The importance of incentives and the network effect for digital startups to scale

Carl Pascal Rostetter

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Claudia Costa

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ABSTRACT

Digital startups are facing high mortality rates and various challenges. According to the statistics, more than 50% of all new ventures fail. Therefore, this thesis highlights the importance to scale as a digital startup. One of the main reasons for lacking ability to scale refers to a missing customer base which hinders digital startups from achieving a CA in the market. As driver for growth, incentives can help the digital startup to scale faster into a large corporation and therefore the influence of different incentives is critical for early stage startups. By using an empirical study this research aims to explore the impact of incentives to foster the network effect and as such the ability of scaling startups, which will eventually lead to the success of the company. The results of the study show that both monetary and non-monetary incentives are a powerful tool to increase referrals and recommendations compared to no incentives offered. However, the likelihood of buying the product is not significantly affected by the presence of incentives. In this case, the importance of the network effect is negligible as success factor for digital startups. Incentives are more effective due to the extrinsic and intrinsic motivation of consumers to recommend and refer, represent a powerful part of a strategy to acquire initial customers, accelerate digital startups growth and ability to scale successfully.

SUMÁRIO

As startups digitais enfrentam altas taxas de mortalidade, bem como vários desafios. De acordo com dados estatísticos, mais de 50% de todos os novos empreendimentos acabam por falhar. Desta forma, a presente tese destaca a importância do crescimento para uma startup digital. Uma das principais razões apontada para a falta de capacidade de crescimento refere-se a uma base de clientes inexistente, que impede que as startups digitais obtenham uma vantagem competitiva no mercado. Como motor de crescimento, os incentivos podem contribuir para que a startup digital evolua mais rapidamente para uma grande empresa e, neste sentido, considera-se que a influência de diferentes incentivos seja fundamental para as startups numa fase inicial. Tendo por base um estudo empírico, esta pesquisa visa explorar o impacto de incentivos em promover o efeito network e, como tal, a capacidade de escalar startups, o que irá conduzir ao sucesso da empresa. Os resultados deste estudo demonstram que tanto os incentivos monetários como os não-monetários constituem uma ferramenta poderosa para aumentar as referências e recomendações, quando em comparação com nenhum incentivo oferecido. No entanto, a probabilidade de compra do produto não é significativamente afetada pela presença de eventuais incentivos. A importância do efeito network revelou-se insignificante como fator contributivo para o crescimento de startups digitais. Assim, os incentivos tornam-se mais eficazes, devido a motivações extrínsecas e intrínsecas dos consumidores para recomendar, e representam uma parte crucial do processo estratégico por forma a angariar clientes, acelerar o crescimento de startups digitais e a sua capacidade de escalar com êxito.

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GLOSSARY

CA – Competitive advantage

DS – Digital startup/Digital startups

KPIs – Key performance indicators

MNE – Multinational enterprise

SME – Small and medium-sized enterprises

WTP – Willingness to pay

CHAPTER 1: INTRODUCTION

1.1 Background and problem statement

Digital startups acting in today's digital world do not only face local competition but also competition on a global scale. Digital has changed the competitive environment (Koch & Windsperger, 2017). As powerful accelerator, the internet helps startups to overcome managerial and physical barriers related to internationalization. At the same, low entry costs, low switching costs for consumers, easiness to replicate digital businesses and disruptive innovations embraced the digital age of easy access for internet-based business. However, this easiness in access embraces risks for digital startups in sustaining a superior positioning (Evans & Schmalensee, 2016; Sinkovics & Bell, 2005).

Starting a new venture is a hit or miss situation (Blank, 2013). According to CB Insights 19% of startups fail due to competition, which shows that startups are not able to sustain a competitive advantage leading to growth and as such to scale to a large enterprise (CBInsight, 2014). Low resource requirements, easiness of experimentation and opportunities for faster scaling make digital increasingly appealing to entrepreneurs. On the other hand, lower capital requirements increase the vulnerability of the digital startups particularly against large multinational enterprises (MNE). Therefore, it may be tougher to scale (growth, speed and liquidity) into a large-scale enterprise, sustain a competitive advantage (CA) and a steady growth rate in the hypercompetitive environment. Hypercompetition refers to an unstable CA in a business environment where CA can be rapidly created or eroded (D'Aveni, 1994; Matzler, Bailom, Anschober, & Richardson, 2009). The network effect plays an important role for startups and works as a trigger for diffusion. Especially the direct network effect, i.e. an increase in usage leads to a direct increase in value, accelerates growth (Stremersch, Lehmann, & Dekimpe, 2010). Thus, scaling increases the probability of achieving steady growth and thereby long-term performance.

Considering the severity of the situation, new ventures have to bear in mind several challenges affecting their business activities which increase the venture's mortality risk. Artinger and Powell (2016) studied the importance of excess entry on startup survival dividing the reasons in two groups; statistical and psychological explanations. Statistical explanations see market entry risky due to uncertainty and incomplete information; thus, even if all actions taken by the entrepreneur are accurate, random errors still lead to an excess entry. Psychological explanations argue that entrepreneurs centralize their own competence, ignoring market conditions and competition; thus, their overconfidence leads to excess entry (Artinger & Powell, 2016). Other explanations studied by scholars consider human and financial capital, experiences of the entrepreneur, timing of market entry, liability of newness, insufficient planning by the entrepreneur and even the entrepreneurs' personality leading to business failure (Bruno & Tyebjee, 1985; Cooper, Gimeno-Gascon, & Woo, 1994; Green, Barclay, & Ryans, 1995; Shepherd, Douglas, & Shanley, 2000; Venkataraman, Van De Ven, Buckeye, & Hudson, 1990).

The recent entrepreneurship literature reviews network externalities for digital startups as a distinct competitive factor. Network externalities function as a trigger for future diffusion and can positively influence the growth phase of new products or services (Stremersch et al., 2010). But there is a need to further investigate how the perception of the dimension of the network can impact the likelihood of adopting a service. An aspect investigates the types of incentives that digital startups can use to foster scale the business and as such to sustain their CA. Several studies demonstrate the network effect and incentives influenced the growth process and by this determine the business success for the company (Evans, 2009; Evans & Schmalensee, 2016; Stremersch et al., 2010). Dropbox, Airbnb and Snapchat demonstrate the power of network externalities. Dropbox, founded in April 2007, created buzz by creating incentives for referrals to friends who gained additional storage space for free when inviting new users to join Dropbox. As such, Dropbox increased awareness, accelerated growth to become a $10 billion business (Statista, 2015).[1]

To make best use of the network effect, different incentives can increase the likelihood of referral and increase a product's value. In general, there is a distinction between monetary and non-monetary incentives. Incentives allow to leverage and speed up growth. To better understand and provide recommendations on the kind of incentives that should be used for digital startups, this dissertation studies the importance of the type of incentives as a way to foster the network effect. By assessing the likelihood of referral, recommendation and the willingness to pay for a service, the effectiveness of monetary and non-monetary incentives will be tested and their effect resulting in the ability to scale and guide digital startups to business success.

[1] Statista (2015) The World's Most Valuable Startups. p. 1. Retrieved on 21st October 2017: https://www.statista.com/chart/3904/worlds-most-valuable-startups/

1.2 Problem Statement

This paper aims to examine and understand the difference between monetary and non-monetary incentives for digital startups which boost growth and enable digital startups to scale into large enterprises. By understanding the impact of different incentives benefitting growth, strategies for startups to scale and sustain their CA can be derived. The problem statement of this thesis paper can be summarized as:

"The importance of incentives and the network effect
for digital startups to scale."

This topic can be addressed by answering the following research questions:

1. Is the network effect relevant for digital startups ability to attract additional customers?
2. Do customers respond differently to monetary and non-monetary incentives?
3. Are monetary or non-monetary incentives more likely to increase the likelihood of referral, recommendations and WTP to accelerate growth and through to scale?

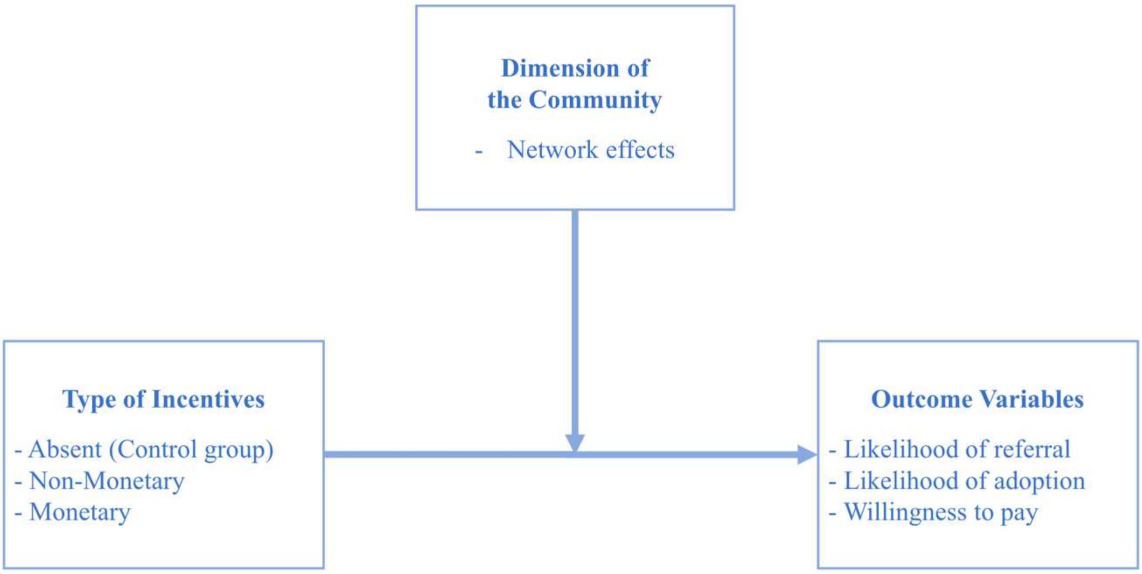

Figure 1: Conceptual framework for the study based on the research question

1.3 Relevance

The survival rate amongst new ventures of 50% shows that one out of two startups is fails. More worryingly this rate is further increasing since the year 2000 (Artinger & Powell, 2016). In this context, startups failure can refer to having difficulties in sustaining a CA (Matzler et al., 2009). Therefore, it is crucial for digital startups acting on a global scale to access the ability of sustaining a CA by making use of the network effect and different incentives. As in the case of Dropbox, incentives helped the digital startup raising awareness, increasing the mass of early adopters and thereby scaling and preventing businesses from failing (Evans, 2009; Evans & Schmalensee, 2016).

