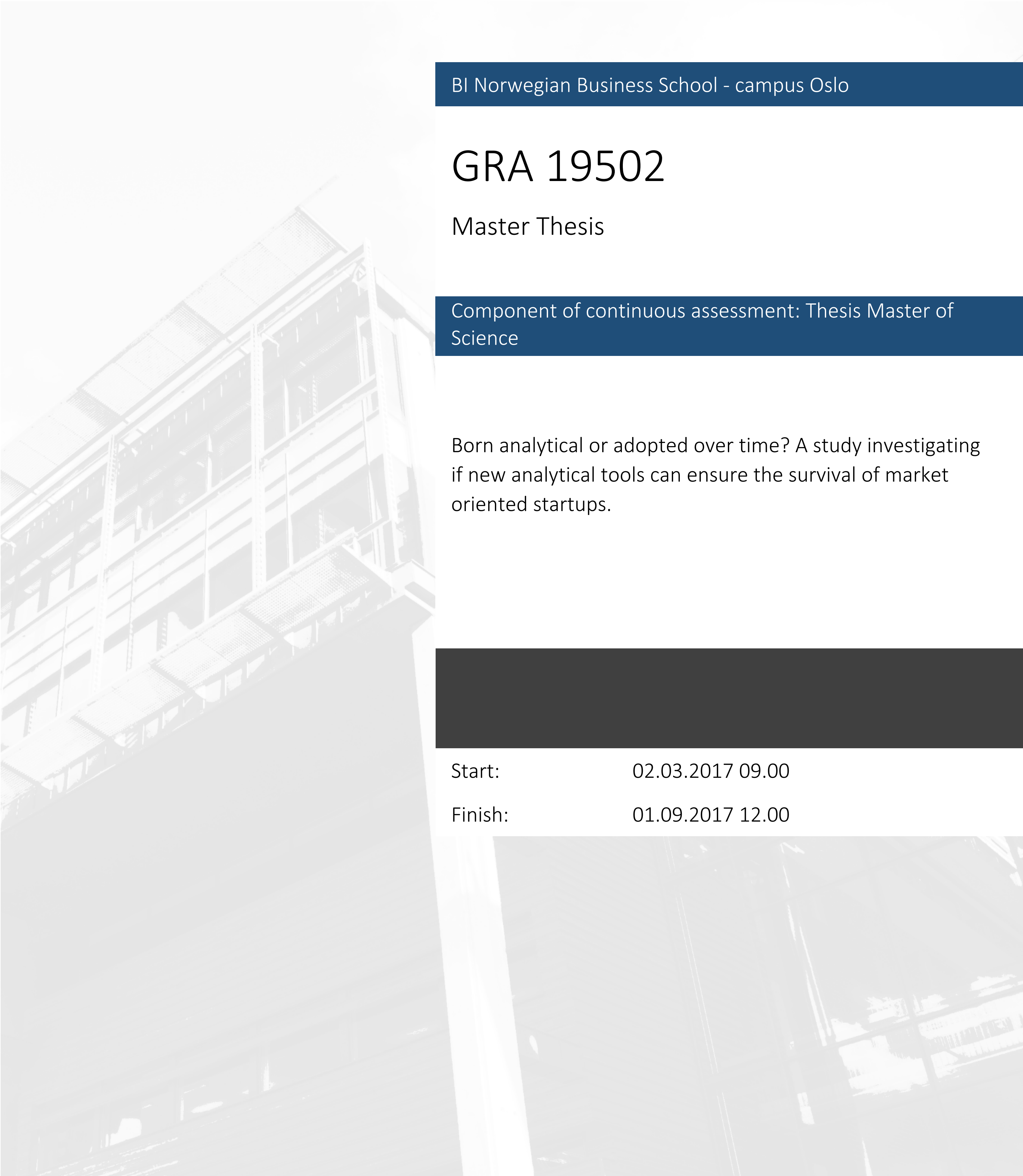

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Master Thesis

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Born analytical or adopted over time? A study investigating if new analytical tools can ensure the survival of market oriented startups.

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Preface

This thesis is the final project of our MSc degree in Strategic Marketing Management at BI Norwegian Business School. The last two years have been a long journey, involving heavy workloads and many long nights. The journey has demanded a lot from us and our fellow classmates. Nevertheless, the tougher the process, the more rewarding the result – and we are very happy with the skills and knowledge we have obtained.

This final project would not have been the same without the support of several people around us. We would like to acknowledge our family and friends who have kept our motivation up through the last two years, in particularly the final eight months. Big thanks are due to the academic staff at BI for providing us with ability and knowledge to perform this study, and thanks to the companies who answered our survey. Finally, our biggest gratitude goes to our supervisor Auke Hunneman for his guidance and steady support throughout this process. Thank you for your patience and enabling us to pull this project ashore.

Abstract

This study investigates whether the prevalence of technological advances within quantitative analytics moderates the effect market orientation has on firm performance, and if startups can take advantage of the potential opportunities to ensure their own survival. For this purpose, the authors review previous literature in marketing orientation, startups, marketing analytics, and firm performance. These four bodies of literature are discussed and combined to design the current study. By gathering quantitative data from startups across Scandinavia, the authors find that the level of market orientation does not have a significant impact on startup's performance in terms of profit, sales growth, nor return on investment. Additionally, the effect is not moderated by digital analytics. In fact, the authors find no evidence of varying levels of market orientation between industries, firm size or firm age, leading to the assumption that startups have not had enough time to truly implement or reap the benefits of market orientation. This can be explained by the short lifetime of startups, both in terms of short time scope and a lagged effect. As the success of startups is important for the modern economy, this study is important for startups as a support to battle the high odds of startup failure, and in turn help economic growth.

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Introduction

Starting a new business is associated with high risks (Baum, Calabrese and Silverman, 2000; McGrath, 1999), with failure rates up to 90% (Furr and Ahlstrom, 2011, p. 9). To battle the odds, it is crucial that academic researchers provide assistance by exploring how startups can survive (Audretsch and Acs, 1994). Decades ago, Schumpeter described startups and entrepreneurial ventures as *"the fundamental engine that sets and keeps the capitalist engine in motion"* (Schumpeter, 1942, p. 83). Scholars have since identified startups as the cornerstone of our economy (Henderson, 2002), both in terms of job creation and productivity growth (Decker et. al, 2014). Thus, helping new ventures succeed is essential for the growth of today's economy (Audretsch and Thurik, 2001; Wennekers and Thurik, 1999). In this study, the authors are on a quest to discover new ways for startups to increase their likelihood of success. The academic contribution in this study is based on an approach to startup survival which stands out from the current literature on the topic, and the inclusion of new technological advances.

Scholars have identified many factors that are essential for startups survival, e.g. a clear business idea and strategy (Chrisman, Bauerschmidt and Hofer, 1998; Sandberg and Hofer, 1987; Van de Ven, Hudson and Schroeder, 1984), market intelligence (Hills, 1984; Song, Wang and Parry, 2010), legitimacy and social status (Shepherd, Douglas and Shanley, 2000; Zimmerman and Zeits, 2002), and team dynamics (Amason, Shrader, Tompson, 2006; Lechler, 2001). According to Gartner, there is no clear-cut answer to what influence the survival and performance of startups, due to a myriad of different success factors (Gartner, 1985; Miller and Friesen, 1984). Trying to accommodate each one individually would be too time- and resource demanding for a startup. Market orientation, a concept popularized by Narver and Slater (1990), and Kohli and Jaworksi (1990), concerns the extent to which a firm gathers, analyzes and utilizes information about their external environment when making strategic decisions. The authors of this study argues that the concept covers many of the factors contributing to the success of new ventures. This is backed up by the fact that market orientation has been proven to have positive effect on both small and large firms (Agarwal, Krishna Erramilli and Dev, 2003; Han, Kim and Srivastava 1998; Hult, Ketchen and Slater, 2005; Kohli and Jaworski, 1990, 1993; Narver and Slater 1990, 1994, 1995; Pelham, 2000). The unique approach stem from this concept; instead of looking at individual success factors, this study embrace a whole concept which may potentially provide several of the important aspects necessary to survive.

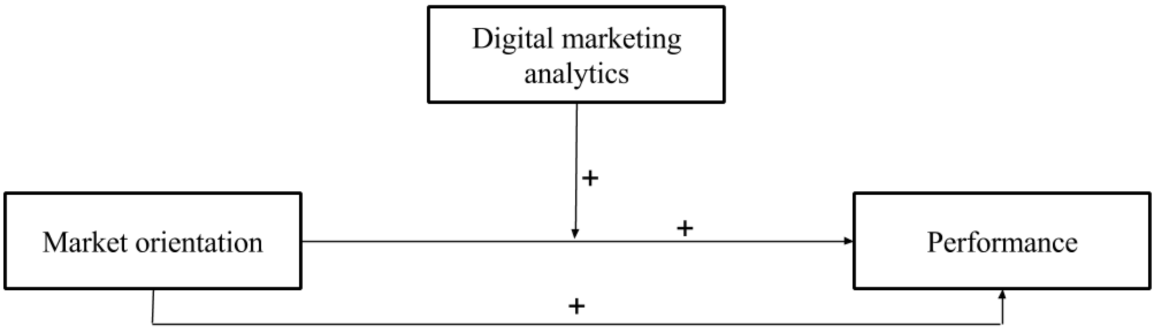
Market orientation is especially interesting in this time and age, due to the vast possibilities made available by technological advancements. Most of the existing research on market orientation was conducted before the digital revolution. Many firms have recognized the key competitive advantages that the digitalization and related technology may provide, which have fueled the development and deployment of digital tools (Davenport, 2006), e.g. the emergence of e-commerce. The technology has made information more readily available, and presents many opportunities in marketing analytics and big data analytics by enabling continuous data collection and advanced processing. In line with this development, it is likely that digital analytics will become an increasingly important tool for businesses to make better, more informed decisions. Scholars have found a positive effect of digital analytics capabilities on firm performance (Germann, Lilien and Rangaswamy, 2013; Wedel and Kannan, 2016; Xu, Frankwick and Ramirez, 2016). The advancements have made market orientation even more relevant today. Greater access to information on consumers and competitors makes the concept more achievable. With additional tools in their arsenal, marketers should be able to fulfil the criteria of market orientation with greater ease.

Research question and scope

An extensive discussion on market orientation has been going on for decades, but drastic changes in the market place make it necessary to renew and re-test many of the previous assumptions. In this paper, the authors investigate to what extent market orientation affects success in new ventures. This study is also designed to contribute with academic evidence on how new technological advances have influenced the effect of market orientation. The objective of this paper is to answer the following research question:

In what way does market orientation influence performance in startups, and how is this relationship affected by the opportunities within digital analytics?

The research question is visually presented in a simplified conceptual model below (see model 1). To find answers, we study the existing literature on multiple fields; market orientation, marketing analytics, startups/new ventures, and business performance. After a thorough review of the current findings, assumptions, and research practices in the respective fields, an extended conceptual model is presented (see model 2).



Model 1: A simplified conceptual model.

Quantitative data has been gathered from 90 startups across Scandinavia. To test our hypotheses, multiple linear regression was performed to identify the significance and strength of the hypothesized relationships. Additionally, the data was analyzed with a one-way ANOVA test to identify significant differences between variables such as firm size, age, and industry.

By answering the research question, the authors hope to add depth to the discussion of market orientation, and the role of digital analytics. The authors also want to investigate if startups can improve their chance of survival by embracing the market orientation concept.

