantly lower promotion focus for those participants assigned to the prevention condition compared to participants in the control condition ($F(1, 119) = 4.33$, $p = .040$; $M_{PreventionCondition} = 2.05$, $M_{ControlCondition} = 2.44$).

In order to accrue further empirical support for the results found in Study 2, we conducted an univariate analysis of variance (UNIANOVA) with the Big Data versus market research manipulation as well as the prevention manipulation versus control condition and their interaction as independent variables. Participants' estimate regarding the number of visitors to the new park in the first year served as the dependent variable. The analysis revealed no significant main effect for the market research versus Big Data manipulation (F(1, 119) = 1.190, p = .278) or for the control versus prevention focus manipulation (F(1, 119) = .752, p = .388). In contrast to this, the respective interaction term was statistically significant (F(1, 119) = 3.636, p = .059), accounting for the main effects. The results remained unchanged when considering various control variables. The results are displayed in Table 19.

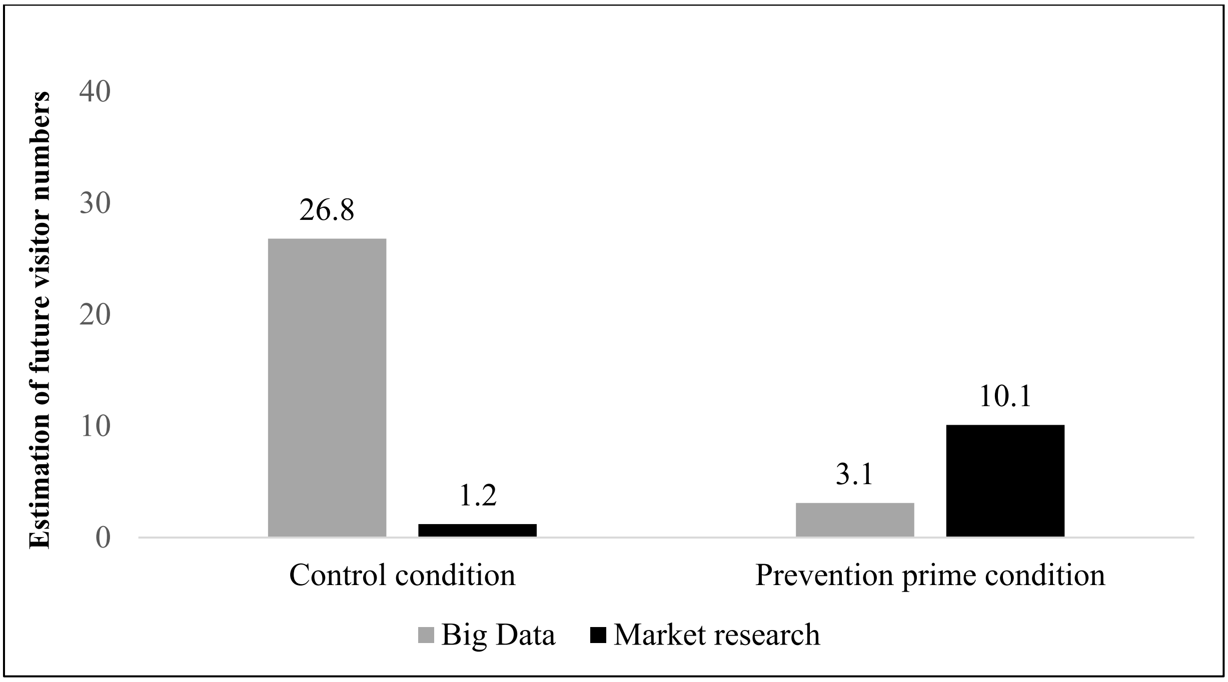
Table 19: Univariate analysis of variance – results

	df	F-Value	*p*-Value
Market research (0) vs. Big Data manipulation (1)	1	1.190	.278
Control (0) vs. prevention-prime manipulation (1)	1	.752	.388
Interaction term of both factors	1	3.636	.059

Adjusted R^2 = .043
Dependent variable: Estimation of future visitor numbers to the new park

To locate the source of this interaction, we further calculated simple contrasts (cf. Figure 12). Informing participants that Amazing Adventures makes use of Big Data and data mining for customer targeting (instead of market research) led to a significantly higher estimate of the future visitor numbers to the new park in the control condition. In contrast, this euphoric effect is neutralized when participants are told that Amazing Adventures pursues a careful corporate policy (F(1, 119) = 3.64, p = .047, $M_{BigData - Control}$ = 26.8 million, $M_{BigData - Prevention}$ = 3.1 million). Thus, we showed that the perception of Big Data makes top executives more euphoric and risk-taking when it comes to decision-making.

Figure 12: Simple contrasts – estimation of future visitor numbers (in millions)



We suspect that top executives' inherent lay belief that "the more data available, the better decisions" further influences the above-mentioned relationship such that top managers with this deactivated lay belief should not be affected by the perception of Big Data. Thus, we used a median-split technique to transform the lay-belief scale into a factor with two characteristics: (1) participants with a low data faith and (2) participants with a high data faith. This approach is often used in experimental research in order to simply interpret the results as well as to find first indications concerning additional influencing factors of a given relationship (e.g., Irwin & McClelland, 2001). With this in mind, we conducted two additional univariate analyses of variance (UNIANOVA) with the same specifications regarding independent, dependent, and moderator variables as in the previous analyses – one each for participants with a low (or high) data faith. For top executives with a high data faith (n = 56), the analysis revealed no significant main effects either for information source ($F(1, 54) = 2.01$, $p = .160$) or regulatory-focus manipulation ($F(1, 54) = 2.12$, $p = .151$). A marginally significant interaction effect ($F(1, 54) = 3.05$, $p = .087$) accounts for the main effects. The subsequent contrast analysis showed that top-level executives in the Big Data condition estimated the visitor numbers to the new park significantly higher when not undergoing the prevention manipulation ($F(1, 54) = 5.54$, $p = .022$, $M_{BigData - Control} = 52.8$ million, $M_{BigData - Prevention} = 0.91$ million). When analysing participants with a low data faith instead ($n = 63$), such interdependencies were not identifiable. The particular information source has no statistically significant influence on the dependent variable ($F(1, 61) = .428$, $p = .516$), and the same applies for the prevention-prime manipulation ($F(1, 61) = 1.62$, $p = .209$). Consequently, the interaction is not statistically significant either ($F(1, 61) = .382$, $p = .539$). With reference to this, the contrast analysis showed no significant differences in the Big Data condition ($F(1, 61) = .216$, $p = .216$, $M_{BigData - Control} = 0.78$ million, $M_{BigData - Prevention} = 5.05$ million).