Providing solutions on the nature of incentives and developing guideline on the use of incentives is the intended goal of the research provided in this dissertation. The lack of a client base is an initial step to use network effects and positive network externalities and thereby scale the startup to achieve a sustainable CA in the market (Acs, Åstebro, Audretsch, & Robinson, 2016). Therefore, it is reasonable to provide research in the field of digital startups to develop strategies for incentive scenarios and network externalities which are beneficial for the entrepreneurial success in nowadays hypercompetitive environment.

1.4 Research methods

In order to answer the research questions, the study uses an experiment a within-subject design technique to assess the likelihood of recommendations based on certain types of incentives through a real digital startup and in order to verify the hypothesis of this dissertation. The sample was reached by conducting an online survey.

1.5 Dissertation outline

In the upcoming section of this dissertation the literature review is presented and the hypothesis guiding this dissertation is developed. The literature review will provide detailed information about differences in characteristics between digital startups and MNE, define the network effect, show different factors affecting digital startups in a hypercompetitive environment, examine monetary and non-monetary incentives and define the hypothesis for the methodology section. The third chapter, represents the methodology used to test the hypothesis, research approach and data analysis on how different incentives work and influences a digital startup ability to sustain CA and accelerate growth.

The goal is to provide a guideline and possible solutions on how to scale successfully by using different incentives as a digital startup. This will be formulated in the result and discussion section in the fourth chapter.

CHAPTER 2: LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

2.1 Definition and Characteristics of Digital Startups

Startups can be defined as ventures which are developed in order to scale into large companies (Blank, 2013). Thus, a distinct feature of digital startups is the intention of growing from a temporary venture to a large company (Kollmann, Stöckmann, Hensellek, & Kensbock, 2016). Startups in an early stage develop and operate under extreme uncertainty (Marmer & Bjoern, 2011). The digital businesses are internet-born and aim at distributing only digital products and services. E-commerce stores as Amazon or services like Airbnb and Uber also deal with the "offline" products or services, but have their distribution channels online. Therefore, the definition focuses on growth through distributing products and services mainly online (Quinones, Nicholson, & Heeks, 2015).

Conversely, MNE exploit an existing market whereas SME and especially digital startups primarily focus on explorative activities in the early stage (Buckley & Prashantham, 2016). This means, MNE are focused on operating in an existing market with their large assets where they lack flexibility. Digital startups have smaller assets and set their focus on the identification and exploration of niches with their greater agility and newness. Their newness gives them a legitimacy deficit. To better visualize the differences, table 1 compares the main characteristics of MNE and SME, namely digital startups. Digital startups therefore can be characterized by their great flexibility, agility to new-to-market technologies, focus on exploration and the need to establish themselves in the market.

MNE (Focus: Exploitation)	DS (Focus: Exploration)
Proactiveness: • Exploting an existing market • Primarily focused on builing existing markets	**Proactiveness:** • Rather focused on identifying and serving a niche • Greater focus on exploration
Innovation: • Large assets and oldness • Greater bureaucracy hinders from radical innovation • Greater scale and stramlined processes leads to higher efficiency	**Innovation:** • Smaller assets and newness • Greater agility to pursue innoative and new-to-market technologies
Risk-Taking: • Flexibility deficit	**Risk-Taking:** • Legitimacy deficit

Table 1: Differentiation between MNEs and DS (Buckley & Prashantham, 2016)

2.2 Definition and Characteristics of Competitive Advantage

The concept of competitive advantage first introduced by Adam Smith (Smith, 1982) received considerable attention in various studies and research papers and is one of the most important topics of economics. A CA is a superior positioning against a firm's competition by using resources in a more efficient way. A comparatively better performance and the company's ability to provide more value to the customer is enabled (Garth, Podolny, & Shepard, 2001; Grünig & Kühn, 1978; Sadri & Lees, 2001). Since Smith introduced his ideas about CA, more advanced perspectives evolved out of his theory. Factors and theories affecting CA will be further investigated in the upcoming sections.

2.2.1 Competitive Advantage Theories

The previously mentioned definition of CA can be reviewed through different theories and points of views. The mostly reviewed theories are based on theories, dynamic capabilities and the learning theory which will be investigated in the following paragraphs.

According to the resource-based view, a firm holds the potential for a sustainable CA if the firms' resources fulfil the following four attributes: a) Resources must be valuable, i.e. they can exploit opportunities and/or neutralize the threats/risks in the competitive environment. b) Resources have to be rare compared to the firm's existing and potential competition. c) Resources cannot be imitated and must be imperfectly imitable. d) Resources must not be substitutable. Applying this theoretical framework shows the relationship between resources in terms of heterogeneity and immobility which defines the CA achieved by the four attributes of (Barney, 1991). This perspective focuses on the internal view and organization of a firms' resources. The approach of dynamic capabilities extends the view of the RBV in which resources are the centrepiece. Dynamic capabilities describe the structured process within an organization. The company synthesizes and acquires knowledge to generate new products from the given resources. Those capabilities consist of well-known processes such as strategic decision making, product development or alliancing. Firms can sustain a CA by their ability to make structural changes in the resource base by using processes (Dynamic capabilities) creating, recombining, releasing and integrating resources (Celec & Globocnik, 2017; Eisenhardt & Martin, 2000). Organizational learning refers to the organization's process of creating, emphasizing the use of knowledge to increase CA and therefore can be seen as another CA approach. According to this theory, a strong orientation and commitment towards learning are prerequisites to gain CA (Cavusgil & Zhao, 2002). Especially for startups, learning should be prioritized over profit (Scott, 2008) as learning is an essential investment which is crucial for a firm's survival (Sinkula, Baker, & Noordewier, 1997).

The network-centric view approach challenges the three previously mentioned traditional approaches (Koch & Windsperger, 2017). The three traditional approaches were built on assumptions which may lack validity in the digital environment. First, they view the environment as stable, which is revised in a turbulent and uncertainty dominated digital world of today (Koch & Windsperger, 2017; Yoo, Henfridsson, & Lyytinen, 2010). The competitive environment becomes increasingly dynamic which results in a decreasing degree of firms' influence whereas digitization is accelerating this change. Therefore, sustaining CA is hard to influence from a firm's perspective due to the dynamic digital ecosystem and frequently changing external industry structures (Yoo et al., 2010). Given a high degree of uncertainty, the need for alliances and value co-creation with other firms is obvious. Secondly, according to this approach, it can be concluded that capabilities and resources of firms go beyond firms' boundaries. The inter-organizational network can be viewed as the main source for a CA of a firm. These networks encompass a firm's relationship to supplier, competitors, customers as well as other players across traditional boundaries (Lavie, 2006). The inter-firm relationships can occur in various forms such as strategic alliances, franchising, joint ventures, long-term contracts, partnerships, buyer-supplier relationships or others (Gulati, Nohria, & Zaheer, 2000; Zaheer, Gözübüyük, & Milanov, 2010). Finally, according to this theory, a firm needs to balance a set of network mechanisms such as trust, power, control, signalling and as well resources in order to gain and sustain CA. Summarizing, the digital economy is perceived as dynamic inter-organizational network, in which companies collaborate, compete or create value through collaborating or competing relationships (Koch & Windsperger, 2017).

The network-centric view gained attention during the last decade shifting the focus from attributes of single players to relationships and interdependencies of players. Therefore, by collaborations and co-creations, firms benefit and can achieve CA (Bergenholtz & Waldstrøm, 2011; Gulati et al., 2000; Kane, Labianca, & Borgatti, 2013). As a result of this, various factors affecting competitive advantage can be concluded.

2.2.2 Factors affecting Competitive Advantage

There are various classical factors such as economies of scale, economies of scope and economies of learning (Smith, 1982). Economies of scale were the drivers for corporate gigantism in the 20th century and refer to factors that cause the average cost of production to decrease as the output of production increases. Scale economies were fundamental for Henry Ford's assembly line and still are a factor influencing CA. Economies of scope are closely linked to economies of scale and refer to factors which enable a cheaper production of a range of products. Centralizing productions or business units is less expensive than producing each on its own (Panzar & Willig, 1977; Sloan, 1990; Smith, 1982). Economies of learning, unlikely as economies of scale and scope, are not correlated to production output, but are influencing production by becoming a specialist in a certain field and by producing a greater amount of outputs of the similar product. Therefore, economies of learning are often derived from the knowledge a firm and its employees possess (Lundvall, 2004).