Literature review

There are currently no previous research tying startups, market orientation and digital marketing analytics together. However, there is sufficient research on all three fields which can be combined to provide guidelines on how to investigate the interaction between the three. Market orientation has been proven to improve chance of success in mature firms (Deshpandé, Farley and Webster Jr., 1993; Han, Kim and Srivastava, 1998; Jaworski and Kohli, 1993; Slater and Narver, 1994), and there is reason to believe that digital marketing analytics enhance this effect.

It is interesting to investigate this topic in the light of startups for a number of reasons which we will discuss in the following literature review. Furthermore, the review also contains conceptualization and definitions of the concepts used in this study, and discussion on relevant findings across bodies of literature.

Market orientation and startups

Market orientation is widely discussed in academic literature and is a construct that researchers have looked at from many angles. Scholars mostly agree on the main aspects of market orientation, many of which were first found and highlighted by Narver and Slater, and Kohli and Jaworski in the early 90's. Market orientation is a concept that embraces how a firm monitors, analyzes and proactively responds to the entire environment in which it operates (Kohli, Jaworski and Sahay, 2000; Slater and Narver, 1998, 1999; Narver, Slater and MacLachlan, 2004). The concept involves the customers and their current needs, but also the actions and the anticipated actions of the customers, competitors, new technology, government regulation, trends, and the customers' latent needs (Kohli and Jaworski, 1990, 1993; Narver and Slater, 1990, 1994, 1995, 1998). The two most widely accepted definitions of the term, are presented by Narver and Slater and Jaworski and Kohli:

"The organizational culture that most effectively and efficiently creates the necessary behaviors for the creation of superior value for buyers and, thus, continuous superior performance for the business."
Narver and Slater (1990, p.21)

"*Market orientation is the organizationwide generation of market intelligence pertaining to current and future customer needs, dissemination of the intelligence across departments, and organizationwide responsiveness to it"*
Jaworski and Kohli (1990, p. 6)

Market orientation has been identified as a prominent variable affecting performance positively in both small and large firms (Agarwal, Krishna Erramilli and Dev, 2003; Han, Kim and Srivastava, 1998; Hult, Ketchen and Slater, 2005; Kirca, Jayachandran and Bearden, 2005; Appiah-Adu, 1998; Baker and Sinkula, 2009; Pelham, 2000; Pelham, and Wilson 1995). Previous literature confirms that both large and small firms can increase their performance by being market oriented. However, there is still one type of firm that has not yet received much attention in this regard - startups. The role of market orientation in new ventures is a topic that is largely un-covered by the current body of literature. It seems that scholars, especially in the marketing field, have been satisfied with researching small firms and not specifically looking into startups. This might be due to difficulties with scale development and measurement, which will be discussed more thoroughly in the methodology section of this paper. We argue that even if startups almost exclusively belong to the category ‘small firms’, it does not necessarily mean that the studies and theories of small firms can be generalized to startups.

Market orientation is a complex construct, and scholars have divided it into more comprehensive components. Jaworski and Kohli (1990) divide the construct into intelligence generation, intelligence dissemination, and responsiveness. Jaworksi and Kohli (1990, 1993) focus on the behavioral aspect and argue that market orientation is the sum of a set of organizational behaviors, and that it can be measured on a continuum, meaning there can be several degrees of market orientation. Their focus on organizational behavior is more relevant for young companies as they are still in the process of creating and implementing their culture. Therefore, for the purpose of this study, the definition by Jaworski and Kohli is found to be more suitable. Also, Jaworski and Kohli’s definition includes the latent needs of the customer, not only the current needs. They focus on the firm’s ability to put the customer first, and make decisions based on what their customers want and need, as well as what they might want and need in the future (Deshpandé, Farley and Webster, 1993; Jaworski and Kohli, 1990; Narver and Slater, 1990). This is also in the very center of the entrepreneurial spirit. Narver and Slater (1990) called this component ‘customer orientation’, highlighting the importance of having the best possible understanding of the customers and their needs. To obtain such an understanding of their target customer, the firm must actively collect and disseminate data about them (Kohli and Jaworski, 1990; Harrison-Walker, 2001). The customer orientation component is prominent because a firm’s ability to satisfy customer needs is proven to increase profitability (Anderson, Fornell and Lehmann, 1994). In today’s quick-paced consumer markets, subject to rapid technological advances, customer insight is an important aspect of market orientation, especially for young firms trying to gain afoothold in the market. Finally, Jaworski and Kohli's interpretation is equally concerned with informal contact as well as formal contact. In small firms like startups, which often work in co-working spaces and networks, informal contact is an important element.

Market orientation is a construct that has continued to evolve in the past decades. With a growing body of literature in which the concept has been continuously studied and debated, new developments change how businesses can implement or induce their market orientation. Examples of this evolution include a focus on marketing capabilities (Day, 1994a; Morgan, Vorhies and Mason, 2009), a focus on innovativeness (Han, Kim and Srivastava, 1998; Hurley and Hult, 1998; Keskin, 2006) or new technology like cloud computing (Buyya, Yeo and Venugopal, 2008). Digital marketing analytics may be a new step in the evolution of marketing orientation.

The digital revolution

Given the technological advancements that have taken place in recent years, and the amount of market data that has been made available, market orientation can and should be discussed in conjunction with a firm's use of analytical tools. The digital revolution and availability of data represents a new development in this regard. The availability of information has increased, in addition to the velocity – the firms no longer get one-time snapshots of the market, but high-frequency, real-time data (Xu, Frankwick and Ramirez, 2016). To stay competitive in today's marketplace, firms must embrace the latest technology to be able to provide the best products or services to the customers (Misra and Mondal, 2011).

We refer to this latest development in marketing analytics as *digital marketing analytics* and define it as: "Quantitative analysis of customer or market data, performed with the help of digital tools and utilized to make marketing-related decisions". With this definition, we want to capture the possibility to collect huge amounts of data with digital tools, and transform it into useful insights about the market. To avoid confusion, note that this definition does not only involve analysis of output from digital marketing, but all marketing analysis performed with digital tools.

More frequent introductions of new technology, higher expectations from customers, and increased competition, mean that the companies must acquire and analyze data at a higher pace and on a more complex level than before (Xu, Frankwick and Ramirez, 2016). These conditions result in a widening gap between the complexity of the market and the company's ability to respond (Day, 2011). To close the gap, two essential capabilities are vigilant market learning and market insight (Day, 2011), both of which are obtainable through digital marketing analytics. This makes digital marketing analytics a useful tool in today's marketing environment (Germann, Lilien and Rangaswamy, 2013; Xu, Frankwick and Ramirez, 2016).

An interesting aspect of digital marketing analytics is that managers sometimes struggle with the realization of possible gains from analytical tools (Germann et al., 2014), making them experience inertia or even resistance to adopt such tools (Germann, Lilien and Rangaswamy, 2013). This may be costly for the firm (Day, 2011; Kayande et al., 2009). German et al. (2014) encountered the same phenomenon when they studied the deployment of customer analytics in the retailing business. The fact that managers are generally slow to adopt new methods and techniques is not a new issue. John Little described this phenomenon nearly 50 years ago: *"The big problem with ... models is that managers practically never use them. There have been a few applications, of course, but the practice is a pallid picture of the promise"* (Little, 1970, p. 466). The result of this study, and others like it, can help practitioners overcome the inertia.

From the previous body of literature, we identify three mechanisms for why capabilities in digital marketing analytics enhances the effect of market orientation on performance. The first mechanism is simply about the availability and speed of data that is associated with digital marketing analytics (Moniruzzaman and Hossain, 2013; Xu, Frankwick and Ramirez, 2016). While market orientation is essentially about how well a firm collects, disseminates and utilizes information about the market (Jaworski and Kohli, 1993), more available data and efficient internal processes makes market orientation more easily obtained. Thus, it is likely that the ability to acquire and use this data (i.e.

capabilities in digital marketing analytics) is connected to market orientation in firms.

The second mechanism is that the availability of digital marketing analytics can be an antecedent to a data-driven decision culture in a company (Wedel and Kannan, 2016), i.e. the employees embrace a mindset of basing decisions on statistical evidence. Down the line, we find that a culture where decisions are driven by data may lead to increased productivity and performance (Brynjolfsson, Hitt and Kim, 2011; Davenport, 2006; Wedel and Kannan, 2016). Having a culture that is supportive of market analytics is also essential to enable the company to realize its potential benefits (Germann, Lilien and Rangaswamy, 2013). However, there is currently no blueprint on how managers should develop their firm and implement the necessary skills and procedures to compete in this new data analytic environment (Wedel and Kannan, 2016). As we argue that startups should have fewer barriers to implement market orientation, the same principle applies to a data-driven decision culture (Wedel and Kannan, 2016). In the implementation phase, startups also have the possibility to leapfrog their advances by learning from their mistakes and implement even better processes and systems (Shepherd, Ettenson Crouch, 2000; Yim, 2008).

A third mechanism is a better understanding of the marketing-mix through digital marketing analytics. Scholars have made a connection between market analytics and the marketing-mix, claiming that analytics can give managers a better understanding of and ability to forecast the effects of marketing-mix (Albers, 2012; Fan, Lau and Zhao, 2015; Wedel and Kannan, 2016). In environments where data on consumers, competitors, and the market are increasingly available, additional tools to better understand both internal and external factors will also surface (Albers, 2012), i.e. more data means more knowledge of the market, depending on the company’s ability to utilize the information through analytics. This can for example make it possible to measure a firm's performance while controlling for trends, competitors and other external drivers. It will also give marketers a better understanding of the marketing-mix and the effect each component has on performance. This can be extremely useful when allocating resources across different products, segments and promotion (Albers, 2012; Wedel and Kannan 2016).

Startups' success

It is not easy for a firm to enter a new market (Lambkin, 1988), and the odds of success decrease drastically when the firm is recently established (Stinchcombe, 1965, p. 148). In the literature on startups, many scholars have weighed in on which factors it is that constitute the greatest threats to young firms, and how to ensure their survival. Three reoccurring themes are the liability of newness, liability of smallness, and the liability of adolescence.

Stinchcombe (1965, p. 148) argues that the liability of newness is present in startups because of two conditions. The first condition is the lack of system, unfamiliar roles and relationships internally. The second condition is the lack of relationship with the customers and suppliers, i.e. the external market. Liability of newness has been found to have significant negative impact on the survival rate of a startup (Freeman, Carrol and Hannan, 1983; Singh, Tucker and House, 1986; Stinchcombe, 1965, p. 184). However, some scholars challenge this interpretation, arguing that size is the determining factor, introducing liability of smallness (Aldrich and Auster, 1986; Bruderl and Schussler, 1990). Liability of adolescence is closely tied to the argument of smallness, and presents a pattern where the risk of failure is shaped like an inverted U. The theory states that chances of survival are higher for startups in the first year, as performance is closely monitored, and that the risk of death is higher between firm age 1 to 15 (Bruderl and Schussler, 1990; Kale and Arditi, 1998). Common for the liability of newness, smallness, or adolescence, is they all assume lack of internal structure (Larson, 1992), uncertainty about one's own product (Hannan and Freeman, 1984; Shepherd, Douglas and Shanley, 2000), and a lack of awareness in the market (Duchesneau and Gartner, 1990; Shepherd, Douglas and Shanley, 2000). Furthermore, they all have similar consequences; increased risk of failure.

