Nudge Marketing with Lead Generation Bots – Framing Avatars for Performance

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Statutory Declaration

I declare in lieu of an oath that I have written this master thesis by myself, and that I did not use other sources or resources than stated for its preparation. I declare that I have clearly indicated all direct and indirect quotations, and that this thesis has not been submitted elsewhere for examination purposes.

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List of Abbreviations

B2B	Business to Business
B2C	Business to Customer
CPC	Cost per Click
CPL	Cost per Lead
Q	Quarter
FIC	Firm Initiated Contact
CIC	Customer Initiated Contacts
Q	Quarter
MQL	Marketing Qualified Lead
SQL	Sales Qualified Lead
UI	User Interface
UX	User Experience
SMS	Short Message Service
CAT	Consumer Acceptance of Technology
AI	Artificial Intelligence
CMC	Computer Mediated Communication
AI	Artificial Intelligence
VR	Virtual Reality
POV	Point of View
3D	Three-Dimensional
UK	United Kingdom
CTA	Call to Action
MA	Master’s Degree
MSc	Master of Science
PhD	Doctor of Philosophy

Abstract

Business-to-business (B2B) and business-to-customer (B2C) sales processes are increasingly reliant on digital lead generation as an integral part of their customer or client acquisition. Chatbots have recently become more prevalent in such campaigns, competing against traditional lead forms. But can chatbots outperform lead forms in lead generation performance? More precisely, can chatbots yield more private information from business prospects than a lead form? The answers to these questions are particularly valuable for B2B companies, as they typically require far more information from leads than B2C companies, consequently resulting in long survey forms that reduce campaign performance and increase costs. Secondly, socially and culturally framed virtual avatars have extensively been shown to induce behavioral effects on individuals embodying or operating them. But can socially framed chatbot avatars prime users to share more private information? If so, can business framed chatbot avatars prime prospects to share more business relevant information? In an experimental study, the hypothesis that B2B lead generation chatbots yield more, higher quality and less costly lead information than traditional lead forms is explored. Additionally, the study also explores the hypothesis that business-salient avatars yield more, higher quality and less costly lead information than non-salient avatars. In line with the first hypothesis, results of the study show that across many related variables, participants assigned to the chatbot condition shared significantly more information than participants assigned to the form condition. Considering the second hypothesis, bot avatars were shown to have behavior and marketing performance impacting priming effects. However, these effects were not always positive. Participants assigned to the business-salient avatar condition provided higher quality leads overall than participants assigned to the other avatar conditions. But across multiple other related variables, the overall advantages were mixed and inconclusive. Practical and operational implications of these results with regards to business and digital marketing are discussed.

1 Introduction

"The social responsibility of business is to increase its profits" (Friedman, 2007, pp.173-178); and the course of generating profit is through the sales of products or services to customers/clients. The obtainment of these customers is necessary for the generation of sales, which are essential for maintaining the business, and they can be acquired both on and offline. They can additionally be gained *organically* (for free) through word of mouth, through strategic physical positioning of a brick and mortar shop, or through online search engine optimization. These methods are otherwise known as pull marketing. Additionally, they can be acquired through paid marketing efforts by means of digital ads or physical adverts. These methods are otherwise known as push marketing (Wiesel, Pauwels and Arts, 2011, pp.604-611).

Often, both in off and online sales, the sales process may require a longer process than traditional instant value exchanges. This is often the case when dealing with higher-involvement more expensive products or services, typical in the business to business (B2B) sector. In such cases, rather than attempting to acquire customers or clients directly and immediately, a fragmented process through aiming for lower-stage goals before the final purchase is often implemented. Typically, a first stage in these fragmented sales steps is the acquisition of the prospect's contact details. Later, these contact details are used to push the sale of the product or service. This step of acquiring pre-sale contact details whether on or offline is commonly referred to as lead generation, which is defined by the Oxford Lexico Dictionary as "The action or process of identifying and cultivating potential customers for a business's products or services" (2020).

Web-based technologies revolutionized methods of lead generation. The web broke the physical boundaries that limited prospecting geographically, and subsequently enabled lead generation methods that were previously impossible, as well as accelerated sales processes (Zumstein & Hundertmark, 2017, pp.96-97; Tiago & Veríssimo, 2014, p.706). For example, a business owner that was previously limited to offline lead generation methods in the form of direct mail and telemarketing, is now able to conduct online lead generation campaigns, internationally and parallelly to potentially an exponential number of customers.

A monumental shift towards online lead generation, caused a rift in traditional marketing methods that have prevailed for centuries (Tiago & Veríssimo, 2014, p.703), with new marketing and lead generation methods being unearthed and continuously being unearthed every day (Yadav, Joshi & Rahman, 2015, p.335-343; Wymbs, 2011, p.93-106). Businesses have adapted to the market and have shifted their customer acquisition strategies and efforts towards areas where their target customers now spend a large percentage of their days and salaries: online and on social media (Zumstein & Hundertmark, 2017, pp.96-97; Tiago & Veríssimo, 2014, p.706).

1.1 Digital Lead Generation

Digital methods for lead generation frequently evolve and thus regularly effect the available digital strategies for yielding potential customer data online. Currently, amongst the most popular methods that are used by practitioners is lead generation through the Facebook Ad platform, as well as through the Google AdWords platform. The following options for lead generation digital marketing campaigns are available through the Facebook platform:

1. Ads linking to an external landing page to be designed on a separate third-party webpage. Typically, these landing pages consist of type-forms to be filled out manually by page visitors; asking for their name, email and phone number.
2. Ads that directly open within-app lead forms that collect the same data as external landing pages. These lead forms have the advantage of much faster loading times and better user experience, thus typically leading to less costly costs per lead; but have the disadvantage of having less control over the design of the form.

   (Facebook, 2020)

Lead generation through the Google AdWords network is enabled through search ads or through display network ads. Prospects are directed to either a custom webpage consisting of a lead form, or to a lead form extension within the ad network (Google, 2020).

However, problems revolving the topic of digital lead generation lie in the matter that the objective of obtaining data through lead generation campaigns is constrained by issues of costs per lead, while still controlling for qualification of the prospects from whom this data is being collected from. Otherwise put, leads must be acquired in as cheap a way as possible; but must also yield high quality information about potential customers, from people who are qualified or likely to indeed be potential customers. The ordinary issues affecting costs and quality per lead are loading times of landing pages, the necessity of manual self-started effort by the prospects to fill in information, data protection fears, and the user experience of the process itself. These issues are accentuated in B2B industries, where typical lead and qualification forms are long and equipped with multiple questions, thus often leading to negative user experiences which reduce effectivity and increase costs.

1.2 Lead Generation Chatbots

A solution for these issues in this research paper relies on the use of digital nudging with chatbots as well the use of behavioral priming with digital avatars. Nudging is defined by the Oxford Lexico Dictionary as "gently prodding or pushing someone in order to draw attention to something" (2020). The theory of Nudging in behavioral economics was introduced by Richard Thaler in 2009 and is defined as the elicitation of favorable behavior of individuals while still respecting their freedom of choice and personal preferences (Meske, Amojo, Poncette & Balzer, 2019, p.323).

Digital nudging is a concept that is used for the same purposes in digital environments. Furthermore, it is a concept that is used in digital marketing campaigns and is studied in marketing settings, showing to partially overcome defiance of individuals to share information (Kroll & Stieglitz, 2019, p.1; Stryja & Satzger, 2019, p.1123). Mirsch, Lehrer and Jung conducted a literature review on digital nudging and phrase the concept as a behavioral economics-deduced strategy to shape environments to elevate the likelihood of specific behaviors (2017, 637). Subsequently, built upon the same foundations of the Nudge theory; chatbots have been developed for the use in digital marketing and lead generation, and have since been experiencing swift growth (Zumstein & Hundertmark, 2017, p.97). As seen in the research of Balasudarsan, Sathish and Gowtham; large companies such as Mercedes Benz SA, Starbucks and Philips are investing in chatbots for their websites and various social media pages (2018, p.1).

Lead generation chatbots have the potential to nudge users into favorable behavior (Zumstein & Hundertmark, 2017, p.107-108). They aim to shape campaign environments and, in that way, nudge prospects into sharing information by actively prodding them to share through personalized message requests. For example, as opposed to traditional lead forms and landing pages, chatbots address prospects directly and personally using their names, and wait for responses before proceeding to ask for the information respectfully, thus simulating a real humanlike conversation. While traditional landing pages and lead forms require self-starter behavior of the prospect to write the information themselves, chatbots nudge the prospect to start, continue and finish the process. Albeit, chatbots have very little been scientifically examined in a nudging context, data-collection context, or online marketing context. Moreover, lead generation bots have yet to have been scientifically examined in the context of B2B marketing. More research on chatbots in B2B marketing is necessary to assess chatbot effectiveness in both data collection, sales and other marketing efforts. These arguments led to the research question:

In B2B campaigns, do lead-generation bots yield more, higher quality and less costly leads than traditional lead forms?

1.3 Framing Avatars

Supplementary to the chatbot, a potential additional way to solve the aforementioned issues could be to further shape the campaign environment and induce desired outcomes through the use of avatars. An avatar is defined as "a visual representation of users in virtual environments" (Oh, Bailenson, Kramer & Li, 2016, p.2). The appearance of Avatars as framed-to-audience characters, has a potential behavior-shifting nudging effect on users. Behavioral Confirmation Theory (Snyder, 1992, p.67-114), a form of a self-fulfilling prophecy posits that people alter their behavior according to the stereotypically driven expectations of their conversational counterparts, only to confirm their preconceived notions. The Proteus Effect, first introduced by Yee and Bailenson (2007, p.271-290) argues that the behavior of individuals when interacting virtually changes in line with the characteristics of avatars.

However, limited research has been done on both the Behavioral Confirmation Theory and the Proteus Effect in a marketing context. Moreover, there is insufficient data on Proteus effects in non-immersive atmospheres. Notwithstanding, this study hypothesizes that an overlap of Behavioral Confirmation and Proteus effects, can occur when users interact with avatars in non-immersive virtual settings, causing shifts in their behavior and elevations in their willingness to share information. Specifically, it is hypothesized that chatbots framed with business characters will cause users to behave more professionally, display more trust and give more information in a professional business-like manner.

Thus, in addition to studying chatbots for the use of B2B lead generation in comparison with traditional lead forms, this study further examines the priming effect of avatars on consumer behavior by split-testing business-framed avatars, non-framed avatars and no avatar in the lead generation bot that is used in this experiment. This is linked to the following research question:

In B2B campaigns, do business-framed bot avatars acquire more, higher quality and less costly leads than non-salient avatars?

1.4 Conceptual Framework

The following section will elaborate the theoretical foundations underlying the topic and guiding the experimental design of the study.

While several theoretical frameworks exist for the topic of marketing in general, digital marketing severely lacks academic research and systematic frameworks of approach to scientific investigation. Topics of lead-generation and online customer acquisition frequently and swiftly evolve technologically and thus render longitudinal scientific observation both acutely difficult to engage in, and quick to become irrelevant. However, digital marketing tech serves but as a tool to aid in achieving goals set forth through theoretical assumptions that may be developed and borrowed from bountiful areas in business, sociology and social psychology. This paper explores human behavioral phenomena through the lens of digital marketing tech that is yet to be scientifically studied.

The topic of lead-generation has recently been explored though indirectly through research on Search Engine Advertising by Castelein, Fok and Paap (2019, p.1-38). The authors developed a Bayesian model that assesses the "probabilities of clickthrough and conversion rates of paid search advertisements" (p.1), primarily providing a model for digital advertisers to attain accurate daily measures of performance of individual ads and landing pages. Their framework closely follows that of Ghose and Yang (2009, p.1605-1622) which developed a hierarchical Bayesian model for clickthrough and conversion rate estimation. Ghose and Yang delved more deeply into the importance of the design of landing pages and their impact on costs per click (CPC). Similarly, Agarwal, Hosanagar and Smith (2015, p.695-713) studied the effect that organic search results have on paid efforts. The above authors approach the topic of lead generation only by addressing the initial touch point of customers where still little to no personal information about prospects are collected. Ghose and Yang (2009) refer to this early stage of customer data acquisition as the "cookie level" (p.4). More research on the adjacent and more data-revealing touch points in the customer research is needed.

Succeeding are groups of research that examined the role of bots in data collection within various industries. Balasudarsun, Sathish and Gowtham (2018, p.1-17) used surveys to understand best business implementation practices of chatbots in Facebook as a marketing tool. While contributing to the research on the topic, surveys can be flawed as they measure "Post Facto" responses to the lead generation sequences and bias prospects' would be real responses to the data collection process.

Johnson, Lewis and Nubbemeyer focus their research on a later step in the customer journey from the point of view of a carryover effect by analyzing display ads on the Google Display Network. (2017, p.1-42) While contributing to the literature by examining effects lasting after the end of campaigns, the authors measure both awareness metrics and purchases but ignore the collected user data in between. Datta, Foubert and Van Heerde (2015, p.217-234) approach the topic from a customer retention standpoint after firms first acquire customers and data with free trials. The authors modeled "customer retention and usage decisions" (p.217) though not with the use of real data, thus also possibly rendering the findings of their study to possess less external validity.

This paper will both test and compare two market-leading lead generation methods: lead forms and chatbots; and will bridge a wide theoretical gap in the existing body of literature on the topic. Additionally, a possible performance enhancing priming effect of the psychological phenomena known as the Proteus Effect and Behavioral Confirmation will also be examined through the use of avatars in this experimental study.

The conceptual framework that guided the design of this experimental study is based on the theory that through digital nudging techniques, chatbots will enhance lead generation performance. In other words, it is assumed that programming a bot with digital nudges will result in increased lead generation performance of the bot. Additionally, it is theorized that socially framing the avatar of a bot will further enhance the lead generation performance of the bot. Specifically, framing its avatar to be with similar characteristics to the characteristics of its targeted users enhances lead generation performance. Programming both these theories onto the bot is hypothesized to lead to a greater number of leads (compared to the lead form), with higher quality information and lower costs (lower costs per lead -CPL).

