DIGITAL INNOVATIONS, THE NEW DRIVER OF SUCCESSFUL STARTUPS?

A study conducted under participants of the Accenture Innovation Awards

Frits Thijs

Submission Date: 13-03-2018

Supervisor: Prof. dr. Thurik, A.R.

Second Reader: MSc. Leung, Y.K.

Abstract:

This study investigates the influence of the use of digital innovations on the business success of firms participating in the Accenture Innovation Awards over the period 2014-2017, in which firms can participate with innovative concepts of maximum three years old. This research shows an increase of the number of concepts that use digital innovations. It also shows an increase of the number of users of concepts that use digital innovations, relative to the number of users of concepts that do not use digital innovations. By using a generalized ordered logistic regression, a significant influence of the use of digital innovations was shown on the turnover of concepts. In contrast to these findings, an ordered logistic regression showed a significantly negative effect of the influence of digital innovation on the number of users of a concept. This study finds, using data of 2,994 participants of the Accenture Innovation Awards, that the trend of digital innovation is not a hype, but is indeed a driver of the creation of new successful businesses in the Dutch innovation ecosystem. Digital innovation is thereby developing as the theory of the Industry Life Cycle suggests, showing an increase of number of firms that use digital innovations entering the market, and a relative growth of the customer base.

Table of Contents

1. Introduction

Economies are disrupted, pushed forward and brought into a new stabilized state by innovations. This has firstly been argued by Schumpeter (1934), and has been discussed by many other economists later on. This led to the development of the theory of the Industry Life Cycle (e.g. Abernathy and Utterback, 1978; Gort and Klepper, 1982; Klepper and Graddy, 1988; Utterback and Suarez, 1992; Klepper, 1997). Currently, many innovations that disrupt the economy are following each other up rapidly. One of the most discussed innovations in the present are blockchain innovations, primarily the cryptocurrency Bitcoin. The blockchain technology can potentially revolutionize the entire economic, legal, and political systems that are used at this moment. Schwab (2017a) even claims that the digital revolution has launched the Fourth Industrial Revolution since the middle of the last century.

With success stories of companies using digital innovations, people might think of these stories as the new way of making successful business. A question one might ask is, if this is indeed the new successful way of making new business, or is this just a hype? Moreover, if companies using these innovations are more successful than companies that do not use these innovations, can we still typify digital innovations as a hype, or is it disrupting the market, leading to a new Industrial Revolution as claimed by Schwab (2017a)? Another question that comes to mind is whether digital innovation is developing as the theory expects? This development is also interesting for policymakers: if digital innovations are leading to more successful startups that push the economy forward, stimulating digital innovation would be of increasing importance for keeping the (national) economy competitive with the world economy.

This research will give an insight in these questions, by researching data provided by the Accenture Innovation Awards. In this yearly award program, firms are able to participate with innovative concepts of maximum three years old. These concepts are products or services brought on the market by the firms. Important hereby, is that the concept participates for the award, not the firm. Therefore, the concept has to be three years old or less. The success will be derived from the turnover and the number of users of participating concepts. This leads to the following research question in this study:

From the participants of the Accenture Innovation Awards, are concepts that use digital innovations more successful than concepts that do not use digital innovations?

In the past, researchers developed the economic framework of the Industry Life Cycle cycle (e.g. Abernathy & Utterback, 1978; Gort and Klepper, 1982; Klepper and Graddy, 1988; Utterback and Suarez, 1992; Klepper, 1997). In this model, there exist three stages of evolution. In the first two stages, a radical innovation, as mentioned by Schumpeter (1934), is the start of a new stream of product innovations. In this phase, entry barriers are low, and competition is high. Small firms play an important role in this phase, entering the industry with new products (Klepper, 1997). The first part of the study investigates if the development of digital innovation is following the trends the Industry Life Cycle expects it to do. Seeing the claim of Schwab (2013a) that a fourth industrial revolution has been launched, this study expects to find digital innovation to be in the first or second stage of the Industry Life Cycle. Descriptive statistics of the past four years of the Accenture Innovation Awards (hereafter, AIA) are analyzed to test this for the Dutch ecosystem. Thereby, the analyses show a significant increase of the use of digital innovations in the AIA over the past four years. Furthermore, the average number of users of concepts that use digital innovations was lower than the average number of users of concepts that do not use digital innovations. However, the difference between both averages decreased over the past four years. This indicates a relative increase of the average number of users of concepts that use digital innovations, in comparison to the average number of users of concepts that do not use digital innovations.

The second part of the analysis investigates the influence of digital innovation on the turnover and the number of users of the participants of the AIA. Using a generalized ordered logistic regression, this study finds a considerable positive effect of the use of digital innovations on the turnover of concept. Contrary to what is expected, the used ordered logistic regression finds a negative effect of the use of digital innovations on the number of users of a concept.

Using data of 2,994 concepts participating in the AIA, this study finds that the trend of digital innovation is not a hype, but is indeed a driver of the creation of new successful businesses. It is thereby developing as the theory suggests, showing an increase of number of firms that use digital innovations entering the market, and a relative growth of the customer base. A recommendation for Accenture is therefore to accentuate digital innovations more in both their own business and in the advice to their clients. Furthermore, the results of this study suggest that creating a more favorable environment for firms that use digital innovations can be interesting for the Netherlands. This can improve the competitiveness of the country, and thereby stimulate economic growth.

The following structure will be handled in this research. The theoretical framework will start in section 2 with an explanation and deliberation on innovation, and why it is important for economic growth. The second part of the theoretical framework will discuss previous literature regarding small business growth and the success of small businesses, followed by a breakdown of digital technologies. Hereby, the importance of digital technologies in the present will be reviewed, as well as the latest trends in digital innovation. Summarizing the theories discussed, section 2 will end with the formulation of the hypotheses this study researches. Third, the used data for this research, from the participants of the AIA, is examined. Based on this data, the methods to test the hypotheses are determined at the end of section 3. Section four will present the results of the research and answer the hypotheses, what will be discussed in chapter five.

2. Theoretical framework and hypotheses formulation

2.1 Innovation and economic growth

The presence of innovation is not a new phenomenon. Since there was mankind, there has been innovation. Think about development of the alphabet a long time ago, but also the rise of mobile phones, in a newer perspective. Seeing this, innovation determines the way we live, and is therefore very important. But is it also important at an economic perspective? To fully understand the importance of digital innovation in the present, understanding the concept of innovation is essential. This section will discuss the importance of innovation in economics. First, by describing what innovation exactly is. Secondly, the influence of innovation on the economic growth and on industries will be illustrated. Concluding, the importance of innovation will be described from a country's point of view.

To start with, there is a conceptual difference between innovation and invention. Schumpeter (1934) describes invention as the discovery of new opportunities. He defines innovation as "new combinations" of existing resources, equipment and so on (Schumpeter, 1934, p. 65). He calls this combining activity "the entrepreneurial function". Thereby, entrepreneurs have a commercial purpose. As Drucker (1998, p. 3). states: "innovation is the specific function of entrepreneurship", and "it is the means by which the entrepreneur either creates new wealth-producing resources or endows existing resources with enhanced potential for creating wealth". On the other hand, invention can also be done in a non-commercial environment, like universities (Fagerberg, 2003). This is an essential distinction for the economic point of view.

As stated above, Schumpeter (1934) saw innovation as an entrepreneurial, commercial activity. He was one of the first economists who connected innovation to economic development. In his "theory of economic development", he distinguished between five types of innovation; new products, new methods of production, new sources of supply, exploitation of new markets, and new ways to organize business. Schumpeter argued that the neoclassical equilibrium theory was not dynamic, and therefore not able to describe the real world. The equilibrating forces of the neoclassical theory were in his view real and strong. However, in theory, these forces would push the economy into an equilibrium, what never occurs in practice. New innovations and opportunities will always be exploited by entrepreneurs, thereby replacing former leading products and technologies. Hence, the economy will always be pushed away from an equilibrium, towards a new equilibrium. Schumpeter described this phenomenon as "creative destruction", and argued this as the main reason for economic development (growth), thereby this leads to dynamic competition.

To understand this dynamic competition, consider an innovation that disrupts the market. Following the theory of Schumpeter (1934), this radical innovation will gain a (large) market share, by that taking this market share away from existing products. The individual that brings this innovation successfully to the market will be rewarded with profits. According to Schumpeter, however, this reward will fade away as soon as the innovation is imitated by a large number of producers. Nevertheless, despite of the diminishing profits of the individual, the economy as a whole grows because of this movement, argues Schumpeter. The new successful innovation attracts new producers and imitators to this market, leading to a growth in the industry. Additionally, a new innovation might trigger new innovations in the same industry (Schumpeter, 1939). Schumpeter argues that these innovations are interdependent, causing innovations to cluster in specific industries, thereby constantly disrupting and developing this industry. This might cause the specific industry to grow faster than the economy as a whole. At a certain point, however, this growth will slow down again. This induces a cyclic development of such clusters. Schumpeter (in Fagerberg, 2003) called this "business cycles".

The business cycles were the base for economists to develop a new model in an appreciative and a formalized way: the industry life cycle (e.g. Abernathy & Utterback, 1978; Gort and Klepper, 1982; Klepper and Graddy, 1988; Utterback and Suarez, 1992; Klepper, 1997). In this model, there exist three stages of evolution. In the first two stages, a radical innovation, as mentioned by Schumpeter (1934), is the start of a new stream of product innovations. In this phase, entry barriers are low, and competition is high. Small firms play an important role in this phase, entering the industry with new products (Klepper, 1997). In the third phase of the industry life cycle, a dominant design is established (Clark, 1985). The industry settles for this dominant design, excluding other designs and narrowing space for new product innovations. On this point, the producers start to focus on process innovation. The competition thereby shifts from product quality to price competition. The competition concentrates, because of higher entry barriers and the elimination of producers that were not able to adopt the dominant design rapidly starts. In the fourth stage of the Industry Life cycle, only incremental (mostly process) innovations will occur, and competition will further concentrate (Malerba & Orsenigo, 1996). At this point, there is room for new radical innovations to disrupt the industry again, starting a new cycle. Otherwise, the industry will decline, as can be seen in Figure 1. The Industry Life Cycle shows that innovation is one of the key inputs for an industry to develop and flourish.