6.5 Discussion

The findings thus perfectly replicate the results of Study 2 and provide further process evidence via experimentation and moderation (Spencer, Zanna, & Fong, 2005). By implementing an experimental setting, we could show that the perception of Big Data leads top executives to become euphoric and less risk-averse when estimating the future visitor numbers of Amazing Adventures' new park. Interestingly, this relationship disappears when participants are exposed to the prevention-focus prime, indicating that the perception of Big Data is the main influencing factor in this case. Since such less defensive and less cautious decision-making behaviour could not be detected in the market research condition, we once again proved that top executives perceive Big Data as a new and different information source. Over and above that, we found first indications concerning a potential debiasing mechanism. It seems that top executives' inherent lay belief that "the more data, the better decisions" further influences the above-described moderation since participants with a low level of data faith did not perceive Big Data as such a powerful tool and, consequently, did not become euphoric and less risk-averse. As a next step, we aim to show the exact psychological mechanism by subconsciously manipulating top executives' lay belief instead of using a scale based on self-assessment. Nevertheless, the present study gives a first hint that this lay belief might be an important lever to avoid the potentially negative effects on managerial decision-making behaviour caused by perceptions concerning Big Data.

7 Study 4: "The more, the better" – Top Managers' Lay Belief as a Debiasing Mechanism[12]

7.1 Overview

We finally conducted Study 4 to analyse which influential factor might help avoid the potentially misleading decision-making behaviour detected in the previous studies. Following up on existing literature and the results of Study 3, we assume that top managers' lay belief "the more, the better" ultimately causes them to become euphoric, egocentric, and risk-seeking when presented with Big Data (H_5). We used an experimental scenario similar to that of Study 3 – enriched with an unrelated task to subconsciously manipulate the relevant lay belief. As a side effect, we also aimed to replicate the results found in Study 3, thereby strengthening the robustness of the findings.

7.2 Participants

For this purpose, we recruited for an online experiment 125 top-level marketing executives (85.3% male, M_{age} = 45.64 years, SD = 11.62), all of them being CEO, CMO, or Head of Sales, from both the alumni pool of a mid-European business school and the membership roster of a national marketing association. The associated incentives remained unchanged: Participants had a chance to participate in a raffle for three bottles of champagne and relevant management literature. We once again included a suspicion-probe question at the end of the questionnaire to test whether the participants were aware of the main purpose of the study. In line with all other studies, no participant was able to detect the true goal of the investigation.

7.3 Procedure

As already mentioned, the experimental scenario was very similar to the one in Study 3. Participants were asked to assume the role of the CEO of Amazing Adventures, and then they had to make decisions regarding the future performance of the company. We chose

[12] This study was presented in a modified form at the European Marketing Conference 2018 in Glasgow.

such an approach in order to ensure comparability and to increase the robustness of the results; however, the current study differed in two aspects. First, to manipulate top managers' lay belief, respondents were asked to take part in a seemingly unrelated study. In this context, a randomly chosen half of the participants had to find reasons for the proposition that more customers do not automatically create additional value for a company (e.g., Belz & Schmitz, 2011). We used this approach in order to deactivate top executives' inherent lay belief "the more, the better". The other half of the participants had to elaborate on advantages and disadvantages of exchange versus communal relationships (Clark & Mills, 1993) with customers. This group serves as the control condition because we believe that the evaluation of exchange versus communal relationships should not activate any self-referential decision-making bias, and besides, it should not confound the deactivation (or rather activation) of the lay belief "the more, the better". The respective scenarios for each condition are provided in Figures 13 and 14.

Figure 13: Study 4 (Scenario: Deactivation of lay belief)

Welcome to the first part of our study that is about customer management.

Determining the right amount of customers is a demanding and critical task for companies, particularly in a business-to-business context. For example, having many customers may be detrimental to the success of a company. The Institute of Marketing at the University of St. Gallen (HSG) currently conducts research in this area, and as a consequence, we would be very interested in your valuable opinion from a practical perspective on this issue. We thus would like to ask you to name and briefly elaborate on reasons why and when serving too many customers may backfire.

Please state reasons that come to your mind spontaneously.

Figure 14: Study 4 (Scenario: Control condition)

Welcome to the first part of our study that is about customer management.

Many companies are currently asking themselves what relationship they should have with their customers, particularly in a business-to-business context. On the one hand, it is possible to have a matter-of-fact and a very professional relationship (i.e., exchange relationship); on the other hand, it is equally possible to have a very close and friend-like relationship (i.e., communal relationship). Both philosophies have advantages and disadvantages. The Institute of Marketing at the University of St. Gallen (HSG) currently conducts research in this area, and as a consequence, we would be very interested in your valuable opinion from a practical perspective on this issue. We thus would like to ask you to name and briefly elaborate on reasons in favour of an exchange relationship and reasons in favour of a communal relationship.

Please name one to two reasons for each relationship.