There are ways to battle these liabilities. Baum, Calabrese and Silverman (2000) recommend that new ventures create alliances and networks to gain access to necessary resources, and to maximize learning opportunities. This practice is widely adopted in the real world, as networks, accelerators and incubators have become an integrated part of the startup scene in all major cities. Investing in human and social capital has also been found to improve startup survival rate (Bosma et al, 2004). Additionally, performing activities that enhance the reliability and accountability of the firm have been proven effective (Delmar and Shane, 2004; Hannan and Freeman, 1984), as well as activities to establish relationships with retailers and customers (Delmar and Shane, 2004; Stinchcombe, 1965, p. 148; Stuart, Hoang and Hybels, 1999). These success factors can be tied together in one concept, namely market orientation.

In this study, the authors present market orientation as an unexplored alternative to battle these liabilities. We argue that market orientation is a concept that addresses several of the issues laid out for startups, including the lack of system, relationships, awareness in and of the market, and internal structure. One argument of why market orientation should be a successful strategy for startups is the lack of an existing culture. Due to its young age, it is less likely to have an ingrained organizational culture. For mature firms, barriers of changing organizational cultures are often intertwined with the existing culture (Bass and Avolio, 1994; Cameron and Quinn, 2005). Without these barriers, it will be easier for startups to adjust to changes (Homburg and Pflesser, 2000). Implementing market orientation can be a difficult and resource demanding process (Bisp, 1999; Greenley, 1995), demanding dramatic changes in the company culture (Gebhardt, Carpenter and Sherry, 2006). In this regard, a startup might obtain advantages, in comparison with their mature counterparts, and be able to enjoy short term rewards without heavily investing time and money in the process of implementation. Additionally, the small size of startup may enhance the effect of market orientation as it should be present though the whole organization (Kohli and Jaworski, 1990, 1993; Narver and Slater, 1990, 1994).

A market-orientated culture with data-driven decision-making can also provide startups with a sound tool to battle liability of newness, smallness or adolescence. Market orientation provides firms with an organizational behavior and culture (Gainer and Padanyi, 2005; Slater and Narver, 1995), where the employees can find their roles. According to Stinchcombe (1965, p. 148) this is essential to reduce the liability of newness. Moreover, it may give an edge in market intelligence (Jaworski and Kohli, 1993), making it easier to allocate resources to the right areas and creating the necessary relationships; another step in combating the liabilities a startup faces (Delmar and Shane, 2004; Stinchcombe, 1965, p.

148; Stuart, Hoang and Hybels, 1999). By nullifying the typical hazards of a startup, the employee can focus on activities driving performance.

The understanding market oriented firms gets of the market is essential in the early phases of their life cycle (Anderson and Zeithaml, 1984). Firms that collect and utilize market intelligence is aware of their customers' needs and its competitive environment, and are also equipped to act upon the information (Kohli and Jaworski, 1990). Thus, it is expected that startups that monitor their current and potential competitors will perform better than those who do not. The effect may even be more prominent for startups as interfunctional coordination is deemed important for market orientation to be effective (Kohli and Jaworski, 1990, 1993; Narver and Slater, 1990, 1994). Smaller firms mean less friction when coordinating between employees and functions, which possibly maximizes the effect. The use of digital marketing analytics will also provide entrepreneurs with a better understanding of the marketing mix (Albers, 2012; Fan, Lau and Zhao, 2015; Wedel and Kannan, 2016), providing further support in how to allocate scare resources, and help provide better products and services to the market (Misra and Mondal, 2011). Additionally, market orientation has been found to be more decisive in volatile markets (Atuahene-Gima, 1995; Kohli and Jaworski, 1990), which often is characteristic of the environment startups operate in.

Hypotheses

By creating a strong organizational culture (Gainer and Padanyi, 2005; Slater and Narver, 1995), providing superior market intelligence (Kohli and Jaworski, 1990, 1993), and increasing the ability to communicate and build relationships with external shareholders (Reid, Luxton and Mavondo, 2005), the assumption is that market orientation can help startups battle the initial liabilities of young firms and increase their performance. We derive the following hypothesis;

H1: A high level of market orientation has a positive effect on the business performance in a startup.

Furthermore, previous research has pointed to several arguments that lead us to hypothesize that the effect market orientation has on success, will be enhanced by the deployment of digital marketing analytics. As argued above, digital marketing analytics makes data more available, and at greater speed (Xu, Frankwick and Ramirez, 2016), it can provide a stronger data-driven decision culture (Wedel and Kannan, 2016), and it gives a better understanding of the marketing mix (Albers, 2012; Fan, Lau and Zhao, 2015; Wedel and Kannan, 2016).Thus;

H2: The level of digital marketing analytics performed, influences positively the effect of market orientation on business performance in a startup.

The ambiguity of market orientation

Although the current body of literature mostly agree that market orientation has a positive impact on firm performance, the authors are well aware of contradictive findings and critique that have amassed over the years. The evidence in the early literature on market orientation, establishing the general assumptions, was mostly based on samples of classic manufacturing and service firms (Jaworski and Kohli, 1990, Kohli and Jaworski, 1993; Narver and Slater, 1990; Slater and Narver, 1994). The change in customer demand and competitive dynamics over the last few years has made it reasonable to question the current validity of the theory of market orientation.

After the explosive development of the internet industry, researchers have found no relationship between performance for firms in this industry, and market orientation (Perry and Shao, 2002). A longitudinal study of highly competitive industries found that only competitor orientation was significant for performance (Noble, Sinhar and Kumar, 2002). In markets with rapid technological change, often driven by high competition, market orientation has also been found not to provide any advantages (Greenley, 1995). These findings are direct contradictions to Jaworski and Kohli (1993) and Slater and Narver (1994), who all found no effect of competitive intensity and technological turbulence on the market orientation/performance association.

In addition to competition, other conditions have also been found to influence the relationship between market orientation and performance, supporting the findings of an ambiguous relationship and challenging the established assumptions. Looking closer at market orientation and innovation in general, Christensen and Bower (1996) found that market orientation can impede a company’s ability to innovate, which in turn can have a devastating effect on performance (Han, Kim and Srivastava, 1998; Kirca, Jayachandran and Bearden, 2005). The study argues that a strong market orientation makes firms too focused on pleasing their current customers. In the process, they fail to come up with disruptive innovations for future markets and potential customers, and can lose their position in the market (Christensen and Bower, 1996). Several other studies identify different conditions that influence the impact of market orientation, such as consumer power (Greenley, 1995), market turbulence and competitive intensity (Atuahene-Gima, 1995, Harris, 2001; Greenley, 1995), and uncertainty (Bhuian, Menguc and Bell, 2005).

Additional questions have been raised related to methods of measurement when studying market orientation. The use of subjective measures versus objective measures has proven to produce different effects. Harris (2001) specifically studied the differences in the relationship between market orientation and objective versus subjective measures of performance. The results show that market orientation is related to performance in an extended degree when subjective measures were used. Interestingly, this is aligned with the findings of Jaworksi and Kohli (1993) themselves. They only observed a relationship between market orientation and performance when using subjective performance measures, but not when using the objective measure market share. The same pattern followed in a study by Pelham and Wilson (1995) where market orientation was found to be linked to a subjective measure of performance, but not to an objective measure.

The vast variation in findings across studies indicates that market orientation is a complicated construct and the measured effect vary with external environments, types of variables included, and how different factors are measured.

Methodology

In defining our constructs, there are two specific areas that have been particularly challenging, that is how to define startups and how to measure their performance. In the following chapter, additional emphasis has been placed on explaining the rationale for the chosen definitions, and the scales of measurement.

Sample

There is no commonly accepted definition of ‘startup’ that two entrepreneurs/investors/scholars can agree on. The definition can be broad, like in the dictionary: *“The action or process of setting something in motion”*, or it can be narrowed down, determined by characteristics like age, profitability, stability, number of employees or growth. The difficulties lie with the range of characteristics that can define a startup and how these characteristics should be weighted relative to each other. The problem with defining startups based on specific criteria is that the strict criteria’s does not apply to all cases. Taking Uber as an example, in 2016 the company was six years old, well within what is reasonable to define as a startup (McDougall and Oviatt, 1996), but with a valuation of about $62.5 billion – far more than what can be characterized as a startup and potentially a source of increased error variance or biases (Rasmussen, 1988; Zimmerman, 1994).

One of the most common ways to define new ventures is to rely on subjective criteria, and let them define themselves, or be defined by their peers. Several studies are based on samples pulled out of various databases with registered startups (Chang, 2004; Davila, Foster and Gupta, 2003; Ensley, Hmielski and Pearce, 2006) or companies that are members of startup networks (Bruton and Rubanik, 2002). Thus, our sample is chosen based on their membership/listing in certain startup networks and/or affiliation with other relevant organizations in Scandinavia, and most importantly; if they identify themselves as a startup. This ensures a more dynamic approach which takes into consideration the startup’s characteristics relative to each other. Among the networks and organizations, we find incubators that offer office space and general support, entrepreneurial networks, recruitment websites specifically for startups, lists of startups for prospective investors and prototype workshops. By pulling companies from such lists, the startup community has predefined which companies belong to the network and can be defined as a startup.

How to obtain the data on startups also provided a challenge. Non-standardized record keeping, lack of historical information, source biases, and the lack of proper standard accounting-based measures make obtaining the data difficult (Dess and Robinson, 1984; Sapienza, Smith and Gannon, 1988). A meta-analysis containing 34 empirical studies, find that most studies measuring startups' performance draw their information from only one source; manager, founders or owners (Brush and Vanderwerf 1992). The same meta-analysis also concludes that this source is highly reliable. Thus, to obtain information on startups, we contacted the founders/managers of the startups and relied on subjective self-reporting.

Measurements

Business performance

In general, measuring the performance of organizations is a complex task (Lenz 1981), there are many variables that could and should be considered. Over the years, researchers have found some common grounds on how to measure this elusive metric with objective (Eccles and Pyburn, 1992; Jacobson, 1987) or subjective measures (Dess and Robinson, 1984). Measuring the performance and success of a startup is even more complicated. Taking into consideration the survival rate of startups, merely staying in business can be considered a success. As with the definition of startups, there are no commonly accepted performance variables or methods used to measure the success of a new venture (Biggadike, 1979). Across 34 empirical studies on the subject, 35 different measurements of performance were used (Brush and Vanderwerf, 1992).

As discussed earlier, obtaining data on startups is challenging due to elements like source bias, lack of historical information and lack of proper standard accounting-based measures (Dess and Robinson, 1984; Sapienza, Smith and Gannon, 1988). Therefore, the use of multiple measures of success is advised. A single measure can be vulnerable to errors like memory problems of the founder/manager, or reporting bias (e.g. social desirability bias) (von Gelderen, Frese and Thurik, 2000). To properly assess the overall business performance, Behn (2003) recommends using several measures, but also to thoroughly evaluate the validity of the chosen measurements. To be able to identify the high performers from the low performers, we have reviewed earlier work to find measurements that are suitable for our purpose.

A study of the relevance, reliability (i.e. internal consistency and inter-rater reliability), and external validity of measurement approaches of performance in startups, found that using growth measures (i.e. perceived growth in market share, change in cash flow, and sales growth) and business volume (i.e. earnings, sales, and net worth) are highly favorable (Chandler and Hanks, 1993). The meta-analysis by Brush and Vanderwerf (1992) identified measurements that were used more frequently than others. Aligned with the findings of Chandler and Hanks (1993), two of the most popular measures are growth in sales and profitability (by Brush and Vanderwerf, 1992). Additionally, return of investments have also been found to be a reliable measurement of performance in startups (Biggadike, 1979; Tsai, MacMillan and Low, 1991). These three metrics are also widely used in more recent research (see table 1).