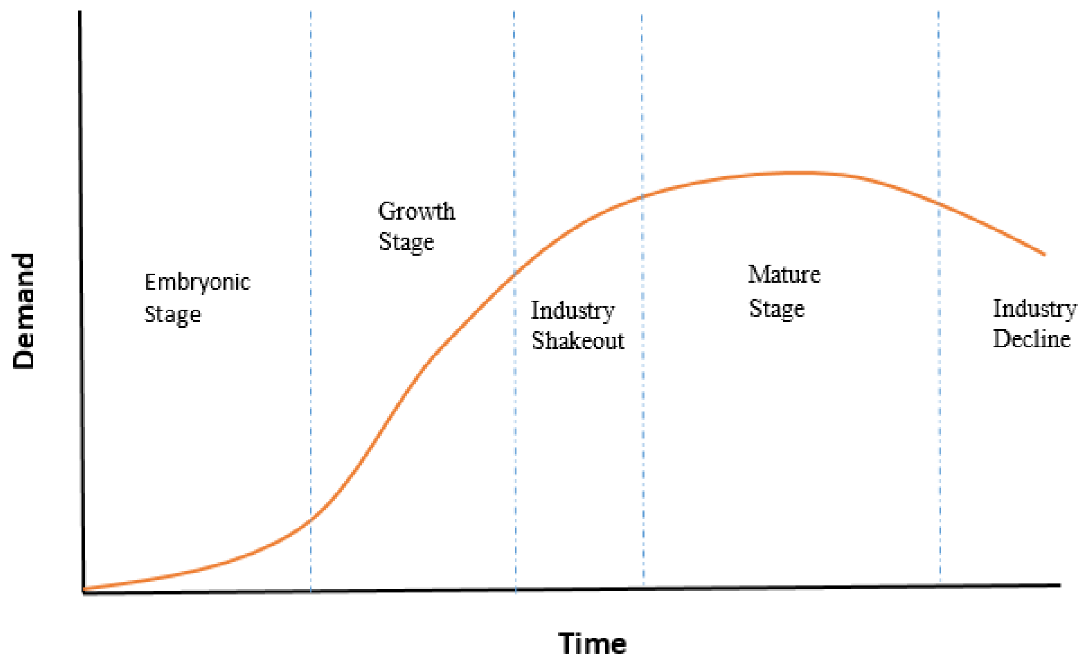


Figure 1. The Industry Life Cycle (source: Stephen, 2013)

Another view that has to be considered when looking at innovation, is the importance of innovation on the country level. Posner (1961) developed a dynamic model to explain the difference in cross-country economic growth. In his model, two countries with different levels of economic and technological development were compared. the first country is the leader (innovator), the second country is the follower (imitator). Posner argued that these differences were caused by two sources, namely innovation (enlarging the difference between the countries) and imitation (reducing the difference between the countries). There is a time gap between the moment the leading country innovates, becoming a temporarily monopolist, and the moment the following country successfully imitates the innovation, thereby becoming competitive again. In this so-called “technology gap” (Fagerberg, 1996), the level of income will be higher in the leading country. For countries it is therefore important to be innovative, leading to a more competitive economy with respect to other countries.

In the following decades, the New Growth Theory arose from the model of Posner. Where the model of Posner considered innovation as an exogenous variable, new theories the new growth theory suggests that innovation is an endogenous variable. In this literature, two strands exist; the first analyses innovation as learning by doing (Romer, 1986; Lucas, 1988), the second sees investments in R&D as most important aspect (Romer, 1990; Grossman and Helpmann, 1991). The most important take-away from this literature is that both views explain long term economic growth comes from 1) private incentives to investments in activities that lead to innovation (learning) and 2) the spillovers from this process on future investments of this kind. Ergo, a country that creates a positive environment (using subsidies and protection) for technological progressive industries (Lucas, 1988) and devotes a large share of its resources to R&D (Grossman and Helpman, 1991), is more likely to display faster growth.

Examining the aforementioned literature, it can be concluded that innovation is an important, if not the most important, driver of economic growth. In general, radical innovations are needed to disrupt economies, thereby pushing the economy further. Looking from a country perspective, innovation is needed to be competitive, since the country with the most innovative environment is considered as the leading country. Moreover, more innovative countries are more likely do display faster growth.

2.2 Small business growth

To be able to analyze the influence of digital innovations on business success in this study, other possible influences should be considered first. This section will summarize multiple theories regarding factors influencing the growth of small businesses.

Companies with 50 employees or less, small businesses, are worldwide identified as significant contributors to economic growth (Morris and Brennan, 2000). During the last century, entrepreneurship and small businesses have been related to innovation and economic growth in multiple ways, both by academics and policy makers (Thurik and Wennekers, 2004). To understand how entrepreneurship and small businesses relate to innovation and economic growth, it is important to look at the definition of both. Stevenson and Gumpert (as cited in Thurik and Wennekers, 2004), state that entrepreneurship can be seen as a type of behavior concentrating on opportunities, rather than resources. This behavior is possible everywhere, both in large, and in small firms. On the other hand, small businesses can be disrupting the market, also called Schumpeterian entrepreneurship, but can also be seen as a vehicle for entrepreneurs to run a business for living (Wennekers and Thurik, 1999). Examples of the latter are small businesses like a grocery store, a bakery, or a clothes store. Entrepreneurs start these businesses not to disrupt the market with it, but run it to earn a living. In the study of Wennekers and Thurik (1999), it is explained that in today's world there has been a shift towards a more important role of small businesses as a vehicle for Schumpeterian entrepreneurship, and thereby an increasingly important role of small businesses regarding innovation and economic growth (Carree and Thurik, 1999; Audretsch and Thurik, 2000; Audretsch et al., 2001; Audretsch et al., 2002; Carree et al., 2002). The present research will focus on small businesses as a vehicle for Schumpeterian entrepreneurship. The success of these small businesses is often measured by financial measures, like turnover, or by the increase of employees of a firm (e.g. Murphy et al., 1996; Chell and Baines, 1998; ; Georgellis et al., 1999; Mäki and Pukkinen, 2000; Perren, 2000; Gray, 2002; Reijonen and Komppula, 2007).

In previous studies, multiple factors that have an influence on small business growth are identified. Following the literature review of Morrison et al. (2003), the influences on small business growth can be distinguished between (1) the ambitions, intentions, and competencies of the entrepreneur; (2) internal characteristics of the business; (3) region specific resources and infrastructure; and (4) external relationships and network configurations (Storey, 1994; Glancey, 1998; Georgellis et al., 1999; Mitra and Matlay, 2000; Shaw and Conway, 2000).

To start with, multiple studies (e.g. Gray, 2000; Maki and Pukkinen, 2000) suggest that growth and success of a small business is not caused by chance, but results from motivated business intentions and associated actions, driven by the belief of delivering the desired outcome by the entrepreneur. Thereby, the research of Maki and Pukkinen (2000) shows that it is important to comprehend the differences between the intention, ability, and opportunity of entrepreneurs to grow their business. Morrison et al. (2003) summarizes all 'pro-growth factors' and 'inhibiting factors' regarding these differences, using previous literature (Bridge, O'Neill, and Cromie, 1998; Rimmington, Williams, and Morrison 1999; Burke and Jaratt, 2000; Heffernan and Flood, 2000; Gray, 2000; Maki and Pukkinen, 2000; Sherwood et al., 2000), displayed in Table 1. The literature shows that the intentions of the entrepreneur, and the way in which they interpret their economic and social worlds are essential for the growth of a small business, because of the impact it has on the abilities of the business (Gray, 2000). Next to that, multiple researches (e.g. Fischer, 1992; Rosa et al., 1996) suggest that gender is a significant influence on success of entrepreneurs. However, in a large study regarding 4200 small businesses, Du Rietz and Henrekson (2000) did not find support for underperformance of female entrepreneurs, relative to male entrepreneurs.

Table 1. Small Business Pro-Growth and Inhibiting Growth Factors

	Pro Growth Factors	Inhibiting Factors
Intention	Demographic variables Personal Characteristics Values and beliefs	Lack of ambition and vision Anti-business “hobbyist” approach Quality of lifestyle protectionism Mature position in life-cycle
Ability	Educational level Knowledge of different fields of business Perception/actual of owner-managers competence Growth potential products, assets and premises Legal format of business Proactive learning through social, informal networks	Constrained managerial competencies Narrow skills base Physical expansion/production limitations Organizational structure results in lack of time and resources
Opportunity	Market conditions Access to finance Public sector regulation Labor market	Weak power position within the industry sector and markets High dependency on externalities Adverse financial and economic conditions Unhelpful local government approach to business development Constraining government regulation and communication

Source: Bridge, O'Neill, and Cromie, 1998; Rimmington, Williams, and Morrison 1999; Burke and Jaratt, 2000; Heffernan and Flood, 2000; Gray, 2000; Maki and Pukkinen, 2000 Sherwood et al., 2000 (in Morrison et al., 2003)

Secondly, Georgellis et al. (1999) focused their research on the internal characteristics of small businesses. They found that small businesses with (1) a capacity to innovate; (2) a capacity to plan ahead; and (3) a willingness to take risk are better able to transform an entrepreneurial strategic intent into successful innovative businesses. Van de Ven et al. (1984) found that a clear structure (e.g. having a single person in demand, active involvement of top management) was positively related to the success of small businesses. Moreover, they found that implementing a startup on a small scale, thereafter expanding it incrementally, was positively related to success.

Thirdly, Van de Ven et al. (1984) investigated the influence of region specific resources on small business growth. In a study of two models it was found that nurturing new business startups through corporate sponsorship places them at a disadvantage in the short term, compared to independent startups which have to compete more for resources and survival. However, the researchers expect this to change in the long run, because of the possibility for more adaptability of startups with corporate sponsorship. In the study of Mambula (2002), it was shown that a poor infrastructure impedes the success of small businesses.

Lastly, the social network of an entrepreneur has an influence on the performance of small businesses (Burt, 2000). Via their social network, entrepreneurs are able to have access to information and different types of (region specific) resources, as discussed in previous paragraph. The greater the size of the network, the greater the probability that the entrepreneur gains access to this information and resources (e.g. Batjargal, 2000; Burt, 2000; Hoang & Antoncic, 2003; Scott, 2000). Prajapati and Biswas (2011) saw a positive influence of the size and centrality of a network on the business performance of small businesses, but a negative influence of a dense network and small business performance. The researchers expect this negative relation to be caused by fierce competition and the transfer of obsolete information in networks with high density.

This section summarized the most important drivers of the success of small businesses. Since this study focuses on small firms with a maximum age of three years old, these factors are also expected to have an influence on the success of the businesses studied in this research. This research will therefore include as much of the mentioned factors as possible to the examined models as control variables. This will be explained in more detail in section 3.2.2.

2.3 Digital innovation

As stated in section 2.1, disrupting technologies have been changing our personal lives and the face of business throughout the history of human being, and is one of the main drivers of the economy. However, at this point, digital technologies are adjusting the economy much faster than in the past (Brynjolfsson & McAfee, 2014). Following Schwab (2017a), since the middle of the last century, the digital revolution of cyber-physical systems has launched the Fourth Industrial Revolution. The development of the connectivity of the world via smart phones makes it possible to connect all people to each other. Combined with roughly unlimited processing power, storage capacity and access to all expertise via smart machines, creates an entire new set of opportunities for business (Demirkan et al., 2016) and creates a paradigm shift in existing industries and strategic planning. In the last century, the speed of this Fourth Industrial Revolution has increased exponentially. This will impact and change the business models and economy as a whole at a large scale in the near future (Evans, 2017; Schwab, 2017a).

Accenture (personal communication, October 8, 2017), defined ten trends in digital technology that are most likely to disrupt the economy in the future. These digital innovation trends in digital innovation will be used in this research:

1. Big Data
2. Artificial Intelligence
3. Blockchain
4. 3D Printing
5. Autonomous Vehicles
6. Augmented & Virtual Reality
7. Internet of Things (IoT)
8. Hybrid Cloud
9. Drone Technology
10. Robotics Process Automation

In this section, the trends will be shortly discussed, thereby explaining why these innovations are disruptive and therefore considered in this research.

2.3.1 Big Data

The IBM *Tech Trends Report* (2011) identified business analytics as one of the four major technology trends in the 2010s, based on a survey among 4000 information technology professionals from 93 countries and 25 industries.

Large, complex data sets (from terabytes to exabytes) that require advance data storage, management, and analysis technologies are considered as big data (Chen et al., 2012). Generation of big data has increased substantially as a result of the adoption of the Internet in the 1970s, and the corresponding increase of users via the World Wide Web in the 1990s. Moreover, since the 2000s the generation of data has increased exponentially, towards the generation of terabytes and even exabytes scale, due to the usage of an overwhelming amount of web-based, mobile applications (The Economist 2010a, 2010b). Following Schönberger & Cukier (2013), big data analytics has the ability to crunch these datasets, analyze it and draw conclusions from it, thereby changing the way we think about business, health, politics, education and innovation in the coming years.