When considering digital startups the network effect and different incentives are critical success factors for the startups CA (Stremersch et al., 2010) which can benefit the awareness of the digital startup, create a greater customer base and accelerate growth. In a hypercompetitive environment, there are as well other factors influencing digital startups and the difficulties of sustaining CA (Wiggins & Ruefli, 2005). The digital economy is perceived as dynamic inter-organizational network, in which companies collaborate, compete or create value through collaborating or competing relationships (Koch & Windsperger, 2017). A hypercompetitive environment is hard to predict and therefore planning for a long-term sustainable CA is almost impossible. Speed, flexibility, innovation, growth and the ability and willingness to change are important bases for competitive success and scaling (Johnson, Scholes, & Whittington, 2008). Therefore, it is crucial to additionally examine CA and find a scale which is suited for digital startups acting in today's dynamic digital environment facing hypercompetition.

2.2.3 Measuring Competitive Advantage

To sustain CA by making use of the network effect and incentives, it is crucial to measure CA adequately either by sales, profit or growth rate of the startups (Marmer & Bjoern, 2011). While the ability to raise capital from professional investors can be seen as indicator for a high growth potential, user growth or growth itself might be as well an option to scale CA and startup success (Marmer & Bjoern, 2011; StartupAUS, 2014). Growth is one KPI which is mostly referred to new ventures objectives (Ensley, Hmieleski, & Pearce, 2006).

Growth can be achieved by incentivizing new user or potential customers. In this case, incentives are used as a driver of startups' growth (Nayman, 2017). Due to this, the likelihood of referral is considered to be a suitable scale to measure a digital startup performance with respect to incentives. Measuring the effect of non-monetary and monetary incentives will show the likeliness of product referrals from existing customers to other individuals and the relation to new user growth.

2.3 Network Effect and Incentives

The network effect, which is sometimes referred to as network externalities, plays an important role for startups launching new products and focusing on growth. Network externalities function as a trigger for future diffusion and can positively influence the growth phase of new products or services (Stremersch et al., 2010). There are various types of network effects. The direct effect is referred to as an increase in usage (user base) leads to a direct increase in value for the product. Anecdotal examples are telecommunication markets or social networks such as Facebook. The network effect in these markets is based on the need for compatibility to exchange information and a strong need for complementary goods. There is a positive correlation in product innovation and number of existing adopters (Weitzel, Wendt, & Westarp, 2000). Word of mouth in connection with incentives can lead to direct network effects as well (Dotan, 2008; Farrell & Saloner, 1985; Katz & Shapiro, 1985). Contrary to direct network effects, indirect network externalities occur when the increased usage of a product increases the value of a complementary product and not the original product, e.g. the usage of computer software increases with the usage of hardware. Nevertheless, this indirect increase may induce an increase in value for the original product (Church, Gandal, & Krauske, 2008; Katz & Shapiro, 1985). Direct network externalities in one market can influence firms' strategies in a market for complementary products (Matutes & Regibeau, 1988). Network effects increase the product value, either in a direct way or indirectly by increasing a complementary product's value.

2.3.1 Monetary Incentives

To make best use of the network effect, different incentives can increase the likelihood of referral and increase a product's value. According to the motivation theory of Ryan and Deci (2000) individuals can perform extrinsic motivated tasks with "resentment, resistance, and disinterest, or alternatively, with an attitude of willingness that reflects and inner acceptance of the value or utility of a task". This shows a strong extrinsic motivation for individuals to perform tasks even if they do not like the task itself. For digital startups and other companies these "pay for performance" strategies can be beneficial to achieve companies target (Osterloh & Frey, 2000; Ryan & Deci, 2000). In general, there is a distinction between monetary and non-monetary incentives. Monetary incentives are frequently suggested as a powerful tool increasing extrinsic motivation of product referral. This kind of incentive works as method for motivation and improving an individual's performance. The monetary benefit triggers a higher financial utility, results in an increase in performance and is a strong extrinsic motivation for the person referring (Bonner & Sprinkle, 2002; Gneezy & Rustichini, 2000; Jin & Huang, 2014). This extrinsic motivation can be seen as a driver in engagement due to the expected monetary outcome for the individual. By using monetary incentives extrinsic motivation is fuelled.

Monetary incentives are presented to consumers on a daily basis; price discounts, payback programs and limited promotions are monetary incentives targeting the end consumer to behave in favour for the advertising company (Tercia & Teichert, 2017). Startups use this kind of incentives as well to increase the number of early adopters and later expand the client or user base. For instance, Airbnb gave credits to new registered members which join the platform as a consequence of referral. Members can invite their friends by sending a link to their network and invite them to join Airbnb. This monetary incentive is benefiting the person referring as well as the referred friend with travel credit for the next stay with Airbnb (Nayman, 2017).

2.3.2 Non-Monetary Incentives

Although it is obvious that monetary incentives can have an effect on performance by extrinsic motivation, also non-monetary incentives can have a powerful influence through intrinsic motivation and altruistic behaviour of an individual (Fehr & Falk, 2002; Gneezy & Rustichini, 2000). Non-monetary incentives differ from monetary incentives based on the fact that the rewarded amount is indifferent to the motivation of the individual (Heyman & Ariely, 2004).

When referring to social and moral acts, monetary incentives can hinder the feeling of doing something valuable and lower the amount of effort from the individuals. Presenting monetary incentives alters the participation of altruistic activities such as donating blood. The number of blood donations lowered when a monetary reward for donation blood was offered due to a lack of motivation in form of a decreasing intrinsic motivation and no altruistic feeling (Gneezy & Rustichini, 2000; Mellström & Johannesson, 2008). Intrinsic motivation is achieved when the individuals do the action without any monetary or external reward. These activities bring joy and satisfaction to the individual in a similar way as performing a marathon run (Anghelcev, 2015; Ryan & Deci, 2000).

As stated above, the research is still debating the relative worth of such incentive: Economists focus on monetary incentives and show the increased effort individuals put in to receive the monetary benefit whereas psychologists see an increase in performance by setting non-monetary incentives (Gneezy & Rustichini, 2000).

2.4 Hypothesis Definition

For digital startups, a clear growth focus is essential to scale into a large enterprise as defined in the beginning of this chapter. Due to the lack of a client base, small digital startups are not able to scale. The network effect helps to overcome the lacking customer base by making use of early adopters to create positive network externalities through different incentives which benefit growth of digital startups. Therefore, I propose that:

H1: "Incentives have a positive impact on the growth of digital startups by increasing the likelihood of recommending, referring and buying compared to delivering no incentive."

By extrinsic motivation, particular action of individuals is taken and a monetary reward promised (Ryan & Deci, 2000). The influence of positive network externalities resulting from monetary incentives provided to the early adopter shall be analysed and by this the hypothesis stated. On the other hand, many corporations focus on non-monetary incentives due to the possible negative effects of monetary incentives on the intrinsic motivation of individuals resulting in declining performance. Due to the individuals high exposure to monetary incentives and the frequent use of payback programs, price discounts and other incentives, it can be assumed that monetary incentives have a stronger influence on consumers buying decisions (Tercia & Teichert, 2017).

H2: "When consumers are presented with monetary incentives they are more likely to refer the service than when consumers are presented with non-monetary incentives."

To evaluate this, the likelihood of recommendation and referral is tested in the experiment. A higher likelihood of referral leads to increase in customers awareness, growing sales and faster scaling. In the end, the comparison shall reveal which incentive affects the likelihood of referring and recommending to a higher degree.

When looking at non-monetary incentives the decision of the individual is triggered by intrinsic motivation (Fehr & Falk, 2002; Heyman & Ariely, 2004). When customers behave altruistic and are interested in benefiting from network effects while not focusing on monetary gains, non-monetary incentives should be more effective. Thus, I propose that:

H3: "When consumers are intrinsic motivated the impact of non-monetary incentives on the likelihood of referral is higher than the impact of monetary incentives."

To evaluate the strength of the network effect, the size of the community has to be taken into account. With increasing members in the community, the value of the product increases (Stremersch et al., 2010). Therefore, one should be able to observe:

H4: "The size of the community has a positive impact on the referral rate."

CHAPTER 3: METHODOLOGY

3.1 Research Approach

An experiment is designed to collect primary data and provide up to date knowledge from the desired target group. The participants in the study were introduced to a referral system based on monetary incentives and non-monetary incentives to refer an online fitness program. Furthermore, to avoid any occurring biases and in order to gain concrete results, a control group in which the incentive was absent was created as well. To collect real-life data, the participants of this online fitness program and potential customers and the likelihood of referral mechanism were tested. The digital startup “Fit mit Pascal” is selected as representative study object due to its business model relying on digital promotion, online distribution and is discussed further in this research.

Data is collected by distributing the survey on the internal #3PhasenProgramm Facebook group and on the social media platforms of Fit mit Pascal. These platforms are used to exchange with the clients, distribute new content and promote updates for the online fitness program. Hereby it is guaranteed, that only members of the program and potential customers are participating in the survey and selection bias cannot occur. To ensure a representative sample size, the target was to collect at least 400 responses.

In total, 402 participants took part in an explanatory approach with an experiment to test the hypothesis understanding how different incentives influence the performance of the new venture. The majority of respondents consist of women (78%), while men account for around one fifth (22%). Most of the participants are between 19 and 29 years old with an average age of 24 years and a standard deviation of 5 years. The youngest participants are 16 years old and the oldest is 52 years old. More than 46% of all respondents are students and the remaining 54% are employed. The majority exercises 2-3 times a week.

3.2 Method

Firstly, the platform is introduced, involvement and control questions are asked to check if they already participate in the program. The whole survey is split in two groups to test the influence of the network effect. One group is informed about a community size of 100 persons, while the second group is told that the number of total members in the community is 1000. By this, the extent of the network effect is tested.