An conceptual illustration can be seen in Figure 1:

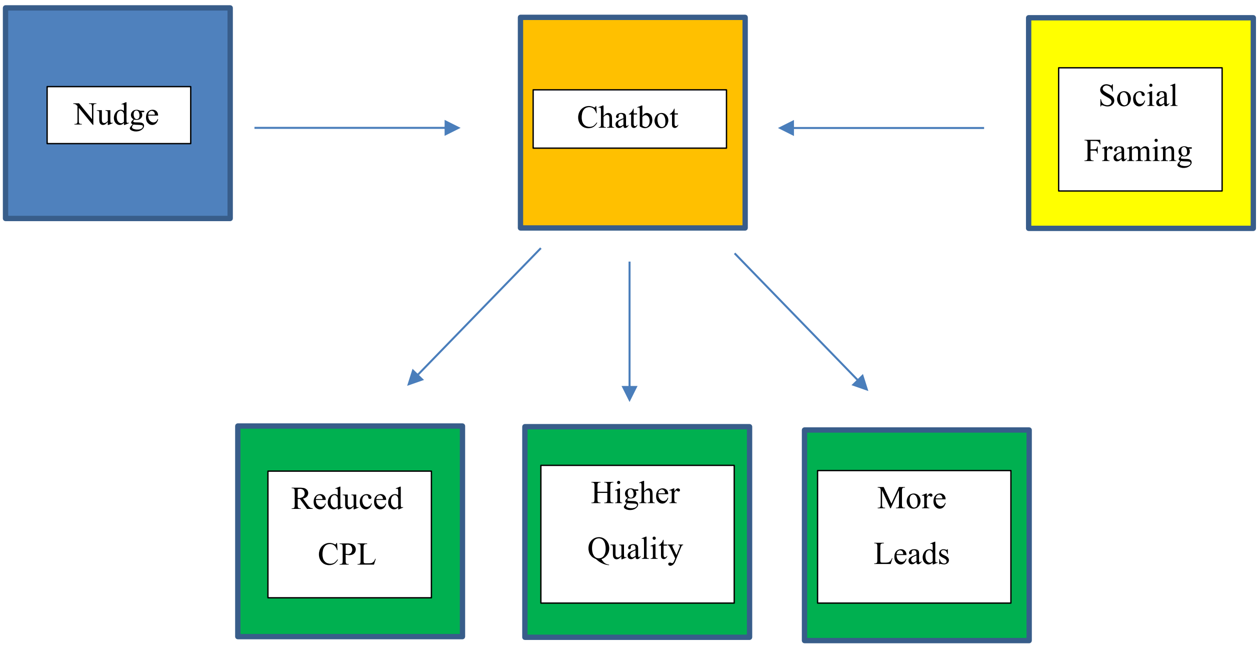

Figure 1 (Conceptual Framework)

1.5 Purpose

With the goal of studying best practices in B2B customer acquisition campaigns, specifically with the objective of lead generation; this research paper will conduct a web-based experiment that will compare the performance of a traditional industry standard lead form, with the performance of a lead generation chatbot. Additionally, this paper will further examine a Proteus Effect-deduced theory of a behavioral confirmation priming effect of avatars; by split-testing business-framed avatars, non-framed avatars and no avatar in the lead generation chatbot that is used in this experiment.

Accordingly, the purpose of this quantitative study is to test the hypotheses that lead generation chatbots yield more, higher quality and less costly leads than traditional industry standard lead forms, by testing independent variable 1 – *chatbot*, on dependent variable 1 – *lead*, and dependent variable 2 – *quality*; in the web-based experiment that will be categorized as the research medium for this study. Additionally, this study will test the theory that the avatar priming effect is pronounced on both lead collection and lead quality in a B2B marketing environment; by assessing the impact of independent variable 2 – *avatar*, on dependent variables 1 – *lead* and 2 – *quality*.

This research paper will cover the main and most current possibilities of companies to perform digital lead generation campaigns. It will provide insight into the performance of lead generation chatbots in a B2B environment, as well as their possible use for customer data collection and user onboarding in various other business sectors. Finally, this paper will shed light onto the role of avatars for use in numerous digital marketing campaigns, primarily for a marketing objective.

This study contributes to the academic community by conducting a never been done before in-depth, lead generation-focused chatbot study, using real data from an experimental web-based experiment. Further audiences that will benefit from this study are B2B and business to customer (B2C) companies as well as professional practitioners; as they will gain insight as to which method of lead generation is most effective in digital marketing campaigns, in addition to further understanding the role of avatars in nudge marketing with lead generation bots.

2 Literature Review

The following section will introduce the literature that guided the formulation of this study's research questions. Additionally, the hypotheses will be introduced as based on the literature, before later being reintroduced as operational hypotheses in 3.9.

2.1 Digital Marketing & Lead-Generation

As digital marketing is a rapidly evolving and changing industry, it hinders the ability of conducting scientific studies with long-lasting meaningful implications, consequently also reducing the motivation to conduct scientific studies (Järvinen, Tollinen, Karjaluoto & Jayawardhena, 2012, p.102). Additionally, as implications of these studies may be of high monetary value, it is often not in the best interest of individuals and companies to publish them. Subsequently, scientific research conducted in the field is often in the form of internal unpublished studies within companies. These result in "considerable shortcomings of existing research in the field, with scientific findings of limited relevance and a large discrepancy between academia and practice." (Lamberton & Stephen, 2016, pp.146-172)

The Merriam-Webster dictionary defines marketing as "the process or technique of promoting, selling, and distributing a product or service" (2020). Therefore, digital marketing may simply be defined as the process of marketing through digital channels. Differently from traditional marketing, digital marketing channels such as social media platforms, e-commerce shops, email and more have revolutionized the accessibility to information and ease of purchase of products or services by both individuals and companies worldwide (Järvinen et al. 2012, p.102). Consequently, in contrast to traditional marketing, competition is no longer limited to geography; and both physical and virtual sellers experience increasingly staggering competition for brand visibility and customer traction. Additionally, often in practice the process of priming individuals to purchase an item or service through the use of online digital channels differs from traditional sales processes in the physical world in many ways. When comparing digital online sales processes to that of a physical retail store for example, the online user or online shop visitor is not encountered with a salesperson. Additionally, as the user is not physically bound to the shop, exiting can be done by an instant, guilt-free click of a button; something that may possibly be or feel impolite in a physical store, and consequently result in longer physical store visits on average in comparison to online store visits. A Salesforce report based on the analysis of data from over 500 million shoppers worldwide shows a short online attention span resulting in average online store visit durations of 4 minutes in Q1 2019. This duration follows a rapidly decreasing trend falling in just two years from 6 minutes on average in Q1 2017 (Salesforce, 2019). People however may spend a larger amount of time overall shopping online than in physical brick and mortar shops (Chiu, Lo, Hsieh & Hwang, 2019, p.24-30), but this duration is typically spread across multiple sites. This total online shopping duration then signifies the length of the decision-making process, rather than the online attention span for a single store visit. When shopping online, users are susceptible to bountiful distractions in their personal and digital environments as well as to an abundance of easily accessible information; all of which promote continual research of the product/service of interest, price comparisons and more. All these ordinarily exceedingly lengthen the sales process of higher-priced, high-involvement online transactions; in comparison to transactions in the physical world.

To effectively navigate through competition and increased lengths of the typical sales process, digital marketing evolved into a process of priming individuals to take desired actions commonly other than purchasing; often in the form of fragmented steps ordinarily known collectively as a marketing or sales funnel. Hu, Du and Damangir (2014, p.300-319) state that when engaged in high-involvement purchases for high-priced products or services, buyers are inclined to seek as much information about that product or service as possible. As thorough product/service research prior to purchasing has largely become the norm for consumers and even more so in the context of B2B products and services, the authors define sales funnels as comprised of two main stages: the information research prior to purchase, and the final stage of purchasing (p.300). Based on this logic, Hu et al. proclaim that marketing can increase sales in two ways that are interlinked: firstly, through creating interest in consumers and prompting them to search for information about the advertised product or service; and secondly, through converting the information seekers into customers. The authors proceeded to analyze Google Trends data for the development of a model framework that separates the impact of marketing on sales into two separate categories; “interest generation and conversion” (p.315). Specifically, they analyzed the search volumes for vehicles and their sales numbers to assess the impact of ad spend on sales. A lack of correlation found between the two draws attention to the importance of separate evaluation of ad spend impacts on the separate stages of the sales funnel rather than on sales as a whole.

The first stage of a common and industry standard marketing/sales funnel is the lead generation stage. Wiesel, Pauwels and Arts (2011, p.604-611) define lead generation as the process of obtaining pre-sales information through information requests (p.606). The authors looked into the channels and stages of on and offline sales funnels by conducting a case study of a B2B company named Inofec. Inofec was in desire for a more data-driven analytical approach to the allocation of recourses to their marketing activities across the various communication channels. Wiesel et al. established a theoretical and econometric model for the empirical investigation of two main topics of interest: 1) the effects of marketing efforts on off and online purchases through the lens of sales funnel metrics; and 2) the profit impacts of both firm and customer-initiated contacts by measures of magnitude and timing. The authors found evidence of dual-channel effects, particularly online marketing efforts affecting offline sales and offline marketing efforts affecting online sales. Additionally, marketing efforts were found to have a direct impact on funnel stages along the entire sales funnel. However, the most impactful finding of the study was that online customer-initiated contacts yielded considerably greater profits than off-line contacts initiated by the company. In their field experiment, higher allocation of marketing budgets to these activities resulted in net profit gains larger by a factor of 14 than the profits yielded by the prior budget allocation (Wiesel et al., 2011, p.604) The authors separated firm-initiated contacts (FIC) and customer-initiated contacts (CIC) as follows: FICs were email campaigns, catalog mail campaigns, fax campaigns and flyers – essentially all push messages by the firm; and CICs were Google AdWords search advertising campaigns – customer initiated interest and search (p.605).

Wiesel et al. describe the central concept of a sales funnel, as the movement of prospects towards the action of a purchase in a sequence of phases. These phases are cognitive, affective and finally conative. “In the cognitive phase, the prospect recognizes a need and initiates an information search. In the affective phase, the prospect undergoes a process of evaluation of alternatives. Finally, in the conative phase the prospect initiates a purchase.” (Wiesel et al., 2011, p.605)

In the conceptual framework of the study, during the cognitive phase of the online funnel, web-visits and leads represent the initiation of the thought process of the prospect. The prospect’s online request for a quote is an indication of offer evaluation representing the affective phase. Lastly, website orders are representative of the final conative phase. The variables used for the off-line funnel were identical to those of the online funnel with the exception of website visits, with which an alternative comparable measure was not found. The field experiment in the study showed that it is crucial to credit marketing activities for earlier stage actions in the sales funnel such as web visits and leads as well, rather than just measuring marketing effectiveness by direct impact on purchases. Google AdWords in particular obtained 73% of its total impact on profit from off-line purchases, which shows a cross-channel effect of marketing activities on both the on and offline sales funnels.

Duncan and Elkan, (2015, p.1751-1758) described a B2B sales funnel in detail in their paper on the development of two probabilistic models for the ranking of leads according to their probability of converting to a sales opportunity, to a successful purchase and the expected revenue the leads should generate. The typical sales funnel as depicted by the authors consists of 5 stages: awareness, leads, marketing qualified-lead (MQL), sales-qualified lead (SQL) and won. Each stage is smaller in diameter, representing the smaller volume of prospects that reach each stage as they progress in the sales process moving through the successive stages. They categorize leads as initial-stage prospects that have yet to have been evaluated. These are also commonly referred to as “cold leads”.

In their study, leads are later qualified according to specific criteria through marketing automation tools. These leads are then defined as MQLs. Afterwards, sales representatives contact the MQLs and assess whether they possess the necessary minimal criteria to qualify as a SQL. Should prospects meet the criteria for being a SQL, they will be pursued by sales representatives and will eventuate as either a successful sale (closed-won) or failure of a sale (closed-lost) (p.1751-1752). For the purpose of the development of an automated lead scoring model, sales and marketing data was collected from Salesforce and Marketo, both industry leading marketing automation platforms. Duncan and Elkan divide the lead measures of information into two categories: static features (demographic) and behavioral features (activity). The static category of information is the information about the individual representative of a company who is making the contact, or information about the company which the individual is representing. These include the “name or company name, the domain name, industry codes, the number of employees, the market value, income or revenue, and the company location.” (p.1753) The behavioral category of information is the information representing the actions taken by the lead over the course of a defined period of time, which are tracked through the marketing automation platform. These include “website visits, email opens, webinar attendance, subscribe and unsubscribe form fill-outs, and demo requests.” (p.1753) The models introduced by the authors following this real data-based experiment indicate that lead quality can be predicted regardless of the availability of behavioral data. (p.1757) However, the behavioral data in their study consists simply of non-static or dynamic data rather than true behavioral data containing personality characteristics, goals, wants, needs and fears. These behavioral data are fundamental for the pre-qualification of firm-initiated leads before allocating resources to converting them into paying customers.

1.1.1 Behavioral Targeting & Social Priming

Summers, Smith and Reczek (2016, p.156-178) explored the manners in which consumers react to behaviorally targeted ads and demonstrated that the mere behavioral targeting of an ad can function as a social label even with the absence of definitive labeling information (p.156). Across four studies, consumers altered their self-perceptions to match the implied social label they were being categorized with. Their altered self-perceptions in turn impacted their behavior and subsequently their intent to purchase the underlying advertised product. Social labels whether explicit or inexplicit, encourage people to observe and learn about themselves by evaluating their self-categorizations as categorized by an external source (p.157). These findings are consistent with both Bem’s self-perception theory (1972, p.1-62), and Snyder et al.’s behavioral confirmation theory (1977, p.656-666). Consumers accept the external validity of the inferences marketers and marketing platforms infer about them, and thus a behaviorally targeted ad signals the consumer that he/she is likely to like the advertised product or service (p.158).

Forehand, Deshpande and Reed (2002, p.1086-1099) explored the influence of identity salience on advertisement response. Their research builds upon the notion that through pronouncing the salience of social identities, people’s perceptions and behavior may be influenced (Giles & Johnson, 1987, p.1086-1099; as cited in Forehand et al. 2002, p.1090). The results of their research suggest that in the context of advertisements, the use of characters of the same social identity of the receiver may induce both favorable and unfavorable responses in consumers. Identity primes were found to have mixed results on receivers, causing behavioral changes also to receivers that do not share the social identity of the character. These results imply that priming consumers with identity cues in advertisements is risky as it can have both significantly favorable, and significantly unfavorable results.

Cowan and Spielmann (2018, p.1-34) found explanatory evidence for these results in their study about identity confirmation in tourist advertisements. The results of their study show that culture or identity is in the eyes of the beholder; and if advertisements imply an identity that contradicts the culture or identity the target associates with him/herself, the advertisement will have negative effects on purchasing behavior (p.2). Consumers actively and subconsciously look for information and products that confirm the identities they associate with themselves. For example, consumers that believe themselves to be athletic or interested in fitness, seek out and notice more advertisements targeting athletes and fitness enthusiasts. It is possible that online behavior data of consumers of which marketers use for behavioral targeting, contradicts the identities that consumers identify themselves with. Namely, a consumer that identifies as an athletics enthusiast may consistently engage with food and beverage content, and hence be targeted with food and beverage advertisements by marketers. However, these advertisements would likely result in negative attitudes of the target towards the advertisements as they negate the self-perceived identity of the target. There is various research linked to identity priming to motivate or shift behavior: e.g. Reed II, Forehand, Puntoni and Warlop (2012, p.310-321) that contented that "consumers behave in ways that are consistent with what it means to *be* the identity the consumer identifies with" (p.310); Klesse, Goukens, Geyskens and de Ruyter (2012, p.355-362) that showed that the exposure of thin models to dieters had an adverse effect on the dieters' motivation to diet, mediated by the "perceived attainability of the thin ideal" (p.355). These findings support the use of social identity priming to manipulate consumer behavior in marketing, yet they accentuate the importance of being precise and the high likelihood of adverse effects in case of impreciseness.