Measurement of performance	**Studies**
Profitability	Amason, Shrader and Tompson, 2006 Bosma et. al., 2004 Ensley and Pearce, 2001 Jo and Lee, 1996 Robinson and McDougall, 2001 von Gelderen, Frese and Thurik, 2000
Growth in sales	Alsos, Isaksen and Ljunggren, 2006 Amason, Shrader and Thompson, 2006 Ensley, Hmielski and Pearce, 2006 Gilbert, McDougall and Audretsch, 2006 Peters and Brush, 1996 Robinson and McDougall, 2001 Zimmerman and Zeitz, 2002
Return on investment	Li and Zhang, 2007 McDougall and Oviatt, 1996 Reid and Smith, 2000 Robinson, 1999 Wu, 2007

Table 1: The use of profitability and sales growth as measurement of performance in startups.

For startups, profit can be an unreliable measurement of performance - strong profitability might not be an important goal for a startup, depending on its current situation (McDougall and Oviatt, 1996). Furthermore, profit might be misleading as startups initial investments (sunk cost) must be earned back (Bosma et. al, 2004; Zahra, 1996). Also, the time it takes to develop a product or service may vary depending on industry, which greatly affects the sales growth (Gilbert, McDougall and Audretsch, 2006). Taking these caveats into account, we ask our respondents for a subjective evaluation of the chosen performance measurements, relative to their competitors.

Market orientation

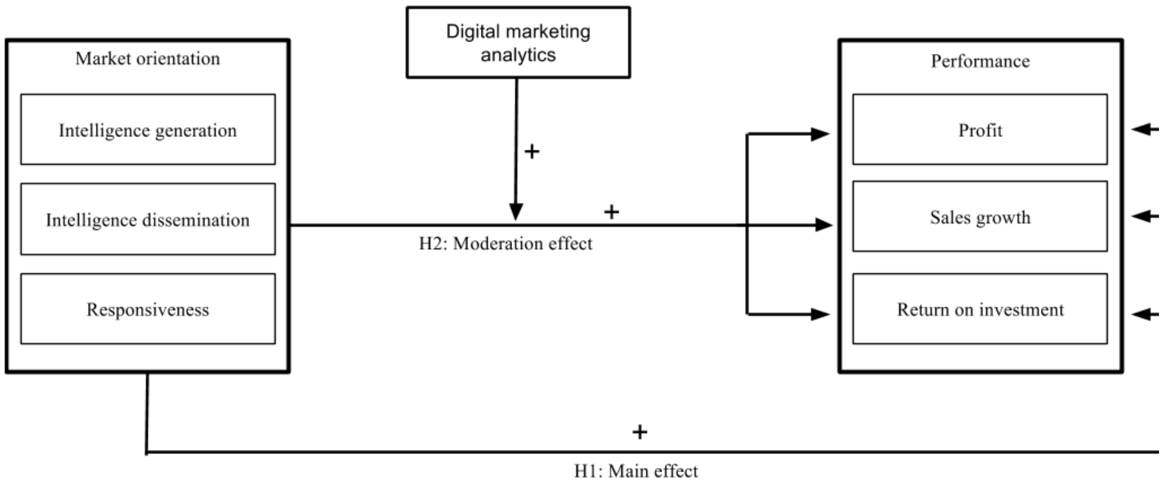
To measure market orientation, we draw on the acknowledged work of Jaworski and Kohli (1993). They developed a scale measuring market orientation consisting of 31 items. These items are set to measure three concepts within market orientation, in accordance with their definition; market intelligence generation, market intelligence dissemination, and responsiveness. The latter was divided into two sub-categories; response design and response implementation. The items had to be adapted to our purpose. In the process, one item concerning reaction to competitor price changes was found irrelevant for some types of startups, and was dropped. This resulted in a 30-item scale to measure market orientation in which 10 of the items are directed at market intelligence generation, 7 items for intelligence dissemination, and 13 to measure responsiveness (6 for design and 7 for implementation). To avoid response set bias, 13 of the items were reverse-scored.

Digital marketing analytics

With the introduction of new technology, digital marketing analytics emerged rather recently. As a result, the body of literature within this specific topic is still underdeveloped. The scale items measuring the digital marketing analytics constructs have been drawn from research on capabilities attitudes toward marketing analytics in general. Some of these studies pursue a capability-based approach (e.g. Germann et. al, 2014; Germann, Lilien, and Rangaswamy 2013; LaValle et. al, 2010). According to the resource-based view, internal resources and capabilities can provide important competitive advantages (Barney, 1991). Exploring such capabilities might give us an insight in how digital marketing analytics affects performance of the company. The digital marketing analytics construct in this study is measured by a 12-item scale and is focused on capabilities and attitudes toward digital marketing analytics. Some alterations have been made to the items to properly measure the construct.

Conceptual model

Based on the conceptualizations, and the respective scales of measurements, the full conceptual model is presented below:



Model 2: Full conceptual model.

Control variables

In this study, we have included a set of variables to control for as much of the variation in performance as possible. Controlling for the correct variables is critical when trying to understand the nature of startups (Murphy, Trailer and Hill, 1996). The same article recommends controlling for firm age, size, and industry. In addition, we control for social desirability bias due to our subjective performance measures.

Firm age and size

As most startups are young and have few employees, these variables are especially important to control for as minor differences between startups can be very influential. In this study, firm size is determined by the number of employees. Age is counted from the year the company was established. All respondents are required to answer these two demographical questions to complete the survey.

Industry

Different industries experience different conditions, e.g. level of competition and resource availability. Thus, it is important to control for the industry to which the startups belong. The startups will be divided into categories representing different industries. The categories are based on an industry classification taxonomy launched by Dow Jones and FTSE Group in 2005, the Industry Classification Benchmark (ICB) (FTSE Group 2012). To ensure the fit with this particular classification taxonomy, the categorization will be performed manually by the authors.

Social desirability bias

We chose subjective performance measure as they have been found to have a stronger relationship with market orientation. By choosing this type of measurement, the study is particularly prone to social desirability bias (Dess and Robinson, 1984; Sapienza, Smith and Gannon 1988; von Gelderen, Frese and Thurik 2000), making it even more important to control for this. To counter for the potential desirability bias, we include the agents' socially desirable responding (ASDR) scale in our survey. The scale was developed specifically to reveal social desirability bias in responses to subjective performance measures (Manning, Bearden and Tian, 2009). The scale has previously been used as a control variable in a study examining the relationship between subjective performance measures of market orientation, providing support for the scale's nomological validity and usefulness (Kirca, Jayachandran and Bearden 2005).

The ASDR scale consists of 8-items measured on a 7-point Likert scale, ranging from strongly agree to strongly disagree.

Pretest

To ensure the preciseness and appropriateness of the items, the questionnaire was pretested. We asked five entrepreneurs, and relevant professionals and experts, to complete the questionnaire and report back on any difficulties. Some items were reported to be ambiguous or irrelevant. These items were either removed or modified.

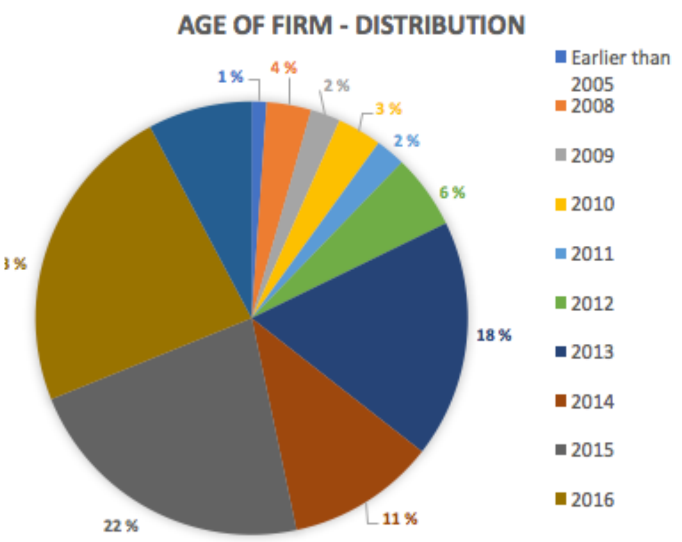
Data and data refinement

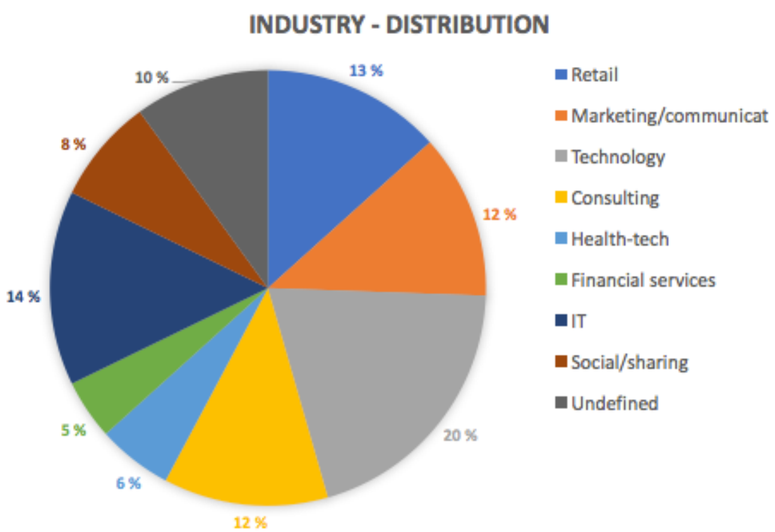
The survey (appendix 1) was distributed directly to 825 startups by email. Most of the companies are located in Norway, Sweden and Denmark, while a few have moved their offices to the U.S. Out of the 825 startups reached, we obtained 103 completed questionnaires, i.e. a response rate of 12,5%. A low response rate was not surprising but it is important to note that it might lead to a non-response bias. In addition to the startups that was contacted directly, 14 incubators and startups networks agreed to distribute the survey to their members. Those networks had a combined membership base of approximately 300 startups. These additional startups have affected the response rate, but as it is difficult to account for potential overlapping between the 825 startups contacted directly and the startups potentially exposed through networks, we do not include them when calculating the response rate.

Of the 103 completed responses, 13 observations were removed as they did not fit our criteria of a startup. This left us with a sample of 90 startups.

Descriptive statistics

From the 90 respondents in our sample, we observe that 48 of 90 (53%) of the startups were founded in 2015 or later (see appendix 2), i.e. they have only been in business for two years or less. 7 of 90 (8%) of the startups are less than one year old, founded later than 2016. 10 of 90 (11%) of the startups were founded in 2014, while 16 of 90 (18%) were founded in 2013. The remaining 16 startups (18%) were founded in 2012 or earlier. One company was founded earlier than 2005. We observe that our sample contains a large proportion of very young firms, indicating that they are in the very early stages of the business life cycle (Miller and Friesen, 1984).





The sample includes startups from eight industries. Technology is best represented, there are 18 of the startups in our sample working in this industry. The smaller categories include 'social/sharing' with seven startups, 'health-tech' with five, and 'financial services' with four. The remaining categories are retail, marketing/communication, consulting, and IT. We have also included an undefined category for startups that proved either impossible to define by a single category or were too niche to be categorized with other startups; nine startups fell into this category.

Factor analysis

This research contains both new and established constructs. Despite using some well-tested and established constructs, we revisit the scale properties to ensure that they are suitable for this particular topic. Since startups are structurally different than larger firms, not all items in the commonly accepted measure of market orientation by Jaworski and Kohli (1993), are guaranteed to be suitable for this analysis.