2.3.2 Artificial Intelligence

Richt (1983) described that the aim of Artificial Intelligence (AI) is to make computers perform actions at which people are better, at this moment. This includes "learning, reasoning, problem-solving, understanding language and perceiving a situation or environment" (Webb, 2017, p. 35). A large part of the development of AI is focused on machine learning. Machine learning can help computers to make decisions independent from human interventions.

According to O´Leary (2013), the importance of AI will increase simultaneously with the growth of the importance of big data. AI-applications will improve the analysis of large, unstructured data, thereby creating chances to use it to better understand big data, or to merge it with other applications. AI can also be applied to other digital innovations, like autonomous cars and drone technology (Hawking et al., 2014). Hawking et al. even suggest that AI can be the biggest event in human history.

2.3.3 Blockchain

Blockchain is mostly known as the technology behind Bitcoin, and other cryptocurrencies. Although cryptocurrencies are the most known user of blockchain, it is not the only application of blockchain. This technology is an open, distributed ledger that is able to record transactions between two parties efficiently, verifiable and on a permanent way without a third entity to control it. Therefore, blockchain can be used for contracts as well. Seeing that contracts and transactions are present in our economic, legal, and political systems, blockchain has the potential to revolutionize business and redefine companies and the economy (Iansiti & Lakhani, 2017).

Iansiti and Lakhani compare the development of blockchain with the rise of TCP/IP (on which the Internet was built). Whilst TCP/IP radically lowered the costs of connections, the blockchain technology has the potential to radically lower the costs of transactions. For example, Iansiti and Lakhani consider a stock transaction: although the transaction takes place in microseconds, the settlement (the ownership transfer of the stock) can take a week, since both parties do not have access to each other's ledgers and therefore are not able to automatically verify the ownership of the stock. As a substitute, intermediaries act as guarantors during the process of verification, and the ledgers are individually updated. In a blockchain system, the ledger is reproduced in multiple identical databases, each hosted by an interested party. When one copy is adjusted, all other copies are updated as well. Therefore, as transactions occur, all ledgers memorize all transactions permanently. Because of this, in the blockchain system a third party as intermediary is not necessary, and transactions can be completed in seconds, instead of weeks, saving large amounts of money and time.

2.3.4 3D Printing

Acoording to Koten (2013), because of 3D printing, we are entering an era where the manufacturing industry will be disrupted like it was disrupted during the Industrial Revolution. A survey of Price Waterhouse Coopers (2014) confirms this development in a survey among 110 manufacturing companies, where 11% already switched to the use of 3D printing and 49% believe that it will be likely or very likely that 3D printing will be used for low volume, specialized printing.

3D printing was originally used for modelling and prototyping. However, as technology improved, it became possible to use 3D printing for similar use as traditional manufacturing. It is now even possible to produce end-products at home with a personal 3D printer. Nonetheless, it is assumed this will not be adopted by the mass consumer, who will find it easier to have it delivered or pick it up at the store (Rayna & Striukova, 2016). Thus, 3D printing will be mostly increase competition in the manufacturing of smaller, specialized production runs (Schubert et al., 2017). The competition will increase radically, since it considerably increases the value creation and value delivery (Rayna & Striukova, 2016).

2.3.5 Autonomous Vehicles

The newest development around car manufacturing is the “connected car”. This is “an automobile designed with direct access to the Internet, enabling automated links to all other connected objects, including smartphones, tracking devices, traffic lights, other motor vehicles — and even home appliances” (Viereckl et al., 2015). The market of autonomous vehicles is still led by the large car manufacturing firms, but tech companies like Apple and Google are also investing in the connected car and autonomous driving. The researchers of PwC (Viereckl et al., 2015) believe that the car manufacturing market will undergo a fundamental change in the next years, starting with a shift towards semi-autonomous driving, and finally towards full autonomous driving. Following Viereckl et al. (2015), car manufacturers will thereby switch from being product suppliers to being providers of mobility services. Seeing that the business experience of car manufacturers is mainly in the production of cars, and not in the digitization of cars, Viereckl et al. (2015) foresee the manufacturers to be forced to cooperate with other businesses to incorporate digital capabilities and remain competitive.

2.3.6 Augmented & Virtual Reality

With Augmented Reality (AR), the view of a physical real-world is edited (augmented) with additional computer-generated information to it. An example is the recently mobile phone game Pokémon Go, where Pokémon virtually appear in the streets when the users turn on the camera on their mobile phone. Virtual Reality (VR) technology, on the other hand, absorbs the users in a synthetic world, without the user able to see the real world (Carmigniani et al., 2011). In this paper, Augmented Reality and Virtual Reality will be combined and considered as one stream in the digitization of business.

AR & VR is still in a very early development stage, and future possible applications are infinite (Carmigniani et al., 2011). Where we nowadays think of head mounted displays, in the future it will be possible to interact with information without the use of such a large intermediate device, but for instance using a small projector mounted on a wearable device (Mistry et al., 2009), or a contact lens only showing information to the user (Schachtman, 2008). Considering the enormous opportunities in many economic regions, like advertising, entertainment education, mobile phone applications and medical applications it is expected that AR and VR will disrupt multiple markets (Carmigniani et al., 2011).

2.3.7 Internet of Things

Despite the fact that the concept Internet of Things (IoT) is widely known and broadly used, there is no common definition of what the Internet of Things exactly includes. This is mainly unclear, because the concept is very broad. Atzori et al. (2010) describe the IoT as “The basic idea of this concept is the pervasive presence around us of a variety of things or objects such as Radio-Frequency IDentification (RFID) tags, sensors, actuators, mobile phones, etc. – which, through unique addressing schemes, are able to interact with each other and cooperate with their neighbors to reach common goals” (p. 2787).

The International Data Corporation (IDC), states that in the present, the discussion regarding IoT is shifting away from the number of devices connected. Moreover, IoT reaches its true value when the combination of software and services are able to capture, interpret and action the data produced by IoT endpoints (IDC, 2017). Thereby, the IDC (2017) expects global total IoT spending to reach nearly $1.4 trillion by 2021. As for the Augmented & Virtual Reality, the possibilities of IoT in the future are large and in multiple industries (Stankovic, 2014). In 2017, the IDC (2017) expects the industries with the largest investments in IoT services to be the manufacturing, transportation, and utilities industries (IDC, 2017). Furthermore, towards 2021, the IDC (2017) expects the fastest spending growth in the insurance industry (20.2% CAGR), consumer industry (19.4%), and cross-industry (17.6%).

2.3.8 Hybrid Cloud

Hurwitz et al. (2012) state that the growing importance of hybrid cloud environments is transforming the entire computing industry as well as the way businesses are able to leverage technology to innovate. The importance of cloud computing with respect to the implementations of other technology has emerged since the development of the hybrid cloud. This cloud employs both private and public cloud services (Hurwitz et al., 2012), thereby the cloud infrastructure is a "composition of two or more distinct cloud infrastructures (private, community, or public) that remain unique entities, but are bound together by standardized or proprietary technology that enables data and application" (Mell & Grance, 2011, p.9). The private cloud is able to let the public cloud capture the extra tasks that cannot be easily run in the private cloud, due to large workloads. It is therefore more flexible than a private or a public cloud (Zhang et al., 2010). This has the potential for the cloud computing market to grow exponentially (Armbrust et al., 2010). Thereby, the hybrid cloud is not only a collection of services running on different platforms. Moreover, it is a pragmatic way for (large and small) companies to search for the best platform to deliver the services they need (Hurwitz et al., 2012).

2.3.9 Drone Technology

The development of drone technology is interesting. In the coming years, if legislation catches up with the technology, it is likely that commercial drone delivery services will be launched by firms like UPS, Amazon and DHL (Webb, 2017). However, drone technology has more potential than only as commercial delivery. The report of Webb (2017) mentions drones to have the potential to be used by news organizations for reports, or microdrones to be used to navigate through tiny spaces to investigate collapsed buildings, for instance. In the meantime, drones have already been used to deliver vital blood deliveries in Rwanda, and to fight wildfires in California. Next to that, researchers at MIT developed autonomous underwater vehicles, which are seen as drones. These Autonomous Underwater Vehicles (AUV's), can be used for environmental mapping, or for military purposes. Conclusively, with respect to surveillance and security, interconnected drones will have the potential to mass track people in concerts, and track traffic on highways (Webb, 2017). Seeing aforementioned possibilities of drone technology, following Evans (2017), drone technology will impact our entire world, from agriculture to construction.

2.3.10 Robotics Process Automation

Within the manufacturing sector, innovations regarding robotics have already been disrupting the market in the last decennia. Following the trend report of Webb (2017), robotics might replace human labor force entirely in the manufacturing industry. This development has already started, mostly in the automotive sector. The development of robotics that are able to communicate with each other, thereby increasing production speed and accuracy, increases quality and quantity of production of the newest automobile factories (Assembly, 2012).

A new trend within the robotics is the Robotics Process Automation (RPA). The Institute for Robotic Process Automation (IRPA) gives the following definition of RPA: "the application of technology that allows employees in a company to configure computer software or a "robot" to capture and interpret existing applications for processing a transaction, manipulating data, triggering responses and communicating with other digital systems" (IRPA, n.d.). Hereby, RPA is not only applicable on manufacturing industries, but in every place where there is a high volume of repetitive tasks. humans will sooner make mistakes while performing monotonous tasks. Therefore, Following Vishnu et al. (2017, p.69), RPA "serves as a good solution to automate these tasks because it offers:

- Improved efficiency and execution quality of tasks
- Increased oversight and control while executing tasks.
- Utilization of existing systems/application interfaces."

There has, however, been debates about how revolutionary this technology really is. Primer (2015, p. 5) responds to claims that RPA is only a product of the evolution of other technologies, stating that "RPA takes artificial intelligence and expert systems to an elevated level. Among leaders in the automation industry, robotic process automation is perceived as offering unique capabilities and advantages over previous technologies".

2.4 Hypotheses formulation

Based on the existing literature and the available data, this section will formulate multiple hypotheses that will be tested in section 4. Unfortunately, as will be discussed in section 3.2, this study has to deal with some data limitations. In the questionnaire of the used data, proper questions regarding turnover are only asked since 2016. It is therefore not possible to measure the development of turnover over multiple years. Next to that, the questionnaires were not filled out largely before 2014. The low number of replies in the years before 2014 make it difficult to analyze these years. Therefore, this research will focus on the last four years.

In the view of multiple researchers discussed in section 2.3, the economy is developing fast, because of digital innovations disrupting the economy (e.g. Brynjolfsson & McAfee, 2014; Evans, 2017 Brynjolfsson & McAfee, 2014; Demirkan et al., 2016; Evans, 2017; Schwab, 2017a) This is also called the Fourth Industrial Revolution (Schwab, 2017a). Combined with the economic framework of the industry life cycle mentioned in section 2.1, it is therefore expected that the development of digital innovation in the economy is in the first or second stage of the industry life cycle, respectively the introduction or growing stage. In this phase, many small firms enter the industry, disrupting the market (Klepper, 1997). This development should induce an increase in number of firms using digital innovation entering the market, and an increase in total turnover of the entrants. Thereby, a large customer base is needed to expand the amount of sales, and thereby turnover (Scott and Bruce, 1987). If digital innovation is developing as the theory expects, the first two hypotheses will be confirmed:

H1: In the Accenture Innovation Awards, the number of participating concepts that use digital innovation has increased, relative to the total of participating concepts over the last 4 years.

H2: In the Accenture Innovation Awards, the number of users of participating concepts that use digital innovation has increased, relative to the total of participating concepts over the last 4 years.