1.1.2 Digital Nudging

In addition to social or identity priming, other techniques have been adopted from the fields of social psychology and behavioral economics for the use in digital marketing and lead generation. Thaler and Sunstein (2008) introduced the Nudge Theory in the context of encouraging individuals to make better choices regarding their health, wealth and overall happiness. Individuals often make irrational choices knowingly, even when they know the choices are irrational and should be decided otherwise. Thaler and Sunstein explain that the reason for this is that individuals have two, often warring, systems in our body: The Automatic System, which acts without thinking and drives the behavior of brushing teeth and driving cars, often thoughtless and automatic (p.42-43); and conversely, The Reflective System which regulates conscious thought. The Automatic System is necessary due to the complicated nature of human life containing millions of pieces of information, and hundreds of thousands of choices every single day. But before anything becomes automatic, it must be taught and conditioned in the brain by The Reflective System. The theory argues that sometimes nudges are needed to guide The Automatic System in the right direction (p.44-45). More precisely, individuals often find great difficulty in making decisions, especially when presented too little or too much information, and it is in these times that the likelihood of making bad decisions increases. While too little information inhibits the decision-maker from making a decision, too much information tends to result in bounded rationality-driven decisions. Bounded rationality (Simon, 1982) contends that human rationality is bounded due to limitations in our thinking capacity, availability and access to information, and time. These limitations result in the development of heuristics or mental shortcuts that enable swift decision-making; but may oftentimes lead to decisions that are not optimal, rational or sufficient. Likewise, individuals may give into the temptation of acting without thinking, sparing themselves the mental cost of putting effort into the decision-making process (Thaler & Sunstein, 2008, pp.46-48).

To nudge therefore is "to push mildly, poke gently in the ribs, especially with the elbow" (p.36). It is setting the alarm clock to help wake up on time. Or it is an app that sends you a push notification to remind you to drink water. A nudge is meant to subtly adjust the context in which you are making a choice, allowing one to make the "good" choice with less pushback, or at least to reduce one's chances of making a bad choice (pp.114, 163, 255, 286, 303). One of the most powerful nudges is *The Default Setting*. Thaler and Sunstein are referred to as "Libertarian Paternalists" (p.21) as in they believe in letting people make their own choices with as little interference as possible from outside forces, especially from business or the government. That being said, they understand that it is difficult for people to make tough but necessary choices; such as the choice to select good healthcare coverage, or the choice to save for retirement (pp.126-131). They therefore propose creating an environment in which individuals can make whichever choice they want, but in which making the right choice is simpler, easier, and more straightforward (pp.131-142). They believe in creating "good defaults" in which individuals are automatically or semi-automatically enrolled in the best choice for the majority of people, but they can adjust it as they see fit. This idea is based on the default bias principle - the concept that most individuals will choose the default, all things considered (pp.25-26). This led to the formulation of the term *Choice Architecture*. Through choice architecture, different choices are presented to consumers in a manner which influences consumer decision-making. While Thaler and Sunstein argue that nudges and choice architecture should be used by governments to promote wise decisions, especially when there are too many choices or individuals' futures at stake; it is not just governments who use them (pp.42-44). Anyone who creates a platform in which individuals must make choices, is a "choice architect." This choice architect designs the context in which others make their decisions (pp.28-32). These theories have since much been put to practice in the context of digital marketing, and in the design of digital sales landscapes.

The authors provide a six-principle framework for creating good choice architecture, and thus an ideal environment for advantageous decision-making or facilitation:

1. Incentives – Individuals must be provided the proper incentives to facilitate good decision making. These must not only be monetary and goods-based incentives; but could also be psychological incentives as well (pp.164-168).
2. Understand Mappings – It is necessary to ensure that users know the implications of each decision they make.
3. Defaults – The default choice should be designed to benefit as many people as possible in any given situation. Social media platforms do this in the interest of boosting engagement. (pp.142-8)
4. Give Feedback – Individuals must see the consequences of their actions, even in situations where these may not immediately be visible. For example, phone cameras possess fake shutter clicks in order to provide individuals with the necessary reciprocal feedback they need in order to know when a photo is actually taken (pp.153-155).
5. Expect Error – Individuals must be given as little room as possible to make mistakes (pp.148-153).
6. Structure Complex Choices – Complex decisions comprised of many possible choices must be supplemented with a clear breakdown of all the possible choices in the process as well as their respective outcomes. For example, instead of alphabetically listing all the paint colors in a hardware shop, they should be sorted

by hues, so that people can find the exact color they want without having to know what the color "cornflower" means (pp.160-164).

Nudge can be summarized as providing people with a *Third Way*. The first way is to let individuals do as they please without any guidance. The second way is paternalism, strict regulation, forcing the "right choice" on everyone. The *Third Way* is in between the two, making it easier for individuals to make choices, but ultimately providing them the freedom to make their own decisions (pp.401-403).

In 2017, Mirsch, Lehrer and Jung (pp.634-648) expanded on the Nudge theory by analyzing nudges and choice architecture in a digital landscape, specifically from a user interface (UI) design perspective. The authors state that as decisions are increasingly being made online through various screens, apps or websites; due to the nature of the digital sphere with vast amounts of available information, people are particularly inclined to make inefficient or faulty decisions. This presents an ideal landscape for nudging, notably due to choice architecture being faster, cheaper, and easier to do online (p.635). Digitally, nudges can also be more personalized due to user tracking possibilities, which can enable more effective designs. Mirsch et al. (2017, p.634); and Weinmann, Schneider and vom Brocke (2016, p.433) define the term *Digital Nudging* "as a behavioral economics-based approach that administers user interface (UI) design to guide the behavior and influence the choices individuals make in digital environments". Mirsch et al. suggest the following main psychological effects that have the greatest effects on the decision-making processes of individuals, and those which need to be considered in the development of effective UI designs:

1. **Framing** - Framing refers to designing the decision-making process in a way that the choices and outcomes can be predicted. This *frame* is a controlled presentation of a choice problem and mainly refers to the accentuation, orientation, and presentation of decision problems. This can be seen on Amazon for example, when "related products" of a purchase are accentuated to encourage users to make more purchases than originally planned (p.640).
2. **Status Quo Bias** – The bias argues that individuals tend to weigh the disadvantages of leaving the current state higher than they weigh the advantages of the new state. It is based on the notion that individuals are more loss-averse than benefit-inclined, and the fear of losing something is stronger than the potential gain. For this reason, default choices are effective. Websites can set their defaults to lead to an optimal decision for

themselves or their customers. Individuals are more likely to stick with the default than to make a change (pp.640-641).

3. **Social Norms** – Social norms are the rules and boundaries created by groups to regulate group behavior. As individuals typically adjust their behavior to conform to the behavior of their social and cultural group, being told that most people behave in a particular manner is an effective method for prompting this behavior in others. On Amazon for example, there is a section that says: "Others who bought this product also bought…". This is a powerful tool for prompting consumers to purchase more (p.641).
4. **Loss Aversion** - Individuals are typically more afraid of losing what they have, than they are of losing the future benefits which they are yet to have. Setting limitations on websites such as informing the user of the number of seats left on a flight at a certain price, or the number of others looking at booking the same hotel room or property, can shorten the decision-making window and encourage faster purchases (p.641).
5. **Anchoring and Adjustment** - When individuals do not have enough information or context to properly judge an option, they often use reference points and anchor their decision to them. For example, when looking for a product online, offering three similar options at three different price points will provide a lower-limit anchor and an upper-limit anchor, making the median-priced choice the most likely to be chosen (pp.641-642).
6. **Hyperbolic Discounting** – Individuals customarily prefer immediate or near-future rewards, even if the rewards in the distant future are worth more. For example, | companies that provide discounts for immediate payments rather than for standard prices later on, often see a rise in purchases, even if the discount is negligible (p.642).
7. **Decoupling** - Decoupling refers to the decoupling of the cost of purchase from its benefit. Individuals commonly spend more on their credit cards than with cash, because "the payment is decoupled from the consumption" (p.642). The market leading European consumer electronics retailer, Media Markt, takes advantage of this bias by offering financing and deferred payment, thereby removing the immediate pain of expenditure from its gain (p.642).
8. **Priming** – Priming can be done through the presentation of specific topics, moods, questions, or information before a decision-making process takes place. This overlaps with framing and is a subtle way to shift individuals towards making a certain

advantageous decision. For example, asking individuals on election day, “Do you plan to vote?” is likely to encourage them to go and vote, without explicitly telling them to do so. On a travel site, this could be done by displaying emotional pictures of destinations, thereby priming site visitors to book (p.642).

9. **Availability Heuristic** - “Individuals tend to evaluate the probabilities of events based on the ease at which they can be recalled” (p.643). Subsequently, repeatedly stating the number of hurricane deaths each year for example, would likely nudge individuals to purchase hurricane insurance regardless of the real probability of a hurricane hitting one’s home. In advertising, online banner ads are used to continuously display offers to individuals. In the moment of the decision, the offer is “in the forefront of their mind” (p.643). This availability of information then nudges the individual towards the decision favorable for the advertising firm.

Despite nudging receiving notable academic attention in the context of behavioral economics, digital nudging has yet to receive much academic attention, especially in a marketing and sales context. In 2018, Huang, Chen, Hong and Wu, studied the effect of digital nudging on online social sharing (pp.1483-1491). Huang et al. conducted a randomized field experiment using website pop-ups and tested four different nudging messages: “direct requests, monetary incentive, relational capital and cognitive capital” (p.1483). The experiment was conducted in 2017 over a period of four and a half months, in a Chinese firm that shares university and career path information online (pp.1485-1486). Unique new visitors to the site were randomly allocated to one of five treatments: control (receiving no nudge), and the four other nudging message groups, nudging the users to share content online. The authors examined whether or not the user clicked on the pop-up, whether or not the user shared the information, and to which social media platform (pp.1485-1487). Specifically, the treatments were: *Control* – No pop-up at all; *The simple ask* - asking individuals to share the content with their friends on their own social media accounts; *Monetary Incentive* – incentivizing users to share the content with a monetary reward of a free subscription to a company; *Relational Capital Message Framing* – suggesting that the friends of the users may find the content useful; *Cognitive Capital Message Framing* – reminding the users to share the content with their friends and express their interest in the content (pp.1485-1486). The results of the research showed that the monetary incentive nudge had a significant positive effect on social sharing of users. Additionally, the relational capital and cognitive capital nudges were both significantly efficient in nudging users to engage in social sharing, in comparison to the no nudge control group. Most notably, the simple request nudge was found to have an even worse effect on user social sharing than no nudge at all.

Following in the lines of previous research on anchoring (Adaval & Wyer, 2011, pp.355-365; Dholakia & Simonson, 2003, pp.206-217; Epley & Gilovich, 2006, pp.311-318; Shen & Chen, 2007, pp.69-80; Simonson & Drolet, 2004, pp.681-690), in 2020, Dennis, Yuan, Feng, Webb and Hsieh (pp.39-65) explored digital nudging in an e-commerce context and whether they have an effect on consumers' willingness to pay. Particularly, through seven experiments, the authors examined the effect of numeric priming and semantic priming through simulated advertisements on an online shop. Numeric priming was found to have a significant impact on consumers' willingness to pay. However, this only held true when the value of the goods was ambiguous and had no impact when a suggested retail price or fixed price was displayed on the goods (p.39). Semantic priming was found to have a stronger and significant impact on consumers' willingness to pay, but weaker with a presence of suggested retail prices on the products. The implications of this research differ from findings from offline research on priming that have often been generalized to online settings. Notably, in online auction settings such as on eBay, customers can be nudged to pay more for products with unclear values through the display of clearly labeled high-priced items near the product the user has searched for. Albeit, such nudges will likely have no effect on consumers' willingness to pay for products whose price is clearly listed, for example on e-commerce websites such as Amazon.

The operational use of digital nudges in online marketing has meager been studied (Dennis et al., 2020, pp.39-65; Huang et al., 2018, pp.1483-1491; Mirsch et al., 2017, p.634; Weinmann et al., 2016, pp.433). This research aims to bridge that gap through this web-based experiment.

1.1.3 Chatbots

Traditional definitions of marketing are flawed as they place focus on one-sided communication by the seller, while ignoring the receiving end of it. Technology innovation as well as increased pressure by customers to be more involved in the sales process, led to the integration of two-way communication in digital sales campaigns. Two-way digital communication with customers and prospects began through the use of phone support, chat support and two-way SMS (short message service) marketing campaigns. However, the high cost and limited and slower scalability of human-based sales and support, led to the development of exponentially scalable online surveys and lead forms. Traditional lead forms however, lack the advantages of two-way communication. Moreover, difficulties in acquiring leads, as well as the lack of "the human touch" of these forms then in turn, led to the development of lead generation chatbots (Zarouali, Van den Broeck, Walrave & Poels, 2018, pp.491-497; Zumstein & Hundertmark, 2017, pp.96-109). "The word *chatbot* is derived from the combination of two words, *chat* and *robot* and is defined as a computer program that simulates human language with the aid of a text-based dialogue system" (Zumstein & Hundertmark, 2017, p.98). Differently from lead and survey forms, in addition to lower costs and potential exponential scalability (p.96); chatbots have the additional advantage of enabling highly personalized communication, addressing the conversational opponent by the name and asking personally adjusted and suited questions (Zarouali et al., 2018, p.491). Thus, it was hypothesized that

> *H1,H2,H3* - Lead generation Bots collect more information than traditional lead forms.

Zarouali et al. conducted a study to predict consumer responses to a brand with a customer service chatbot on Facebook. The authors programmed a Facebook Messenger chatbot designed to aid users with making movie ticket reservations. To test for consumer responses, the study was modeled after the Consumer Acceptance of Technology (CAT) model. Their model tested for three cognitive and three affective determinants, with the potentiality of influencing the attitude of consumers towards brands using chatbots. The cognitive determinants were perceived usefulness, perceived ease-of-use, and perceived helpfulness; and the affective determinants were pleasure, arousal and dominance (p.491-493). To test for these variables, participants were provided a link to begin a chat with the Facebook messenger bot. After following the instructions to book a movie ticket, the participants were directed towards a survey which assessed all the variables in the study. The findings of the study revealed that the two cognitive predictors of perceived helpfulness and perceived usefulness, were positively associated with respondents' attitudes towards the brand (fictitious) providing the chatbot. Additionally, all three of the affective predictors significantly predict respondents' attitudes towards the brand providing the chatbot.

While this study was conducted on the Facebook platform and therefore potentially being of high external validity, Zarouali et al. did not test the usefulness of the chatbot itself, namely in its ability to extract firm-valuable information from consumers. Additionally, the study assessed consumer responses towards the brand but not the chatbot itself. Nonetheless, their findings show that both what consumers think and feel about chatbots have a significant influence on the effectiveness of the chatbot. Since chatbots can be programmed in almost endless ways, respondents' attitudes towards them may be highly unpredictable. Zarouali et al.'s study offers insight into programming chatbots in a manner that overcomes this uncertainty. The authors recommend including jokes and emojis into the conversation with the aim of increasing pleasure, as well as responding quickly and efficiently to increase usefulness.