Afterwards, each of the groups is further divided into three scenarios. The first scenario represents the control group. In this scenario, the likelihood of referral, recommendation and willingness to pay is tested without any incentive. In the second scenario, the influence of the monetary incentive in form of 10€ Cashback is tested whether it affects the likelihood of referral, recommendation and willingness to pay for the program. The third and last scenario sets a non-monetary incentive in form of a free eBook. When presenting this scenario, the likelihood of referral, recommendation and willingness to pay for respondents is recorded. From this testing, conclusions can be drawn on the effectiveness of incentives, how people value the network effect concerning a big and rather small community and if people prefer monetary or non-monetary incentives.

Respondents are guided through the testing by explaining the aim of this experiment and giving background information. Three different scenarios are used to manipulate incentives to capture the likelihood of referral, recommendation and willingness to buy the program. The aim is to measure the dependent variable (likelihood of referral) by varying the independent variable and therefore investigating their causal relationship. For the incentive questions a 5-Point-Likert scale was used. For the full survey see Appendix 1.

The distribution is conducted by delivering a survey to existing members of the community and potential customers according to the following figure 1:

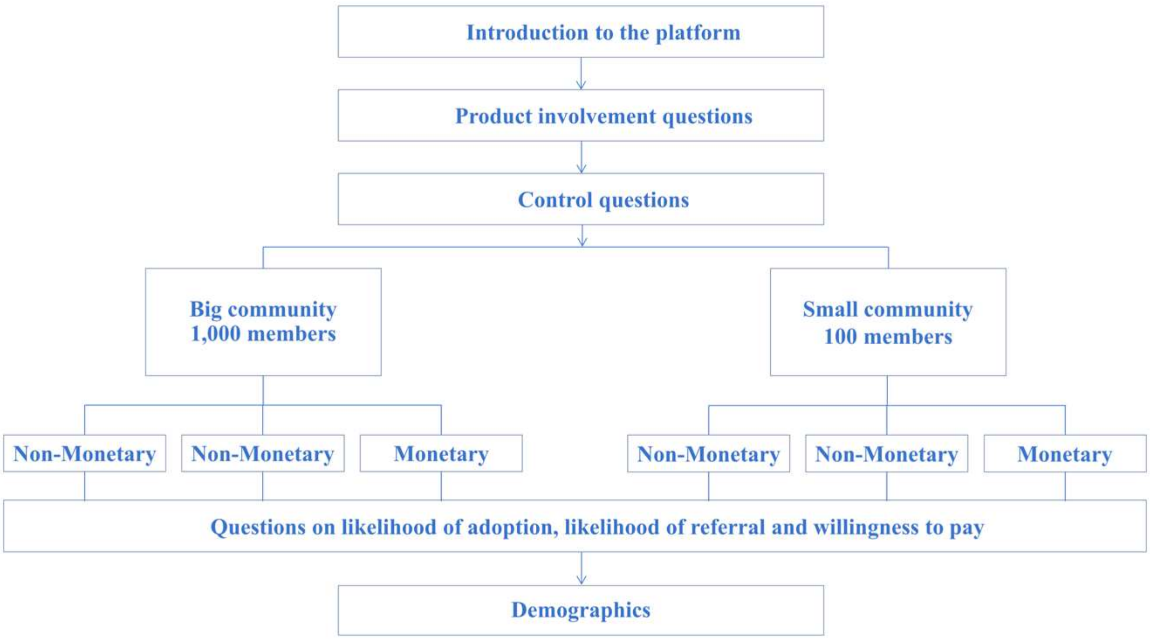

Figure 2: Framework of the survey for Fit mit Pascal

3.3 Fit mit Pascal

The digital startup used is Fit mit Pascal, a German startup focusing on online fitness programs and launched in 2015. It is currently in the maturity stage and an approximately annual turnover of 100.000€ per year. Fit mit Pascal builds on an existing client base of around 3.000 individuals but is facing serious issues concerning future growth. The #3PhasenProgramm is the core product which includes a customized nutrition plan, several training plans and a big community to exchange results and motivation. By adapting the product to each customers' characteristics, the program focuses on customer satisfaction and depends on reviews and word of mouth. The active community provides a network effect; by the increasing number of users a unique feeling of belonging is created, customers are more motivated in sharing their experiences in the Facebook community, receive faster feedback to questions and start the program in groups which increases the probability of succeeding for the participants. Therefore, it is perfectly suited as objective of this dissertation to examine the network effect with respect to monetary and non-monetary incentives. When studying the effects of these incentives, guidelines can be designed to further improve this startups performance and scale growth.

3.4 Measures

The dependent variable is the likelihood of referral, the likelihood of recommendation and the likelihood of buying the program. For these three dependent variables, the experiment is focused on examining which incentive increases the chances of referral, recommendation or willingness to pay. To control the effectiveness of incentives, a control group with the absence of an incentive is introduced as well. The independent variable in this experiment are the incentive scenario delivered to the respondent and the size of the community. The size of the community is either 100 or 1000 members and the scenario can be divided into monetary, non-monetary or no incentive scenario. Until now, the online fitness program #3PhasenProgramm does not offer any incentives. In this experiment, the respondents are confronted with three different kind of incentives: No incentive (control group), non-monetary incentive (free recipe eBook) and monetary incentive (10€ Cashback). Thus, three different scenarios were created to manipulate the incentives. The value of the incentives is chosen according to the value of the recipe eBook of 10€. The incentives are intentionally kept equal and the survey is randomly assigned with a different scenario to each participant. As control variables, age, gender and profession are introduced to control for the effect on the dependent variable. The items measured are the likelihood of referring, recommending and buying the program resulting from the survey results. All items are measured on a 5-Point-Likert scale 1 = Very likely; 5 = Very Unlikely**.** By decreasing points on the scale an improvement of the likelihood can be observed.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Results

In order to test the hypothesis, linear regressions were run in IBM SPSS as most common statistical test for this study. To test H1 where we argue that incentives have a positive impact on the growth of digital startups by increasing the likelihood of recommending, referring and buying compared to delivering no incentive we run a linear regression with the type of incentive as independent variable and the likelihood of recommending the program as dependent variable. The analysis is run in SPSS. Monetary and mon-monetary incentives are introduced as independent variable and in three different models the likelihood of recommending the program (likelihood of adoption), likelihood of referring the program and likelihood of buying the program by the respondent measured as dependent variables.

Likelihood of recommending the program (y_i) = $\beta_0 + \beta_1$Type of incentive$_i$ + u_i

The upcoming table demonstrates the results for testing if the introduction of a type of incentive has an impact on the likelihood of recommending the program. The type of incentive as independent variable has a significant effect on the dependent variable which is the likelihood of recommending the program ($p < 0.05$). Therefore, one can conclude that introducing a type of incentive increases the likelihood of recommending the program by $\beta = .234$ (1 = Very likely; 5 = Very Unlikely) as shown in table 2.

Regression 1	B	Std. Error	Beta	t	p
Intercept	2,927	0,138		21,159	0,000
Type of Incentive	-0,234	0,063	-0,181	-3,689	0,000

Table 2: Coefficients table for Regression 1 (Likelihood of recommending the program)

Likelihood of referring the program (y_i) = $\beta_0 + \beta_1$Type of incentive$_i$ + u_i

In the upcoming table the results for testing if the introduction of an incentive scenario has an impact on the likelihood of referring the program is tested. The type of incentive as independent variable has a significant effect on the dependent variable which is the likelihood of referring the program ($p < 0.05$). Therefore, one can conclude that introducing an incentive scenario increases the likelihood of referring the program by $\beta = .293$ as shown in table 3.

Regression 2	B	Std. Error	Beta	t	p
Intercept	3,274	0,143		22,918	0,000
Type of Incentive	-0,293	0,065	-0,219	-4,479	0,000

Table 3: Coefficients table for Regression 2 (Likelihood of referring the program)

Lastly, in order to check H3, the effect of the type of incentive on the likelihood of buying the program is tested.

Likelihood of buying the program (y_i) = $\beta_0 + \beta_1$Type of incentive$_i$ + u_i

The type of incentive as independent variable has no significant effect on the dependent variable which is the likelihood of buying the program ($p > 0.05$). Therefore, one can conclude that introducing a type of incentive increases the likelihood of buying the program by $\beta = .126$ but not significantly as shown in table 4.

Regression 3	B	Std. Error	Beta	t	p
Intercept	3,059	0,16		19,078	0,000
Type of Incentive	-1,26	0,073	-0,085	-1,714	0,087

Table 4: Coefficients table for Regression 3 (Likelihood of buying the program)

The performed regression analysis aim to present the effect of monetary and non-monetary incentives on the dependent variables. Appendix 2 shows that the control variables do not change the significant of the main effect on the dependent variable ($p_{Gender}, p_{Age}, p_{Profession} >$ 0.05). When looking at the coefficients table for the regressions, it can be concluded that the awareness of different type of incentives has a significant impact on the likelihood of recommending, likelihood of referral and likelihood of buying the program. There is a significant correlation between the type of incentive and likelihood of recommending and referring to a friend. As stated in the measure section a negative correlation has a positive impact for the results as shown in table 5.

Correlation	Scenario	Likelihood of Recommend.	Likelihood of Referring	Likelihood of Buying
Type of Incentive	1	-0,181**	-0,2,19**	-0,085

Table 5: Correlation of type of incentive on the likelihood of recommending, referring and buying

The previous linear regressions 1,2 and 3 show a positive effect of the type of incentive on the likelihood of either recommending, referring or buying the program, thus, H1 can be accepted and the introduction of a type of incentive has a positive impact on the growth of digital startups by increasing the likelihood of recommending, referring and buying the program. Thus, both intrinsic and extrinsic motivations might be proxies of the type of motivations and have a positive impact on people's decisions.