Following the theory of the Industry Life Cycle, and the assumption that the market is in the first or second stage of this process, the concepts that use digital innovations are disrupting the market with their innovations. Therefore, at this point, concepts using digital innovations are expected to further disrupt the market in the coming years, thereby outcompeting the rivals that do not use digital innovations. For this to happen, concepts using digital innovations have to be more successful than concepts that do not use digital innovations. It is thereby important that the use of digital innovations is one of the key drivers of success. As discussed in the section regarding small business growth, success is often measured by financial measures, like turnover, but also by the growth of the number of employees of a firm (e.g. Murphy et al., 1996; Chell and Baines, 1998; ; Georgellis et al., 1999; Mäki and Pukkinen, 2000; Perren, 2000; Gray, 2002; Reijonen and Komppula, 2007). Due to limitations of the dataset, growth rates of individual firms cannot be used in this research. Nevertheless, the variable turnover can be used as indicator of financial success of a small business. Seeing this, this research expects to find a considerable positive effect of the use of digital innovations on the turnover of concepts. At the same time, it is difficult for businesses to be successful with only a few customers. As mentioned above, a large customer base is needed to expand the amount of sales, and thereby turnover (Scott and Bruce, 1987). Since this study only includes very young initiatives, it might be the case that a business already has a customer base but has not implemented a revenue model at this point in time. Consequently, this study expects to find a positive effect of the use of digital innovations on the number of users of a concept. This leads to hypothesis 3 and 4:

H3: The use of digital innovations has a positive effect on the turnover of concepts.

H4: The use of digital innovations has a positive effect on the number of users of concepts.

3 Data and methods

To test the hypotheses formulated in the previous section, the participants of the AIA will be analyzed. This section will first briefly discuss the AIA. Secondly, the variables that are used will be presented, followed by the descriptive statistics of these variables. Finally, the methods of the study will be explained.

3.1 Accenture Innovation Awards

Since 2006, Accenture yearly organizes the AIA. This started as an award program, where firms can participate with their innovative concepts of maximum three years old. Important hereby, is that the concept participates for the award, not the company. Therefore, the concept has to be three years old or less. This way, also older firms are able to participate. Despite this, the vast majority of the contestants are startups. In the present, the AIA has developed into a year-round program with the goal ‘to create an extensive ecosystem to connect all innovators and to drive innovation together’.

The AIA program consists of multiple events throughout the year, where startups are learning from each other and from corporate firms. Also, during these events, developments within the innovation ecosystem are discussed with panels of experts; previously winning concepts, participants, AIA jury members, and over 100 innovation partners. The program ultimately leads to the Innovation Summit, the place where all corporates, innovators, influencers, partners and the best Dutch innovators connect, learn and get inspired. Conclusively, the 11 (one per theme) most promising innovating concepts of the year will be awarded.

Since 2016, the AIA strives to have a more international orientation, thereby also letting companies from other countries participate in the program. This has not yet lead to a large increase of participants from foreign countries, leaving the largest part of contestants coming from the Netherlands. This does not prohibit this research from being relevant, however. The Netherlands can be seen as a country with a favorable innovation climate, with a first place of Europe on the Startup Nation Scorebord (Osimo, 2016), a fourth place in the GCI Global Competitiveness Index (Schwab, 2017b), a third spot in the Global Innovation Index (Dutta et al., 2017), combined with Amsterdam as the European Capital of Innovation (European Commission, 2016), and Amsterdam ranked as 19th of the Global Startup Ecosystem Ranking (Genome, 2017). With respect to the Netherlands, the AIA can be seen as the initiator of the largest startup ecosystem, following Manon van Beek, the country managing Director of Accenture Netherlands (as cited in Duurzaam Ondernemen, 2017).

3.2.1 Dependent variables

Every year, the participants of the AIA are asked to fill in a questionnaire with respect to their company and their innovative concept. During the first years of the AIA, the ecosystem was not as large as it currently is, and the questionnaire was often not filled out correctly. Next to that, the questionnaire participants had to fill in did not always have the same set up, leading to varying answers that are difficult to compare. For instance, the turnover of participating concepts was only asked since 2016. Previously, it was asked what percentage of the company its turnover was generated by the participating concept, without knowing the total turnover of the company. This study is therefore only able to use the turnover of the concepts of the last two years. However, with approximately 3000 contestants in the AIA over the past four years, the size of the ecosystem is large enough to represent a large share of the innovating ecosystem of the Netherlands. Therefore, this study will use the data of the last four years (2014-2017) to test the hypotheses. Important to note is, that all observed concepts participate only once. Therefore, it is not possible to measure growth rates of concepts since it is not possible to observe every concept for multiple years.

Use of Digital Innovation

The main independent variable this research uses is the dummy variable use of digital innovation. This variable indicates if the concept uses a digital innovation (1), or not (0). Based on the description of the concept, combined with the digital innovations as explained in section 2.3, concepts are assigned with either 0 or 1. Hereby, it was not possible to distinguish between concepts using a digital innovation as a production function for the concept, and digital innovations being the end product of the concepts. Therefore, as both cases relate very closely to digital innovations, both are indicated as being a digital innovation in this research (1). This variable will be used to answer Hypothesis 1 with descriptive statistics, but also Hypothesis 3, with the help of a generalized ordered logistic model.

Turnover

As discussed in the literature review in section 2.2, there are multiple ways of measuring the success of a (small) businesses. In this study, turnover is one of the variables that will be analyzed. As stated before, until 2015 the participating concepts were asked what percentage of the turnover of the company was generated by the innovative concept. Since the total turnover of the companies was not asked, the data regarding turnover before 2016 is not usable for this study. Since 2016, the participants of the AIA were asked to fill in the turnover of their concept of the past year. Thereby, five options were given, what led to a categorical variable with five categories:

0. €0
1. €0 – €10,000
1. €10,001 - €100,000
2. €100,001 - €1,000,000
3. €1,000,001 - €5,000,000
4. > €5,000,000

Number of Users

A second measure of measuring business success in this study is the number of users. A large customer base is needed to drive sales growth (Scott and Bruce, 1987). The categorical variable number of users will be used as a measure of business performance in Hypothesis 2 and Hypothesis 4. The variable has six categories, representing the number of users a concept had over the last year:

1. 0 – 10 users
2. 11 – 100 users
3. 101 – 1000 users
4. 1001 – 10,000 users
5. 10,001 - 100,000 users
6. >100,000 users

3.2.2 Control variables

This section will discuss the control variables of this study. Based on the literature regarding small business growth discussed in section 2.2, multiple control variables are selected. In an ideal situation, all factors that influence small business growth as discussed by Morrison et al. (2003) are represented in the study. However, as stated in the introducing paragraph of section 3.2, the questionnaire of the AIA did not always have the same set up, and some questions were not filled answered at all. This lead to the absence of some variables that would have improved this study considerably.

Concept Age

Over time, small businesses have the opportunity to grow over the years. Since a concept is allowed to be three years old when participating in the AIA, this can make a substantial difference. To control for this influence, this variable is added to the model. It is measured by distracting the variable year of launch from the variable year of participation for every concept. Therefore, the minimum value is 0, when the concept is launched in the same year as it participated, and the maximum value is 3, the maximum age a concept is allowed to have to participate in the AIA.

Introduced Other Concepts

The second control variable regarding the knowledge and experience of the entrepreneurs that is added to the model, is introduced other concepts. This variable represents the entrepreneurs to have introduced other concepts before or not. This leads to a dummy variable, taking value 1 if the entrepreneur has introduced a concept before, and taking value 0 if the entrepreneur has not introduced a concept before.

Internal and External Access to Finance

A financial pro-growth factor mentioned in Table 1, is the access to finance. To control for this influence, two variables are added to the model; internal access to finance and external access to finance. The entrepreneurs were asked "To what extent have the following factors been an obstruction for the innovation activities of projects within the last 3 years?" This multiple choice question consists of four answers, ranging from 'severe obstruction' to 'not perceived'.

This leads to another categorical variable in the model. This question was asked for the "lack of financial resources in company or corporation" and "lack of access to external financial resources". The first will be used as an indicator for internal access to finance, the latter will be used as an indicator for external access to finance.

Access to Market Information and Access to Information about Technology

The same question as for the access to finance, accompanied with the same answer possibilities, was asked for the possible lack of market information and lack of information about technology. As discussed in section 2.2, the accessibility to resources and information has a positive influence on the success of small businesses. The variables access to market information and access to information about technology are added to control for this effect.

3.3 Descriptive statistics

The means, standard deviations, frequencies and percentages of the variables that are used in this study are summarized in Table 2.

To start with the dependent variables, only 741 (24.75%) out of the 2994 contestants filled in the turnover of their concept. A total of 207 (27.94%) of these concepts, do not have any turnover at this moment. Almost the same number of concepts, 203 (27.4%) have a turnover between €100,001 and €1,000,000. The question regarding the number of users was filled in by 2,452 concepts (81.89%). This variable is fairly distributed in the lowest four categories. Cumulatively, 2118 (86,37%) of the concepts that answered the question have between 0 and 10,000 users.

Digital innovation will be used as the explanatory variable. 675 out of 2,994 concepts are labeled as using a digital innovation. This stands for 22.55% of the total number of concepts participating in the AIA over the last four years.

Concerning the control variable concept age, most of the concepts have started in the same year as the year they participated (51.60%). Only 106 (3.82%) of the concepts are of the maximum age of three years. Looking at the experience of the entrepreneurs, slightly more than half of the entrepreneurs have introduced a concept before (51.29%). Both the Internal Access to Finance and the External Access to Finance are considered as an obstruction to innovate from the viewpoint of the entrepreneurs. 84.48% of the entrepreneurs see Internal Access to Finance as a weak to severe obstruction, whereas 15.52% did not see Internal Access to Finance as an obstruction to innovate. With respect to the latter, 18.48% of the concepts did not perceive External Access to Finance as an obstruction to innovate. On the subject of the accessibility of information, both the Lack of Market Information and the Lack of Information about Technology are in general not seen as severe obstructions to innovate. With both questions, most of the respondents answered that they did not perceive this as an obstruction (45.94%, and 46.68%, respectively).

Table 2. Descriptive Statistics

Variable	Mean (S.D.)	Observations	Percentage
Turnover		**741**	
€0		207	27.94%
€0 – €10,000		32	4.32%
€10,001 - €100,000		72	9.72%
€100,001 - €1,000,000		203	27.4%
€1,000,001 - €5,000,000		110	18.84%
> €5,000,000		117	15.79%
Number of Users		**2,452**	
0 – 10		643	26.22%
11 – 100		523	21.33%
101 – 1000		565	23.04%
1,001 – 10,000		387	15.78%
10,001 – 100,000		235	9.58%
>100,000		99	4.04%
Use of Digital Innovation	0.22 (0.42)	**2,994**	
No		2319	77.45%
Yes		675	22.55%
Concept Age		**2,775**	
0 years		1432	51.60%
1 year		902	32.50%
2 years		335	12.08%
3 years		106	3.82%
Introduced Other Concepts	0.51 (0.50)	**1,587**	
No		773	48.71%
Yes		814	51.29%
Internal Access to Finance		**2146**	
Severe obstruction		609	28.38%
Obstruction		672	31.31%
Weak obstruction		532	24.79%
Not perceived		333	15.52%
External Access to Finance		**2,143**	
Severe obstruction		572	26.69%
Obstruction		649	30.28%
Weak obstruction		526	24.55%
Not perceived		396	18.48%
Lack of Market Information		**2,142**	
Severe obstruction		85	3.97%
Obstruction		367	17.13%
Weak obstruction		706	32.96%
Not perceived		984	45.94%
Lack of Information about Technology		**2,140**	
Severe obstruction		126	5.89%
Obstruction		358	16.73%
Weak obstruction		657	30.70%
Not perceived		999	46.68%

Note. Standard deviations are given in parenthesis.