Zumstein and Hundertmark (2017, pp.96-109) further explored the necessary language and techniques with which to program chatbots for effective personalized communication. They summarized *best practices* for designing the communicative language of chatbots in 7 parts:

1. **The chatbot as a team member**: Individuals display more trust towards chatbot characters when they are perceived as team members (*humanlike*), rather than as programmed lifeless applications. Chatbots should communicate in a way that places them on the same *team* as the individual it is communicating with (p.99).
2. **Scope of the messages**: A particular courtesy is expected of chatbots. Thus, its users expect the questions or answers being addressed to them to be accurate, polite and not overloaded with information (p.99).
3. **Personality traits**: Studies show that individuals express themselves with words depending on their level of extroversion. For example, extroverted individuals typically use far more adjectives and adverbs in their speech than introverted individuals. Additionally, people most often prefer to converse with people of similar traits. Chatbots should be designed with wording that is adapted to the type of individual it is conversing with. If artificial intelligence (AI) based adaptation to language is impossible or out of scope, unique chatbots should be tailored to the

personality type of the group it is targeting. If more than one personality type is targeted, multiple chatbots should be designed to be effective (p.100).

4. **Specialists vs. generalists**: Research shows that people believe the words of specialists more than they believe the words of generalists. Chatbots are therefore recommended to offer specific characters for specific topics and should communicate in a manner that makes them seem like experts. Human traits and natural language output are essential for the design of chatbots (p.100).
5. **Gender stereotypes**: The sex of the avatars of chatbots may have an effect on chatbot effectivity. For example, according to Reeves and Nass (1996, pp.1-305), for technical related issues, users display far higher confidence in chatbots with male avatars than they do for chatbots with female avatars. Conversely, for service requests such as with hotels or in the fashion industry, users typically expect chatbots with female avatars (p.100).
6. **Credibility**: False or insufficient answers from chatbots, as well as redundant or repetitive questions, results in the loss of credibility of the chatbot (p.100).
7. **Emotions**: Finally, if adequate emotions are expressed by chatbots, they are deemed more trustworthy and credible. In particular, chatbots should project positive emotions such as happiness and excitement to enhance the engagement rate and strengthen the relationship between the chatbot and its user. Additionally, chatbots should display empathy to the user on a minimal level. Ideally, chatbots are perceived as more credible when they do not respond immediately, but rather make small pauses as do people in natural conversations (p.100).

Due to the unique ability of a chatbot (as opposed to forms) to create a feeling of a trustable relationship with users; to establish a sense of a credible authority in users' eyes; to evoke feelings of joy and empathy; to be perceived as of a similar personality as the user and to use a similar type of language; it is hypothesized that

H4 – Lead generation bots collect more words from collected leads than traditional lead forms.

Based on the recommendations of Zarouali et al. (2018, pp.491-497) and Zumstein & Hundertmark (2017, pp.96-109), the bot in this present study was programmed with positive emojis and jokes. Additionally, it was programmed to reply to questions and to follow up on replies to questions quickly and efficiently, though in a realistic timeframe as would be in an otherwise real conversation. These are possibilities that are not possible to integrate within forms. Thus, it was hypothesized that

H5 – Lead generation bots induce better subjective experience ratings from collected leads than traditional lead forms.

H6 – Lead generation bots induce higher quality information from collected leads than traditional lead forms.

2.2 Behavioral Confirmation Theory & The Proteus Effect

The Proteus Effect is a theory first introduced in 2007 by Nick Yee and Jeremy Bailenson from the Department of Communication in Stanford University. It describes the transformation of self-representation on behavior in virtual environments. The question raised with their research was posited on the ability and ease of altering one's digital self-representation in virtual environments; and whether or not changing one's digital self-representation alters one's behavior in turn. (Yee & Bailenson, 2007, p.271) Specifically, it was hypothesized that individuals will conform their behavior to their digital representations regardless of how they are perceived by others.

The authors referred to literature from 2002 by Flanagin, Tiyaamornwong, O'Connor, and Seibold (pp.66-93) that addressed the gap between the virtual and real self, although focused on the impact of anonymity and authenticity on behavior in computer-mediated communication (CMC), and how this behavior differs between men and women. Yee and Bailenson rather focused on how digital avatars alter one's behavior, thus specifically the effect of one's virtual self-representation as a whole on their behavior as opposed to the mere effect of anonymity or authenticity. Moreover, Yee and Bailenson addressed Behavioral Confirmation Theory (Snyder, Tanke, & Berscheid, 1977, pp.656-666) which is the phenomenon whereby people conform their behavior to the expectations of their counterpart. In Snyder et al.'s study, over telephone interaction, male participants that were made to believe they were talking to attractive females caused a shift in the female's behavior regardless of the actual level of her attractiveness. Specifically, the male participants caused the female participants to behave in a more positive, playful and flirtatious manner. Later in 2002, Ridge and Reber (pp.1-14) explored Behavioral Confirmation in a professional setting by examining 60 male undergraduate students interviewing 60 female undergraduate students for a teaching assistant position. Half the male participants were made to believe that the female applicant was attracted to them, while the other half were made to believe the female applicant was not attracted to them. Consistent with Behavioral Confirmation Theory, the male interviewers in the attraction belief condition evoked unwitting flirtatious behavior from the female applicants, whom did not perceive any change in their own behavior. Based on Behavioral Confirmation theory and the 1977 and 2002 experiments; Yee and Bailenson speculated that similarly, in an online setting, a perceiver (affected by the condition) may cause a target using an attractive avatar to shift his/her behavior to a more friendly, positive, charming, or flirtatious manner. But Yee and Bailenson wondered how might avatars alter one's own behavior independent of how others perceive them? (p.272) Yee and Bailenson made a distinction between Behavioral Confirmation, that lays the focus on the altering behavior of another individual (target of a conversation) that is not manipulated by the experimented condition; and shifted the focus towards the individual under the manipulated condition.

The authors explored research revolving the Self-perception Theory and Deindividuation Theory to gain more insight as to how and why an individual's behavior can change due to the virtual avatar, he/she is using. Bem (1972, pp.1-62) pioneered the Self-perception Theory with the argument that, when they have no prior experience, people develop their attitudes after the observation of their own behavior, and the conclusion of what must have caused that behavior. His experiment was revolutionary in that, that it shows that people construe their own behaviors rationally, just as they would seek to analyze others' behaviors.

Later, it was attempted in other studies to manipulate participants' behavior and assess their attitudes and affections afterwards. It was shown that participants described their attitudes and affections formed on the behaviors they were practicing during the experiment despite having been told to behave that way. Participants were split into two groups where half were told to conduct facial exercises of contracting certain facial muscles, causing them to unknowingly smile; while the other half were told to conduct exercises that relax the facial muscles, causing them to unknowingly frown. The frowning group reported themselves as angrier after the experiment, while the smiling group reported themselves as happier. This showed that physical expressions can cause emotional states. Rather than smiling due to being happy, people can smile to make themselves be happy; as well as frown oppositely to make themselves be sad (Laird, 1974, pp.475-486).

Progressed research has later shown that behavioral changes are stronger when deindividuation of individuals occurs. Deindividuation has been shown to lead to both directions of behavioral change, both antisocial as reasonably expected, and social. While Zimbardo (1969, pp.237-307) initially used Deindividuation Theory to argue that largely crowded areas such as urban environments, cause deindividuation that leads to antisocial behavior; Gergen, Gergen, & Barton (1973, pp.129-131) contrarily used darkness to show that deindividuation can promote friendly and affectionate behavior as well.

Online avatars do not only enable anonymity that causes deindividuation, but also act as complete digital representations of ourselves. Thus, Yee and Bailenson hypothesized that digital avatars will have a significant impact on how people behave online. People that are deindividuated online may comply to new identities that are implied from the avatars that represent them. Just like in the study by Frank and Gilovich (1988, pp.74-85) where participants in black uniforms conformed to more aggressive behavior than those in white uniforms; people interacting in online environments may conform to the identity traits that are inferred by the avatars that represent them in this environment. More precisely, in "line with Self-perception theory, people conform to the behavior they believe others would expect them to have." (Yee & Bailenson, 2007, p.274) This is what Yee and Bailenson termed as the Proteus Effect. To test this effect, they conducted a series of studies where the attractiveness, or height of the participants' avatar was manipulated. To isolate the effect from behavioral confirmation, the confederate that the participant (under the manipulated condition) was interacting with was blind to the condition, in that the avatar of the participant they were interacting with appeared to them blurry or untextured. It was hypothesized that participants with attractive avatars will move closer to confederates, and participants with tall avatars will be more willing to make unfair splits in negotiation tasks. The results from the experiments were that in line with the Proteus Effect and the study hypotheses, participants under the attractive condition moved closer to the confederates, revealed more personal information about themselves and displayed more intimate behavior, specifically after less than one minute of exposure to their altered avatar; and participants under the tall condition displayed more willingness to make unfair splits in negotiation tasks than those with short avatars, whereas participants with short avatars were more willing to accept unfair splits in negotiation tasks than participants with tall avatars.

Following Yee and Bailenson's study, multiple other research has been conducted on the Proteus Effect. In 2009, Lee (pp.34-49) studied the effects racial-salient avatars have on stereotype threat responses of African American participants. Stereotype threat (Steele & Aronson, 1995, pp.797-811) refers to an identity-related threat that hinders the motivation and performance of individuals with a group identity that suffers from negative stereotypes. Lee studied the presence and implications of the effect in computer-mediated settings (CMC) by testing whether individuals' performance of a task will differ when using identity-salient avatars in comparison to identity-cloaking avatars. As African Americans often suffer from stereotypes, Lee hypothesized that when given a challenging task (in this case an unsolvable anagram), African Americans under a condition of a racial-salient revealing avatar would persist significantly shorter than African Americans under a racial non-salient non-revealing avatar condition. The results of the study were in line with the hypotheses and showed presence of a Proteus Effect and how it can play role in affecting an individual's performance in addition to his/her behavior, as revealed in the original study by Yee and Bailenson.

In 2012, Van der Heide, Schumaker, Peterson and Jones (pp.1-23) examined the Proteus Effect on computer-mediated dyadic communication between couples. Specifically, the explorative experiment assigned male participants to see either an attractive, unattractive or no avatar (control) portrayal of their female partners; and assigned female participants to see either an attractive, unattractive or no avatar (control) portrayal of themselves. The results were in support of the hypotheses that suggested that female participants will behave in a more positive and friendly manner toward their male partners when assigned to an unattractive avatar, as opposed to when assigned to attractive avatars or no the avatar condition. Building on top of Yee and Bailenson's findings, Van der Heide et al. found that the Proteus Effect may alter one's behavior also independent of anonymity as a contributing factor.

The Proteus Effect was found to have effects on creativity. Buisine and Guegan found that creative avatars resembling inventors induced higher creative performance among users than users with non-creative avatars, however only with the exclusion of social identity-bearing cues (2019, pp.1-13).

In 2016, Oh, Bailenson, Krämer and Li (pp.1-18) expanded on Laird's study (1972, pp.575-486) on the positive effects of forced smiling on attitudes; and studied whether the effect is present in a virtual environment through the use of digital avatars manipulated by different smiling conditions. Avatar smiles were designed in a way that they were either representative of the actual user's smile, or a slightly enhanced version of the smile. Despite only being able to see their interaction partners' avatars, participants that interacted in the enhanced smile avatar condition reported a more positive experience and stronger feeling of social presence, than participants in the normal smile avatar condition. The results potentially have a greater validity as over 90% of the participants were not able to identify the smiling manipulation.

After numerous studies published on and in relation to The Proteus Effect, the boundaries of the effect were brought into question by virtue of determining the extent and length of a Proteus carryover effect following the termination of the avatar embodiment experience. Namely, Reinhard, Shah, Faust-Christmann and Lachmann (2019, pp.293-315) studied the presence of a carryover Proteus Effect after leaving virtual reality and found that participants that previously virtually embodied older avatars, walked a predetermined distance significantly slower than participants that previously embodied younger avatars. Additionally, in a recent study, Ratan, Beyea, Li and Graciano (2019) assessed the reliability of the Proteus effect in a meta-analysis of 46 quantitative studies with avatar manipulations and found that "avatars have a meaningful effect on the behaviors and attitudes of their users" (p.19).

However, most studies relating to The Proteus Effect were done through the use of virtual reality (VR) systems that enabled enhanced embodiment of avatars in comparison to non-VR games, particularly those employing characters in the third person. As findings from previous studies show an enhanced Proteus Effect when embodiment of the avatar is greater, it raises questions whether there lay differences in the effect when playing in the first person, through the eyes of the avatar in Point Of View (POV) mode; or in the third person, in non-POV mode. Additionally, this raises questions whether the effect is prevalent when embodiment of the avatar is done through methods other than in virtual reality, notably through computerized video games with the use of game characters.

Ash (2016, pp.22-430) conducted a study with the use of non-VR technology through a video game "*Fight Night 4*" on the *Xbox 360* console. The research followed the studies of Frank and Gilovich (1988, pp.74-85), Lee (2009, pp.34-49) and examined the potentiality of a racial effect on both in-game and post-game behavior and aggression. The results of the study were not in congruence with the Proteus Effect and hypotheses as the participants using a Black avatar did not exhibit a higher degree of aggression than participants using a White avatar, nor did they characterize the Black avatars using a higher degree of Black stereotypes than did the participants that used the White Avatar. These findings were also contradictory to the findings of a previous study by Eastin, Appiah, Cicchirillo (2009, pp.337-356) which was able to "demonstrate a Proteus Effect of race on cognition" (Ash 2016, p.437, in reference to Eastin et al., 2009, pp.337-356) and found that displaying attributes of racial nature evokes stereotyping and more hostile thoughts and behavior. The study by Eastin et al. was also conducted with the use of a video game "*Unreal Tournament*" but differently from Ash's study, the study was conducted with the use of a game that is played in the first person in POV mode, as opposed to the game played in the third person that was used in Ash's study. Additionally, the participants in Eastin's study played for 15 consecutive minutes, as opposed to the 3 separate rounds of 3 minutes that were played in Ash's study. Both these differences could have accounted for the contradictory findings of Ash's study. Moreover, it is reasonable to assume that short 3-minute rounds would not likely be sufficient to facilitate substantial embodiment of an avatar, which is shown to be a crucial driving element of the Proteus Effect. The results of the study further support this statement as only individuals with a high level of perceived embodiment revealed behavioral differences. (Ash, 2016, p.436) Another possible contributing factor to the lack of Proteus Effect found in the study by Ash, relates to the technical nature of the game "*Fight Night 4*". The game demands frequent button clicking from the user, and careful attention to the opponent, to other game elements and to the fighting itself. These may likely hinder the process of avatar embodiment and may likely ultimately inhibit a Proteus Effect.

Considering these differences, further studies employing third person games, particularly those in which the user is the "hero" of the story should be carried out. There is legitimate reason to assume that types of games such as these, under different study designs, using longer periods of gaming; may enable stronger user-embodiment of the avatar, and an environment in which there is enough capacity to capacitate a Proteus Effect.