In order to check whether this technique of manipulation of the inherent lay belief was successful or not, we asked participants to indicate whether they agree with the overall statement that more data always lead to better results (3 items; 7-point Likert-scale, 1 = I totally disagree, 7 = I totally agree, $M = 4.75$, $SD = 1.24$, $\alpha = .578$). Furthermore, they indicated their current regulatory focus by using a semantic differential scale (Pham & Avnet, 2004; 1 = high situational prevention focus, 7 = high situational promotion focus, $M = 2.49$, $SD = 1.01$, $\alpha = .687$). In addition to that, as dependent variable, we captured another important aspect of defensive and cautious decision-making: joint decision-making (Ashforth & Lee, 1990). Consequently, participants were not asked to estimate the future visitor numbers to the new park. Instead, we told them that the other board members of Amazing Adventures recommend against building the new park. Then they had to make a final decision about whether to build the new park or not (7-point Likert-scale, 1 = I totally disagree with the other board members, 7 = I totally agree with the other board members, $M = 3.86$, $SD = 1.64$). In addition, we used the same Big Data versus market research manipulation as in Study 3, with participants told that the customer target figure is either based on sophisticated algorithms (Big Data manipulation) or on quantitative and qualitative market research techniques (market research manipulation). In sum, we established a 2x2 between-subjects experimental design with the lay-belief manipulation as well as the Big Data versus market research manipulation as factors. Finally, participants indicated their age, gender, quantitative skills, and position in the company. Table 20 shows the corresponding items, measures, and scales.

Table 20: Study 4 – measures

Measure	***Scale***	***Items***
Final decision regarding the building of the new park	7-point Likert scale (1 = I totally disagree, 7 = I totally agree)	To what extent do you agree with the other board members' estimate?
Current regulatory focus (adapted from Pham & Avnet, 2004)	Semantic differential scale	I would do … what is right (= 1) vs. whatever I want (= 7).
		I would … pay back my loans (= 1) vs. take a trip around the world (= 7).
		I would … do whatever it takes to keep my promises (= 1) vs. go wherever my heart takes me (= 7).
Lay-belief scale (new scale)	7-point Likert scale (1 = I totally disagree, 7 = I totally agree)	If more data are available, decision-making becomes much easier.
		The quality of decision-making processes increases with a higher availability of data.
		Miscellaneous data sources facilitate decision-making processes.

7.4 Results

The initial manipulation of top executives' lay belief "the more, the better" was successful. An analysis of variance (ANOVA) with lay-belief manipulation versus control condition predicting participants' agreement with the statement that more data always lead to better decisions demonstrated a (marginally) lower agreement for those top executives assigned to the lay-belief manipulation group compared to participants in the control condition ($F(1, 121) = 3.10$, $p = .081$; $M_{LayBeliefManipulation} = 4.58$, $M_{ControlCondition} = 4.98$).[13]

We further conducted an univariate analysis of variance (UNIANOVA) with participants' current regulatory focus as dependent variable[14], and information source (Big Data vs. market research) as well as the lay-belief manipulation as independent factors. The analysis revealed no significant main effects for either the information source ($F(1, 123) = 2.24$, $p = .137$) or lay-belief manipulation ($F(1, 123) = .809$, $p = .370$). More interestingly, the interaction effect of the two independent variables is highly statistically significant ($F(1, 123) = 5.50$, $p = .021$). To locate the source of this interaction, we calculated simple contrasts. The information that Amazing Adventures has access to Big Data (instead of market research) in order to target customers more individually leads to an activation of participants' situational promotion focus in the control condition. This euphoria-related effect is neutralized when the individual lay belief "the more, the better" is deactivated (cf. Figure 15). We further tested a related contrast code and it confirmed this pattern ($F(1, 123) = 5.86$, $p = .017$, $M_{BigData – Control} = 0.95$, $M_{BigData – LayBeliefDeactivation} = 0.70$; $F(1, 123) = .950$, $p = .332$, $M_{MarketResearch – Control} = 0.66$, $M_{MarketResearch – LayBeliefDeactivation} = 0.77$). We thus perfectly replicate the results found in Studies 2 and 3. In addition, we found that the lay belief "the more, the better" causes an activation of top managers' situational promotion focus when presented with Big Data. In order to clarify whether this moderation effect also affects top managers' decision-making behaviour, we further calculated a bootstrapped mediated moderated model (Hayes, 2009).

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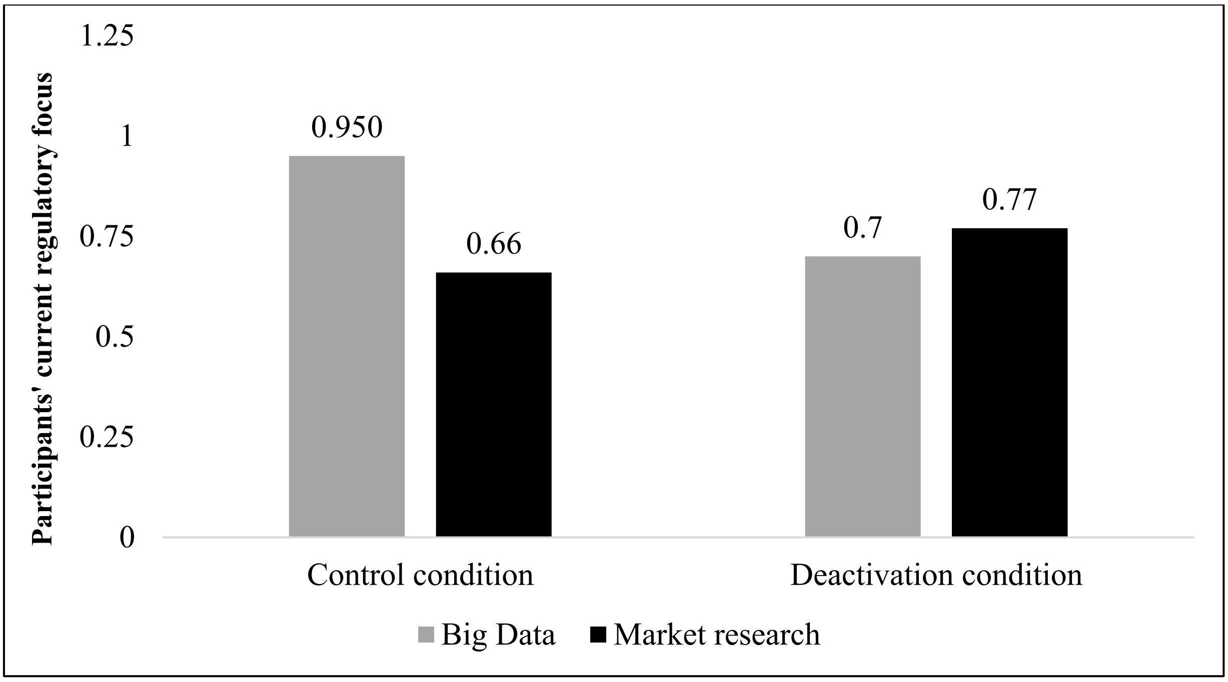
[13] The Lay-belief scale variable contains two missing values, explaining the lower amount of participants involved in this analysis (n=123).