3.4 Methods

The hypotheses established in section 2.4 are tested using both descriptive statistics and ordered logistic regressions. For Hypothesis 1 and 2 descriptive statistics of the dataset are used. Given the nature of the categorical dependent variables turnover and number of users, a generalized ordered logistic model, and ordered logistic models are created to test Hypothesis 3 and 4.

To test the first two hypotheses, descriptive statistics for the years 2014-2017 regarding respectively the number of concepts using digital innovation, the turnover, and the number of users of concepts will be analyzed. Thereby, a comparison will be made between concepts that are considered as using a digital innovation and concepts that are considered as not using a digital innovation. To investigate Hypothesis 1, a relative development of the number of concepts that use a digital innovation with respect to all concepts is used. To investigate Hypothesis 2, a relative development of the customer base, represented by the number of users of a concept, is used.

The models in the second part of the research consists of multiple variables. First, the dependent variable to test Hypothesis 3 is turnover. The dependent variable to test Hypothesis 4 is number of users. Second, the main independent variable of the models is, as mentioned in section 3.2, digital innovation. Third, based on the literature discussed in section 2.2, control variables for the models are included. By holding these variables constant while analyzing the dependent and independent variables there is controlled for these effects. The control variables that are included in the models are concept age, introduced other concepts, access to internal finance, access to external finance, access to market information, and access to information about technology.

Seeing that the dependent variables are categorical variables, an ordered probit or logit model normally fits best. An ordered logit regression is more robust than ordinal regression techniques for categorical variables, since it takes account of the discrete and ordinal nature of the dependent variables (Wooldridge, 2015). Next to that, a multinomial logit model would not fit this data perfectly, since that does not account for the ordering of the dependent variables (Wooldridge, 2015). An important assumption that has not to be violated in the ordered logit model, is the parallel lines assumption. This assumption considers the relationship between each pair of outcome groups to be the same. In other words, it is assumed that the coefficient of an independent variable that describes the relationship between, for instance, the lowest two categories is the same as the coefficient of this independent variable describing the relationship between the highest two categories. When this assumption holds, an ordered logit model can be used. However, if this assumption is violated, alternative models have to be considered (Long and Freese, 2006). Using the Likelihood-Ratio (LR) test created by Wolfe and Gould (1998) and the Wald test created by Brant (1990), the parallel lines assumption is tested for violation.

The LR test creates a model in which the effects of all explanatory variables are different at each category, and tests if this model fits the data better than the model provided by the ordered logistic regression. The null-hypothesis thereby is that there is no difference regarding the coefficients of both models. If this hypothesis is rejected, there is a difference between both models and the parallel lines assumption does not hold. Next to that, the Brant tests the parallel lines assumption for each variable individually. As for the LR test of Wolfe and Gould, significant test results imply a violation of the parallel lines assumption. Hereby, the variables causing this violation can be found.

Table 3 shows the results for the LR tests regarding the two hypothesis this research tests, with the dependent variables Turnover, and Number of Users representing Hypothesis 3 and Hypothesis 4, respectively. The LR test regarding Hypothesis 3 shows a p-value of 0.000, a significant outcome on a 1% significance level. This implies a violation of the parallel lines assumption for this model. The LR test on the second model shows a p-value of 0.7833, an insignificant outcome on a 10% significance level. Therefore, there is no violation of the parallel lines assumption found of this model.

Table 3. Likelihood Ratio Tests

Hypothesis 3			**Hypothesis 4**		
Chi²	**p>Chi²**	**df**	**Chi²**	**p>Chi²**	**df**
93.04	0.000	28	21.96	0.7833	28

Table 4 displays the outcome of the Brant test for both models. In these tests, the same outcomes are seen as in the LR tests. For the full models, p-values of 0.000 and 0.767 are found, implying a violation of the parallel lines assumption by the model regarding Hypothesis 3, and no violation of the parallel lines assumption by the model regarding Hypothesis 4. In the case of the first model, the violation of the parallel lines assumption is mostly caused by the significant outcome regarding the variable concept age (0.000). Because of abovementioned outcomes, an ordered logit model cannot be used to test Hypothesis 3, but can be used to test Hypothesis 4.

Table 4. Brant Test

Variable	Hypothesis 3 Chi²	p>Chi²	df	Hypothesis 4 Chi²	p>Chi²	df
All	83.66	0.000	28	22.30	0.767	28
Use of Digital Innovation	4.76	0.313	4	1.35	0.852	4
Concept Age	38.98	0.000	4	9.68	0.046	4
Introduced Other Concepts	10.43	0.034	4	4.14	0.387	4
Internal Access to Finance	8.53	0.074	4	1.65	0.800	4
External Access to Finance	2.21	0.697	4	2.74	0.602	4
Lack of Market Information	7.21	0.125	4	0.74	9,47	4
Lack of Information about Technology	7.52	0.111	4	3.79	0.436	4

To test Hypothesis 3, the generalized ordered logit (gologit) model of Fu (1998) and the thereat inspired generalized ordered logit (gologit2) model of Williams (2005), offer an alternative where the parallel lines assumption will not be violated. A problem that arises with the gologit model, is that all variables are free from the parallel-lines constraint of the ordered logit model, although the assumption might be violated by only a few of the used variables. This was seen in Table 4, seeing that the violation of the parallel lines assumption is mostly caused by the variable Concept Age. In the gologit2 model, this problem can be fixed using the autofit option in Stata (Williams, 2005). Going through an iterative process, with the help of Wald tests, the gologit2 model is thereby fitted so that the parallel-lines constraint is relaxed only for those variables where it is not justified. In the end it performs a global Wald test on the final model with constraints, versus the unconstrained model. Table 5 shows the outcome of this test for the final model regarding Hypothesis 3. With a p-value of 0.000 this test is insignificant on a 10% level shows that the final model does not violate the parallel lines assumption anymore. Therefore, the gologit2 model is used to test Hypothesis 3.

Table 5. Global Wald Test Final Model

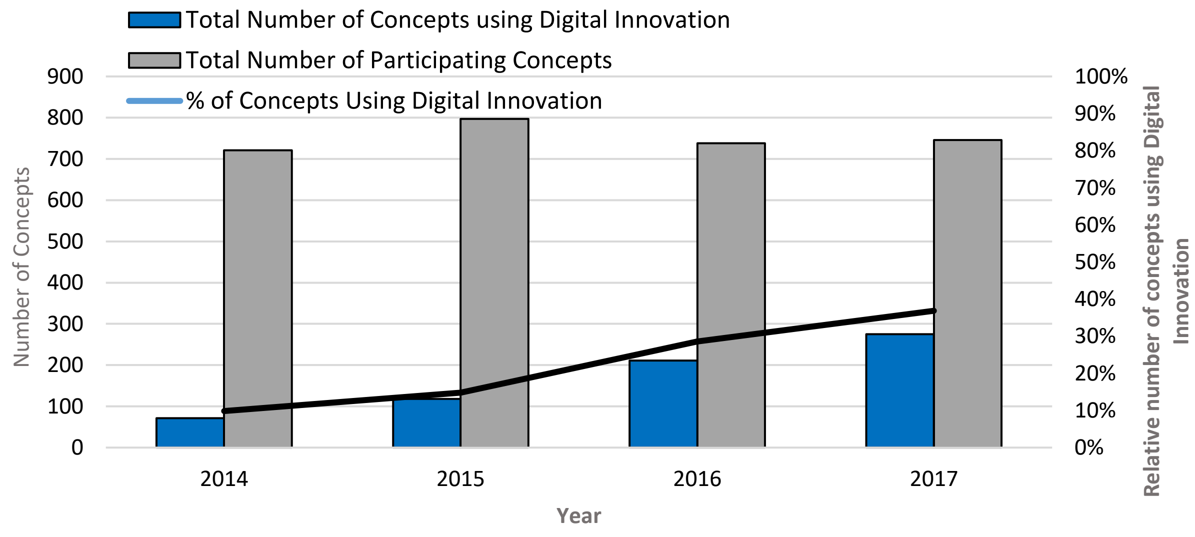
Hypothesis 3		
Chi²	**p>Chi²**	**df**
93.04	0.000	28

4 Results

As discussed in section 3.4, descriptive statistics, a generalized ordered logistic model, and an ordered logistic model are used to test the hypotheses of this study. This section discusses the main findings of the research and provides answers on the hypotheses this research developed in section 2.4.

Figure 2 shows the development of the total number of concepts using digital innovations relative to the total number of concepts participating in the AIA for the past four years. Where the total number of concepts has been stable over the past years, between 720 and 800 concepts, the number of concepts using a digital innovation has increased from 71 in 2014 to 275 in 2017. As displayed by the increasing black line in Figure 2, this is a growth of 27 percentage points, from 10% to 37% of the total number of participating concepts. In percentages, this is an increase of 287%.

Figure 2. Development of Concepts using Digital Innovation



This growth can also be seen in Figure 3, where all digital innovation trends are displayed individually. All trends of digital innovation show an increase in the number of concepts that use them. What stands out here is the difference between the different trends. Especially the number of concepts that use big data, augmented virtual reality, the internet of things, hybrid cloud, and artificial intelligence has grown. Because of the stability of the total number of concepts participating in the AIA, the absolute growth of the number of concepts using digital innovations is also a relative increase of the number of concepts using digital innovations. To summarize, the total number of concepts that use digital innovation has increased with 287%, and all trends separately show an increase. Hypothesis 1, expecting that '*In the Accenture Innovation Awards, the number of participating concepts that use digital innovation has increased, relative to the total of participating concepts over the last 4 years*', is therefore confirmed.