By the same token, while most studies on the Proteus Effect have focused on the observation of behavioral changes within individuals experiencing the effect, few studies have attempted to study the effect as a method of inducing favorable behavioral changes, namely in the context of purchasing behavior or in business in general. In 2014, Peña and Yoo brought the latter to light and sought to examine the impact of the Proteus Effect on shoppers' purchasing behavior, particularly in the context of salespeople trustworthiness and bidding (pp.18-32). Peña and Yoo employed a first-person 3D virtual store with interactive gameplay on a computer with a keyboard, mouse and a 23-inch screen where avatars of male and female salespeople were dressed in either black or white clothing. The results of the study were consistent with the findings of previous studies on the effects of both race, and clothing on cognition and behavior (Frank & Gilovich, 1988, pp.74-85; Lee, 2009, pp.34-49; Eastin et al., 2009, pp.337-356), as the "study participants displayed significantly more negative attitudes toward avatars dressed in black in comparison to avatars dressed in white" (Peña & Yoo, 2014, p.22). Avatars dressed in black were perceived as less persuasive and less trustworthy than avatars dressed in white. Additionally, participants that interacted with avatars dressed in black offered significantly less money for the same product as opposed to participants that interacted with avatars dressed in white (p.26).

One year later in 2015, Yoo, Peña and Drumwright expanded on Peña's study and examined the impact of the Proteus Effect on shoppers' purchasing behavior and product perceptions; specifically, whether the operation of young or elderly avatars have different effects on these perceptions and behaviors. Additionally, they investigated a possibility whereby virtual shopping experiences may translate into prosocial behavior in favor of a non-profit organization that supports the elderly (pp.62-71). The conceptual framework of their study was based on the evidence-supported notion that the operation of avatars bears a priming effect, and can induce cognitive, emotional and behavioral influence. In 2011, Peña contended that priming effects can theoretically explain how avatar operators are influenced by the physical characteristics of the avatars they are operating. (Peña, 2011, pp.150-168; as seen in Yoo et al., 2015, p.63) While participants did not show significant positive changes in attitudes towards the non-profit organization for the elderly, partially explained by *ceiling effects* (Yoo et al., 2015, p.70), product choices were affected as participants that operated elderly avatars selected the elderly-related product more often than participants that operated young avatars.

Socially, culturally and demographically framed avatars have been extensively shown to have character confirming behavioral effects on users. Additionally, framing chatbots to look and behave in a manner that is similar to that of the user, has been shown to have priming effects that nudge the user to take favorable actions (Zumstein and Hundertmark, 2017, pp.96-109). Thus, it is hypothesized that

H7-17 - *Business-salient* avatars collect more leads and information than *non-salient* avatars.

The previous research revolving the topic of avatars and the Proteus Effect leaves unanswered questions regarding the susceptibility of individuals to behavioral influence by exposure to and interaction with avatars in less immersive, less controlled virtual environments such as online shops and websites. Is there a minimum required time period of avatar interaction necessary to induce a Proteus Effect on behavior? How immersive must the virtual experience be to bring about behavioral changes? More importantly in a business context; to which degree can individuals be primed by avatars for the purpose of purchasing real, non-fictitious products with real money? Can findings from previous research on fluctuations of trustworthiness towards avatars be expanded towards efforts to extract personal and business-related information from individuals?

3 Methodology

The following chapter will present the design of this study with the aim of answering the research questions and testing the hypotheses. The various measurements and subsets of measurements for fulfilling this purpose will be elaborated on in detail both textually and graphically. Succeeding, the procedure as well as the participants will be described. The hypotheses will be reintroduced as operational hypotheses; and finally, the statistical proceedings are defined.

3.1 Experimental Design

An experiment has been conducted for the purpose of testing whether there lay performance differences between lead generation bots and lead forms in the context of B2B client acquisition. Moreover, the contribution of digital avatars to the performance of digital lead generation was subject to examination in the course of this study. Specifically, avatars were socially framed to assess a possible priming effect on participants. For the fulfillment of the purpose of this study, the following conditions were set forth:

The experiment was divided into two main conditions; lead generation bot, (nudge marketing), and lead form (industry standard). A between-subjects design was adopted, randomly assigning participants to one of the two conditions. Additionally, the bot condition was split into three sub-conditions where participants of the bot condition were randomly assigned to; *business-salient* avatar (business priming effect), *non-salient* avatar, and *no avatar* (control). A randomization tool (Kartra Split Testing) was used for the allocation of the participants with the following proportions: lead form (40%), bot (60% split into 20% for each sub-condition). These proportions were allocated to enable comparisons with similar group sizes. The design of the study is depicted in

Figure 2:

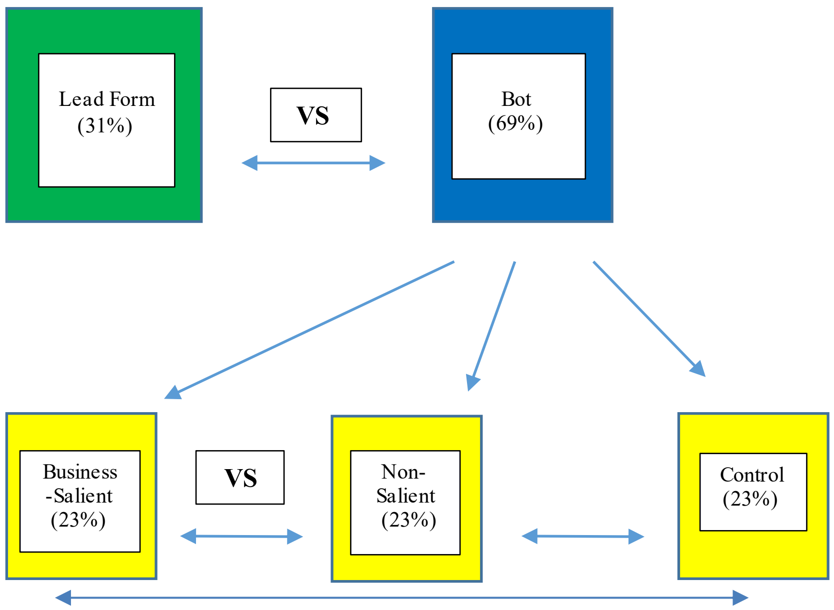

Figure 2 (Experimental Design)

To simulate business conditions of client acquisition and lead generation, the participant is in the role of the business prospect whose interest was stimulated for a particular product or service and is engaged in the process of sharing necessary information with the inquirer in exchange for that product or service. The market standard definition of a business lead primarily constitutes of the name and email address of the prospect, but most often includes the phone number as well. Oftentimes a B2B environment necessitates specific criteria beyond the standard scope of traditional lead criteria and requires industry-specific information to fit qualification or other purposes of the inquiring business. These may include but are not limited to company name, website, address, company registration number, number of employees, business needs, category of operation, incoterms and certifications. In the environment of a study, participants are not expected to possess and actual business interest that would facilitate a lead. Therefore, the business interest in this study was substituted by the chance of winning one of three moderately-valued prizes (€55, €30, and €15 Amazon gift cards). For the selection of the winners, 20 participants were randomly chosen and ranked by the amount of answers and quality of revealing information the participant provided, giving the prize to the top 3. The name, email address and cellular phone number of the participants were used as leads; as in a typical real B2B scenario. The B2B industry-specific questions were substituted by questions revolving every-day-life topics that any of the participants can elaborate on in detail. In both the form and the bot, there were no mandatory questions. On the form, the participant had the possibility of leaving the field blank; and on the bot, the participant had the possibility of clicking a button: "I'd rather not say".

3.2 Measurements of Disclosure

The goal was to achieve (acquire) primary leads initially, followed by predetermined second and third tier lead information. The classification of the lead information tiers was developed based on a real-world B2B lead generation campaign of a UK B2B supply chain company. The company's main area of business is individualized matching of supplier and buyer business profiles based on the bespoke needs of the respective companies with the use of artificial intelligence (AI). The campaign was designed and led by the author of this study. The lead qualification question in the case campaign may be structured into three tiers.

3.2.1 Primary Lead Information Tier

The lead information of primary necessity for the company as well as for other typical B2B and B2C companies alike consists of indispensable information necessary to build a business relationship with the leads. This information typically comprises of the contact data of the prospect. Without this primary information, any secondary or third tier information is useless for the company. In the real-world case of the UK company, this information consisted of the name, email address and phone number of the prospect. For the purposes of the present study, these contact information questions remained unchanged. In real-world scenarios, it is the freedom of the prospect to choose whether or what to share, as well as to abandon the process at any point in time. Identically, no question required mandatory answer in any of the experimental conditions.

3.2.2 Secondary Lead Information Tier

The lead information of secondary importance for the company enhances the quality and usability of the primary lead information. While the secondary lead information is useless with the absence of the primary information, the primary information is usable though limited in its power without the additional secondary lead information. This information mainly consists of qualifying questions about the "hard facts" of the company of the prospect. In the B2B UK company, these consisted of the size of the company/number of employees, the company registration number, the average monthly or annual revenue, area of operation and operating category. In the present experiment, these questions could not have been used without adaptation because this information was business specific and therefore not applicable for a random sample. Hence, other "hard fact" questions were chosen for the simulation of a business scenario. The selected secondary lead information questions were: *age, gender, weight, height, country* and *monthly income*.

3.2.3 Third Lead Information Tier

The third tier of lead information though supplementary to the primary and secondary tiers, empowers the inquirer to complete the full picture which fulfills the objective of the process of lead generation. The primary information tier answers the question of "who", the secondary tier answers the question of "what" and the third-tier answers further questions of "how" or "why". While primary and secondary tier questions demand short factual answers, the third-tier questions are open-ended where the prospect is encouraged to share as much information as he/she deems important for either the possible facilitation of a personally advantageous business relationship with the inquirer, or for the gain of something of desired advantageous value. In the case of the UK B2B company, this value offering to the prospect in exchange for his/her lead was in the form of 5 free business profile matches. The real-world case "how" and "why" questions were the "soft facts" of the goals, needs, obstacles, detailed description of the company characteristics, detailed description of the daily operations, "dream" business partner, competitors, and past trials and what went wrong. Like the secondary tier questions, these third-tier questions were implausibly replicable in the context of the random sample used in the present experiment, with participants not necessarily possessing a business background as well as definitely lacking business interest and motivation for sharing information. Therefore, alternative questions had to be found to simulate the B2B open-ended questions by enabling a situation whereby anyone is able to share as much information as they deem important for heightening the chance of winning the prize. These open-ended questions in the present study were life goal, obstacle to reach the life goal, detailed description of yesterday, detailed description of the personality, the best day of the participant's life, the role model and why, life reflection and advice to younger self.

In Table 1 (Real B2B Form VS Simulated Form)is a comparison of the real-world B2B case of a structured lead qualification form, with the simulated lead qualification form of the present study.

Table 1 (Real B2B Form VS Simulated Form)

B2B Lead Questions	Experiment Lead Questions
Name	
Email	
Phone	
Annual Revenue	Monthly Income
Country of Operation	Country of Residence
Category of Operation	Tell me something interesting about your hometown!
Company Name	Gender
Registration Number	Age
Company Website	Weight
Number of Employees	Height
Description of Company	Description of Job
Dream Business Partner	Best Day of Life
Company Goal	Life Goal
Obstacle for Reaching the Company Goal	Obstacle for Reaching the Life Goal
Detailed Description of Daily Operations	Detailed Description of Yesterday
Main Company Competitors	Personal Role Model
Detailed Description of Company Characteristics	Detailed Description of Personality
Past Trials and What Went Wrong	Life reflection and advice to younger self

3.3 Measurement of Digital Nudging

For the purpose of measuring digital nudging effects on lead generation performance, as written in section 1.1, a messenger bot was used in comparison to the traditional lead form. The bot enables two-way communication between the inquiring business and prospect. AI or rule-based messaging enhances the ability of the business to obtain information compared to a static form by digitally nudging the prospect to share more information. A form is limited to its predefined sequential questions and is not responsive and flexible to the responses of the user. It does not analyze responses in real time and is not able to adapt its questions nor provide feedback to the user. Additionally, a form has no active possibility of keeping the user engaged in the action of filling it out, whereas a messenger bot motivates continuous engagement of the user through personalized and dynamic interaction. To fulfill the purpose of the study, a relatively simple bot was designed without the use of artificial intelligence or machine learning. This enabled simplified and easily accessible forms of digital nudging, whereas far greater and more personalized nudging is possible with more meticulously and higher technologically programmed bots. The effect therefore measured in this study could likely be an underestimation of the potentially larger effect achievable with superiorly complex bots. A few techniques were used with these bots to nudge users to share more information: a) positive reinforcement b) motivational cues c) first name personalization d) requests to share more e) negative feedback for non-disclosure f) compassion g) choice architecture h) reminders of importance. These methods were chosen for the use of the bot because they were possible to incorporate in the sequence as opposed to the form. The aim of these methods was to enhance the probability of getting as much information as possible from the participants. On the form, it does not make sense to reinforce the users with additional requests as they would see these reinforcing questions beforehand. Another issue brought into investigation is the fact that the form questions and scope (length) are fully visible upon glance, whereas with the bot, the questions were posed one after the other as in two-way communication. In Table 2 concrete examples of these techniques are exhibited:

Table 2 (Nudging Examples)

Positive Reinforcement	That’s awesome! 😎 Super interesting! You’re doing great! 💪 Thanks for trusting me 🙏 Thanks name! I appreciate your openness 😉 Thanks for clarifying “first name”. You're my hero! 💪 Never give up! You're my favorite respondent yet! Thanks again for being a part of this research 🙏 
Motivational Cues	Would you be so kind to tell me your email address? I need it to send you the Amazon gift card in case you win! *P.S. I'm reminding you I won't be using any of your information for marketing or any other purposes other than this Master Thesis! How about your phone number? Giving it will HIGHLY increase your chances in winning. *P.S. I'm reminding you I won't be using any of your information for marketing or any other purposes other than this Master Thesis! Are you comfortable telling me your monthly income? 💵 *P.S. This is a friendly reminder that the more questions you answer, the better your chance of winning an Amazon Gift Card! Just 3 more questions! This is the last time I promise!
First-Name Personalization (using the name Ben as an example)	Great, Ben, nice to meet you. Can you please tell me what do you do for a living Ben? 💼 Thanks for clarifying Ben.
Requests to Share More	Super interesting! Tell me more 😍 Please? 🙏 Mmm interesting.... 🤔could you please tell me more about that? Can you share more about that? I want ALLL the details... Perhaps you have some more details you can share? Be the best and tell me more! 🙌 This is so important for the study. Could you please tell me more? Please tell me more about why you feel that way... Tell me more...
Negative Feedback for Non-disclosure	😟 😭 You don't want the gift card? 
Compassion	No biggie! Let's proceed There is still so much to be discovered! 😻 Not a big deal for someone as smart as you! (if unemployed) I appreciate your honesty 😉 (if no income) But I understand 😉 this topic can be sensitive for some... (if no disclosure of monthly income) That's ok. Thanks for your patience 🙏 (for reconsideration of income disclosure) Now some of these questions might seem weird
Choice Architecture	Ready to take the survey? 😎 – (1 option) Sure! I changed my mind, I'll tell you! (after negative feedback for non-disclosure)
Reminders of Importance	They are crucial for the study! This is so important for the study.