[14] Once again, we had to transform the regulatory-focus variable (by using a logarithm) because the Kolmogorov-Smirnov test has revealed that the residuals are not normally distributed.

Figure 15: Simple Contrasts – Information source and lay-belief manipulation on situational regulatory focus (scale logarithmized)



In this context, the Big Data versus market research manipulation serves as the independent variable, the individual (current) regulatory focus as the mediator variable, the lay-belief manipulation as the respective moderator variable, and participants' final agreement with the board members' estimate regarding the building of the new park as the dependent variable. Once again, we used Hayes' PROCESS macro (2012), and the regression analyses revealed no direct effect of the Big Data versus market research manipulation on the dependent variable (β = -.083, t = -.283, *p* = .778), which is in line with the results found in studies 2 and 3. In contrast to this, the analyses further demonstrated an indirect effect of the independent variable on the final agreement with the other board members' estimate through regulatory focus when top managers' inherent lay belief "the more, the better" was not deactivated (β = -.259, SE = .1651; 95% CI [-.6410, -.0113]). This means that top managers have a higher tendency to disagree with the other board members' estimate regarding the building of the new park when told that Amazing Adventures uses Big Data and sophisticated analytical algorithms for customer targeting, due to an activated (situational) promotion focus. Compared with this, a deactivation of top managers' inherent lay belief "the more, the better" prevents an activation of their situational promotion focus triggered by the perception of Big Data (β = -.065, t = -.672, $p = .503$). In line with this observation, the respective indirect effect was not statistically significant either (β = .0572, SE = .0934; 95% CI [-.1167, .2644]), meaning that there is no influence of the regulatory-focus variable on executives' decision-making behaviour. Over and above that, the overall index of moderated mediation further validates these findings because it contains no zero, indicating statistical significance (β = .3157, SE = .2039; 95% CI [.0123, .7938]).

7.4 Discussion

In this study, we generated two different findings. First, we could further replicate that the perception of Big Data activates top executives' situational promotion focus, leading to a less cautious and less defensive decision-making behaviour (e.g., no joint decision-making). From this it follows that Big Data is perceived as a new and distinctive information source transforming traditional decision-making processes of top managers in marketing. In addition, we found an associated debiasing mechanism, since a simple activation of top executives' prevention focus to avoid non-defensive and less cautious decision-making may be neither practical nor effective. Research shows that such an approach leads to procrastination or status quo biases (Ariely & Wertenbroch, 2002) – two outcomes that should be avoided at all costs due to the negative consequences on firm performance. In contrast to this, we found that the individual activation of the situational promotion focus is driven by top executives' inherent lay belief "the more, the better". In line with the results of Study 3, this individual lay belief might explain why top managers become euphoric when presented with Big Data, resulting in a less cautious and non-defensive decision-making behaviour. Thus, H_5 can be verified. This finding is of greatest importance for the daily work of top managers because we found one workable approach to prevent the potentially negative effects of Big Data on their decision-making and associated behaviour.

8 Conclusions and Implications

8.1 Summary of Key Findings

According to George, Osinga, Lavie, and Scott (2016, p. 1493), “Big Data and data science have potential as new tools for developing management theory”. Indeed, there is an increasing research interest in marketing that focuses almost exclusively on Big Data’s value-added potential for organisations. However, quantitative and psychological research on how marketing managers precisely react to data has remained surprisingly scarce despite the question’s importance. To our best knowledge, no prior work has investigated how marketing managers’ perception of Big Data changes their decision-making processes. With reference to this, we conducted five studies with 773 experienced marketing executives in order to respond to this need and close the research gap in this context. Our results show that executives’ perception of Big Data changes traditional managerial decision-making quite substantially – both in terms of specific management outcome and on a more general behavioural level.

Our research results can be summarized in three key findings. First (1), marketing executives perceive Big Data as a new and impressive information source when it comes to decision-making, as indicated by higher tendencies to rely on its respective recommendations for action – compared to other information sources (market research and practical experience). Interestingly, this relationship is especially evident for top executives (i.e., CEO, CMO, and Head of Sales). Referring to this, the difference between Big Data and market research must be emphasized. Apparently there is no congruent perception of these two information sources, leading to the conclusion that managers do not treat Big Data as an extension of market research. We find support for this across two studies, independent of both self-rated and trained quantitative skills of managers. Second (2), Big Data causes top executives to become less cautious (e.g., more risk-seeking and exhibiting a tendency to ignore employees’ voices) and more euphoric, as they might perceive it as a new and powerful tool to derive successful decisions, hence their higher tendency to rely on it. We find support for this across three different studies with approximately 400 experienced marketing executives using a multi-method approach (correlational as well as experimental studies). This result is particularly impressive since the opposite effect would have been conceivable too (i.e., top management perceive Big Data as a justification tool in case of failure, hence becoming more cautious in their decision-making behaviour). Third (3), top managers' decision-making behaviour is determined by the inherent lay belief "the more, the better". Thus, we have discerned a reasonable approach for preventing the potentially negative decision outcomes of Big Data in an organisational setting without activating other important decision-making biases (Ariely & Wertenbroch, 2002).