Likelihood of recommending the program (y_i) = $\beta_0 + \beta_1$Type of incentive$_i$ + β_2Size$_i$ + β_3Type of incentive$_i$ * Size$_i$ + u_i

Regression 4	B	Std. Error	Beta	t	p
Intercept	2,253	0,154		14,649	0,000
Type of Incentive	0,267	0,067	0,197	4,009	0,000
Size	-0,017	0,107	-0,008	-0,161	0,872
Type of Incentive*Size	0,037	0,133	0,014	0,278	0,781

Table 6: Coefficients table for Regression 4 (Likelihood of recommending the program)

As presented in table 6, including the number of members in the community (size) and the moderation of type of incentives, the size does not have a significant effect on the likelihood of recommending the program ($p = .872$).

To test the moderation effect, extend the first model and the remaining hypotheses, a multiple regression with interaction terms is conducted. To ensure the accuracy of the study, age, gender and profession are controlled even if they are not significant. With the introduction of the size of the community a change in the model fit is observed.

Likelihood of recommending the program (y_i) = $\beta_0 + \beta_1$Type of incentive$_i$ + β_2Gender$_i$ + β_3Age$_i$ + β_4 Profession $_i$ + u_i

Regression 5	B	Std. Error	Beta	t	p
Intercept	3,143	0,394		7,978	0,000
Type of Incentive	-0,24	0,064	-0,186	-3,753	0,000
Gender	-0,076	0,125	-0,03	-0,609	0,543
Age	0,002	0,012	0,011	0,201	0,841
Profession	-0,082	0,114	-0,04	-0,726	0,468

Table 7: Coefficients table for Regression 5 (Likelihood of recommending the program)

Adding the control variables leads to a decreasing adjusted R square for the likelihood of recommending the program and as table 7 shows, gender, age and profession are not significant (see Appendix 2, regression 1).

Likelihood of referring the program (y_i) = $\beta_0 + \beta_1$Type of incentive$_i$ + β_2Gender$_i$ + β_3Age$_i$ + β_4 Profession $_i$ + u_i

Regression 6	B	Std. Error	Beta	t	p
Intercept	3,747	0,403		9,287	0,000
Type of Incentive	-0,309	0,066	-0,23	-4,717	0,000
Gender	-0,142	0,128	-0,054	-1,113	0,266
Age	0,011	0,012	0,046	0,866	0,387
Profession	-0,291	0,116	-0,134	-2,501	0,013

Table 8: Coefficients table for Regression 6 (Likelihood of referring the program)

As well when adding the control variables, the adjusted R square for the likelihood of referring the program (see Appendix 2, regression 2) decreases. Adding the control variables like gender, age and profession shows they are not significant as presented in table 8.

Likelihood of buying the program (y_i) = $\beta_0 + \beta_1$Type of incentive$_i$ + β_2Gender$_i$ + β_3Age$_i$ + β_4 Profession$_i$ + u_i

Regression 7	B	Std. Error	Beta	t	p
Intercept	3,874	0,446		8,676	0,000
Type of Incentive	-0,153	0,073	-0,104	-2,115	0,035
Gender	-0,256	0,142	-0,089	-1,809	0,071
Age	0,019	0,013	0,077	1,431	0,153
Profession	-0,506	0,129	-0,212	-3,931	0,000

Table 9: Coefficients table for Regression 7 (Likelihood of buying the program)

Lastly, when adding the control variables for the likelihood of buying the program, the adjusted R square decreases as well (see Appendix 2, regression 3). Therefore, it means when introducing the community size in all three cases of likelihood the adjusted R square decreased. Table 10 presents the results for the importance of the community size. When including the moderator with the interaction between size and type of incentive one can observe that the size is no longer significant ($p_{Size} > 0.05$) for the likelihood of buying the program

Likelihood of buying the program (y_i) = $\beta_0 + \beta_1$Type of incentive$_i$ + β_2Size$_i$ + β_3Type of incentive$_i$ * Size$_i$ + β_4Gender$_i$ + β_5Age$_i$ + β_6Profession + u_i

Regression 8	B	Std. Error	Beta	t	p
Intercept	3,839	0,452		8,501	0,000
Type of Incentive	-0,155	0,073	-0,105	-2,133	0,034
Size	0,059	0,116	0,025	0,509	0,611
Type of Incentive*Size	-0,064	0,145	-0,022	-0,442	0,659
Gender	-0,254	0,142	-0,088	-1,792	0,074
Age	0,02	0,014	0,079	1,461	0,145
Profession	-0,51	0,129	-0,214	-3,949	0,000

Table 10: Coefficients table for Regression 8 (Likelihood of buying the program)

According to the analysis, the number of members in the community (size) does not have a significant effect on the likelihood of buying the program (p = .611). Therefore, H4 which claims that the size of the community has a positive impact on the referral rate can be rejected.

After stating that age, gender and size do not have an impact on the likelihood on buying the program, the type of incentive (p = -.155) and profession (p = -.510) do have a positive impact. The same effect occurs for the likelihood of recommending the program where gender (p = .548), age (p = .853), profession (p = .473) and size (p = .917) are no longer significant (see Appendix 3). When looking on the likelihood of referring the program gender (p = .267), age (p = .389) and size (p = .948) are as well no longer significant (see Appendix 3).

Before conducting a t-test to evaluate the effectiveness of incentives Levene's test for equality of variances is performed. Levene's test reveals p > 0.05 which implies variances are not significantly different and therefore we can conduct an independent t-test. To better evaluate the significance, the t-test in table 11 reveals that the likelihood of buying the program is not significant with p = .291. Recommending (p = .001) and referring (p = .003) the program is significant for the monetary and non-monetary incentive.

		Levene's Test for Equality of Variances		t-test for Equality of Means				
		F	p	t	df	p	Mean Diff.	Std. Error Diff.
Likelihood of recommending	Equal Variances assumed	1,082	0,299	3,441	264	0,001	0,464	0,135
	Equal Variances not assumed			3,451	262,616	0,001	0,464	0,134
Likelihood of referring	Equal Variances assumed	2,913	0,089	2,986	264	0,003	0,414	0,141
	Equal Variances not assumed			2,998	263,225	0,003	0,414	0,142
Likelihood of buying	Equal Variances assumed	0,005	0,945	-1,058	264	0,291	-0,154	-0,440
	Equal Variances not assumed			-1,058	260,210	0,291	-0,154	-0,440

Table 11: Independent t-test for the likelihood for the type of incentives

In order to evaluate the effectiveness of the incentives, an independent t-test for the likelihood of recommending, referring and buying the program is conducted with respect to different types of incentives. The following table 12 presents the likelihood for the type of incentives.

Type of Incentive		N	Mean	Std. Deviation	Std. Mean Error
Likelihood of recommending	Monetary	125	2,78	1,07	0,96
	Non-Monetary	141	2,31	1,12	0,94
	No Incentive	136	3,29	0,83	0,71
Likelihood of referring	Monetary	125	3,02	1,09	0,97
	Non-Monetary	141	2,61	1,16	0,98
	No Incentive	136	3,40	0,95	0,08
Likelihood of buying	Monetary	125	2,83	1,18	0,11
	Non-Monetary	141	2,99	1,18	0,10
	No Incentive	136	3,68	1,10	0,09

Table 12: Likelihood for the monetary, non-monetary and no incentives

Due to having more than two levels (monetary, non-monetary and no incentive) a post-hoc test is conducted. The Tukey HSD (honest significant difference) test reveals for the likelihood of recommending a statistically significance between the type of incentives as seen in table 13.

(I) Type of Incentive	(J) Type of Incentive	Mean Diff.	Std. Error	p
Monetary	Non-Monetary	0,46*	0,125	0,001
	No Incentive	-0,51*	0,126	0,000
Non-Monetary	Monetary	-0,46*	0,125	0,001
	No Incentive	0,97*	0,122	0,000
No Incentive	Monetary	0,51*	0,126	0,000
	Non-Monetary	0,97*	0,122	0,000

Table 13: Multiple comparison with Tukey HSD on the likelihood of recommending

When comparing the means of table 12 one can observe that the mean for the monetary incentive is higher except for the likelihood of buying the program by themselves. A higher mean implies a lower likelihood due to the chosen Likert scale from 1 = Very likely; 5 = Very Unlikely.

Therefore, the H3 which states the referral rate for monetary incentives is higher than the referral rate for non-monetary incentives can be accepted as well as H3 stating the impact of non-monetary incentives on the likelihood of referral is bigger than the impact of monetary incentives due to altruistic behaviour.

4.2 Discussion

The main objective of this dissertation was to provide knowledge and insights into the importance of the network effect and incentives to accelerate growth for digital startups and sustain CA. Creating an initial user base and acquiring customers is crucial for almost every startup's survival and continuation of their business activities. As presented in the literature review and many scholars, monetary incentives trigger extrinsic behaviour of individuals and might be a good way to overcome the critical issue of acquiring customers for digital startups. Nevertheless, the literature is not consistent on the most effective way of incentivizing. Non-monetary incentives appeal different than monetary incentives due to intrinsic motivation and altruistic behaviour of the individual.