3.4 Measurement of Social Priming

For the purpose of measuring social priming effects on lead generation, as written in section 3.1; in the bot condition, socially framed avatars were used. In addition to a standard messenger bot, two additional bots employing personified avatars and characters were introduced. Firstly, a business-salient avatar and character, *Ron Business Analyst* dressed in a business-formal suit and tie; and secondly, a non-salient avatar and character *Ron Virtual Assistant* dressed casually in a t-shirt. Based on Behavioral Confirmation Theory (Snyder et al. 1977, pp.656-666) and the Proteus Effect (Yee & Bailenson, 2007, pp.271-290), a notion was proposed that people would conform to the supposed behavior that is expected of them when interacting with a business-salient character. Behavioral Confirmation Theory proposes that individuals conform to the behavior that is supposedly expected of them by the individual they are communicating with. This however has yet to have been examined with the use of avatars, nor has it been used in the context of lead generation. The Proteus Effect proposes that an individual conforms to the characteristic behavior of the avatar he/she embodies. However, in this study, when using a bot, the participant does not embody the avatar but rather communicates with it. The Proteus Effect led the author to the idea of using avatars for performance marketing, namely lead generation. Behavioral Confirmation led the author to the idea of assessing a Behavioral Confirmation effect with avatars. Henceforth, a business-salient avatar and character is hypothesized to elicit more formal information from the participants.

The avatars are exhibited in Table 3:

Table 3 (Bot Avatars)

Business-salient *Ron Business Analyst*	Non-salient *Ron Virtual Assistant*
	

3.5 Quantitative Assessment of Responses

The central measurement of this study will be the disclosed or non-disclosed information of the primary and secondary information tiers. This will be denoted on a categorical nominal dichotomous scale (Yes/No). With the third information tier, the answers had to be transformed into a categorical nominal dichotomous scale through a content analysis. This was conducted by two raters who measured the answers against a constructed ideal B2B answer sheet of the form of the UK company, and rated them on a scale from 0-10 (No detail to very detailed). The analyses of both raters were then compared using the Intraclass Correlation Coefficient to measure inter-rater reliability. In addition to “Age” as a categorical nominal dichotomous scaled variable, it was also used as a numerical variable and analyzed for associations with disclosure of primary information. A similar procedure was used for the variable *Gender*. It was used once as disclosed or a non-disclosed information, and additionally for the assessment of *Gender* differences. Moreover, at the end of both the bot and the form, participants were asked to rate their personal experience with their respective treatment (bot or form) on a scale from 1-10. With the third information tier, an additional measure of a word count was introduced for the analysis.

3.6 Qualitative Assessment of Responses

In the secondary and third tier lead information questions, respondents were asked to answer open-ended questions in as much detail as possible. Before beginning the study, respondents were motivated to elaborate on answers as this would increase their chances in winning one of the prizes. In the secondary tier, the question: “Tell me something interesting about your hometown!” was posed. The third-tier question group was comprised entirely of open-ended questions. The questions were identical for the form and the bot, other than nudges to share more information by the bot. Apart for the word count that was analyzed in the quantitative analysis of the study, the content of the answers was analyzed qualitatively for a level of detail. The qualitative analysis was assessed by two independent raters which each ranked answers on a scale from 0 (not detailed at all) to 10 (detailed in full). To prevent subjective rankings, the procedure for evaluating each answer was through benchmarking the answer’s level of detail to model answers for each question that were created beforehand. These answers were modeled after answers of the real B2B survey conducted by the author for the UK B2B supply chain company. Detail was measured by the level of usefulness of the information provided in the answer for marketing and sales purposes. This information helps understand the prospect's needs, desires, fears and personality traits which enable the formulation of a tailor-suited offer and sales strategy. Like in a real B2B case, each answer was ranked on its ability to provide a good understanding of the respondent (lead) and his/her environment. In this study, this was for an understanding on a personal level, rather than on a business level. As listed in section 3.2, for example, respondents were asked about personal goals instead of business goals.

The ratings of the two raters were then correlated for a measure of inter-rater reliability using the intra-class correlation coefficient. Both the raters analyzed the answers of 73 of the same respondents each. The ratings of each were correlated with a result of $r = .901$, $p < .001$. Due to the very high similarity of the ratings between the two raters, the rest of the respondents were rated once. The model answers for both the B2B and the study surveys are listed in Table 4 and Table 5.

Table 4 (Model Answers – B2B Survey)

What is your company email address?	John.doe@company.com
What is your full name?	John Doe
What's your business phone number?	+43-100-200-33445
What is the annual revenue of your company?	Our average annual revenue is €500,000.
What is your country of operation?	We operate in Austria and sell all over the world but primarily in Europe.
What is your company name?	Fit Mom
What is your company registration number?	01234567
Does your company have a website?	www.company.com
How many employees are in your company?	We have 22 employees in the company.
Please describe your company and niche.	Our niche is athletic lifestyle clothing for young mothers. We sell personalized outfits according to body dimensions online.
What is your dream business partner?	Our dream is to find a wholesale supplier of high-quality athletic wear that is based in Europe, is ethical and has competitive prices. Additionally, they must be able to produce according to accurate bespoke measurements. Preferably, they will be able to produce quickly on short notice as well.
What is your biggest company goal?	Our goal is to surpass €1,000,000 of revenue in 2021. This will enable me to hire a full-time CEO and spend more money on digital marketing.
What is your obstacle to reaching that goal?	Our suppliers are too expensive and thus our margins are too low. This hurts our ability to spend more on marketing from a fear of losing profitability if our return on ad spend (ROAS) will not be high enough to cover our marketing management fees. That is why I am filling out this form and looking for new suppliers.
Please describe your operations in as much detail as possible.	We have a Shopify store and we advertise our products on Facebook, Instagram and Google. Additionally, we run email marketing and newsletter follow-up campaigns. We source our products from a supplier in China and order them in bulk so that we can keep our inventory in Amazon warehouses and use their logistics services to ship our products fast (much faster than from China) within Europe. When the customer purchases, their order is automatically dispatched from the warehouse. We monitor our inventory manually and order new stock manually as well.
What are your company's main competitors?	Our main competitors are Gymshark and Lululemon which control the majority of the market despite not operating precisely in the same niche. They have a huge database of influencers worldwide and spend huge budgets on marketing.
Please describe your company characteristics in as much detail as possible.	Our company is young (2 years old) and employs young workers under the age of 30. We are very growth hungry and work very long hours. We are innovative and creative and use humor in our marketing.
What have you tried in the past when looking for suppliers and what went wrong?	We have been searching for suppliers primarily on Alibaba which proved to be a big mistake. The prices are not as competitive as they used to be compared to European producers and the quality control is difficult. Additionally, preventing design and intellectual property theft is difficult in the Chinese market.

Table 5 (Model Answers – B2B Survey)

How should I call you?	John Doe
Could you specify your gender?	Male
Which country are you from?	Austria
Tell me something interesting about your hometown!	My hometown is Vienna, Austria and it is a beautiful city with amazing classic architecture that is well preserved. It has 23 districts and is on the Danube river. It has a large amount of green areas and lush parks. It is a city of vast history and is incredibly peaceful and safe.
What is your age?	30
What is your height in CM?	175
What is your weight in KG?	70
What is your email?	john.doe@email.com
What is your phone number (with country code)?	+43-600-500-30200
Type your monthly income in USD please.	$5,000
What is your #1 goal in life?	My goal is to grow my business through helping other business grow theirs. I plan to build a software that automates tasks that I do every day and eventually sell this software or earn money from it through a subscription model, thus shifting my work from service-based to product based. Eventually I aim to work less and enjoy time with my family and travel with them. I hope to be self-employed for the rest of my life and aspire to be financially wealthy.
What is your biggest fear when it comes to achieving that goal?	My biggest fear is that my hard work still won't be a match for big companies, and I won't be able to achieve the financial wealth I aspire to have and provide for my family. I fear that my own weaknesses and procrastination will hinder my success.
Please tell me about your day yesterday in as much detail as possible.	I woke up at 7:00 am just like most other days of the week. I stayed in bed for about 30 minutes answering emails, checking appointments and going over my schedule for the day. I got up washed my face, brushed my teeth and made my first morning coffee. I made myself a smoothie bowl and ate it while I proceeded to cross off the most critical work tasks off my list. After a few hours of focused work using the pomodoro method, I took my lunch break and ate leftover quinoa and tempeh from the day before. I made another coffee and did a few more pomodoro rounds of work for the rest of my tasks for the day. At 17:00, I went to the gym where I did a full-body 60-minute workout. I took a shower at the gym and went home. I made myself a spinach salad with chickpeas and ate it while planning the day ahead. I brushed my teeth, went to bed, read the book I'm currently reading: "Principles" by Ray Dalio which I love, and went to sleep.
Tell me about the best day of your life!	The best day of my life was the day I got married. I never would have thought that my wedding day would be so emotional for me, but it really was. My wife and I made sure to invite only close friends and family to ensure an environment of love, support and utmost comfort. We had all our loved ones with us, and the food and music were perfect to our taste. We were also lucky with the weather which was very pleasant. The moment my wife and I danced to my favorite song was the best moment.
Tell me about your role model in life. Why is he/she your role model?	My role model in life is my father because he is the most goal-oriented and hard-working person I know. He is a man of his principles and always stands by them no matter what. He is very financially successful despite not coming from a wealthy family which I respect very much. Additionally, he is one of the most intelligent people I know, both cognitively and emotionally and is a very fast learner. He keeps setting new goals for himself and achieving them, and he is an amazing father and husband and does everything for his family.
Describe your personality. What are you like as a person?	I am a creative thinker and a great copywriter. I am quick to find solutions to problems and am good at teaching myself new things. Once I set myself a goal, I achieve it and nothing can stop me. I never avoid hardships and even seek them. I challenge my comfort every day and work to live the life I dream of. I am honest, extroverted and find it easy to meet people and make friends. I like to use humor to get passed difficult moments in life.
If you could go back in time and meet your younger self, what advice would you give your-self? Would you do anything differently?	I would tell myself that every time I attempt to get something I want by doing something I fear is worth it, and I should do things I fear more often. I would tell myself that everything I want to achieve is achievable if I work hard at it now. I would tell myself to follow my passion and invest in it earlier and not care what others do or think.

3.7 Procedure

The experimental study was conducted in May 2020 between the 17th and the 29th. A website was designed as an introductory page explaining the terms of the study and directions. Following the terms and instructions, the participants were presented a Call to Action (CTA) button to begin with the survey. In a real-world B2B scenario, interested people click a CTA to initiate a process and are presented the underlying process page. Identically, people that were interested in participating in the study clicked the CTA to initiate the process of the study. Upon clicking, the participants were randomly directed to one of the 4 treatments with the following proportions: *lead form* (40%), *bot* (60% split into 20% for each sub-condition).

Therefore, participants were reached via online channels. The introductory page was advertised through public Facebook and LinkedIn posts, in addition to posts in private Facebook groups comprised of masters (MA/MSc), doctoral (PhD) and post-doctoral students and researchers around the world. In real business scenarios, the procedure would be similar with the exception of paid targeting options.

Upon reaching the assigned treatment page, participants had the freedom to bounce (quit) the page and leave at any moment. Additionally, no question was mandatory. The length of the study was open-ended, and participants were free to invest as much time as they wanted. The survey was comprised of 21 questions, however the bot nudged with additional follow-up questions which lengthened the condition.

The winning participants were drawn in June 2020 and the prizes were delivered.

3.8 Participants

A total of 741 people participated in the study. A few respondents that have jokingly answered questions have been removed from the analysis. Participants that clicked the CTA and reached the procedure page they were randomly allocated to are referred to as visitors (*n*=741). There was a total of 292 visitors for the form treatment (39.4%), 148 visitors for the no avatar bot treatment (20%), 144 visitors for the *non-salient* bot treatment (19.4%) and 157 visitors for the *business-salient* bot treatment (21.2%). Visitors that proceeded to begin answering questions are referred to as respondents (*n*=396). The nature of the experiment as in real business scenarios, enabled tracking of visitors to each of the procedural pages, but personal data such as gender was only possibly tracked for the respondents. There were 385 valid respondents for gender reveal: 69% female (*n*=266), 31% male (*n*=119). There were 319 valid respondents for *Age* reveal. Corresponding respondents' ages spanned between 18-73 years. The *mean* age was 34.7 years (*SD*=12.6). The *median* age was 31 years was representing the student population. The distribution of age was right skewed explainable by older members on the LinkedIn platform. Respondents originated from a total of 72 countries from all 6 continents. Considering that the platforms used to recruit participants are banned from a sizeable number of countries around the world, the sample may be considered as very widespread and international. There were 206 valid respondents for income reveal. The income span of the respondents spanned from $0 - $70,000/monthly (25% > $3,000, 10% > $5,000) with a median income of $1,550/monthly (21% unemployed with $0 income). The histogram for *Age* is illustrated in Figure 3, and the pie chart for *Country* is presented in Figure 4.

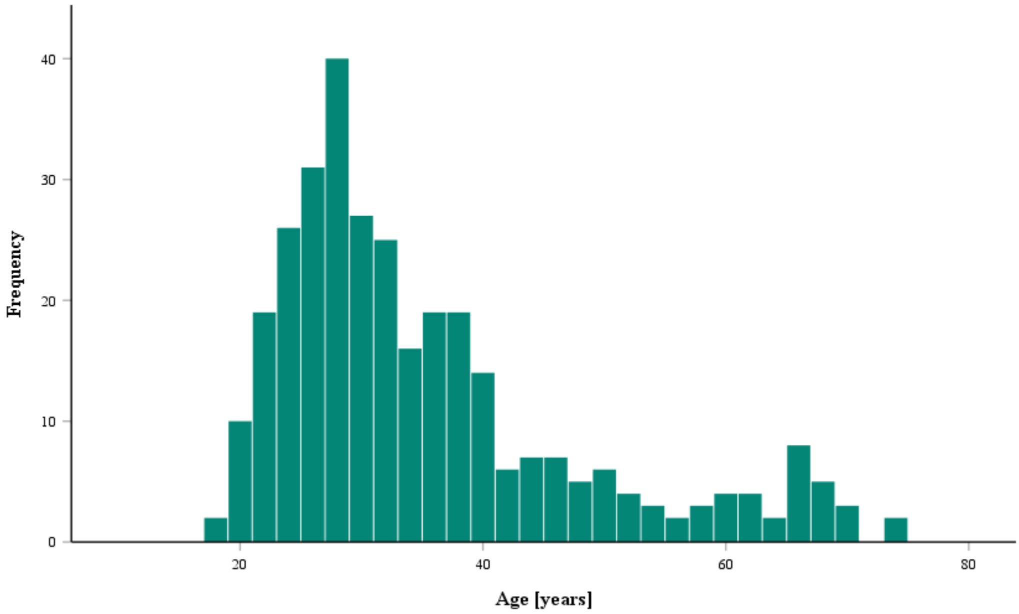

Figure 3 (Age Distribution)

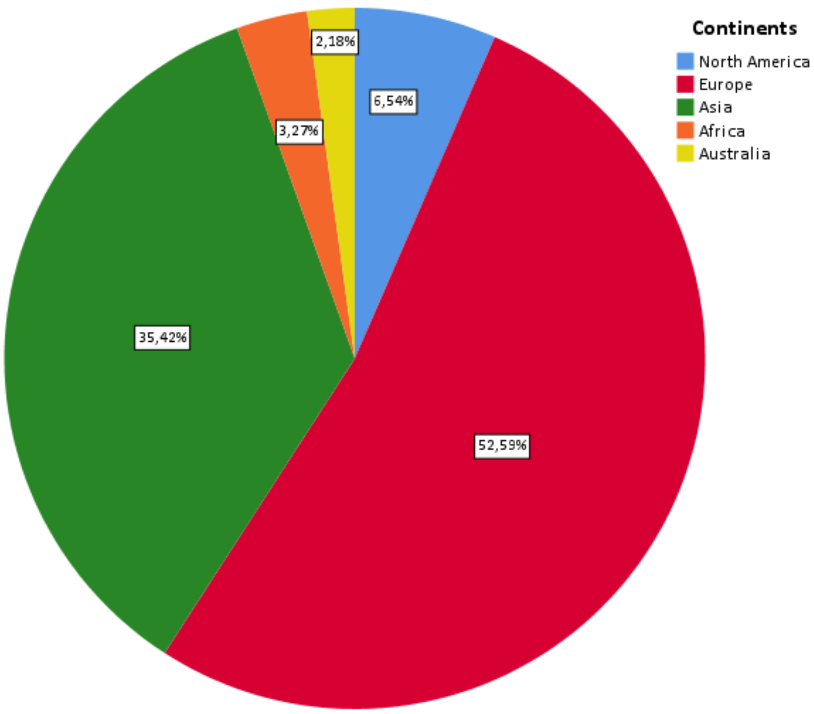

Figure 4 (Continents)

3.9 Hypotheses

The hypotheses were initially presented as deducted from the literature and argued in the theoretical background and conceptual framework of this study. Having already specified the methodological framework and procedure of the study for studying these hypotheses, they will be reintroduced as operational hypotheses.