8.2 Theoretical Implications

Our research makes several important theoretical implications that we highlight and explain in this section. First, we contribute to work done in the research area of how marketing managers make use of market research information (e.g., Deshpande & Zaltman, 1982, 1984; Moorman, Zaltman, & Deshpande, 1992). We extend the exclusive focus on market research information by introducing a new information source: Big Data. Our comparative analyses indicate that marketing managers perceive these information sources in very different ways. One major difference is that top managers have a greater tendency to rely on recommendations for action generated from Big Data compared to market research, whereas such a behaviour cannot be detected when analysing lower-level managers. This finding is in line with existing research stating that more experienced managers prefer generally more and diverse information when it comes to decision-making (Perkins & Rao, 1990). On a related front, prior research in this field demonstrates that outcome-related variables (e.g., technical quality of the information; Deshpande & Zaltman, 1984) figure prominently in the usage of market research information. Our research builds on this finding by showing that the perceived credibility level of the information source (Big Data vs. market research) determines the respective utilization to a certain degree. Top executives associate Big Data with a higher credibility level, resulting in a higher tendency to rely on it. In contrast, lower-level managers attribute a significantly lower degree of credibility to Big Data. Apart from this, we have also shown that individual psychological and cognitive processes play a major role when it comes to the explanation of actual managerial behaviour – something that is rather neglected in existing research so far. Finally, it becomes clear that research in the realm of utilization of market research by marketing managers must pursue a comparative approach in the future. Market research is no longer the only information source used by marketing managers. There are new and diverse data sources that will determine their work in the future.

Second, we contribute to the well-known theory of technology dominance (Arnold & Sutton, 1998) by supplementing the original standard model with the influencing factor of perceived credibility. We believe that this adjustment is especially relevant for the marketing sector, assuming that there is a lower familiarity with (technological) decision aids and data-driven decision making – compared to other business divisions (e.g., logistics and supply chain). From this it follows that the perception of various information sources becomes important, emphasizing a more emotional assessment. Undoubtedly, internal and external influences determine how human decision-makers perceive their environment. We believe that the ubiquitously postulated superiority of Big Data (McAfee & Brynjolfsson, 2012) leads to a higher perceived credibility, resulting in a higher tendency to rely on it. Our results support this assumption – especially for top management. To summarize, we are of the opinion that our adjusted model is suitable to be used in marketing research, thereby expanding the sphere of action of the original model.

Third, our research further provides valuable insights to the literature on algorithm aversion. According to Dietvorst, Simmons, and Massey (2015), human beings often prefer a human forecaster and not a sophisticated algorithm after seeing their respective performance. Our results suggest the opposite effect – an algorithm appreciation – however, we utilize a different approach. Most importantly, we did not show executives the respective performance of the information source. Our focus is on top managers' perception and how this determines individual decision outcomes. In other words, we make use of a different abstraction level. Referring to this, one might assume that the acceptance of technological advice depends on the associated abstraction level. While a high abstraction level (e.g., just presenting the term Big Data with a few additional explanations to the respondents) is associated with a higher acceptance rate among marketing managers, a lower abstraction level (e.g., presenting the actual performance of the information source) makes them more suspicious when it comes to the utilization.

Fourth, we contribute to existing research outlining work-related antecedents of regulatory focus (Gorman et al., 2012). Our analyses reveal that the perception of information sources has the potential to activate top executives' regulatory foci (in our case, the individual promotion focus). Consequently, the list of potential antecedents has to be extended by this influencing factor – especially when it comes to decision-making in marketing.

Finally and more generally, our work aims to tackle the existing research gap concerning the usage of Big Data in marketing. So far, Big Data does not play a major role in marketing research. Existing studies in this field examine the associated value-added potential. In contrast to this, literature is extremely scarce on the related organisational anchorage as well as on how decision-making might be influenced. Thus, the present work establishes a starting point to further close the existing research gap in this context. In addition, our research helps to build a general understanding of "how marketing managers make decisions to improve the quality of marketing decision making" (Wierenga, 2011, p. 89). In this context, the analysis of how marketing executives make use of information sources (e.g., market research) did not seem attractive for a long time due to the extensive work done by Deshpande and Zaltman (e.g., 1982, 1984, etc.). The rise of Big Data changes this situation completely because it has so many distinctive features compared to market research. Thus, our research acknowledges this new aspect and aims to transform this impoverished research area into a prosperous one.

8.3 Managerial Implications

The findings from the current research carry important implications for the daily work of marketing managers and top executives.

Our research demonstrates that the perception of Big Data changes traditional managerial decision-making processes. Top executives have a greater tendency to rely on its recommendations for action, they attribute a higher credibility level to this information source, and they become more egocentric and risk-seeking when relying on it. One can assume that as data-driven decision-making becomes more and more important, human beings will be increasingly less involved when making a decision. According to Lilien (2011), there are three different approaches when it comes to managerial decision-making in marketing: the subjective marketing decision-making approach, the (traditional) marketing decision-modelling approach, and the automated marketing decision-modelling approach. The first-mentioned approach exclusively relies on managerial judgment (e.g., intuition, gut feeling, etc.) when it comes to decision-making. The second one is based on the assumption that there is an interplay between a specific model (market research, for instance) and managerial judgment, with the human being making the final decision in the end. In contrast to this, the third-mentioned approach goes one step further and excludes any kind of managerial judgment from the decision-making process. Thus, an automated marketing decision model makes the final decision. With reference to our results, it is reasonable to assume that Big Data might lead to a shift towards an automated decision-making approach due to its high perceived credibility and the ubiquitously postulated superiority and value-added generation potential (e.g., Müller, Fay, & vom Brocke, 2018). We believe that the exclusion of any kind of managerial judgment from the decision-making approach poses a problem for organisational performance and the daily work of marketing managers in at least three ways.