In order to answer the research questions, an empirical study was designed by creating an experiment in form of an online survey. The survey revealed that respondents' motivation varies when they are referring or recommending a product to someone else and when buying the product for themselves. When buying it for themselves, the outcome shows that incentives are not significantly changing consumers perception of purchasing the product or not. Furthermore, the result suggests that incentives in general have a significant and positive impact on consumers likelihood of referral and recommending the program. Therefore, the H1 could be verified and incentives have a positive impact on the growth of digital startups by increasing the likelihood of recommending, referring and buying compared to delivering no incentive.

The t-test revealed that for the likelihood of buying the program, the type of incentive is not significant with $p = .291$, which is greater than 0.05. Therefore, one could conclude that the kind of incentive is not relevant for the respondents for the likelihood of buying the program for themselves. Furthermore, to compare the impact of non-monetary and monetary incentives the likelihoods of recommendation, referral and buying the program were analysed. On average, the likelihood of referring and recommending the program is higher for non-monetary incentive which means, people are more likely to recommend the program in order to receive a recipe Ebook for free instead of receiving a 10€ cashback. Therefore, one can conclude that H2 "When consumers are presented with monetary incentives they are more likely to refer the service than when consumers are presented with non-monetary incentives" can be rejected according to the outcome of the survey. On the other hand, the regression reveals that H3 "When consumers are intrinsic motivated the impact of non-monetary incentives on the likelihood of referral is higher than the impact of monetary incentives" can be verified, i.e. respondents show a higher referral and recommendation rate when non-monetary incentives are present. This shows that appealing on intrinsic motivation is more effective than monetary gains which strengthen the theories published by Gneezy & Rustichini (2000) and Mellström & Johannesson (2008).

Nevertheless, when discovering the impact of the network effect, the results slightly differed from the expectations. The perceived value when joining a community with 100 members or 1000 members was not significant which implies that the size of the community did neither increase nor decrease their likelihood of referral, recommending or buying the program. Thus, H4 "The size of the community has a positive impact on the referral rate" can be rejected. Even though the outcome of the regression shows that the size of the community does not play a significant role, it was proven people that care about the network due to valuing non-monetary incentives more. Thus, although the size of the community itself is not significant, the network might be valued by the respondents.

CHAPTER 5: CONCLUSIONS AND LIMITATIONS

5.1 Main Findings & Conclusions

The results from the hypotheses tests show that people's decisions are influenced by incentives in general. A digital startup may achieve a larger initial user base by setting incentives to recommend and refer customers. When introducing types of incentives, the likelihood for recommending and referring a product increased significantly. This shows the importance for digital startups and all kind of startups to incentivize people to spread the message about the product they are selling. Concerning the effectiveness of different kinds of incentives, the research is not decisive: Economists focus on monetary incentives and show the increased effort individuals put in to receive the monetary benefits whereas psychologists argue that there is an increase in performance by setting non-monetary incentives (Gneezy & Rustichini, 2000). As result of the conducted survey, people prefer non-monetary incentives which means they have an actual interest, realize the value in the product itself and share their recommendations due to intrinsic motivation. This outcome was supported by the study of Fehr & Falk (2000) and Gneezy & Rustichini (2000) stating the powerful influence of non-monetary incentives. Respondents of the conducted survey had no knowledge about the actual value of the non-monetary incentive. Nevertheless, the likelihood of referral and recommending was higher for the non-monetary incentive (free Ebook) than for the monetary incentive (10€ Cashback). When setting non-monetary incentives, the awarded amount is indifferent to the motivation of the individual (Heyman & Ariely, 2004).

The network effect plays an important role for digital startups launching new products and focusing on growth. Those network externalities work as a trigger for future diffusion and possibly influence the growth of new products or services positively (Stremersch et al., 2010). This direct network effect can only partly be verified. According to the conducted survey, the results were different than expected. The size of the community and perceived value for a community with 100 members or 1000 members were not significantly influencing the decisions of the respondents. Due to this, digital startups benefit more from different incentives than by the direct network effect. Nevertheless, the non-monetary incentive can trigger a network effect by distributing the recipe Ebook. As already stated, the non-monetary incentive increases the likelihood of referral and recommendation. This effect might increase even more if respondents actually receive the free Ebook and develop a feeling of belongingness in terms of the community for the featured program. Thus, through this non-monetary incentive an additional branding effect and indirect network effect might occur with more people having the recipe Ebook and sharing their experience.

To summarize the main findings, one could say that incentives benefit digital startups when it comes to achieve a higher rate of recommendation and referral. By appealing people's intrinsic and extrinsic motivation, the rate of referral and recommendation is increased presenting monetary and non-monetary incentives. Using these incentives can accelerate digital startups' growth in an effective way and thereby sustain CA. However, the likelihood of buying the product is not significantly affected by presenting monetary and non-monetary incentives. Nevertheless, the respondents were not significantly influenced by the size of the community which demonstrates a higher effectiveness of incentives rather than of the network effect for digital startups. Non-monetary incentives have shown to greater effect the likelihood of referring and recommending the product. It can be concluded that using monetary and non-monetary incentives feed the extrinsic and intrinsic benefits and therefore can be used as a powerful strategy to acquire additional customers and accelerate digital startups' growth.

5.2 Managerial / Academic Implications

For startups trying to scale and achieve a superior positioning by sustaining a CA, attracting new customers incentives may hold great significance. This dissertation contributes and supports the theories of money and social market by Heyman and Ariely (2004) in which they propose two sides of markets where people compensate effort and payment. Closely linked to their predictions, the consumer in money market (receiving a monetary reward) and social market (receiving a non-monetary reward) are more willing to make an effort (Heyman & Ariely, 2004). Thus, by setting incentives, the likelihood of recommending and referring can be increased which is predicting the same outcome as observed in this dissertation.

Companies like Airbnb, Uber and Dropbox apply incentives to attract customers to join their service. This dissertation offers the opportunity to help digital startups evaluating strategies for designing their incentives to increase likelihood of referral and recommendation. There exist other managerial examples of incentives such as Uber. When Uber established their service, free rides as incentive were provided during the Austin SXSW Conference. At this time, transportation was a problem due to the high number of attendances. By giving away free rides the startup could gain a huge awareness and create an initial customer base by this incentive (Holiday, 2014).

This dissertation highlights the accuracy of the example about Uber and provides a guideline for digital startups concerning types of incentives. Word of mouth is a powerful tool to create awareness for the product or service. To gain customers' attention and increase attractiveness, it is advised to deliver monetary and non-monetary incentives due to positive effects delivered when referring or recommending a product. For example, a cashback can be offered to the recommender for referring and recommending the product or service of the digital startup to other potential customers. As well, a non-monetary incentive in form of a gift can create a rather intrinsic motivation and altruistic behaviour of the recommender. By offering these incentives, user growth can be achieved and new customers acquired.

Acquiring new customers is the first step for digital startups to scale and in order to sustain CA. Nevertheless, additional effort is needed to increase the likelihood of buying the product. One suggestion could be offering a free trial for customers to truly experience and test the product, risk and uncertainty of a purchase would decrease and it would help attract additional customers and achieve a larger user base. Thus, delivery of a product preview and the opportunity of an initial customer experience would most certainly increase the willingness to pay (Yoon, 2013).

The recent literature concerning academic implications for incentives focuses greatly on the motivation of customers and employees, but less on concrete implications for startups. This dissertation supplements the view and outcomes of the study from Jin and Huang (2014) exploring the reward type and referral success. According to their study, consumers prefer monetary incentives over non-monetary due to the greater value from an economical point of view. Nevertheless, higher social costs associated with monetary incentives makes them inferior when the recommendation is not well justified (Jin & Huang, 2014). The outcome of the study provides a similar result. People react positively to monetary and non-monetary incentives, but if it comes to recommend or refer the program to their friends they have a stronger preference for non-monetary incentives due to the social costs implied when referring. Nevertheless, the economic value and opportunity of receiving a monetary incentive is as well a driver for the likelihood of recommendation and referral.

When looking at non-monetary incentives, intrinsic motivation triggers the decision of the individual (Fehr & Falk, 2002; Heyman & Ariely, 2004). When customers behave altruistically and are interested in benefiting from network effects while not focusing on monetary gains, non-monetary incentives should be more effective as based on the data collected for this dissertation. On the other hand, the dependency and significance for digital startups on the network effect could not be fully verified. Binken, Franses, Stremersch and Tellis (2007) showed the indirect network effect and its importance. Nevertheless, according to the outcome, the number of community members is not relevant for the likelihood of recommending and referring the product.

5.3 Limitations and Further Research

The main limitation of this dissertation is related to the causal relationship between the independent and dependent variable. When testing the effect of incentives scenario on the likelihood of recommending the program, the adjusted R square shows a comparatively low value of .030 (see Appendix 2, Regression 1). This indicates that the independent variable only explains a limited part of the dependent variable. When adding additional variables, the value did not increase. The sample size could bias this result. When splitting the total sample size of 402 in six scenarios, the average scenario size is n= 67. This could bias the outcome of this research concerning sampling bias with having a too small sample size. Another reason might be due to other variables impacting the likelihood of recommending, which could result in the low adjusted R square and therefore in a low model fit. These omitted variables might bias the results of this dissertation. Thus, it would be more adequate for future research to choose a larger scenario size which may result in the independent variable better explaining the dependent variable and increasing the adjusted R square. As well, the chosen variables size of the community and type of incentive are not the only variables explaining the likelihood of recommending, referring and buying the program. Therefore, the existence of other variables and their effect might limit the dissertation to an extent.