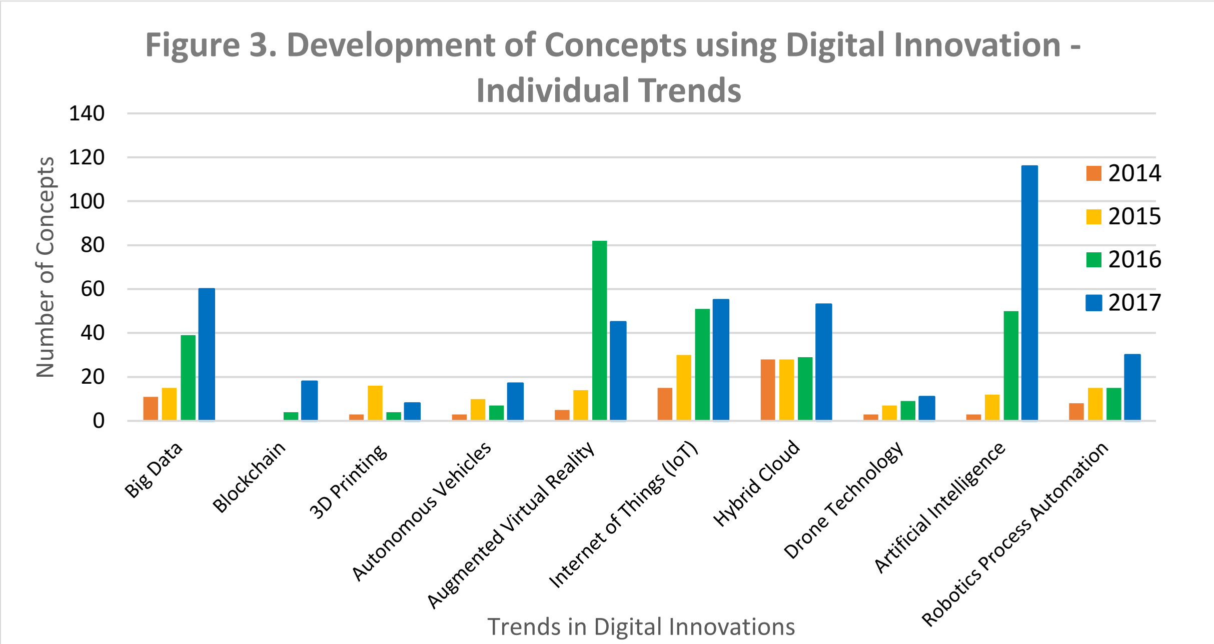
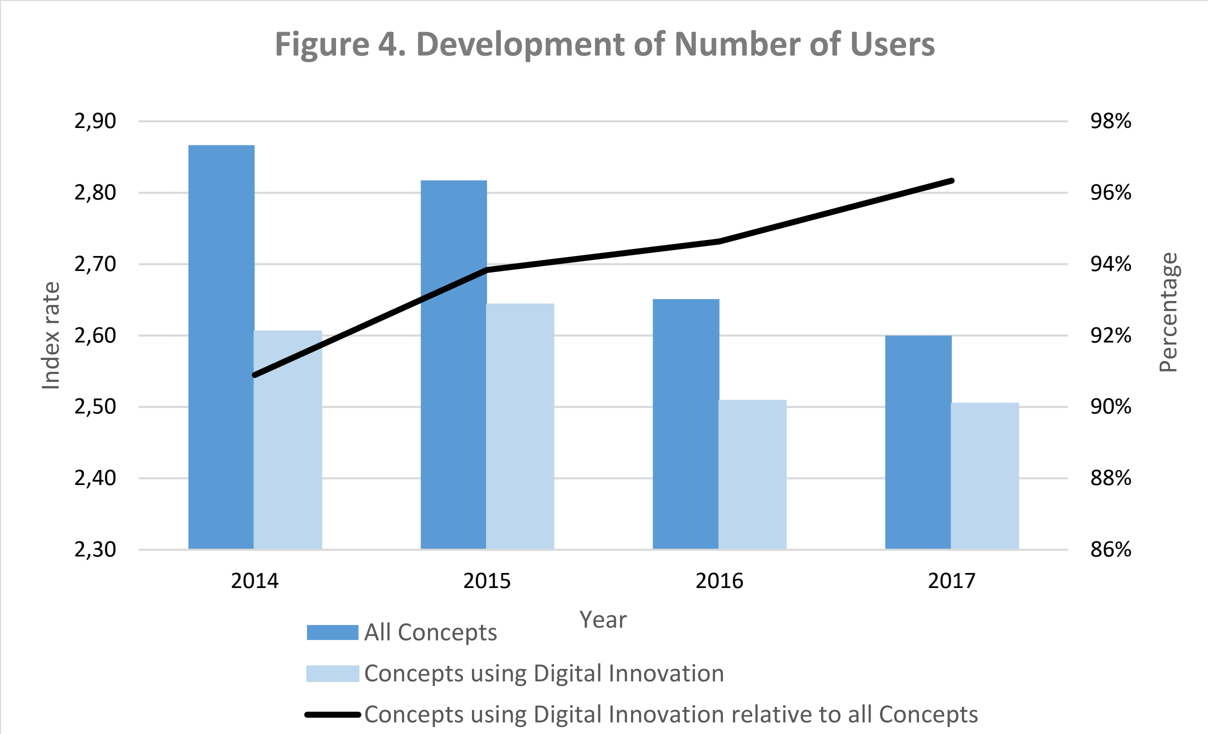


Figure 4 displays the development of the number of users of the participating concepts in the AIA. As discussed in section 3.2.1, the variable regarding number of users is a categorical variable, ranging from 1 to 5. In the period 2014 – 2017, the mean diminished slightly, from 2.87 in 2014, to 2.60 in 2017. This means that the average number of users of the participating concepts is between 11-100 users, but close to 101-1000 users. What can be seen in Figure 4 is that this decrease in the average number of users comes mostly from the concepts that do not use digital innovations. Although the average number of users of concepts that use digital innovations (from 2.61 to 2.50) is also decreasing, the average number of users of all participants of the AIA is decreasing faster. Seeing the increasing black line representing the relative size of the average number of users of concepts using digital innovation versus the total sample, this is clear visible. This confirms Hypothesis 2, that '*in the Accenture Innovation Awards, the number of users of participating concepts that use digital innovation has increased, relative to the total of participating concepts over the last 4 years'*. However, taking a look at the percentages on the right vertical axis and the blue columns, it becomes clear that despite the fact of a relative increase of the number of users of concepts using digital innovations, the average number of users of these concepts is still lower than the average number of users of the total sample. Thereby, a decreasing average number of users is not a sign of having a successful business.



The outcome of the generalized ordered logistic regression on the variable turnover is presented in Table 6. This model splits the effects of the variables in different categories, representing the categories of the dependent variable. Thereby, it contrasts category 0 with the four last categories; the first category with category 0, 2, 3, 4 and omitted category 5; the second category with category 0, 1, 3, 4 and 5; the third category with category 0, 1, 2, 4, and 5; and the fourth category with category 0, 1, 2, 3, and 5. A positive coefficient thereby indicates that a higher value of the independent variable make it more likely that the dependent variable is in a higher category than in the current one. A negative coefficient indicates that higher values of the independent variable increases the possibility of being in the current or a lower category (Williams, 2006).

Positive, statistically significant outcomes are found for the use of digital innovation in the first three categories. In the fourth category, this variable is not significant anymore. This means, that the chance of turnover to be in a higher category than in category 0, 1, 2, or 3 increases, if a concept uses a digital innovation, holding other variables constant. A distinction between category 4 and 5 is hereby not possible, because of the insignificance of use of digital innovation in category 4. The strongest effect of the use of a digital innovation is found in category 0. The strength of this effect diminishes towards higher categories but stays positive.

The insignificance of most of the control variables is unexpected. The age of the concept shows similarities to the use of a digital innovation, with significant, positive (but diminishing) coefficients in the first three categories. In the case of the age of the concept, the variable is already insignificant in category 3. Thus, a concept that is older, has a higher chance of a turnover in a higher category than 0, 1, or 2, than younger concepts, holding other variables constant.

The effect of internal access to financial resources on the turnover of a concept is only significant on a 5% significance level in category 0. What mostly surprises hereby, is the negative coefficient, although it is only a small coefficient (-0.280). This implies that concepts with a higher variable of internal access to financial resources are more likely to be in category 0 than in higher categories, holding other variables constant. An increase in the variable internal access to financial resources suggests the lack of internal resources were less seen as an obstruction to innovate. Hence, this outcome suggests that, holding other variables constant, concepts that perceived lack of internal resources a minor obstruction to innovate have a higher likelihood of being in category 0, than in higher categories. This contradicts the literature. Unfortunately, this cannot be compared with the external access to finance since all coefficients of this variable are insignificant on a 5% significance level.

As for the variable regarding the access to internal finance, the coefficient of the variable Lack of Market Information is negative and statistically significant, but only in category 1. In this case, concepts that perceive a lack of market information as a smaller obstruction to innovate, are more likely to be in category 0 or 1, than in a higher category, holding other variables constant. The lack of information about technology was found significant and positive in category 0. Therefore, when holding other variables constant, concepts that perceive a lack of information about technology as a smaller obstruction to innovate, are more likely to be in a higher category than category 0. In other categories, this variable was also insignificant. Next to that, the variable that represents the experience of the entrepreneur, introduced other concepts, was not found to be significant in any category. Additionally, if we look at the turnover of the concepts in 2017 (Figure 5), concepts that use a digital innovation have, on average, a higher turnover than the concepts that do not use a digital innovation.

To summarize, most of the control variables were found to be insignificant on a 5% significance level. However, the main variable this study investigates, the use of digital innovation, was mostly significant on a 1% significance level, thereby showing a positive coefficient, as expected. '*The use of digital innovations has a positive effect on the turnover of concepts'*, as stated with Hypothesis 3, is therewith confirmed.

Table 6. Generalized Ordered Logistic Regression for Turnover

	Turnover	
0	Use of Digital Innovation	1.272 (5.00)**
	Concept Age	1.156 (6.67)**
	Introduced Other Concepts	-0.175 (0.83)
	Internal Access to Financial Resources	-0.280 (2.25)*
	External Access to Financial Resources	-0.087 (0.88)
	Lack of Market Information	-0.240 (1.84)
	Lack of Information about Technology	0.066 (3.41)**
1	Use of Digital Innovation	0.712 (3.30)**
	Concept Age	0.808 (5.63)**
	Introduced Other Concepts	0.218 (1.12)
	Internal Access to Financial Resources	-0.052 (0.45)
	External Access to Financial Resources	-0.087 (0.88)
	Lack of Market Information	-0.337 (2.77)**
	Lack of Information about Technology	0.066 (0.70
2	Use of Digital Innovation	0.558 (2.86)**
	Concept Age	0.583 (4.78)**
	Introduced Other Concepts	0.349 (1.93)
	Internal Access to Financial Resources	-0.005 (0.04)
	External Access to Financial Resources	-0.087 (0.88)
	Lack of Market Information	-0.124 (1.11)
	Lack of Information about Technology	0.066 (0.70)
3	Use of Digital Innovation	0.522 (2.78)**
	Concept Age	0.135 (1.25)
	Introduced Other Concepts	-0.100 (0.55)
	Internal Access to Financial Resources	0.083 (0.72)
	External Access to Financial Resources	-0.087 (0.88)
	Lack of Market Information	-0.100 (0.89)
	Lack of Information about Technology	0.066 (0.70)
4	Use of Digital Innovation	0.420 (1.85)
	Concept Age	-0.177 (1.22)
	Introduced Other Concepts	0.080 (0.35)
	Internal Access to Financial Resources	-0.115 (0.84)
	External Access to Financial Resources	-0.087 (0.88)
	Lack of Market Information	0.029 (0.20)
	Lack of Information about Technology	0.066 (0.70)
	Number of Observations	571

* *p*<0.05; ** *p*<0.01

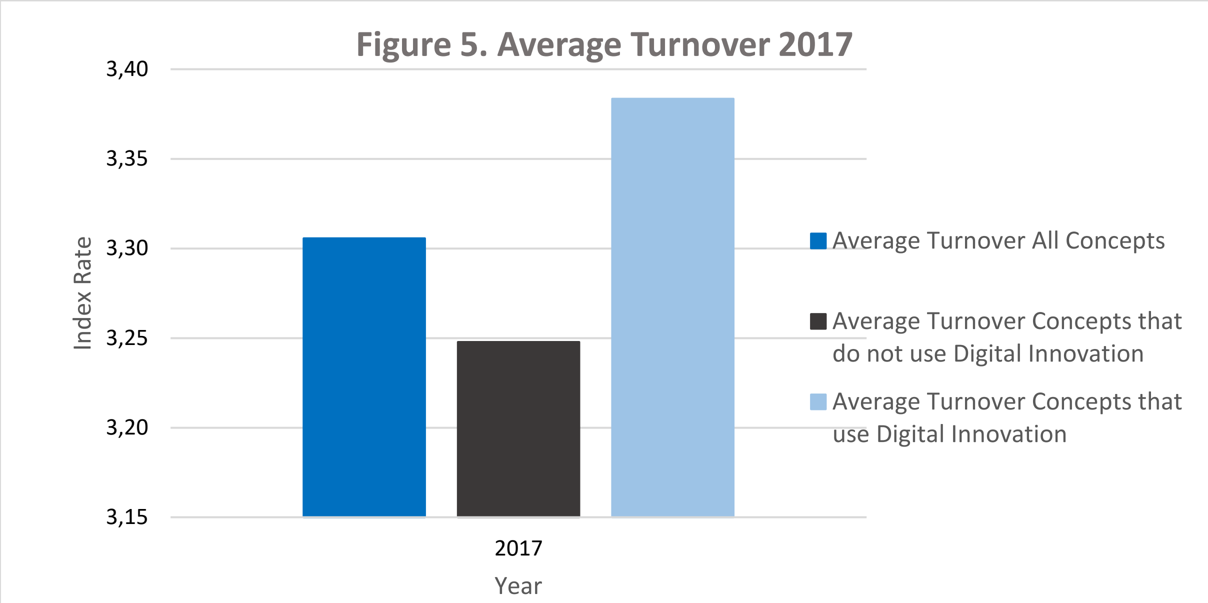


Table 7 shows the ordered logistic regression for the dependent variable number of users. This model used 1388 observations. Thereby, the variables concept age, lack of information about technology are statistically significant on a 1% significance level. The variables use of digital innovation and lack of market information are significant on a 5% significance level. Again, the variable representing the experience of the entrepreneur, introduced other concepts, is not significant on a 5% significance level. The two variables serving as indicators for the accessibility of financial resources, internal and external access to financial resources, are not significant on a 5% significance level as well. The variables concept age and lack of market information are positive, as the literature expects. The variables lack of information about technology, and for this study more important, use of digital innovation, show unexpected negative coefficients. This implies a negative effect of the use of digital innovations on the number of users a concept reports. Therefore, Hypothesis 4, stating *'The use of digital innovations has a positive effect on the number of users of concepts'* is rejected.