A confirmatory factor analysis is conducted to assess the three constructs 'intelligence generation', 'intelligence dissemination, and 'responsiveness', the underlying dimensions of market orientation. As the structure is built on the research of Jaworski and Kohli (1993), who tested its validity, the authors have some understanding of the underlying structure and a factor analysis is appropriate (Fabrigar et al,. 1999; Suhr, 2009). Each construct is analyzed individually by a confirmatory factor analysis. Based on statistical and practical significance of the factor loadings, we regard 0.5 as an appropriate cut-off point for acceptable factor loading to a construct.

The construct digital marketing analytics is not based on an existing scale. The factor analysis show that item 'attitude to digital marketing analytics (2)' has an unsatisfying factor score (< 0.5) and is therefore removed from the construct. The remaining ten items show the following loadings:

Digital marketing analytics (DMA)

Construct items	Factor loading
Attitude to DMA (1)	.770
Use of DMA	.888
Highlight the use of DMA	.674
Consequences of not doing DMA	.723
Skills with DMA	.710
Relative skills with DMA	.668
DMA improving ability to satisfy customers	.695
Strategic use of DMA	.842
Collection of data	.664
Strategic use of DMA (2)	.850

Table 2: Factor loadings of digital marketing analytics scale items

For the construct Agent's social desirable responding, items measuring 'employee judgement', 'hiring decisions', and 'ignoring customers' removed due to low factor loadings (< 0.5). The remaining five items of the construct have the following factor loadings:

Construct: Agent's social desirable responding

Construct items	Factor loading
Job satisfaction	.731
Ability to cooperate	.628
Employee performance	.749
Management	.565
Trust within firm	.683

Table 3: Factor loadings of ASDR scale items

In terms of the three constructs making up marketing orientation, a total of seven items were removed. The item measuring 'alertness to industry changes' was removed from the intelligence generation construct, one of the items measuring 'quickness of circulation' was removed from the intelligence dissemination construct. In terms of the responsive construct, five items were removed; 'use of market segmentation', 'divers of business plans', 'cross-functional coordination', 'external reaction time', and 'internal reaction time (2)'. After removing the items, the three constructs all have items with satisfactory loadings to their respective construct:

Market orientation

Construct item	Factor loading
Meeting with customers	.596
Interaction with customers	.645
In-house market research	.595
Alert to customer preferences	.510
Feedback from end-users	.692
Feedback from third parties	.646
Informal channels	.536
In-house competitor research	.579
Review business environment	.598
Discussing trends and development	.497
Spread of customer intelligence	.557
Information circulation	.762
Quickness of circulation	.649
Information circulation	.660
Cross-functional coordination	.653
Reaction to changes in market	.665
Review of product/service fit	.577
Driver of product/service development	.610
Cross-functional coordination	.649
Handling of complaints	.638
Internal reaction time (1)	.543
Reaction to complaints	.676
Reaction to feedback	.557

Table 4: Factor loadings of market orientation scale items

Reliability

Based on the remaining variables in the constructs, a reliability analysis was performed to further assess the reliability of the constructs. A Cronbach's alpha of 0.7 is considered acceptable (Nunally, 1978) and is one of the most frequently used criteria for reliability of constructs (Peterson, 1994). According to Janssens, de Pelsmacker and Kenhove (2008, p. 274), an alpha level above 0.6 can be considered 'good', while an alpha level above 0.8 can be considered 'very good'. In this analysis, we observe acceptable alphas for all constructs, some only acceptable after removing items from the constructs. Items that did not have acceptable level of either inter-item or item-total correlation is eliminated to ensure internal consistency of the scales. The most important findings are reported in the paragraphs below, the full overview over the reliability analysis is found in appendix 3. To ensure that no items were too correlated, a bivariate Pearson correlation test was performed to identify items measuring the same facet of the construct (see appendix 4). No variables were removed due to too high correlation.

The Cronbach's alpha of the construct digital marketing analytics is 0.912 with ten items, which is considered very good. The overall Alpha of the ASDR construct is 0.691 with 5 items. It is on the low side but still considered sufficient (Janssens, de Pelsmacker and Kenhove, 2008, p. 274; Peters, 2002). For the intelligence generation construct with 9 items, the overall alpha is 0.77, the alpha of intelligence dissemination is 0.699 (6 items), while responsiveness has an alpha of 0.752 (8 items) – all of which are acceptable.

The reliability analysis of the market orientation concept corresponds with the findings of the scale developers (Jaworski and Kohli, 1993). For intelligence generation, Jaworski and Kohli achieved a coefficient Alpha of 0,71 with ten items, compared to the alpha in this study of 0.752 with nine items. In terms of intelligence dissemination, the alpha of the construct in this study is on the lower side. Jaworski and Kohli obtained an alpha of 0.82 (8 items), while this study we find an alpha of 0.699 (6 items). For responsiveness, Jaworski and Kohli obtained an alpha of 0.8 (averaged from two constructs measuring responsiveness) with a total of 15 items, while this study finds an alpha of 0.752 with eight items.

The difference in number of items after refinement, and the small difference in coefficient alphas is put down to the fundamental difference of samples. The characteristic differences of companies surveyed in the two studies dictate which item is relevant and how they correlate.

Validity

There are several types of validity, some of which are more important for this study than others. In this section, the different types of validity relevant to this study will be discussed and assessed.

Validity is difficult to determine. De Vaus (1991, p. 51-53) recommends using several types of data to ensure validity, e.g. both quantitative and qualitative data. In this study, only quantitative data has been obtained. However, some qualitative feedback was given in the process of pretesting the survey. That feedback was given by entrepreneurs, and relevant professionals and experts, and gave as positive indication of face validity. Furthermore, the qualitative feedback was used to clarify the concepts and constructs in this study, improving the overall validity (Peters, 2002).

Construct validity is essential for this study, alas, assessing the overall construct validity is not simple. However, the relatively high correlation between measures found in the factor analysis and the reliability analysis, suggest that there is convergent validity (see table 2 – 4 and appendix 3) (Zaltman, LeMasters and Heffring, 1982). As the constructs in this study consist of many items, it is important that these items are sufficiently related. The use of previously tested scales, i.e. the scales for market orientation and ASDR, provide additional reassurance of construct validity.

Summated scales

From the reliability and factor analysis, 11 variables were deemed unfit for further analysis and removed. Nevertheless, all constructs have sufficient number of items to still be reliable (Peterson, 1994). With the remaining items, summated scales are calculated for each construct. The market orientation score is the un-weighted sum of the three constructs intelligence generation, dissemination and responsiveness. The use of summated scales is consistent with previous work on the market orientation concept (e.g. Baker and Sinkula, 1999; Hult, Ketchen and Slater, 2005; Jaworski and Kohli, 1993; Narver and Slater, 1990; Slater and Narver, 1994).

The mean score of market orientation is 128.42 (SD = 14.85). The range varies from 90 to 157 out of a possible range of 23 to 161. The correlation between the constructs measures 0.416 ($p < 0.001$) between intelligence generation and dissemination, 0.383 ($p < 0.001$) between intelligence generation and responsiveness, and 0.442 ($p < 0.001$) between intelligence dissemination and responsiveness. The overall market orientation corresponds 0.816 (p < 0,001) with intelligence generation, 0,752 ($p < 0.001$) with intelligence dissemination, and 0.766 ($p < 0.001$) with responsiveness. Furthermore, the Cronbach alpha of the marketing orientation construct is 0.664, consisting of three items. The construct also shows strong factor loadings on all variables; intelligence generation (α = 0.762), intelligence dissemination (α = 0.800), and responsiveness (α = 0.779).

Market orientation: Number of items = 3, Cronbach's Alpha = 0.664

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	Factor loading
Intelligence generation	.469	.609	.762
Intelligence dissemination	.513	.545	.800
Responsiveness	.481	.563	.779

Table 5: Factor loadings and reliability of market orientation construct.

Analyses

Hypothesis testing

Regression analysis was used to test the hypotheses of this study. To ensure the quality of the analysis and that all assumptions of linear regression are satisfied, all data was tested for normality (with Kolmogorov-Smirnova test with Lilliefors correction, and Shapiro-Wilk's test), homoscedasticity (with graphic indications from (ZPRED, ZRESID) graph), and multicollinearity (with bivariate correlations, condition index analysis and VIF values). To eliminate problems with multicollinearity related to moderation analysis, the predictor variables and the moderator were mean centered (Aiken, West and Reno, 1991; Baron and Kenny, 1986). After centering, no violations of the assumptions to linear regression were found. Only models which were significant at a 95% confidence level were considered for further analysis.

In addition, to account for potential relevant variables to the dependent variable, a number of control variables were included in the analysis; firm size, firm age, industry, and Agent's social desirable responding (ASDR).

For full overview of the summery statistics for all regression models, see appendix 8. The most important figures and findings are presented in the paragraphs below and in Table 6.

Effect of market orientation on profit

The model testing main effects of market orientation on the startup's profit was found to be insignificant at a 95% confidence level (0.439 > 0.05). When adding an interaction term of digital marketing analytics and market orientation, the model was still found to be insignificant (0.318 > 0.05). The increase in the explanatory power of the model was also found to be insignificant (0.156 > 0.05) (see table 6).

These results show that market orientation is not a significant predictor of profit in a startup, neither with or without digital marketing analytics moderating the effect. The parameter estimates of the restricted and full models are as following:

$Restricted\ model: Profit = 0.976 + Market\ orientation * 0{,}031$

$Full\ model: Profit = 8.159 + Market\ orientation * (-0.27) +$
$Digital\ marketing\ analytics * (-0.91) * (Market\ orientation *$
$Digital\ marketing\ analytics) * 0{,}001$

Effects of market orientation on sales growth

The model testing the main effect of market orientation on sales growth is also found to be insignificant at a 95% confidence level (0.056 > 0.05), while the model with the interaction term is significant at a 95% level (0,018 < 0,05). The analysis indicates that there is a moderating effect as R^2 has small, but significant increase by 0.064 (0.04 < 0.05) between the two models (see table 6). However, the interaction term is found to be insignificant in the model (0.392 > 0.05).

The analysis shows that there is no significant effect of market orientation on sales growth. Furthermore, digital marketing analytics does not moderate the effect. The parameter estimates of the models are:

$Restricted\ model: Sales\ growth = -0.930 + Market\ orientation * 0{,}030$

$Full\ model: Sales\ growth = 5.944 + Market\ orientation * (-0.25) +$
$Digital\ marketing\ analytics * (-0.59) * (Market\ orientation *$
$Digital\ marketing\ analytics) * 0{,}001$

Effects of market orientation on ROI

Neither main effect model (0.771 > 0.05), nor the model with interaction term (0.652 > 0.05) is found to be significant. The explanatory power of the model does not increase significantly when the interaction term is included (0.211 > 0.05) (see table 6).

We can therefore conclude that market orientation does not affect ROI, and there is no moderating effect of digital marketing analytics. The parameters of the models are:

$Restricted\ model: ROI = 0.621 + Market\ orientation * 0{,}019$

$Full\ model: Sales\ growth = 3.957 + Market\ orientation * (-0.007) + Digital\ marketing\ analytics * (-0.004) * (Market\ orientation * Digital\ marketing\ analytics) * 0{,}000$

Dependent variable	***Model***	**ANOVA sig.**	**R^2**	**R^2 square change**	**Sig. chang**
Profit	Main effect	0.439	0.137	0.042	0.156
	With moderator	0.318	0.179		
Sales growth	Main effect	0.056	0.223	0.064	0.040
	With moderator	0.018	0.287		
ROI	Main effect	0,771	0,095	0,037	0,211
	With moderator	0,652	0,132		

Table 6: Regression findings of market orientation and performance variables.