First, the glorification of an automated decision-making modelling approach grossly neglects the power of managerial intuition and experience. Various studies demonstrate that managerial intuition outperforms sophisticated analytical models in some contexts (e.g., Wübben & von Wangenheim, 2008; Gigerenzer, 2014). However, it is important to mention that managers' intuition should be used only when it is based on practical experience and expertise (Dane, Rockmann, & Pratt, 2011). Thus, we agree with the statement of Hoch and Schkade (1996, p. 63) that "it is naïve to think that decision makers can be completely removed (…) and replaced with even an excellent model". We believe that a successful decision-making process depends on the utilization of analytical models and managers' intuition, as well as creative ideas.

Second, because automated decision-making models and Big Data are exclusively based on historical data, their usage is especially limited when forecasting future events with high uncertainty (Gigerenzer, 2014). We chose an innovation-management context (new product development) in two of our studies to illustrate this. To start with, new and innovative products (also known as disruptive innovations) can hardly be developed and designed by simply relying on Big Data, as such algorithms are (as mentioned above) exclusively based on historical data (e.g., customer wishes and needs) and are therefore an insufficient predictor for something that has never happened before. Besides, such algorithms and models cannot account for external shocks and developments (e.g., technological change, foreign competition, etc.) – events likely to occur in the innovation-development phase (e.g., Tushman & Nadler, 1986). Thus, executives should be cautious when using Big Data analytics in an innovation-management context, as this does not lead to disruptive innovations, and besides, it might stifle managers' creative potential, resulting in a competitive disadvantage for firms.

Third, the implementation of Big Data and the related automated decision-making modelling approach is associated with massive investment in firms' technological infrastructure (Tambe, 2014). But given this fact, a comprehensive value generation for different kinds of firms and industries has not been proven yet – despite countless contrary white papers and articles of renowned consultancies. Thus, an abrupt shift towards automated decision-making might pose a considerable cost risk for many firms. We recommend that they rather begin with small "proof-of-concept" projects before making huge investments in the implementation of Big Data. Such an approach allows rapid adjustments and organisation-wide learning effects that are important influencing factors for a successful execution.

Over and above that, our research shows that Big Data changes top managers' decision-making behaviour such that they become more egocentric and risk-seeking, and less cautious. Given the importance of employee participation and organisational "checks and balances", such behaviour obviously is worrisome and might have negative consequences for employees' working motivation. It is thus reasonable to assume that Big Data aggravates existing hierarchy differences in firms, as we demonstrated that top executives are not interested in joint decision-making when presented with Big Data. In the end, they might not be motivated to lead due to perceiving Big Data as a new and powerful tool to become successful in their business career, resulting in a negation of transformational leadership (Bass, 1985), for instance. Such hierarchy differences between top- and lower-level management might inhibit employees' motivation to speak up and, consequently, to challenge top-management decisions, resulting in a lower firm performance. Existing research shows that a lower level of employee participation is associated with lower employee motivation (Zapata-Phelan et al., 2009) as well as lower managerial effectiveness (Morrison, 2011). Besides, employees who are willing to speak up constitute one of the main factors by which leaders can initiate organisational change processes (Morrison & Milliken, 2000). Ironically, it seems that Big Data inhibits or discourages transformation processes – a limitation given the urgent need for change in most companies in the digital transformation era.

Due to these potentially negative consequences of Big Data, the question arises as to how these managerial outcomes can be expediently tackled. With reference to our research results, one starting point would be to simply activate top managers' prevention focus. However, such an approach may be neither practical nor effective, as it may lead to other negative consequences such as procrastination or status quo biases (Ariely & Wertenbroch, 2002). As an alternative, the results of Study 4 indicate that the deactivation of top managers' inherent lay belief "the more, the better" proves very valuable in this regard, as it prevents the positive perception of Big Data from activating executives' situational promotion focus and leading to the above-mentioned potentially negative managerial outcomes. Hence, top executives should be made aware of this lay belief and encouraged to question its practical applicability for their daily work (i.e., communicating that more of something does not necessarily lead to better decision outcomes). Establishing internal workshops and trainings might be one suitable approach in this context, as cognitive research shows that explicit training in this regard has the potential to limit cognitive biases (Fong & Nisbett, 1991). With reference to this, organisations could make use of a so-called boosting technique – a very recent and popular approach adopted from behavioural science (e.g., Hertwig & Grüne-Yanoff, 2017). To be more precise, this technique boosts target-specific competencies and simultaneously facilitates specific behaviour. There has to be a high degree of transparency concerning a boost's objective, allowing an individual decision-maker to accept it or not. In the end, individuals may integrate a "boosted" competence into their decision-making process. Therefore, organisations should aim to foster Big Data and analytics competencies among top executives. As a consequence, it might be reasonably assumed that top managers can better evaluate what Big Data is all about and realize that more data/information does not necessarily lead to better decision outcomes.

Another possible way to prevent the potentially negative consequences of Big Data might be to hire managers with profound knowledge in analytics. Those people know the strengths and weaknesses of Big Data, resulting in a lower likelihood of showing any kind of data faith and, thus, a lower tendency to behave in an egocentric and less cautious manner when presented with Big Data. In line with the excessively used term "war of talents", organisations should pay more attention to the relevant knowledge in analytics and data science when recruiting for top-management positions.

Apart from this, there is – at least – one other potential debiasing mechanism that is worthwhile to discuss. Research has demonstrated that decision accountability leads managers to think more deliberatively and to make more cognitive effort due to the fact that they have to justify their decisions to others (Brown, 1999). Thus, we believe that an active stressing of top managers' decision accountability might lead to a more critical reflection of Big Data and a lower reliance on it. One way to achieve a high level of decision accountability might be collaborative decision-making. In this context, it seems necessary to expand the existence of top-management teams (e.g., West & Anderson, 1996) in order to prevent egocentric decision-making behaviour and to build up an internal control system.