Secondly, the respondents' preference for non-monetary incentives may not be not for the sole reason of the individuals' intrinsic motivation. The startup Fit mit Pascal already is present on the market and has successfully established a customer base. Therefore, respondents might be reacting different due to the awareness of the brand of Fit mit Pascal. Thus, it is important to further examine and study the potential reasons why consumers prefer the non-monetary incentive. As well, the amount offered through the incentive can be considered as a tool to influence respondent's perception. As stated in chapter 3.4 Measures, the amount of the incentive is designed according to the value of the recipe Ebook of 10€. A bias might occur in the subjective perception of the value because some respondents might regard this amount as comparatively low and others as comparatively high. With people differently valuing the non-monetary incentive, this can affect the likelihood of recommending or referring the program. Again, the brand awareness may positively or negatively influence the perceived value of the non-monetary incentive. However, this dissertation mainly focuses on providing hints for rather incentivizing consumers with an incentive than no incentive. Nevertheless, presenting small monetary incentives can negatively influence the performance according to the experiment by Gneezy and Rustichini (2000). The experiment showed a better performance for offering no incentive than offering a small monetary incentive. Therefore, the amount of the monetary incentive might be perceived as too low and interpreted as an insult which may lead to biased outcomes of the survey. Even though there is no rule, every individual has their own perception of high and low values which makes it hard to label in a real-life situation (Gneezy & Rustichini, 2000). For future study, one could explore the extent to which the increase of the monetary incentive will affect consumers likelihood. Meaning, by increasing the economic value received or decreasing the high social costs associated with monetary incentives, one might restore the effectiveness of monetary rewards as incentives. As well, a two-sided monetary incentive scenario might work even better when the receiver of the incentive and the recommender are rewarded with an equal monetary reward.

Furthermore, participants of the survey were given two scenarios for the size of the community with either 100 or 1000 members. The size of the community can possibly be a subjective matter. Being confronted with a specific community size without being given a benchmark to compare, the respondents' decisions could be altered and therefore not clearly highlight the true perception of a community size. Therefore, for the future research presenting a comparison might give the respondent a better understanding and state the importance of the network effect for digital startups.

Lastly, this dissertation tests the hypothesis with an example from the health sector. This industry might not be representative for the whole digital startup ecosystem and the obtained outcome from this dissertation might change when other sectors or industries are researched. Therefore, the outcome of this thesis can be limited to explain the performance of digital startups in the health sector and has to be reviewed carefully when adapting for other sectors.

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APPENDICES

Appendix 1:

Questionnaire for the digital startup "Fit mit Pascal" with 3 different scenarios (Non-Monetary Incentive, Monetary Incentive and No Incentive). These scenarios are performed with respect to a community size of 100 and 1000 to evaluate if the network effect has an impact.

Start of Block: M100, Non-Monetary Incentive

Welcome and thank you for participating in this study for my thesis. The following survey is about testing the likelihood of participating and referring an online fitness program called #3PhasenProgramm. The whole survey will take no longer than 5 minutes and all your answers will be used for internal academic purposes only. All answers are anonymous and data will remain confidential. Thank you for taking your time!

Q1 How often do you exercise?

- ◯ Daily
- ◯ 2-3 times a week
- ◯ Once a week
- ◯ Less than once a week
- ◯ Never

Q2 How concerned are you about eating healthy?

- ◯ Very concerned
- ◯ Concerned
- ◯ Moderately
- ◯ Slightly
- ◯ Not at all

Q3 Have you ever heard of #3PhasenProgramm before this survey?

◯ Yes

◯ No

Q4 Did you already participate in the #3PhasenProgramm?

◯ Yes

◯ No

The experiment is aimed to understand the likelihood of referring the **fitness program #3PhasenProgramm by Fit mit Pascal**. This online program includes delicious meal plans, various training plans for the gym and at home and offers an active community! **To keep you motivated, the program offers a platform which will help you to keep fit, eat healthy and lose weight.** The community has now reached **100 members**, is creating a space for like-minded persons just like you, open to questions and you can motivate yourself by connecting with other members on this platform!

Q4 Do you consider a community with 100 members as high or low?

◯ Very High

◯ Above Average

◯ Average

◯ Below Average

◯ Very Low

Now imagine we are running a promotion campaign for #3PhasenProgramm. Apart from all the benefits you receive when joining the program, you can also earn a **recipe ebook for free** when you refer the program to a friend.

Q6 How likely is it that you will recommend the program to a friend in order to receive the free ebook?

- ◯ Very Likely
- ◯ Somewhat Likely
- ◯ Moderately
- ◯ Somewhat Unlikely
- ◯ Very Unlikely

Q7 How likely is it that you will refer a friend to purchase the program in order to receive the free ebook?

- ◯ Very Likely
- ◯ Somewhat Likely
- ◯ Moderately
- ◯ Somewhat Unlikely
- ◯ Very Unlikely

Q8 How likely is it that you will buy the program by yourself in order to receive the free ebook?

- ◯ Very Likely
- ◯ Somewhat Likely
- ◯ Moderately
- ◯ Somewhat Unlikely
- ◯ Very Unlikely

Q9 What is your gender?

◯ Male

◯ Female

Q10 What is your age?

____

Q11 What is your profession?

◯ Student

◯ Employed

Please continue to the following page to end the survey.
Thank you for participating in this survey. All your results will be saved and serve to improve the #3PhasenProgramm and help me conducting my master thesis!
If you have further questions concerning the #3PhasenProgramm or this survey feel free to send me an email to info@fitmitpascal.de or check on www.fitmitpascal.de :)

End of Block: M100, Non-Monetary Incentive

Start of Block: M100, Monetary Incentive

Welcome and thank you for participating in this study for my thesis. The following survey is about testing the likelihood of participating and referring an online fitness program called #3PhasenProgramm. The whole survey will take no longer than 5 minutes and all your answers will be used for internal academic purposes only. All answers are anonymous and data will remain confidential! Thank you for taking your time!

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- ◯ 2-3 times a week
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- ◯ Less than once a week
- ◯ Never

Q2 How concerned are you about eating healthy?

- ◯ Very concerned
- ◯ Concerned
- ◯ Moderately
- ◯ Slightly
- ◯ Not at all

Q3 Have you ever heard of #3PhasenProgramm before this survey?

- ◯ Yes
- ◯ No

Q4 Did you already participate in the #3PhasenProgramm?

- ◯ Yes
- ◯ No

The experiment is aimed to understand the likelihood of referring the fitness program #3PhasenProgramm by Fit mit Pascal. This online program includes delicious meal plans, various training plans for the gym and at home and offers an active community! To keep you motivated, the program offers a platform which will help you to keep fit, eat healthy and lose weight. The community has now reached 100 members, is creating a space for like-minded persons just like you, open to questions and you can motivate yourself by connecting with other members on this platform!

Q5 Do you consider a community with 100 members as high or low?

- ◯ Very High
- ◯ Above Average
- ◯ Average
- ◯ Below Average
- ◯ Very Low

Now imagine we are running a promotion campaign for the #3PhasenProgramm. Apart from all the benefits you receive when joining the program, you can also earn **10€ Cashback** when you refer the program to a friend.

Q6 How likely is it that you will recommend the program to a friend in order to receive the 10€ Cashback?

- ◯ Very Likely
- ◯ Somewhat Likely
- ◯ Moderately
- ◯ Somewhat Unlikely
- ◯ Very Unlikely

Q7 How likely is it that you will refer a friend to purchase the program in order to receive the 10€ Cashback?

- ◯ Very Likely
- ◯ Somewhat Likely
- ◯ Moderately
- ◯ Somewhat Unlikely
- ◯ Very Unlikely

Q8 How likely is it that you will buy the program by yourself in order to receive 10€ cashback?

- ◯ Very Likely
- ◯ Somewhat Likely
- ◯ Moderately
- ◯ Somewhat Unlikely
- ◯ Very Unlikely

Q9 What is your gender?

- ◯ Male
- ◯ Female

Q10 What is your age?

____

Q11 What is your profession?

◯ Student

◯ Employed

Please continue to the following page to end the survey.
Thank you for participating in this survey. All your results will be saved and serve to improve the #3PhasenProgramm and help me conducting my master thesis!
If you have further questions concerning the #3PhasenProgramm or this survey feel free to send me an email to info@fitmitpascal.de or check on www.fitmitpascal.de :)

End of Block: M100, Monetary Incentive

Start of Block: M100, No Incentive

Welcome and thank you for participating in this study for my thesis. The following survey is about testing the likelihood of participating and referring an online fitness program called #3PhasenProgramm. The whole survey will take no longer than 5 minutes and all your answers will be used for internal academic purposes only. All answers are anonymous and data will remain confidential. Thank you for taking your time!

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◯ Daily

◯ 2-3 times a week

◯ Once a week

◯ Less than once a week

◯ Never

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- ○ Concerned
- ○ Moderately
- ○ Slightly
- ○ Not at all

Q3 Have you ever heard of #3PhasenProgramm before this survey?

- ○ Yes
- ○ No

Q4 Did you already participate in the #3PhasenProgramm?

- ○ Yes
- ○ No

The experiment is aimed to understand the likelihood of referring the fitness program #3PhasenProgramm by Fit mit Pascal. This online program includes delicious meal plans, various training plans for the gym and at home and offers an active community! To keep you motivated, the program offers a platform which will help you to keep fit, eat healthy and lose weight. The community has now reached 100 members, is creating a space for like-minded persons just like you, open to questions and you can motivate yourself by connecting with other members on this platform!

Q5 Do you consider a community with 100 members as high or low?

- ◯ Very High
- ◯ Above Average
- ◯ Average
- ◯ Below Average
- ◯ Very Low

Now imagine you know about the #3PhasenProgramm and are talking with a friend.

Q6 How likely is it that you will recommend the program to a friend?