Market orientation on performance

As a complementary analysis, we have looked closer at the individual components of market orientation and how they may affect different variations of performance. Only regression models in which the whole model, including control variables, are statistically significant at a 90% confidence level are considered relevant and presented.

Dependent variables	*Profit*	*Sales growth*	*ROI*
Independent variables			
Intelligence generation	Not significant	0.06*	Not significant
Intelligence dissemination	Not significant	Not significant	Not significant
Responsiveness	Not significant	Not significant	Not significant

* *$p < 0.1$*

Table 7: Regression of individual components of market orientation on performance variables

The analysis show that the only significant effect is intelligence generation on sales growth, but the strength of the relationship is very small (β = 0.06, p = 0.082). A model testing digital marketing analytics as a moderator of intelligence generation's effect on sales growth was tested, but no significant results were found (R^2 change = 0.001; p = 0.706).

Variance in market orientation

While the focus of this paper is how market orientation affects performance, with or without a possible moderation effect, the data collected provides an opportunity to investigate how market orientation varies across startups' firm age, firm size, and industry. To investigate the variance across categories, one-way ANOVA tests are used. With this test, we simply want to identify the differences in level of market orientation in terms of the demographic variables, not how it is related to performance. The test was performed three times to seperately assess the difference in mean across age, industry and size. As a part of the analysis, all data was tested for outliers, normal distribution (with Shapiro-Wilk's test) and homogeneity (with Levene's test for homogeneity of variances).

When testing the variance of market orientation across firm age, one observation was removed. There was only one firm in the category '12 years of age or older', and therefore it was excluded from this particular analysis. As there was no observation with the age 9 to 11, the firms ranged from age zero to eight. The one-way ANOVA revealed that there was no statistically significant difference between any of the groups as the p-value is well above a 0.05 confidence level at $F(9,76) = .68$, $p = 0.727$ (see appendix 5).

The means of market orientation across firm size, in terms of employees, was also tested. For the ANOVA test, the startups were grouped in size intervals. The groups were 0 – 5 employees (n = 63), 6 – 10 employees (n = 14), 11 – 15 employees (n = 4), and 15+ employees (n = 8). The sample sizes were not equally distributed, but believed to be of sufficient size to get an indication of the variation in means between groups. The one-way ANOVA test shows that the differences are insignificant $F(3,86) = 1.19$, $p = 0.319$ (see appendix 6).

In terms of industry, we do observe a significant difference in means between some of the different industries, $F(8,81) = 2.77$, $p = 0.009$. The p-value allows us to conclude that the findings are significant. However, a Tukey post hoc test revealed that only the undefined category was significantly different from some of the other industries ($p < 0.05$) (see appendix 7). As this category consists of startups that were not possible to assign to a certain category or too niche to be grouped with others, this finding provides very little information.

Discussion

The results of this study suggest that market orientation is not related to performance for startups. For new ventures, market orientation is not found to be a significant driving factor for performance, neither in the form of increasing sales, the return on investment, or profitability. The present research also finds that capabilities in digital marketing analytics do not moderate the effect of market orientation on performance, as was hypothesized. As startups are fundamentally different from mature firms, this research does not necessarily contradict the existing findings in this field, but rather compliment them to build a more nuanced view of market orientation.

From the initial data refinement, we learned that measuring market orientation in startups differs from measuring it in mature firms. Several items measuring the constructs of market orientation in our sample were removed due to its lack of relevance. We believe the reason for this is the differences of characteristics between startups and mature firms. Kimberly (1979) finds that the drivers of success are drastically different for new ventures versus mature firms; accordingly, the focus of the firm should differ depending on its degree of maturity. The findings in this study suggest that startups do not benefit from focusing on market orientation early on. The differences between young and mature firms become even greater in emerging industries, often characterized by turbulent and volatile conditions (Aldrich, 1999). In our sample, many of the startups operate in industries with similar characteristics, e.g. technology, IT, social and/or sharing economy platforms.

Time scope

There may be many underlying reasons for why market orientation is not a significant factor for performance in startups. One aspect of it may be the time scope, which is not identified in the cross-sectional design of this study. Market orientation is an extensive concept, requiring dedication both in terms of organizational culture and behavior (Bisp, 1999; Gebhardt, Carpenter and Sherry, 2006). In our sample, the average firm was founded in 2014, i.e. less than four years ago. Considering our findings, we argue that this is not enough time to implement and reap the benefits of marketing orientation. While Narver and Slater (1990) argue that market oriented behavior can be quickly implemented and will provide immediate positive effect on profitability, several other studies depict a more cumbersome transition (Bisp 1999, Gebhardt, Carpenter and Sherry, 2006). Hunt and Morgan (1995) argue that certain market orientation elements can be easily adopted by firms. But to gain a competitive advantage and truly reap the benefits associated with market orientation, a culture that gathers all the elements and learning processes into a synergic capability is required. This culture takes time to create and cement in a company (Dickson, 1996; Hunt and Morgan 1995). According to the classical strategy literature, identifying customer needs and buyer focus is essential in the introductory and growth stages of a new product or firm (Anderson and Zeithaml, 1984; Hofer, 1975). The quickly implemented activities described by Narver and Slater (1990), and Hunt and Morgan (1995) might therefore be considered failure preventing, rather than long-term success-drivers.

A case study following two agricultural firms, found that *how* you use market intelligence is important when implementing market orientation (Beverland and Lindgreen, 2007). Successfully using market intelligence requires the systems and processes to acquire the information – all of which are obtainable with enough resources. But success also hinges on what you do with this information. With vast amounts of information, analysts and marketers must be able to identify the valuable information amidst the noise, and they must be able to transform the information into usable knowledge. Such decision rules and skills are often tacit and require time to develop (Day 1994b). The findings of the one-way ANOVA analysis in this study support the findings of Day (1994b). The analysis shows that the level of market orientation does not vary in terms of the number of employees in a startup, indicating that tacit and difficult-to-learn decision rules and skills are very important, and that dedicated resources are not enough. This element of transition to market orientation might also contribute to the explanation of why there was no moderating effect of digital marketing analytics. If marketers are unable to generate usable knowledge and create value by utilizing the information, it is reasonable that there is no effect to be found.

Lagging effect

An extension of the time scope explanation, is that when successfully implemented, it is not given that market orientation has immediate effect on performance. When unable to identify a direct effect of market orientation on market share, Jaworski and Kohli (1993) describe a lagged effect, meaning that market orientation will affect market share over a long period of time. The lagged effect can be explained by the initial cost of implementing market oriented behaviors and activities (Greenley, 1995), which reduces the short-term effect, but provides positive performance over time (Ruekert, 1992). The description of lagged effect of market orientation on performance complements findings from strategy literature on growth firms and product life cycles stating that efforts done in the early growth stages will yield results in the later stages (Anderson and Zeithaml, 1984). This means that startups' efforts of to become market oriented might not be in vain, even if they do not have any impact on their performance in the first years. Instead the startups should be patient and be ready to reap the rewards in later years. However, this also implies that market orientation is not a suitable tool for short-term survival, which is often the most pressing matter for startups, but a driver for long-term success.

Lack of variance in market orientation

The ANOVA analysis showed no significant differences in the levels of market orientation across the firm size, age or industry. As argued above, the lack of variance between firm sizes support the argument that market orientation takes time to implement. It is not about the quantity of resources, but the quality, and it takes time to learn the tacit skills market orientation, thus delaying the speed of implementation.

The age of the firms in our sample ranges from zero to nine years of age. Interestingly, no significant difference in the level of market orientation was found across firm age. This finding implies that it might even take longer than nine years from the birth of a firm, to successful implementation of market orientation. This is reasonable as the first stage of a firms' life cycle, characterized by inception and mobilization, can last up to 11 years (Smith, Mitchell and Summer, 1985)

These findings, in addition to the lack of differences between industries and the lack of support of the hypothesis, advocate that startups are simply too young to reap the benefits of market orientation. However, previous research argues that it might prove beneficial in a longer time aspect (Anderson and Zeithaml, 1984; Dickson, 1996; Hunt and Morgan 1995).

Conclusion and contributions

We believe that our findings are valuable contributions to the discussion on market orientation, digital marketing analytics, and startups. To prevent problems with publishing bias in the academic community, it is important that papers with null results are lifted and considered when discussing different topics (Begg and Mazumdar, 1994; Kepes, Banks and Oh, 2014). Therefore, we strongly believe that these finding are of high relevance in the body of literature on any of the featured topics in this study.

In general, our findings contradict previous findings which conclude that market orientation is inherently positive – an assumption that was established by Narver and Slater (1990, 1994), and Jaworski and Kohli (1990, 1993). Instead, our findings argue for a more nuanced view of the concept. Alas, as our hypothesis was rejected the findings do not give any indication of any specific relationships or directions, except for the lack of one.

The lack of relationship might suggest that it is time consuming to implement market orientation. None of the startups in our sample showed any positive benefits from market orientation, suggesting that the culture, systems and processes have not had enough time provide actual results. This is supported by the fact that there were no significant differences in market orientation across firm age (0 – 9 years old), and suggests that it takes more time. This evidence is contradicting the findings of Narver and Slater (1990) which claims that the effects of market orientation will be obtained almost immediately. However, it complements the findings of several other scholars (Bisp, 1999; Dickson, 1996; Gebhardt, Carpenter and Sherry, 2006; Hunt and Morgan, 1995).

Future research

Although it is heavy on the theory-side, the literature on market orientation is relatively silent on how firms can implement market orientation in the real world. Longitudinal case-studies of the implementation and how to reap benefits in practice could provide valuable insights on market orientation. Furthermore, the current research on digital marketing analytics and how it may enhance the efficiency of marketers is limited. Research on this topic is important to guide practitioners to implement the use of such tools in their firms, and how to maximize the benefits. Lastly, the field of startups is in constant change and in need of new academic perspectives and guidelines. However, we believe that research on individual success factors is becoming increasingly redundant as the body of literature is saturated on this particular angle. Instead, we recommend that the focus should be targeted at feasible and realistic concepts which can more easily be implemented by entrepreneurs. Ideally, these concepts should entail several of the success factors that previous research has identified.

Limitations

The authors of this paper have both limited experience of conducting scientific research, and limited resources at hand. These factors have put some constraints on this study.

First of all, a bigger sample size would have been ideal to ensure the generalizability of our research (Barlett, Kotrlik, and Higgins, 2001). However, a sample size of 90 firms can be considered acceptable in terms of the number of independent variables in our conceptual model (Halinski and Feldt, 1970; Miller and Kunce, 1973). A more pressing issue is the low response rate, indicating a non-response bias. If potential respondents refrain from answering the survey because their firm does not have either market orientation or digital marketing analytics, and thus, do not find the survey relevant, the quality of the analysis will suffer. To control for non-response bias, Donald (1960) and Miller and Smith (1983) recommend performing a follow-up analysis of a sample of the non-respondents. Due to lack of resources, such an analysis was not performed for this study.

In this study we rely on subjective, self-reported, performance measures, which makes it prone to response biases, especially social desirability bias. This type of measure was chosen based on recommendations from previous research, but the authors still expected issues with this particular response bias. The potential issue was addressed by including the ASDR-scale in the survey to measure social desirability responding. The ASDR variable was later used as a control variable in the linear regression and was found to be not significant at a 95% confidence level in any of the models. Nevertheless, ASDR might have some influence of the findings in this study.