Finally, we do not wish to generally depreciate the usefulness of Big Data in an organisational setting. On the contrary, we believe that there is huge potential to derive sound marketing activities, optimize the buying process, and to target customers more individually – especially in data-rich environments with relatively little uncertainty (LaValle et al., 2011; Gigerenzer, 2014; Wedel & Kannan, 2016; Trusov, Ma, & Jamal, 2016). Thus, we appreciate a successive implementation of Big Data Analytics in firms. However, our research shows that an exclusive reliance on Big Data might cause harmful managerial outcomes such as the dampening of disruptive innovation and a rise in egocentric and risk-seeking managerial behaviour. Thus, our research results encourage and facilitate a responsible approach of top executives considering the use of Big Data.

8.4 Methodological Limitations

We used a multi-method research approach in order to derive our theoretical as well as managerial implications. More precisely, we ran four different controlled experiments and one field study. Thus, we analysed experimental as well as correlational data in order to answer our research question. Notwithstanding the substantial insights of this research, in this section we want to point out some important methodological limitations.

First, we exclusively relied on cross-sectional data, meaning experiments or "surveys completed by a single respondent at a single time" (Rindfleisch, Malter, Ganesan, & Moorman, 2008, p. 262). This might lead to a systematic error in the results and a biased derivation of causal inference. One potential solution is the implementation of a longitudinal design, because the temporal separation avoids anchor-effects that might occur when respondents have to answer different variables at the same time. We are aware that such an approach would have been especially beneficial for our field study (Study 2), but we decided to do otherwise since it is nearly impossible to incite top managers in marketing to participate in several consecutive studies. In addition, we are of the opinion that especially studies about the utilization of Big Data underlay temporal fluctuations. Our assumption that Big Data is not comprehensively implemented in our management sample allowed us to analyse the associated perception and its subsequent consequences for executives' decision-making behaviour. An extension of the survey period caused by the implementation of a longitudinal research design could lead to the situation where we no longer investigate the perception of Big Data because its actual implementation in firms is moving forward very quickly.

Second, in recent years the discussion about scale format characteristics has become more and more important (e.g., Weijters, Cabooter, & Schillewaert, 2010). Across our five studies, we make use of different scale formats (e.g., Likert scale, semantic differential scale, etc.), and we labelled only the endpoints of our scales (e.g., 7-point Likert scale with 1 = I totally disagree and 7 = I totally agree). This approach can be criticized in many ways. To start, recent research shows that a fully labelled scale leads to higher reliability and makes the intermediate options more salient to the respondents (Weng, 2004). Thus, the exclusive labelling of the endpoints might distort the results such that the participants consider the intermediate options to a lesser extent. In addition, the continuous utilization of this endpoint-labelling format might lead to a so-called common-scale anchor, meaning that the repeated contact with this particular format lowers individual cognitive processing, which might cause respondents to ignore actual item content (Rindfleisch et al., 2008). Apart from this, we use several single-item measures in three different studies (e.g., participants' strategic choice as to whether they accept the proposed product idea or not; Studies 1a/b). However, "the use of single-item measures in academic research is often considered a 'fatal error' in the review process" (Wanous, Reichers, & Hudy, 1997, p. 247) due to producing low levels of reliability. We are aware of this limitation and used single-item measures only when participants had to make a final choice or had to indicate how much they agree with a decision made. Thus, we avoided single-item measures for psychological constructs justifying our procedure.

Third, one can claim that our measure for defensive and cautious decision-making in Study 2 is not fully developed, as indicated by the relatively low reliability level (α = .539). Other than one existing single-item-measure approach (Gigerenzer, 2014) that we find inadequate for a psychological and behavioural construct, there is no established scale available. Thus, we had to develop our own scale by referring to previous literature on defensive behaviour in an organisational setting (Ashforth & Lee, 1990). We used different sophisticated statistical analyses and came up with five items measuring the extent of top executives' defensiveness in the decision-making behaviour. However, future research could use this scale as a starting point to develop a new version that also includes insights from qualitative approaches (e.g., asking executives what they understand by the term "defensive and cautious decision-making" in an expert interview setting, for instance), resulting in a potentially higher reliability score.

Fourth, another limitation of this research lies in the area of ecological rationality. According to the famous social scientist Herbert A. Simon, "human rational behaviour is shaped by a scissors whose blades are the structure of task environments and the computational capabilities of the actor" (1990, p. 7). This is the main idea behind ecological rationality. You always have to consider the environment of your research finding, meaning that it is not acceptable to transfer specific implications into general ones since the environment determines the results. With reference to this, we have to admit that our results are very context-specific. For instance, we found that top managers have a higher tendency to accept recommendations for action in an innovation-management context. However, this does not automatically mean that the same applies for other contexts. Moreover, we found that the perception of Big Data drives top managers to behave less defensively and less cautiously concerning an opening of a new amusement park. This decision situation is artificially created in an experimental setting. Thus, we cannot deduce that Big Data always leads to questionable managerial outcomes – it just depends on the decision context. Future research could investigate whether the perception of Big Data leads to similar results when analysing pricing decisions, for instance.

Fifth, another criticism of our research might relate to the measurement-of-mediation design used in Study 4 (Spencer, Zanna, & Fong, 2005), meaning that the proposed mediator is measured and not experimentally manipulated. Amongst other things, one major drawback is that there is only correlational evidence for having a mediation between the independent and dependent variables. Spencer, Zanna, and Fong (2005) suggest experimentally manipulating the mediation variable instead. We made use of this recommendation in Study 3, showing that top executives with an activated prevention focus are more defensive and cautious (i.e., risk-averse) in their decision behaviour.

Thus, we believe that the simple measurement of participants' regulatory focus is a reasonable approach in Study 4 in order to replicate the results. In addition, we had already manipulated top managers' inherent lay belief "the more, the better" in Study 4. An additional manipulation of the respective situational regulatory focus would have led to a very complex experimental design (2x2x2 between-subjects design), resulting in the need to recruit a substantial number of additional participants.

Lastly, we are aware of a potential omitted-variable bias in our field study causing the problem of endogeneity that affects the significance of the results (e.g., van Heerde, Dekimpe, & Putsis, 2005). While we cannot definitely exclude this phenomenon without conducting highly sophisticated econometric analyses, we included several company-specific control variables (e.g., legal form, etc.) in our general analysis. These covariates did not change the results, and thus we are confident that endogeneity is not a severe problem in our case.