- ◯ Very Likely
- ◯ Somewhat Likely
- ◯ Moderately
- ◯ Somewhat Unlikely
- ◯ Very Unlikely

Q7 How likely is it that you will refer a friend to purchase the program?

- ◯ Very Likely
- ◯ Somewhat Likely
- ◯ Moderately
- ◯ Somewhat Unlikely
- ◯ Very Unlikely

Q8 How likely is it that you will buy the program by yourself?

- Very Likely
- Somewhat Likely
- Moderately
- Somewhat Unlikely
- Very Unlikely

Q9 What is your gender?

- Male
- Female

Q10 What is your age?

____

Q11 What is your profession?

- Student
- Employed

Please continue to the following page to end the survey.
Thank you for participating in this survey. All your results will be saved and serve to improve the #3PhasenProgramm and help me conducting my master thesis!
If you have further questions concerning the #3PhasenProgramm or this survey feel free to send me an email to info@fitmitpascal.de or check on www.fitmitpascal.de :)

End of Block: M100, No Incentive

Appendix 2:

Results of the linear regressions.

Regression 1

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,181[a]	,033	,030	1,024

a. Predictors: (Constant), Scenario

b. Dependent Variable: How likely is it that you will recommend the program to a friend?

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	14,264	1	14,264	13,606	,000[b]
	Residual	419,338	400	1,048		
	Total	433,602	401			

a. Dependent Variable: How likely is it that you will recommend the program to a friend?

b. Predictors: (Constant), Scenario

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2,927	,138		21,159	,000	2,655	3,199
	Scenario	-,234	,063	-,181	-3,689	,000	-,359	-,109

a. Dependent Variable: How likely is it that you will recommend the program to a friend?

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2,23	2,69	2,45	,189	402
Residual	-1,693	2,775	,000	1,023	402
Std. Predicted Value	-1,206	1,274	,000	1,000	402
Std. Residual	-1,654	2,710	,000	,999	402

a. Dependent Variable: How likely is it that you will recommend the program to a friend?

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	3,143	,394		7,978	,000	2,369	3,918
	Scenario	-,240	,064	-,186	-3,753	,000	-,366	-,114
	Gender	-,076	,125	-,030	-,609	,543	-,322	,170
	Age	,002	,012	,011	,201	,841	-,021	,026
	Profession	-,082	,114	-,040	-,726	,468	-,306	,141

a. Dependent Variable: How likely is it that you will recommend the program to a friend?

Regression 2

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
2	,219[a]	,048	,045	1,057

a. Predictors: (Constant), Scenario

b. Dependent Variable: How likely is it that you will refer a friend to purchase the program?

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
2	Regression	22,431	1	22,431	20,064	,000[b]
	Residual	447,174	400	1,118		
	Total	469,604	401			

a. Dependent Variable: How likely is it that you will refer a friend to purchase the program?

b. Predictors: (Constant), Scenario

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
2	(Constant)	3,274	,143		22,918	,000	2,993	3,555
	Scenario	-,293	,065	-,219	-4,479	,000	-,422	-,165

a. Dependent Variable: How likely is it that you will refer a friend to purchase the program?

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2,39	2,98	2,68	,237	402
Residual	-1,980	2,606	,000	1,056	402
Std. Predicted Value	-1,206	1,274	,000	1,000	402
Std. Residual	-1,873	2,465	,000	,999	402

a. Dependent Variable: How likely is it that you will refer a friend to purchase the program?

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
2	(Constant)	3,747	,403		9,287	,000	2,953	4,540
	Scenario	-,309	,066	-,230	-4,717	,000	-,438	-,180
	Gender	-,142	,128	-,054	-1,113	,266	-,394	,109
	Age	,011	,012	,046	,866	,387	-,013	,034
	Profession	-,291	,116	-,134	-2,501	,013	-,520	-,062

a. Dependent Variable: How likely is it that you will refer a friend to purchase the program?

Regression 3

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
3	,085[a]	,007	,005	1,187

a. Predictors: (Constant), Scenario

b. Dependent Variable: How likely is it that you will buy the program by yourself?

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
3	Regression	4,136	1	4,136	2,937	,087[b]
	Residual	563,339	400	1,408		
	Total	567,475	401			

a. Dependent Variable: How likely is it that you will buy the program by yourself?

b. Predictors: (Constant), Scenario

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
3	(Constant)	3,059	,160		19,078	,000	2,744	3,374
	Scenario	-,126	,073	-,085	-1,714	,087	-,270	,019

a. Dependent Variable: How likely is it that you will buy the program by yourself?

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2,68	2,93	2,80	,102	402
Residual	-1,933	2,319	,000	1,185	402
Std. Predicted Value	-1,206	1,274	,000	1,000	402
Std. Residual	-1,629	1,954	,000	,999	402

a. Dependent Variable: How likely is it that you will buy the program by yourself?

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
3	(Constant)	3,874	,446		8,676	,000	2,996	4,751
	Scenario	-,153	,073	-,104	-2,115	,035	-,296	-,011
	Gender	-,256	,142	-,089	-1,809	,071	-,535	,022
	Age	,019	,013	,077	1,431	,153	-,007	,046
	Profession	-,506	,129	-,212	-3,931	,000	-,759	-,253

a. Dependent Variable: How likely is it that you will buy the program by yourself?

Appendix 3:

Coefficients of the regressions for the significance of the size of the community.

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound
7	(Constant)	3,839	,452		8,501	,000	2,951	4,727
	What is your gender?	-,254	,142	-,088	-1,792	,074	-,534	,025
	What is your age?	,020	,014	,079	1,461	,145	-,007	,046
	What is your profession?	-,510	,129	-,214	-3,949	,000	-,764	-,256
	Scenario	-,155	,073	-,105	-2,133	,034	-,298	-,012
	Size	,059	,116	,025	,509	,611	-,170	,288
	Scenario_Size_Centered	-,064	,145	-,022	-,442	,659	-,350	,221

a. Dependent Variable: How likely is it that you will buy the program by yourself?

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound
8	(Constant)	3,139	,399		7,871	,000	2,355	3,923
	What is your gender?	-,075	,125	-,030	-,601	,548	-,322	,171
	What is your age?	,002	,012	,010	,185	,853	-,021	,026
	What is your profession?	-,082	,114	-,039	-,718	,473	-,306	,142
	Scenario	-,240	,064	-,186	-3,731	,000	-,366	-,113
	Size	,011	,103	,005	,105	,917	-,191	,213
	Scenario_Size_Centered	,028	,128	,011	,218	,827	-,224	,280

a. Dependent Variable: How likely is it that you will recommend the program to a friend?

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound
9	(Constant)	3,750	,408		9,184	,000	2,947	4,553
	What is your gender?	-,143	,128	-,054	-1,112	,267	-,395	,110
	What is your age?	,011	,012	,046	,863	,389	-,013	,035
	What is your profession?	-,291	,117	-,134	-2,491	,013	-,520	-,061
	Scenario	-,309	,066	-,230	-4,700	,000	-,438	-,180
	Size	-,007	,105	-,003	-,065	,948	-,214	,200
	Scenario_Size_Centered	-,003	,131	-,001	-,019	,985	-,261	,256

a. Dependent Variable: How likely is it that you will refer a friend to purchase the program?

Appendix 4:

Independent t-test and pos-hoc Tukey test

Between-Subjects Factors

		Value Label	N
Scenario	1	Monetary	125
	2	Non-Monetary	141
	3	No Incentive	136

Descriptive Statistics

Dependent Variable: How likely is it that you will recommend the program to a friend?

Scenario	Mean	Std. Deviation	N
Monetary	2,78	1,069	125
Non-Monetary	2,31	1,122	141
No Incentive	3,29	,834	136
Total	2,79	1,091	402

Levene's Test of Equality of Error Variances[a]

Dependent Variable: How likely is it that you will recommend the program to a friend?

F	df1	df2	Sig.
6,194	2	399	,002

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + Scenario

Tests of Between-Subjects Effects

Dependent Variable: How likely is it that you will recommend the program to a friend?

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	65,788[a]	2	32,894	31,871	,000	,138
Intercept	3124,847	1	3124,847	3027,617	,000	,884
Scenario	65,788	2	32,894	31,871	,000	,138
Error	411,814	399	1,032			
Total	3598,000	402				
Corrected Total	477,602	401				

a. R Squared = ,138 (Adjusted R Squared = ,133)

Multiple Comparisons

Dependent Variable: How likely is it that you will recommend the program to a friend?

Tukey HSD

(I) Scenario	(J) Scenario	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Monetary	Non-Monetary	,46*	,125	,001	,17	,76
	No Incentive	-,51*	,126	,000	-,81	-,21
Non-Monetary	Monetary	-,46*	,125	,001	-,76	-,17
	No Incentive	-,97*	,122	,000	-1,26	-,69
No Incentive	Monetary	,51*	,126	,000	,21	,81
	Non-Monetary	,97*	,122	,000	,69	1,26

Based on observed means.
The error term is Mean Square(Error) = 1,032.

*. The mean difference is significant at the ,05 level.

Homogeneous Subsets

How likely is it that you will recommend the program to a friend?

Tukey HSD[a,b,c]

Scenario	N	Subset		
		1	2	3
Non-Monetary	141	2,31		
Monetary	125		2,78	
No Incentive	136			3,29
Sig.		1,000	1,000	1,000

Means for groups in homogeneous subsets are displayed.
Based on observed means.
The error term is Mean Square(Error) = 1,032.

a. Uses Harmonic Mean Sample Size = 133,659.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

c. Alpha = ,05.