Since the research did not yield the expected results, it is natural to question the construct validity of our measures (De Vaus, 1991, p. 53; Huck and Cormier, 1996). The fact that several items were removed from the various constructs due to low reliability supports this potential issue. Especially for the construct digital marketing analytics where the authors have little empirical research to lean on when creating the measurements. As the authors have limited experience with scale development, there is a possibility of issues with construct validity of this scale. However, it is difficult to say if the reason for unexpected results are due to the theory and relevance for startups, or the measures. There are many variables to account for, and this study could not possibly account for all of them.

In terms of design, a cross-sectional design was chosen. This does not give us an overview of the effects over time, only a snapshot of the current situation. As we argue that the time scope and lagging effects might explain the lack of support of our hypotheses, this is a big caveat of the study. A longitudinal study design would have given us the opportunity to observe the effects over time, giving us a more complete understanding of the topic. As students we only had a limited time scope ourselves, meaning that a longitudinal study design was not feasible.

Another methodological limitation in this study is the assumptions in our conceptual model. Based on findings in previous literature, we propose a hypothesis that market orientation has a direct effect on performance. Linear regression was used to test the hypothesis. This type of statistical tool is well suited for testing the relationship between variables, but it does not consider the cause-and-effect relationship (Montgomery, Peck and Vinning, 2015, p. 3-5).

Even if we believe there are strong evidence of the direction of the relationship between market orientation and performance, it is not necessarily that simple. As market orientation is difficult and resource-demanding to implement (Gebhardt, Carpenter and Sherry, 2006), it might be that entrepreneurs must wait until they have the required resources, i.e. better performance and more resources will add to implementation of market orientation. If this reversed relationship is true, it might limit the interpretation of our analysis. Looking at how performance and market orientation evolve over time would have given answer to this potential issue, arguing for a longitudinal design.

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Appendices

Appendix 1: Survey

This survey is a part of our Master Thesis in Strategic Marketing Management at BI Norwegian Business School.

There is no right or wrong answer, and we urge you to answer as truthfully as possible. It is important to note that **all your answers will be treated as confidential information** and will not be used for any purposes other than this study.

The survey is divided into 4 sections and will take approximately 6 minutes to finish.

Thank you for participating in our study!

Kind regards,
Hege J. Skogen and Kai H. K. de la Cruz

If you have any questions, or if you would like to receive the findings of the study, please contact us at khk.delacruz@gmail.com.

In this section, we want to uncover the company's use of digital marketing analytics.
The definition of digital marketing analytics is:
"Quantitative analysis of customer- or marked data performed with the help of digital tools, and used to make marketing related decisions".

Examples of digital tools are Goole Analytics, Adobe Analytics (or Target, Audience, etc.), Enalyzer, or programs like SPSS, STATA and SAS.

Section 1 of 4
Please consider the following statements and answer to the best of your ability:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Our company has a favorable attitude towards digital marketing analytics.	○	○	○	○	○	○	○
In our company, we extensively use digital marketing analytics	○	○	○	○	○	○	○
Our annual reports and other publications highlight the use of digital marketing analytics as a core competitive advantage.	○	○	○	○	○	○	○
If we reduce our digital marketing analytics activities, our company's profit will suffer.	○	○	○	○	○	○	○
Most people in my company are skeptical of any kind of analytics-based results.	○	○	○	○	○	○	○
The employees master many different digital marketing analysis tools and techniques.	○	○	○	○	○	○	○

The employees working with analysis can be considered experts in digital marketing analytics.							
We are certain that the use of digital marketing analytics improves our ability to satisfy our customers.							
When making decisions, we back arguments with digital marketing analytics-based facts.							
In general, we collect more data than our immediate competitors.							
We use digital marketing analytics to gain a competitive advantage.							

Section 2 of 4

Please consider the following statements:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
None of the employees at my firm feel dissatisfied with their jobs.							
Different functional areas within my firm, such as marketing and production, sometimes lack the ability to cooperate.							
At my company, all of the employees are outstanding performers.							
Sometimes my firm fails to exercise good judgment.							
Employees at my firm are sometimes afraid to voice their disagreement with a higher level manager's ideas.							
Employees at my company are always trustworthy.							
At my company, hiring decisions have always been based only on qualifications.							
My firm has downplayed an event that customer might view as negative.							

Section 3 of 4

Please consider the following statements:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
We meet with customers at least once a year to find out what products or services they will need in the future.	○	○	○	○	○	○	○
Individuals working with product/service development interact directly with customers to learn how to serve them better.	○	○	○	○	○	○	○
In our company, we do a lot of in-house market research.	○	○	○	○	○	○	○
We are slow to detect changes in our customers' preferences.	○	○	○	○	○	○	○
We ask our end users at least once a year to assess the quality of our product or services.	○	○	○	○	○	○	○
We often talk to or survey those who can influence our end users' purchases (e.g. retailers, distributors).	○	○	○	○	○	○	○
We collect industry information through informal means (i.e. lunch with industry friends, talks with trade partners).	○	○	○	○	○	○	○
In our company, we do a lot of in-house competitor research.	○	○	○	○	○	○	○
We are slow to detect fundamental shifts in our industry (e.g. competition, technology, regulation).	○	○	○	○	○	○	○
We periodically review the likely effect of changes in our business environment (e.g. regulations) on our customers.	○	○	○	○	○	○	○

Please consider the following statements:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
We have meetings at least once every three months to discuss market trends and developments.	○	○	○	○	○	○	●

The people working with marketing spends time discussing customers' future needs with other employees.	○	○	○	○	○	○	○
Our company periodically circulate documents (e.g. reports, newsletters) that provide information about our customers.	○	○	○	○	○	○	○
When something important happens to a major customer or market, everyone knows about it within a short period of time.	○	○	○	○	○	○	○
Data on customer satisfaction are disseminated at all levels in the company on a regular basis.	○	○	○	○	○	○	○
There is minimal communication between employees working with marketing and employees working with development concerning market developments.	○	○	○	○	○	○	○
When someone finds out something important about competitors, he/she is slow to alert others.	○	○	○	○	○	○	○

Please consider the following statements:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Principles of market segmentation drive product/service development efforts in the company.	○	○	○	○	○	○	○
For one reason or another, we tend to ignore changes in our customers' product or service needs.	○	○	○	○	○	○	○
We periodically review our product/service development efforts to ensure that they are in line with what customers want.	○	○	○	○	○	○	○
Our business plans are driven more by technological advances than by market research.	○	○	○	○	○	○	○

Employees get together periodically to plan a response to change taking place in our business environment	○	○	○	○	○	○	○
The product/services we sell depend more on internal politics than real market needs.	○	○	○	○	○	○	○

Please consider the following statements:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
If a major competitor were to launch an intensive campaign targeted at our customers, we would implement a response immediately.	○	○	○	○	○	○	○
The activities of the different employees in the company are well coordinated.	○	○	○	○	○	○	○
Customer complaints fall on deaf ears in the company.	○	○	○	○	○	○	○
Even if we came up with a great marketing plan, we probably would not be able to implement it in a timely fashion.	○	○	○	○	○	○	○
We are quick to respond to significant changes in our competitors' pricing structures.	○	○	○	○	○	○	○
When we find that customers are unhappy with the quality of our service, we take corrective action immediately.	○	○	○	○	○	○	○
When we find that customers would like us to modify a product or service, the company make concerted efforts to do so.	○	○	○	○	○	○	○

Section 4 of 4

What is the name of your company?

In what year was your company established?

In which country is your company located?

Is your company a member of an entrepreneurial/startup network?

- No
- Yes

What is your position in the company?

- Founder/owner/CEO
- Middle manager
- Full-time employee
- Part-time employee

How many paid full-time employees does your company currently employ?

0 10 20 30 40 50 60 70 80 90 100

Number of full-time employees

Do you identify your company as a startup?

- Yes
- No
- I don't know

Please describe the performance of your firm in the following areas relative to your average competitor (consider the immediate past year in responding to these items).

	Far below average	Moderately below average	Slightly below average	Average	Slightly above average	Moderately above average	Far above average
Total sales growth	O	O	O	O	O	O	O
Profit	O	O	O	O	O	O	O
Return on investment	O	O	O	O	O	O	O

Thank you for participating in our study, your contribution is greatly appreciated.

If you have any questions, or if you would like to receive the end result of the study, please contact us at khk.delacruz@gmail.com.

Hege J. Skogen and Kai de la Cruz

Appendix 2: Descriptive statistics of the sample

Industry: Descriptive statistics

Industry	**Frequency**	**Percent**
Retail	12	13,3
Marketing/communication	11	12,2
Technology	18	20,0
Consulting	11	12,2
Health-tech	5	5,6
Financial services	4	4,4
IT	13	14,4
Social/sharing	7	7,8
Undefined	9	10,0
Total	**90**	**100,0**

Age: Descriptive statistics

Year of establishment	**Frequency**	**Percent**	**Cumulative percent**
Earlier than 2005	1	1,1	1,1
2008	3	3,3	4,4
2009	2	2,2	6,7
2010	3	3,3	10,0
2011	2	2,2	12,2
2012	5	5,6	17,8
2013	16	17,8	35,6
2014	10	11,1	46,7
2015	20	22,2	68,9
2016	21	23,3	92,2
Later than 2016	7	7,8	100,0
Total	**90**	**100,0**	

Appendix 3: Reliability analysis

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Digital marketing analytics: Number of items = 10, Cronbach's Alpha = 0,912		
Digital marketing analytics 1	,698	,903
Digital marketing analytics 2	,843	,892
Digital marketing analytics 3	,602	,908
Digital marketing analytics 4	,639	,906
Digital marketing analytics 6	,647	,905
Digital marketing analytics 7	,601	,908
Digital marketing analytics 8	,613	,907
Digital marketing analytics 9	,790	,897
Digital marketing analytics 10	,585	,909
Digital marketing analytics 11	,797	,896
Agent's social desirable responding: Number of items = 5, Cronbach's Alpha = 0,691		
ASDR 1	,498	,621
ASDR 2	,432	,652
ASDR 3	,518	,609
ASDR 5	,378	,670
ASDR 6	,425	,651
Intelligence generation: Number of items = 9, Cronbach's Alpha = 0,775		
Intelligence generation 1	,439	,756
Intelligence generation 2	,504	,752
Intelligence generation 3	,462	,753
Intelligence generation 4	,375	,765
Intelligence generation 5	,533	,742
Intelligence generation 6	,502	,747
Intelligence generation 7	,412	,760
Intelligence generation 8	,457	,754
Intelligence generation 10	,471	,752
Intelligence dissemination: Number of items = 6, Cronbach's Alpha = 0,699		
Intelligence dissemination 1	,323	,692
Intelligence dissemination 2	,376	,676
Intelligence dissemination 3	,572	,606
Intelligence dissemination 4	,450	,655
Intelligence dissemination 5	,455	,651
Intelligence dissemination 6	,428	,660
Responsiveness: Number of items = 8, Cronbach's Alpha = 0,752		
Responsiveness 2	,515	,713
Responsiveness 3	,412	,735
Responsiveness 6	,452	,727
Responsiveness 8	,491	,718
Responsiveness 9	,495	,720
Responsiveness 10	,401	,745
Responsiveness 12	,504	,719
Responsiveness 13	,405	,734

Appendix 4: Pearson bivariate correlation matrices

Correlations: ASDR

		1	2	3	5	6
ASDR 1	Pearson Correlation	1	,281**	,387**	,280**	,450**
	Sig. (2-tailed)		,007	,000	,008	,000
	N	90	90	90	90	90
ASDR 2	Pearson Correlation	,281**	1	,377**	,394**	,132
	Sig. (2-tailed)	,007		,000	,000	,214
	N	90	90	90	90	90
ASDR 3	Pearson Correlation	,387**	,377**	1	,194	,476**
	Sig. (2-tailed)	,000	,000		,067	,000
	N	90	90	90	90	90
ASDR 5	Pearson Correlation	,280**	,394**	,194	1	,179
	Sig. (2-tailed)	,008	,000	,067		,091
	N	90	90	90	90	90
ASDR 6	Pearson Correlation	,450**	,132	,476**	,179	1
	Sig. (2-tailed)	,000	,214	,000	,091	
	N	90	90	90	90	90