8.5 Future Research Opportunities

The current investigation raises a plethora of additional questions and serves as a starting point for future research. We are aware that there are manifold application areas of Big Data where future research is needed; however, we focus on managerial behaviour and thus remain on a behavioural level.

First, we have shown that the perception of Big Data causes top executives to rely on its recommendations for action in an innovation-management context. In a way, the participants were less willing to contribute their own valuable ideas once confronted with Big Data. In this case, we did not elaborate on the creativity level of each statement because this multidimensional construct is extremely difficult to measure objectively. Thus, it would be interesting to examine whether the perception of Big Data also affects managerial creativity. According to Im and Workman (2004, p. 114), "the ability to generate and market creative ideas in new products (…) and relative marketing programs (…) in response to changing market needs is key to the success of a firm", underlining the strategic importance of this construct. In addition, existing research demonstrates that organisational effectiveness and creativity are positively correlated (Mott, 1972). It seems likely that the perception of Big Data reduces managerial creativity such that top executives exclusively rely on its recommendations without thinking of divergent solutions or approaches. But this divergent thinking is in fact the source of novelty, unusualness, and surprise, resulting in the production of variability (Cropley, 2006). Given the fact that an objective measure of top managers' creativity is hard to find, we encourage future research to address this interdependency.

Second, we used regulatory focus theory (Higgins, 1997) in order to detect a psychological mechanism behind top executives' reliance on Big Data. We chose this theory because it seems to have the strongest impact on organisational behaviour – compared to other theories from social and cognitive psychology (e.g., Higgins & Cornwell, 2016). Even though we expect a weaker influence on managerial decision-making and behaviour, future research could investigate how other constructs from social psychology interact with the perception of Big Data. An interesting starting point would be to observe whether the perception of Big Data induces a feeling of normative organisational commitment (Meyer, Becker, & Vandenberghe, 2004) among executives such that they feel obliged to make use of Big Data in their decision-making processes. Future research could also investigate whether the perception of Big Data leads to a lower perceived self-efficacy, resulting in a higher probability that top managers rely on Big Data's recommendations for action. According to Wood and Bandura (1989, p. 408), "self-efficacy refers to beliefs in one's capabilities to mobilize the motivation, cognitive resources, and courses of action needed to meet given situational demands". Thus, it seems reasonable to assume that the perception of Big Data might lower executives' level of perceived self-efficacy, leading to a higher tendency to accept associated recommendations. Big Data might induce a feeling that one's work and ideas become less relevant and appreciated, which in turn makes a manager increasingly reluctant to contribute his or her own opinion. Along these lines, it would also be interesting to analyse whether there is a difference between top- and lower-level management. A related psychological construct in this case is locus of control, meaning that a human being either perceives outcomes as controllable by one's own actions or as determined by external factors that cannot be controlled (e.g., Rotter, 1966). From this it follows that one could assume that the perception of Big Data reinforces the view that outcomes are determined by non-behavioural factors due to the ubiquitously postulated superiority of Big Data (McAfee & Brynjolfsson, 2012). This might lead to a higher likelihood that managers rely on recommendations for action generated from Big Data. Once again, future research should focus on hierarchy differences (top management vs. lower-level management) in this case.

Third and relatedly, a remaining question is how the perception of Big Data affects decision-making behaviour of lower-level management. We already found that lower-level managers (e.g., marketing/communication managers, etc.) have a lesser tendency to rely on recommendations for action generated from Big Data than do people in top management (e.g., CEO, CMO, etc.). Amongst other things, we explained this phenomenon by stating that lower-level managers might have more time and resources to critically reflect on the term Big Data, and they also are more likely to have to justify decisions. However, we did not analyse whether lower-level managers perceive Big Data as an identity threat, fearing economic rationalisation processes as well as substitution, since employee voices are no longer sought or heard by top management. With reference to this, it would be interesting to examine how the perception of Big Data affects lower-level managers' interaction with top management. One might catalyze an active questioning of the term Big Data by highlighting top management's intuitive potential in order for it to be recognized. In addition, future research could investigate whether the perception of Big Data affects cautious and defensive decision-making among lower-level managers.

Lastly and more generally, we need more context-specific research regarding the influence of Big Data on managerial decision-making. We have demonstrated that top management relies on Big Data in an innovation-management context, which might backfire due to stifling the innovation potential of firms. However, we have not yet analysed other areas and contexts. For instance, future research could elaborate on whether the perception of Big Data also leads to a higher tendency to accept its recommendations for action among top executives when it comes to pricing decisions. The price-management context is especially interesting since it is associated with a high uncertainty due to the potential influence of external events (e.g., fluctuations in commodity prices, etc.). Beyond that, we believe in the meaningfulness of qualitative research because our collective knowledge remains limited about how marketing executives perceive Big Data. Conducting personal expert interviews or focus groups might generate new insights about what is at the top of executives' minds when thinking about and perceiving Big Data. Ultimately, this would make a substantial contribution toward the demystification of Big Data in marketing management.

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Curriculum Vitae

Christoph Wortmann

Personal Information

Date of Birth	30.07.1988
Place of Birth	Lüdenscheid, Germany

Education

2015 – 2018	*University of St. Gallen*, Switzerland Doctoral Studies in Management/ Marketing Advisors: Sven Reinecke und Christian Belz
2012 – 2014	*University of Erlangen-Nuremberg*, Germany Master of Science (M.Sc.) in Marketing Management
2013	*University of Jönköping*, Sweden Master in Marketing, semester abroad
2008 – 2011	*University of Mannheim*, Germany Bachelor of Arts (B.A.) in Political Science

Work Experience

Since 2019	*Swisscom AG*, Switzerland Marketing Manager, Enterprise Customers
2018 – 2019	*Dr. Marc Rutschmann AG*, Switzerland Consultant
2015 – 2018	*University of St. Gallen – Institute of Marketing*, Switzerland Research Associate