3.9.1 Bot vs Lead Form

H1 - Lead generation Bots collect more leads (primary tier information) than traditional lead forms.

H2 - Lead generation Bots collect more secondary tier information than traditional lead forms.

H3 – Lead generation bots collect more detailed information (third tier) from collected leads than traditional lead forms.

H4 – Lead generation bots collect more words from collected leads than traditional lead forms.

H5 – Lead generation bots induce better subjective experience ratings from collected leads than traditional lead forms.

H6 – Lead generation bots induce higher quality information from collected leads than traditional lead forms.

3.9.2 Business-Salient Avatar vs No Avatar

H7 – Business-salient avatars collect more leads (primary tier information) than the *no avatar* condition.

H8 - Business-salient collect more secondary tier information than the *no avatar* condition.

H9 - Business-salient avatars collect more detailed information (third tier) from collected leads than the *no avatar* condition.

H10 - Business-salient avatars collect more words (third tier information) from collected leads than the *no avatar* condition.

H11 - Business-salient avatars induce better subjective experience ratings from collected leads than the *no avatar* condition.

H12 - Business-salient avatars induce higher quality information from collected leads than the *no avatar* condition.

3.9.3 Business-Salient Avatar vs Non-Salient Avatar

H13 - *Business-salient* avatars collect more leads (primary tier information) than the *non-salient* avatar.

H14 - *Business-salient* avatars collect more secondary tier information than the *non-salient* avatar.

H15 - *Business-salient* avatars collect more detailed information (third tier) than the *non-salient* avatar.

H16 - *Business-salient* avatars collect more words (third tier information) than the *non-salient* avatar.

H17 - *Business-salient* avatars collect more higher quality information from collected leads than the *non-salient* avatar.

3.10 Statistics

For the analysis, IBM SPSS Statistics version 26 was used. In the first stage of the analysis, categorical variables were described with absolute frequencies and percentages. Continuous variables were described with appropriate measures of location and dispersion. For skewed distributions of values, the arithmetic mean would not be representative of the central tendency and the median would be more reliable. Additionally, the standard deviation would not be representative for dispersion of the distribution and rather inter quartile range (IQR) or percentiles would be more representative.

In the second stage of the analysis, in the bivariate context, associations between variables were analyzed. For differences between two independent samples in terms of a categorical variable, the Chi Square test was conducted. For differences between two independent samples in terms of an ordinal or metric variable where the distribution was skewed, the Mann-Whitney U-Test was conducted. For differences between more than 2 independent samples, the Kruskal-Wallis test was conducted followed up by pair-wise Mann-

Whitney U-Tests with the Bonferroni correction due to multiple testing (Field, 2009, p.373). The design of the study was firstly to compare form versus bot, and secondly to compare the 3 bot conditions with one another. Following this idea, the statistical analyses were conducted hierarchically, firstly comparing bot versus form with planned orthogonal contrasts and secondly a within bot comparison with post-hoc tests. For the second analysis (within bots), post-hoc tests were used instead of planned comparisons due to the explorative nature of the comparisons (Field, 2009, p.362). In the third stage of the analysis after univariate and bivariate analyses, multivariate analyses were conducted using logistic regressions for categorical dichotomous dependent variables; and a multiple linear regression for metric dependent variables. A list of independent and dependent variables used in the analysis is presented in **Error! Reference source not found.**. In the multivariate regressions, only the dependent variables which showed significant associations or statistical trends in the bivariate context are displayed. (Hosmer, Lemeshow, Sturdivant, 2013, p.89) For linear regressions, some assumptions had to be considered: 1) a linear relationship between metric predictors and outcome, 2) homogeneous, normally distributed and linear residuals. 3) no multicollinearity between predictors 4) no influential cases. (Field, 2009, p.248) Similarly, for logistic regressions, no multicollinearity between predictors should be present and there must be a linear relationship between the metric predictor and the logit of the outcome (p.273). Regressions were calculated once for the contrast between form and bot, and secondly for the avatar bots compared to the no avatar bot. When appropriate, charts were presented.

In all the statistical tests, it was tested whether the data fit the null hypotheses. The probability of obtaining the data given that the null hypothesis is true was calculated. When the probability (p - value) is smaller than 5%, the null hypothesis is rejected. Subsequently, a maximum Type-I (α) error rate of 5% was tolerated. To accomplish that, for multiple testing, the alpha level was corrected with the Bonferroni-Holm correction method. Despite the hypotheses being formulated as one-directional; a more conservative approach was taken to avoid overestimation. For all statistical procedures, 2-tailed P-values were reported.

Table 6 (Variables)

List of independent and dependent variables.

Type of variables	Variable name	Scale
Independent Variables	Type of Procedure (Form, Bot)	Categorical Dichotomous
	Type of Bot (No Avatar, Non-salient, Business salient)	Categorical Polytomous
	Respondent (Visitor / Respondent)	Categorical Dichotomous
	Continent (Europe / World)	Categorical Dichotomous
	Age (years)	Ratio
	Gender (female / male)	Categorical Dichotomous
	Income (monthly in US$)	Ratio
	Procedure Completed (Fully completed / not completed)	Categorical Dichotomous
Dependent Variables	Primary Tier Lead (lead / no lead)	Categorical Dichotomous
	Secondary Tier Lead (lead / no lead)	Categorical Dichotomous
	Third Tier Lead (lead / no lead)	Categorical Dichotomous
	Third Tier Word Count	Absolute
	Number of Questions	Absolute
	Rating of Experience (1 – 10)	Ordinal
	Time (minutes, seconds)	Ratio
	Quality Assessment (0 – 10)	Ordinal

4 Results

In the following chapter, the results of the statistical tests will be listed. The data will be elucidated and displayed with the use of tables and figures.

4.1 Lead by Demographics

The demographics of the respondents were analyzed according to various lead generation parameters. As described in section 1.2 of the measurements of disclosure, the lead information was split into three information tiers which were used for this analysis. These parameters are used for the evaluation of the level of quality and usefulness of the obtained lead information. Additional parameters were therefore used as well to attain a deeper understanding of the quality; namely the experience rating of the respondent with the experimental condition (form/bot), whether or not the respondent fully completed all the survey questions, the word count of the third tier open-ended responses, and the word count increase due to the digital nudges. Furthermore, as mentioned in section 1.6, the responses were analyzed for a level of detail/quality on a scale from 0-10.

No gender difference was found on any of the lead generation parameters, $p > .05$. Significant associations were found for *Age* across all the lead generation parameters with the exception of the *Experience Rating* of the respondents. The older the respondent, the less primary tier information
($r = -.185$, $p = .001$), secondary tier information ($r = -.126$, $p = .024$), and third tier information ($r = -.150$, $p = .007$) was disclosed. Additionally, the older the respondent, the less often the survey was fully completed ($r = -.114$, $p = .041$). Moreover, the older the respondent, the less words were written in the responses for the open-ended third tier information questions ($r = -.297$, $p < .001$).

The bot condition applied digital nudging techniques to elicit more information from the respondents by continually asking them to write more. For *Age*, a significant association was found. The older the respondent, the less additional words were elicited through the nudges ($r = -.261$, $p < .001$). Despite these negative associations with *Age*, no significant association was found for *Age* with *Experience Rating* ($r = -.092$, $p = .151$). In the same light, for the level of quality, an additional significant association was found for *Age* with the level of quality of the responses ($r = -.282$, $p < .001$). The older the respondent, the less quality the responses were.

For *Income*, no significant associations were found with any of the lead generation parameters ($p > .05$). The parameters were analyzed for a level of association with the *Continent*. Europeans significantly less often disclosed primary tier lead information, $\chi^2(1) = 6.919$, $p = .009$. Primary tier lead information (*Name*, *Email*, *Phone*) was disclosed by 59.3% of the outer European respondents. Contrarily, only 40.7% of the European respondents disclosed primary tier lead information. The results showing the particularity of European respondents will be discussed in detail further on.

The results are displayed in Table 7 and Table 8:

Table 7 (Leads by Demographics)

Parameter	Primary Tier Lead	Secondary Tier Lead	Third Tier Lead	Completed	Experience Rating
Gender n = 385					
Female (n=266)	96 (36.1)	111 (41.7)	150 (56.4)	53 (19.9)	$Md = 8$
Male (n = 119)	54 (45.4)	54 (45.4)	64 (53.8)	30 (25.2)	$Md = 8$
	$\chi^2(1) = 2.982$, $p = .084$	$\chi^2(1) = 0.447$, $p = .504$	$\chi^2(1) = 0.227$, $p = .634$	$\chi^2(1) = 1.358$, $p = .244$	$U = 6946$ $z = -0.085$ $p = .932$
Age	$r = -.185$, $p = .001$	$r = -.126$, $p = .024$	$r = -.150$, $p = .007$	$r = -.114$, $p = .041$	$r = -.092$, $p = .151$
Monthly Income [€]	$r = -.031$, $p = .662$	$r = -.097$, $p = .168$	$r = -.002$, $p = .974$	$r = -.037$, $p = .593$	$r = -.042$, $p = .574$
Continent					
Europe n = 193	61 (40.7)	79 (47.9)	101 (46.8)	36 (43.4)	$Md = 8$
World n = 200	89 (59.3)	86 (52.1)	115 (53.2)	47 (56.6)	$Md = 8$
	$\chi^2(1) = 6.919$, $p = .009$	$\chi^2(1) = 0.172$, $p = .678$	$\chi^2(1) = 1.060$, $p = .303$	$\chi^2(1) = 1.385$, $p = .239$	$U = 8405$, $z = -0.073$, $p = .942$

Note. Numbers are absolute values (percentages). Chi-Square Test for two categorical variables, U-Test for two samples, r = correlation

Table 8 (Quality by Demographics)

Parameter	Qualitative Rating (Scale 0 – 10)	Word Count	Nudge Word Increase
Gender n = 385 Female (n=266) Male (n = 119)	*Md* = 4.83 *Md* = 4.61 *U* = 5559.5 *z* = -.035 *p* = .972	*Md* = 94.5 *Md* = 105 *U* = 15670, *z* = -0.156, *p* = .876	*Md* = 41 *Md* = 50 *U* = 4893.5 *z* = -1.467 *p* = .142
Age	*r* = -.282 *p* < .001	*r* = -.297, *p* < .001	*r* = -.261, *p* < .001
Monthly Income [€]	*r* = -.131 *p* = .164	*r* = -.075, *p* = .285	*r* = -.021, *p* = .827
Continent Europe World	*Md* = 4.44 *Md* = 4.94 *U* = 6606.0, *z* = -.568, *p* = .570	*Md* = 89 *Md* = 105 *U* = 18919.5, *z* = -0.340, *p* = .734	*Md* = 35 *Md* = 50 *U* = 6067.5, *z* = -1.602, *p* = .109

4.2 Demographics Within the Experimental Conditions

The demographics of the respondents were compared across the four experimental conditions. The demographics described in this section were collected by the form or bot. Hence, the collection was part of the experimental condition, and no information is therefore present for visitors who bounced or for respondents that were reluctant in disclosing. Accordingly, in the interpretation of associations with demographics, it should be considered that bouncing or non-disclosure could be a consequence of the condition. As in real-world scenarios, where bouncing or non-disclosure may be a result of the lead generation technique (e.g. lead form, funnel, bot), these results may give valuable insight to practical applications. The demographics reported may be a result of systematic bias (e.g. females are less likely to disclose weight). Due to the randomization, we can assume that such biases are equally distributed amongst the conditions, especially considering the relatively large sample size of 741 participants. Therefore, deviances in demographics between the conditions must be due to the condition itself either because of bouncing or non-disclosure.

No significant difference was found for *Gender*, $\chi^2(3) = 2.273$, $p = .518$. A significant difference between the experimental conditions was found for the disclosure of *Age*. In the *form* condition (n=292), 27.4% of the visitors disclosed age. In the *no avatar* condition

(n=148), 57.4% of the visitors disclosed *Age*. In the *non-salient* condition (n=144), 40.3% of the visitors disclosed *Age*. In the *business-salient* condition (n=157), 61.6% of the visitors disclosed *Age*. The visitors of the *form* condition disclosed *Age* significantly less than the bot conditions, $\chi^2(1) = 48.158$, $p < .001$. Within the bot conditions, significantly fewer visitors disclosed *Age* for the *non-salient* condition (40.3%) compared to the *no avatar* condition (57.4%), $\chi^2(1) = 8.595$, $p = .003$ (corrected $p = .006$); and compared to the *business-salient* condition (61.6%), $\chi^2(1) = 13.091$, $p < .001$ (corrected $p = .003$). No significant difference for the disclosure of *Age* of visitors was found between the *no avatar* condition and *business-salient* condition, $\chi^2(1) = 0.436$, $p = .509$. The results are displayed in Figure 5:

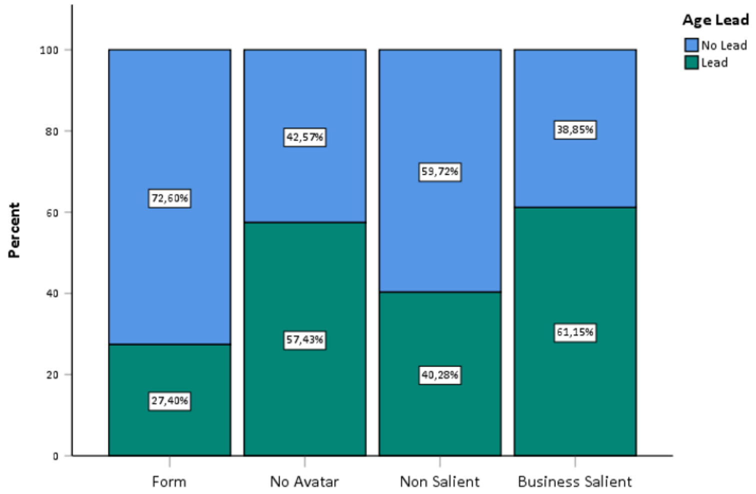

Figure 5 (Age Lead Disclosure)

The disclosed variable *Age* was analyzed further for the respondents. A significant difference between the four conditions was found for *Age*, $H(3) = 13.771$, $p = .003$.
The post-hoc analysis with the Bonferroni-Holm correction revealed respondents for the *non-salient* condition to be significantly younger ($M = 30.24$ years, $Md = 28$) compared to the *no avatar* ($M = 37.69$, $Md = 34$) condition, $U = 1579$, $z = -3.643$, $p < .001$ (corrected $p = .006$); and revealed respondents to be non-significantly but tendentially younger for the *non-salient* condition compared to the *business-salient* ($M = 35$, $Md = 31$) condition, $U = 2143$, $z = -2.392$, $p = .017$ (corrected $p = .085$). A possible explanation for these results is that older participants more frequently bounced when encountering the *non-salient* avatar.