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations: Intelligence generation

		1	2	3	4	6	7	8	9	10
Intelligence generation 1	Pearson Correlation	1	,453**	,162	,085	,511**	,347**	,309**	,095	,196
	Sig. (2-tailed)		,000	,128	,426	,000	,001	,003	,375	,064
	N	90	90	90	90	90	90	90	90	90

Intelligence generation 2	Pearson Correlation	,453**	1	,280**	,322**	,531**	,363**	,156	,092	,199
	Sig. (2-tailed)	,000		,007	,002	,000	,000	,141	,387	,060
	N	90	90	90	90	90	90	90	90	90
Intelligence generation 3	Pearson Correlation	,162	,280**	1	,310**	,226*	,243*	,138	,535**	,358**
	Sig. (2-tailed)	,128	,007		,003	,032	,021	,195	,000	,001
	N	90	90	90	90	90	90	90	90	90
Intelligence generation 4	Pearson Correlation	,085	,322**	,310**	1	,251*	,322**	,143	,158	,267*
	Sig. (2-tailed)	,426	,002	,003		,017	,002	,178	,137	,011
	N	90	90	90	90	90	90	90	90	90
Intelligence generation 5	Pearson Correlation	,511**	,531**	,226*	,251*	1	,416**	,279**	,174	,228*
	Sig. (2-tailed)	,000	,000	,032	,017		,000	,008	,102	,030
	N	90	90	90	90	90	90	90	90	90
Intelligence generation 6	Pearson Correlation	,347**	,363**	,243*	,322**	,416**	1	,292**	,244*	,212*
	Sig. (2-tailed)	,001	,000	,021	,002	,000		,005	,021	,044
	N	90	90	90	90	90	90	90	90	90
Intelligence generation 7	Pearson Correlation	,309**	,156	,138	,143	,279**	,292**	1	,373**	,292**
	Sig. (2-tailed)	,003	,141	,195	,178	,008	,005		,000	,005
	N	90	90	90	90	90	90	90	90	90
Intelligence generation 8	Pearson Correlation	,095	,092	,535**	,158	,174	,244*	,373**	1	,531**
	Sig. (2-tailed)	,375	,387	,000	,137	,102	,021	,000		,000
	N	90	90	90	90	90	90	90	90	90
Intelligence generation 10	Pearson Correlation	,196	,199	,358**	,267*	,228*	,212*	,292**	,531**	1
	Sig. (2-tailed)	,064	,060	,001	,011	,030	,044	,005	,000	
	N	90	90	90	90	90	90	90	90	90

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations: Intelligence dissemination

		1	2	3	4	5	6
Intelligence dissemination 1	Pearson Correlation	1	,397**	,307**	,146	,198	,040
	Sig. (2-tailed)		,000	,003	,170	,062	,708
	N	90	90	90	90	90	90
Intelligence dissemination 2	Pearson Correlation	,397**	1	,245*	,077	,093	,455**
	Sig. (2-tailed)	,000		,020	,472	,385	,000
	N	90	90	90	90	90	90
Intelligence dissemination 3	Pearson Correlation	,307**	,245*	1	,399**	,447**	,369**
	Sig. (2-tailed)	,003	,020		,000	,000	,000
	N	90	90	90	90	90	90
Intelligence dissemination 4	Pearson Correlation	,146	,077	,399**	1	,441**	,326**
	Sig. (2-tailed)	,170	,472	,000		,000	,002
	N	90	90	90	90	90	90
Intelligence dissemination 5	Pearson Correlation	,198	,093	,447**	,441**	1	,247*
	Sig. (2-tailed)	,062	,385	,000	,000		,019
	N	90	90	90	90	90	90
Intelligence dissemination 6	Pearson Correlation	,040	,455**	,369**	,326**	,247*	1
	Sig. (2-tailed)	,708	,000	,000	,002	,019	
	N	90	90	90	90	90	90

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations: Responsiveness

		2	3	6	8	9	10	12	13
Responsiveness 2	Pearson Correlation	1	,371**	,431**	,209*	,315**	,305**	,385**	,207
	Sig. (2-tailed)		,000	,000	,048	,002	,004	,000	,050
	N	90	90	90	90	90	90	90	90
Responsiveness 3	Pearson Correlation	,371**	1	,237*	,269*	,259*	,145	,345**	,239*
	Sig. (2-tailed)	,000		,025	,010	,014	,173	,001	,023
	N	90	90	90	90	90	90	90	90
Responsiveness 6	Pearson Correlation	,431**	,237*	1	,229*	,373**	,217*	,289**	,214*
	Sig. (2-tailed)	,000	,025		,030	,000	,040	,006	,043
	N	90	90	90	90	90	90	90	90
Responsiveness 8	Pearson Correlation	,209*	,269*	,229*	1	,427**	,347**	,348**	,349**
	Sig. (2-tailed)	,048	,010	,030		,000	,001	,001	,001
	N	90	90	90	90	90	90	90	90

Responsiveness 9	Pearson Correlation	,315**	,259*	,373**	,427**	1	,314**	,296**	,118
	Sig. (2-tailed)	,002	,014	,000	,000		,003	,005	,266
	N	90	90	90	90	90	90	90	90
Responsiveness 10	Pearson Correlation	,305**	,145	,217*	,347**	,314**	1	,175	,257*
	Sig. (2-tailed)	,004	,173	,040	,001	,003		,098	,014
	N	90	90	90	90	90	90	90	90
Responsiveness 12	Pearson Correlation	,385**	,345**	,289**	,348**	,296**	,175	1	,426**
	Sig. (2-tailed)	,000	,001	,006	,001	,005	,098		,000
	N	90	90	90	90	90	90	90	90
Responsiveness 13	Pearson Correlation	,207	,239*	,214*	,349**	,118	,257*	,426**	1
	Sig. (2-tailed)	,050	,023	,043	,001	,266	,014	,000	
	N	90	90	90	90	90	90	90	90

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations: Market orientation

		Intelligence generation	Intelligence dissemination	Responsiveness
Intelligence generation	Pearson Correlation	1	,416**	,383**
	Sig. (2-tailed)		,000	,000
	N	90	90	90
Intelligence dissemination	Pearson Correlation	,416**	1	,442**
	Sig. (2-tailed)	,000		,000
	N	90	90	90
Responsiveness	Pearson Correlation	,383**	,442**	1
	Sig. (2-tailed)	,000	,000	
	N	90	90	90

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations: Digital marketing analytics

		1	2	3	4	6	7	8	9	1	11
Digital marketing analytics 1	Pearson Correlation	1	,731**	,454**	,569**	,359**	,359**	,623**	,578**	,376**	,663**
	Sig. (2-tailed)		,000	,000	,000	,001	,001	,000	,000	,000	,000

	N	90	90	90	90	90	90	90	90	90	90
Digital marketing analytics 2	Pearson Correlation	,731**	1	,585**	,625**	,591**	,555**	,543**	,705**	,559**	,705**
	Sig. (2-tailed)	,000		,000	,000	,000	,000	,000	,000	,000	,000
	N	90	90	90	90	90	90	90	90	90	90
Digital marketing analytics 3	Pearson Correlation	,454**	,585**	1	,485**	,435**	,389**	,412**	,488**	,399**	,460**
	Sig. (2-tailed)	,000	,000		,000	,000	,000	,000	,000	,000	,000
	N	90	90	90	90	90	90	90	90	90	90
Digital marketing analytics 4	Pearson Correlation	,569**	,625**	,485**	1	,377**	,304**	,642**	,535**	,230*	,625**
	Sig. (2-tailed)	,000	,000	,000		,000	,004	,000	,000	,029	,000
	N	90	90	90	90	90	90	90	90	90	90
Digital marketing analytics 6	Pearson Correlation	,359**	,591**	,435**	,377**	1	,705**	,291**	,602**	,479**	,525**
	Sig. (2-tailed)	,001	,000	,000	,000		,000	,005	,000	,000	,000
	N	90	90	90	90	90	90	90	90	90	90
Digital marketing analytics 7	Pearson Correlation	,359**	,555**	,389**	,304**	,705**	1	,348**	,532**	,464**	,429**
	Sig. (2-tailed)	,001	,000	,000	,004	,000		,001	,000	,000	,000
	N	90	90	90	90	90	90	90	90	90	90
Digital marketing analytics 8	Pearson Correlation	,623**	,543**	,412**	,642**	,291**	,348**	1	,536**	,249*	,566**
	Sig. (2-tailed)	,000	,000	,000	,000	,005	,001		,000	,018	,000
	N	90	90	90	90	90	90	90	90	90	90
Digital marketing analytics 9	Pearson Correlation	,578**	,705**	,488**	,535**	,602**	,532**	,536**	1	,598**	,692**
	Sig. (2-tailed)	,000	,000	,000	,000	,000	,000	,000		,000	,000
	N	90	90	90	90	90	90	90	90	90	90

Digital marketing analytics 10	Pearson Correlation	,376**	,559**	,399**	,230*	,479**	,464**	,249*	,598**	1	,649**
	Sig. (2-tailed)	,000	,000	,000	,029	,000	,000	,018	,000		,000
	N	90	90	90	90	90	90	90	90	90	90
Digital marketing analytics 11	Pearson Correlation	,663**	,705**	,460**	,625**	,525**	,429**	,566**	,692**	,649**	1
	Sig. (2-tailed)	,000	,000	,000	,000	,000	,000	,000	,000	,000	
	N	90	90	90	90	90	90	90	90	90	90

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Appendix 5: One-way ANOVA – Variance of market orientation between firm age

	Sum of Squares	df	Mean Square	F
Between Groups	1325,252	9	147,250	,678
Within Groups	17169,107	79	217,330	
Total	18494,360	88		

Appendix 6: One-way ANOVA – Variance of market orientation between firm size

	Sum of Squares	df	Mean Square	F
Between Groups	781,263	3	260,421	1,189
Within Groups	18842,692	86	219,101	
Total	19623,956	89		

Appendix 7: One-way ANOVA – Variance of market orientation between industry

	Sum of Squares	df	Mean Square	F
Between Groups	4217,345	8	527,168	2,772
Within Groups	15406,610	81	190,205	
Total	19623,956	89		

Appendix 8: Summary statistics of regression models

Dependent variable: Profit

Model	**R**	**R square**	**Adj. R square**	**R square change**	**Sig. of R square change**	**ANOVA sig.**
Restricted	0.370	0.137	0.003	0.137	0.439	0.439
Full	0.423	0.179	0.026	0.042	0.156	0.318

Dependent variable: Sales growth

Model	**R**	**R square**	**Adj. R square**	**R square change**	**Sig. of R square change**	**ANOVA sig.**
Restricted	0.472	0.223	0.102	0.223	0.056	0.056
Full	0.535	0.287	0.154	0.064	0.040	0.018

Dependent variable: Return on investment

Model	**R**	**R square**	**Adj. R square**	**R square change**	**Sig. of R square change**	**ANOVA sig.**
Restricted	0.308	0.095	-0.046	0.095	0.771	0.771
Full	0.363	0.132	-0.030	0.037	0.211	0.652