Table 7. Ordered Logistic Regression for Number of Users

Number of Users	
Use of Digital Innovation	-0.240 (2.11)*
Concept Age	0.312 (5.17)**
Introduced Other Concepts	0.014 (0.15)
Internal Access to Financial Resources	0.029 (0.30)
External Access to Financial Resources	0.080 (0.84)
Lack of Market Information	0.157 (2.56)*
Lack of Information about Technology	-0.187 (3.37)**
Number of Observations	1,388

* p<0.05; ** p<0.01

To summarize the results section, the first three hypotheses are confirmed, the fourth hypothesis is rejected. Important to note thereby is that Hypothesis 2 is confirmed, but the average number of users of concepts using digital innovations is still lower than the average number of users of concepts that do not use digital innovations.

5 Discussion and conclusion

The goal of this study was to answer Accenture's question whether the use of digital innovations is just a hype, or if this is a driver of the creation of new successful business. The answer to this question can help Accenture gaining new insights in the present innovative environment in the Netherlands, thereby increasing the value of the advice to their clients. Next to that, this development is also interesting for policymakers: if digital innovations are leading to more successful startups that push the economy forward, it is prosperous to create an environment that is favorable for startups that use digital innovations.

Innovation is important for economies to develop (Schumpeter, 1934). New innovations will push the economy away from equilibria, thereby replacing former products and technologies, also called creative destruction (Schumpeter, 1934). Later on, Schumpeter (1939) argued that innovations might cluster in specific industries, thereby constantly disrupting and evolving the specific industries. However, at a certain point this growth will slow down, leading to business cycles (Fagerberg, 2003). Newer literature evolved this theory of Schumpeter, creating the so-called Industry Life Cycle (e.g. Abernathy & Utterback, 1978; Gort and Klepper, 1982; Klepper and Graddy, 1988; Utterback and Suarez, 1992; Klepper, 1997). In this model, three stages of evolution are considered. First, radical innovations will start a new stream of product innovations entering the market, with low entry barriers and high competition. Second, a dominant design is established where the market settles. During this stage, other designs are excluded and the space for new product innovations is narrowed. In the third of the Industry Life Cycle, the maturity stage, only incremental innovations will occur. This offers room for new radical innovations to disrupt the industry, starting a new cycle. Hypothesis 1 and Hypothesis 2 examined if digital innovations are disrupting the market as the theory expects. Seeing the claim of Schwab (2017a) that a new Industrial Revolution has started, this study expected digital innovations to be in the first or maybe second stage of the Industry Life Cycle. Therefore, the data of the participants of the Accenture Innovation had to show a relative growth in the number of firms entering the market with digital innovations (Hypothesis 1), and a relative increase in the volume of the customer base of the firms that use digital innovations, represented by the number of users (Hypothesis 2). Hypothesis 1 was confirmed showing an absolute and relative increase of the number of concepts that use a digital innovation. 275 concepts that use a digital innovation participated in 2017, relative to 71 concepts in 2014. This is a 287% increase, and with respect to the overall number of participating concepts, an increase from 10% to 37% of all concepts using a digital innovation. Next to that, relative to the average volume of the number of users of all concepts, the average volume of the number of users of concepts that use digital innovations grew over the past four years. The second hypothesis is thereby also confirmed. However, the customer base of the concepts that use a digital innovation was, on average, still lower than the average customer base of all participating concepts. Next to that, the average number of users of all concepts showed a decrease over the past four years.

To investigate if the use of digital innovation is a key driver of the success of businesses participating in the AIA, Hypothesis 3 and Hypothesis 4 were formed. These hypotheses tested the influence of the use of a digital innovation on respectively the turnover and the number of users of the concepts. While testing, the models controlled for other variables influencing the dependent variables. These control variables are derived from theories regarding small business growth, and represent the age of the concept, the experience of the entrepreneur, the internal and external accessibility of financial resources, and the accessibility of information regarding both the market and technologies. Unfortunately, not all of the discussed aspects of small business growth are included in the models, because of data limitations. This was caused by omitted questions regarding potential control variables, and questions not answered by the participants. Nevertheless, a positive, statistically significant effect of the use of digital innovations was found on the turnover of concepts, thereby confirming Hypothesis 3. On the other hand, with respect to the customer base, an unexpected negative effect of the use of digital innovations on the number of users of a concept was found. Hypothesis 4 was therefore rejected. An explanation for this can be the fact that most of the participating concepts, namely 51.60% of the participants, were launched in the same year as the year they participated. One should be careful with interpreting the results, however. Analyzing the turnover of the concepts was only possible since 2016. Next to that, more control variables might be needed to be more certain about the found effect of the use of digital innovations on the turnover and on the number of users of the concepts. Nonetheless, with 2,994 investigated concepts, the sample of this study is a large representation of the Dutch innovative ecosystem. Thereby, multiple years regarding descriptive statistics were investigated, leading to strong statistics, confirming the expectations.

This study confirms that the trend of digital innovation is not a hype, but is indeed a driver of the creation of new successful businesses. It is thereby developing as the theory suggests, showing an increase of number of firms that use digital innovations entering the market, and a relative growth of the customer base. A recommendation for Accenture is therefore, to include digital innovations (even) more in both their own business and their advice to clients. To gain more benefit out of the large ecosystem Accenture created, participants in the AIA need to fill out the questionnaires more completely, and the questions asked in the questionnaire should remain the same over multiple years. Thereby, future studies can find more stable results. A suggestion for the Dutch policymakers to create an environment that is (even more) favorable for startups that use digital innovations, to improve the competitiveness of the country, and to stimulate growth.

6 References

Abernathy, W. J., & Utterback, J. M. (1975). A dynamic model of process and product innovation. *Omega*, *3*(6), 639-656.

Abernathy, W. J., & Utterback, J. M. (1978). Patterns of industrial innovation. *Technology review*, *80*(7), 40-47.

Armbrust, M., Fox, A., Griffith, R., Joseph, A. D., Katz, R., Konwinski, A., Lee, G., Patterson, D.,

Rabkin, A., Stoica, I., & Zaharia, M. (2010). A view of cloud computing. *Communications of the ACM*, *53*(4), 50-58.

Assembly (2012). "Assembly in Action: Robots Provide Chinese Automaker With Faster, Stronger Welding". May 1. Retrieved from: https://www.assemblymag.com/articles/ 90054-assembly-in-action--robots-provide-chinese-automaker-with-faster-stronger-welding

Atzori, L., Iera, A., & Morabito, G. (2010). The internet of things: A survey. *Computer networks*, *54*(15), 2787-2805.

Audretsch, D. B., & Thurik, A. R. (2000). Capitalism and democracy in the 21st century: from the managed to the entrepreneurial economy. *Journal of evolutionary economics*, *10*(1-2), 17-34.

Audretsch, D. B., Carree, M. A., & Thurik, A. R. (2001). *Does entrepreneurship reduce*

unemployment? (No. 01-074/3). Tinbergen Institute discussion paper.

Audretsch, D. B., Thurik, A. R., Verheul, I., & Wennekers, A. R. M. (2001). *Does*

entrepreneurship reduce unemployment? (No. 01-074/3). Tinbergen Institute discussion paper.

Batjargal, B. (2000). Social capital and entrepreneurial performance in Russia: A panel study.

Brant, R. (1990). Assessing proportionality in the proportional odds model for ordinal logistic regression. *Biometrics*, 1171-1178.Bridge, S., & O'Neill, K. (1996). *Understanding enterprise: entrepreneurship and small business*. London. Macmillan Business.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company.

Burke, G., & Jarratt, D. (2004). The influence of information and advice on competitive strategy definition in small-and medium-sized enterprises. *Qualitative Market Research: An International Journal*, *7*(2), 126-138.

Burt, R. S. (2000). The network structure of social capital. *Research in organizational behavior*, *22*, 345-423.

Carmigniani, J., Furht, B., Anisetti, M., Ceravolo, P., Damiani, E., & Ivkovic, M. (2011). Augmented reality technologies, systems and applications. *Multimedia Tools and Applications*, *51*(1), 341-377.

Carree, M. A., & Thurik, A. R. (1999). *Industrial structure and economic growth* (pp. 86-110). Cambridge, UK: Cambridge University Press.

Carree, M., Van Stel, A., Thurik, R., & Wennekers, S. (2002). Economic development and business ownership: an analysis using data of 23 OECD countries in the period 1976–1996. *Small business economics*, *19*(3), 271-290.

Chell, E., & Baines, S. (1998). Does gender affect business 'performance'? A study of microbusinesses in business services in the UK. *Entrepreneurship & Regional Development*, *10*(2), 117-135.

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS quarterly*, *36*(4).

Clark, K. B. (1985). The interaction of design hierarchies and market concepts in technological evolution. *Research policy*, *14*(5), 235-251.

Demirkan, H., Spohrer, J. C., & Welser, J. J. (2016). Digital Innovation and Strategic Transformation. *IT Professional*, *18*(6), 14-18.

Drucker, P. F. (1998). The discipline of innovation. *Harvard business review*, *76*(6), 149-157.

Du Rietz, A., & Henrekson, M. (2000). Testing the female underperformance hypothesis. *Small Business Economics*, *14*(1), 1-10.

Dutta, S., Lanvin, B., & Wunsch-Vincent, S. (2017). The global innovation index 2017: Innovation feeding the world. *Geneva, Switzerland, by the World Intellectual Property Organization (WIPO), and in New Delhi, India, by the Confederation of Indian Industry (CII)*.

Duurzaam Ondernemen. (2017). *Finalisten Accenture Innovation Awards 2017* bekend. Retrieved from: https://www.duurzaam-ondernemen.nl/finalisten-accenture-innovation-awards-2017-bekend/

European Commission. (2016, April 8). *Amsterdam is the European Capital of Innovation 2016* [Press Release]. Retrieved from: http://ec.europa.eu/research/prizes/icapital/index.cfm?pg=2016

Evans, G. L. (2017). Disruptive technology and the board: the tip of the iceberg 1. *Economics and Business Review*, *3*(1), 205.

Fagerberg, J. (1996). Technology and competitiveness. *Oxford review of economic policy*, *12*(3), 39-51.

Fagerberg, J., & Verspagen, B. (2002). Technology-gaps, innovation-diffusion and transformation: an evolutionary interpretation. *Research policy*, *31*(8), 1291-1304.

Fagerberg, J. (2003). Schumpeter and the revival of evolutionary economics: an appraisal of the literature. *Journal of evolutionary economics*, *13*(2), 125-159.

Fagerberg, J. (2004). Innovation: a guide to the literature. Georgia Institute of Technology.

Fischer, E. (1992). Sex differences and small-business performance among Canadian retailers and service providers. *Journal of small business & entrepreneurship*, *9*(4), 2-13.

Fu, V. K. (1999). Estimating generalized ordered logit models. *Stata Technical Bulletin*, *8*(44).

Georgellis, Y., Joyce, P., & Woods, A. (2000). Entrepreneurial action, innovation and business performance: the small independent business. *Journal of small business and enterprise development*, *7*(1), 7-17.

Gort, M., & Klepper, S. (1982). Time paths in the diffusion of product innovations. *The economic journal*, *92*(367), 630-653.

Gray, C. (2000, June). Formality, intentionality, and planning: features of successful entrepreneurial SMEs in the future?. In *ICSB World Conference*.

Grossman, G. M., & Helpman, E. (1991). Trade, knowledge spillovers, and growth. *European economic review*, *35*(2-3), 517-526.

Hawking, S., Russell, S., Tegmark, M., & Wilczek, F. (2014). Stephen Hawking:\'Transcendence looks at the implications of artificial intelligence-but are we taking AI seriously enough?\'. *The Independent*, *2014*(05-01), 9313474.

Heffernan, M. M., & Flood, P. C. (2000). An exploration of the relationships between the adoption of managerial competencies, organisational characteristics, human resource sophistication and performance in Irish organisations. *Journal of European Industrial Training*, *24*(2/3/4), 128-136.

Hoang, H., & Antoncic, B. (2003). Network-based research in entrepreneurship: A critical review. *Journal of business venturing*, *18*(2), 165-187.

Hurwitz, J., Kaufman, M., Halper, F., & Kirsch, D. (2012). *Hybrid cloud for dummies*. John Wiley & Sons.

Genome, S. (2017). Global Startup Ecosystem Report 2017. Retrieved from: https:// startupgenome.com/report2017/

Glancey, K. (1998). Determinants of growth and profitability in small entrepreneurial firms. *International Journal of Entrepreneurial Behavior & Research*, *4*(1), 18-27.

Iansiti, M., & Lakhani, K. R. (2017). The Truth About Blockchain. *Harvard Business Review*, *95*(1), 118-127.

IBM (2011). The 2011 IBM Tech Trends Report: The Clouds are Rolling In...Is Your Business Ready? November 15. Retrieved from: https://ai.arizona.edu/sites/ai/files/MIS510/2011ibmtechtrendsreport.pdf

IDC (2017). Worldwide Spending on the Internet of Things Forecast to Reach Nearly $1.4 Trillion in 2021, According to New IDC Spending Guide. June 14. Retrieved from: https://www.idc.com/getdoc.jsp?containerId=prUS42799917

IRPA (n.d.). What is Robotic Process Automation? Retrieved from: https://irpaai.com/what-is-robotic-process-automation/

Klepper, S., & Graddy, E. (1990). The evolution of new industries and the determinants of market structure. *The RAND Journal of Economics*, 27-44.

Klepper, S. (1997). Industry life cycles. *Industrial and corporate change*, *6*(1), 145-182.

Koten, J. (2013). A Revolution in the Making. *The Wall Street Journal*, R1.

Kraus, S., & Schwarz, E. (2006). The role of pre-start-up planning in new small business. *International Journal of Management and Enterprise Development*, *4*(1), 1-17.

Long, J. S., & Freese, J. (2006). *Regression models for categorical dependent variables using Stata*. Stata press.

Lucas, R. (1988). On the mechanisms of development planning. *Journal of Monetary Economics*, *22*(1), 3-42.

Maki, K., & Pukkinen, T. (2000). Barriers to growth and employment in Finnish small enterprises. In *ICSB World Conference*.

Malerba, F., & Orsenigo, L. (1996). The dynamics and evolution of industries. *Industrial and Corporate change*, *5*(1), 51-87.

Mambula, C. (2002). Perceptions of SME growth constraints in Nigeria. *Journal of Small Business Management*, *40*(1), 58.

Mell, P., & Grance, T. (2011). The NIST definition of cloud computing.

Mistry, P., Maes, P., & Chang, L. (2009, April). WUW-wear Ur world: a wearable gestural interface. In *CHI'09 extended abstracts on Human factors in computing systems* (pp. 4111-4116). ACM.

Mitra, J., & Matlay, H. (2000, June). Toward the new millennium: The growth potential of innovative SMEs. In *ICSB World Conference, Brisbane, Australia, June*.

Morris, R., & Brennan, G. (2000, June). Creating a seamless local government and small business interface for better regional economic development outcomes. In *ICSB World Conference*.

Morrison, A., Breen, J., & Ali, S. (2003). Small business growth: intention, ability, and opportunity. *Journal of small business management*, *41*(4), 417-425.

Murphy, G. B., Trailer, J. W., & Hill, R. C. (1996). Measuring performance in entrepreneurship research. *Journal of business research*, *36*(1), 15-23.

O'Leary, D. E. (2013). Artificial intelligence and big data. *IEEE Intelligent Systems*, *28*(2), 96-99.

Osimo, D. (2016). The 2016 Startup Nation Scoreboard. In *How European Union Countries are Improving Policy Frameworks and Developing Powerful Ecosystems for Entrepreneurs. European Digital Forum*.

Perren, L. (2000). Factors in the growth of micro-enterprises (part 2): exploring the implications. *Journal of small business and enterprise development*, *7*(1), 58-68.

Prajapati, K., & Biswas, S. N. (2011). Effect of entrepreneur network and entrepreneur self-efficacy on subjective performance: a study of handicraft and handloom cluster. *The Journal of Entrepreneurship*, *20*(2), 227-247.

Price Waterhouse Coopers (2014). 3D printing and the new shape of industrial manufacturing. June. Retrieved from: https://www.pwc.com/us/en/industrial-products/publications/assets/pwc-3d-printing-new-shape-industrial-manufacturing.pdf

Primer, A. (2015). Introduction To Robotic Process Automation. Retrieved from https://irpaai.com//wp-content/uploads/2015/05/Robotic-Process-Automation-June2015.pdf

Rayna, T., & Striukova, L. (2016). From rapid prototyping to home fabrication: How 3D printing is changing business model innovation. *Technological Forecasting and Social Change*, *102*, 214-224.

Reijonen, H., & Komppula, R. (2007). Perception of success and its effect on small firm performance. *Journal of Small Business and Enterprise Development*, *14*(4), 689-701.

Rich, E. (1983). Users are individuals: individualizing user models. *International journal of man-machine studies*, *18*(3), 199-214.

Rimmington, M., Williams, C., & Morrison, A. (2009). *Entrepreneurship in the hospitality, tourism and leisure industries*. Routledge.

Romer, P. M. (1986). Increasing returns and long-run growth. *Journal of political economy*, *94*(5), 1002-1037.

Rosa, P., Carter, S., & Hamilton, D. (1996). Gender as a determinant of small business performance: Insights from a British study. *Small business economics*, *8*(6), 463-478.

Schachtman, N. (2008, August). Pentagon: 'Augment' Reality With 'Videogame' Contact Lenses (Updated). *Wired.* Retrieved from https://www.wired.com/2008/03/darpa-wants-con/

Scott, J. (2000). *Social network analysis*: a Handbook. London: Sage Publications.

Scott, M., & Bruce, R. (1987). Five stages of growth in small business. *Long range planning*, *20*(3), 45-52.

Shaw, E., & Conway, S. (2000). Networking and the small firm. *Enterprise and small business*, 367-383.

Sherwood, A. M., Parrot, N., Jenkins, T., Gillmor, D., Gaffey, S., & Cawley, M. (2000). *Craft producers on the Celtic fringe: marginal lifestyles in marginal regions?*.

Schönberger, V. M., & Cukier, K. (2013). Big data: A revolution that will transform how we live, work, and think. *Houghton Mifflin Harcourt*.

Schubert, C., Van Langeveld, M. C., & Donoso, L. A. (2014). Innovations in 3D printing: a 3D overview from optics to organs. *British Journal of Ophthalmology*, *98*(2), 159-161.

Schumpeter, J.A. (1934). The Theory of Economic Development. *Harvard University Press*.

Schumpeter J.A. (1939) Business cycles: a theoretical historical and statistical analysis of the capitalist process (2vol). McGraw-Hill, New York

Schwab, K. (2017a). *The Fourth Industrial Revolution*. Crown Business.

Schwab, K. (2017b). *The Global Competitiveness Report*. World Economic Forum.

Stankovic, J. A. (2014). Research directions for the internet of things. *IEEE Internet of Things Journal*, *1*(1), 3-9.

Stephen, A. (2013, September 11). Marketing Diary. Retrieved from: https://annettestephen-marketingjournal.blogspot.nl/2013/09/product-life-cycle.html

Storey, D. (1994). Understanding Small Business. *London: Routledge.*

Suarez, F. F., & Utterback, J. M. (1995). Dominant designs and the survival of firms. *Strategic management journal*, *16*(6), 415-430.

The Economist. 2010a. "The Data Deluge," Special Report on Managing Information, Technology Section. February 25. Retrieved from: http://www.economist.com/node/15579717

The Economist. 2010b. “All Too Much,” Special Report on Managing Information, Technology Section. February 25. Retrieved from: http://www.economist.com/node/15557421

Thurik, R., & Wennekers, S. (2004). Entrepreneurship, small business and economic growth. *Journal of small business and enterprise development*, *11*(1), 140-149.

Van de Ven, A. H., Hudson, R., & Schroeder, D. M. (1984). Designing new business startups: Entrepreneurial, organizational, and ecological considerations. *Journal of management*, *10*(1), 87-108.

Viereckl, R., Ahlemann, D., Koster, A., & Jursch, S. (2015). “Connected Car Study 2015: Racing ahead with autonomous cars and digital innovation”. *Strategy&,*. Retrieved from: http://www.inovasyon.org/pdf/Richard.Viereckl_et%20al._Connected.Car.Study_Sept.2015.pdf

Vishnu, S., Agochiya, V., & Palkar, R. (2017). Data-centered Dependencies and Opportunities for Robotics Process Automation in Banking. *Journal of Financial Transformation*, *45*, 68-76.

Webb, A. (2017). *2017 tech trend report*. Retrieved from: https://futuretodayinstitute.com/2017-tech-trends/

Wennekers, S., & Thurik, R. (1999). Linking entrepreneurship and economic growth. *Small business economics*, *13*(1), 27-56.

Williams, R. (2006). Generalized ordered logit/partial proportional odds models for ordinal dependent variables. *Stata Journal*, *6*(1), 58.

Wolfe, R., & Gould, W. (1998). An approximate likelihood-ratio test for ordinal response models. *Stata Technical Bulletin*, *7*(42).

Wooldridge, J. M. (2015). *Introductory econometrics: A modern approach*. Nelson Education.

Zhang, Q., Cheng, L., & Boutaba, R. (2010). Cloud computing: state-of-the-art and research challenges. *Journal of internet services and applications*, *1*(1), 7-18.