The results can be seen in Figure 6:

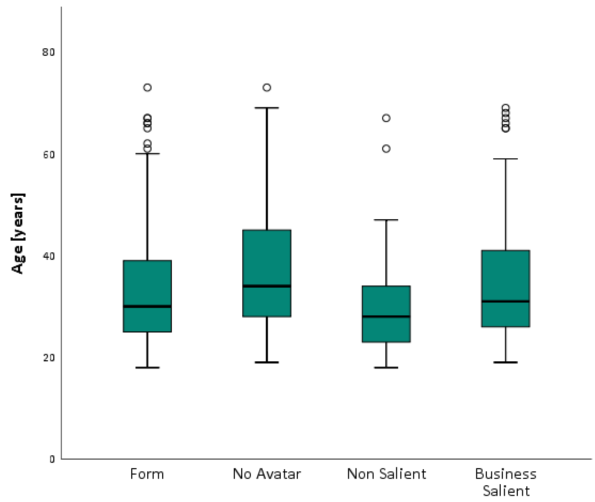

Figure 6 (Age Lead)

A significant difference for the disclosure of *Income* was found between the *form* and *bot* conditions. Significantly more visitors disclosed *Income* in the *form* condition (64.2%) than in the *bot* condition (48.9%), $\chi^2(1) = 6.050$, $p = .014$. Within the *bot* conditions, significantly more visitors disclosed *income* in the *non-salient* condition (61.8%) compared to the *no avatar* condition (39.5%), $\chi^2(1) = 9.135$, $p = .003$ (corrected $p = .009$). No difference was found between the other conditions ($p > .05$). The disclosed variable *Income* was analyzed further for the respondents and a significant difference was found between the experimental conditions, $H(3) = 14.478$, $p = .002$. The post-hoc analysis with the Bonferroni-Holm correction revealed that revealing respondents in the *non-salient* condition disclosed significantly lower *Income* values (M = \$1,172.45 monthly, Md = \$850) compared to respondents in the *no-avatar* condition (M = \$4,350.13 monthly, Md = \$2,000), $U = 578.5$, $z = -3.761$, $p < .001$ (corrected $p = .006$). There was a tendency for significantly lower *Income* values for the *non-salient* condition compared to the *business-salient* condition (M = \$2,582.5 monthly, Md = \$1,607.5), $U = 1047.5$, $z = -2.529$, $p = .011$ (corrected $p = .055$). Reassuming the differences in the *Age* values, respondents for the *non-salient* condition were not only younger, but also had lower incomes than the respondents for the other conditions. Potentially, older and wealthier participants bounced more often when encountering the *non-salient* avatar.

Results can be seen in Figure 7:

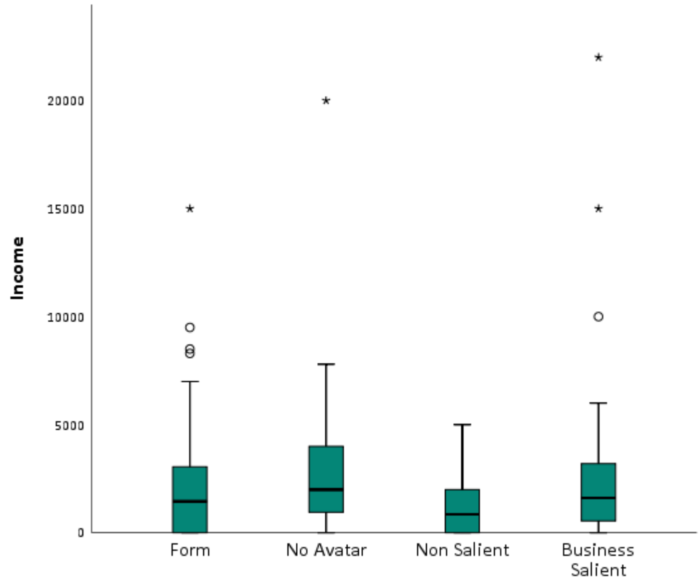

Figure 7 (Income Disclosure)

Note: A participant in the no avatar condition with an income of $70,000 was excluded from the chart

There was a tendency for participants in the *form* condition to be more often from Europe (60.3%) than from other continents, compared to participants in the *bot* conditions (48.6%), $\chi^2(1) = 3.416$, $p = .065$. Within the *bot* conditions, respondents of the *no avatar* condition originated significantly less often from Europe (41.2%) compared to the *business-salient* condition (59.2%), $\chi^2(1) = 7.704$, $p = .006$ (corrected $p = .018$). Potentially, non-European respondents bounced more often from the *form* and *business-salient* conditions compared to Europeans. Additionally, Europeans potentially bounced more often from the *no avatar* and *non-salient* conditions than non-Europeans. It is possible to assume that Europeans feel more comfortable with the traditional *lead form* and formally dressed *business-salient bot* when disclosing information. The results can be seen in Figure 8:

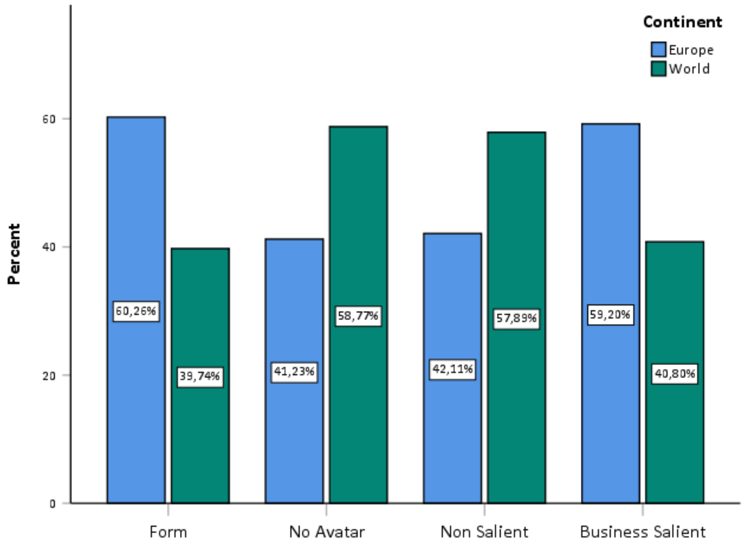

Figure 8 (Continents Within Conditions)

An overview of the results can be seen in Table 9:

Table 9 (Participation by Continent)

Parameter		**Form** ***n* = 292**	**No Avatar** ***n* = 148**	**Non Salient** ***n* = 144**	**Business Salient** ***n* = 157**	**Statistical Test**
Gender n = 385						
Female *n*=266		59 (75.6)	77 (69.4)	47 (66.2)	83 (66.4)	$\chi^2(3) = 2.273, p = .518$
Male *n* = 119		19 (24.4)	34 (30.6)	24 (33.8)	42 (33.6)	
Age lead (from visitors)		80 (27.4)	85 (57.4)	58 (40.3)	96 (61.6)	**form vs bot:** $\chi^2(1) = 48.158, p < .001$
						within bots: $\chi^2(2) = 14.706, p < .001$
						no avatar – non salient: $\chi^2(1) = 8.595, p = .006$ [a]
						no avatar – business: $\chi^2(1) = 0.436, p = .509$ [a]
						non salient – business: $\chi^2(1) = 13.091, p < .003$ [a]
Age lead (from respondents) *n* = 319		80 (98.8)	85 (74.6)	58 (76.3)	96 (76.8)	**form vs bot:** $\chi^2(1) = 21.557, p < .001$
						within bots: $\chi^2(2) = 0.174, p = .917$
Age in years						
M	34.41	34.44	37.69	30.24	35	$H(3) = 13.771, p = .003$
Md	31	30	34	28	31	
SD	12.56	13.34	13.29	9.44	12.27	**form – no avatar**
Min	18	18	19	18	19	$U = 2753, z = -2.111, p = .140$ [a]
Max	73	73	73	67	69	**form - non salient**
						$U = 1959, z = -1.559, p = .357$ [a]
	n = 319	80	85	58	96	**form – business**
						$U = 3594, z = -0.732, p = .464$ [a]
						no avatar – non salient
						$U = 1579, z = -3.643, p < .006$ [a]
						no avatar – business salient
						$U = 3534{,}5, z = -1.552, p = .242$ [a]
						non salient – business salient
						$U = 2143, z = -2.392, p = .085$ [a]
Income Lead (from visitors)		52 (64,2)	45 (39,5)	47 (61,8)	62 (49,6)	**form vs bot:** $\chi^2(1) = 6.050, p = .014$
						within bots: $\chi^2(2) = 9.173, p = .010$
						no avatar – non salient: $\chi^2(1) = 9.135, p = .009$ [a]
						no avatar – business: $\chi^2(1) = 2.473, p = .116$ [a]
						non salient – business: $\chi^2(1) = 2.854, p = .182$ [a]
Monthly Income [€]						$H(3) = 14.478, p = .002$
M	2550	2199.16	4350.13	1172.45	2582.50	
Md	1550	1450.00	2000.00	850.00	1607.50	**form – no avatar**
IQR	2703,75	3075	3111	2000	2712.5	$U = 880, z = -2.103, p = .140$ [a]
Min	0	0	0	0	0	**form - non salient**
Max	70000	15000	70000	5000	22000	$U = 991.5, z = -1.641, p = .303$ [a]
						form – business
n = 206		52	45	47	62	$U = 1458.5, z = -0.878, p = .380$ [a]
						no avatar – non salient
						$U = 578.5, z = -3.761, p < .006$ [a]
						no avatar – business salient
						$U = 1182.5, z = -1.344, p = .358$ [a]
						non salient – business salient
						$U = 1047.5, z = -2.529, p = .055$ [a]
Continent						
Europe (*n* = 193)		47 (60.3)	47 (41.2)	32 (42.1)	74 (59.2)	**form vs bot:** $\chi^2(1) = 3.416, p = .065$
World (*n* = 200)		31 (39.7)	67 (58.8)	44 (57.9)	51 (40.8)	**within bots:** $\chi^2(2) = 9.386, p = .009$
						no avatar – non salient: $\chi^2(1) = 0.014, p = .904$ [a]
						no avatar – business: $\chi^2(1) = 7.704, p = .018$ [a]
						non salient – business: $\chi^2(1) = 5.541, p = .028$ [a]

[a] Bonferroni-Holm-correction

4.3 Leads Within the Experimental Conditions

As in a real-world B2B scenario, participants could bounce at any given moment. Of all the participants (n = 741), 47% bounced immediately and did not begin the survey. A significant difference in terms of bounce rates was found between the *form* and *bot* conditions, $\chi^2(1) = 127.937$, $p < .001$. The *form* displayed significantly higher bouncing rates (72.3%) than the *bot* (30.5%). Within the *bot* conditions, the *non-salient* condition displayed significantly higher bouncing rates (47.3%) than the *no avatar* (23%), $\chi^2(1) = 18.882$, $p < .001$ (corrected $p = .002$) and the *business-salient* (22.3%) conditions, $\chi^2(1) = 24.389$, $p < .001$ (corrected $p = .002$). The focus in this chapter will not be on the content of the answers but rather the presence or absence of answers (yes/no). The results are displayed in Figure 9:

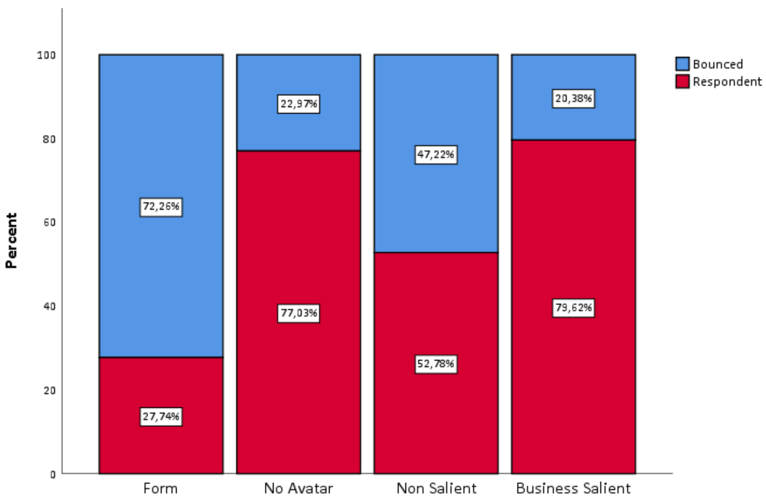

Figure 9 (Bounce Rates Within Conditions)

There was no significant difference between the four conditions for full completion of the survey, $\chi^2(1) = 2.556$, $p = .556$. Full completion of the survey is measured when the respondent has answered all given questions without missing any, regardless of the quality of the answers. However, as mentioned in section 1.8, nonsensical values were removed before the analysis (e.g. 12345678 as phone number). As mentioned in section in section 1.2, the lead information in this survey has been split into three information tiers, ranked by the level of importance.

4.3.1 Primary Tier Information

A total of 152 people (20.5% of visitors) fully disclosed primary tier information (*Name, Email* & *Phone*). A significant difference was found between the *form* and the *bot* conditions. Significantly more primary tier information was disclosed from visitors of the *bot* (23.8%) compared to visitors of the *form* (15.4%), in support of *H1*, $\chi^2(1) = 7.693$, $p = .006$. It can be seen that forms lose significantly more prospects than bots. In real-world B2B scenarios, the most meaningful values are those of the visitors because the price of the leads are directly influenced by the number of clicks (visits). Within the *bot* conditions, no significant difference for the disclosure of primary tier information was found for the visitors, $\chi^2(2) = 2.179$, $p = .336$. Therefore, there is insufficient evidence for the support of *H7* or *H13*. The results are displayed in Figure 10:

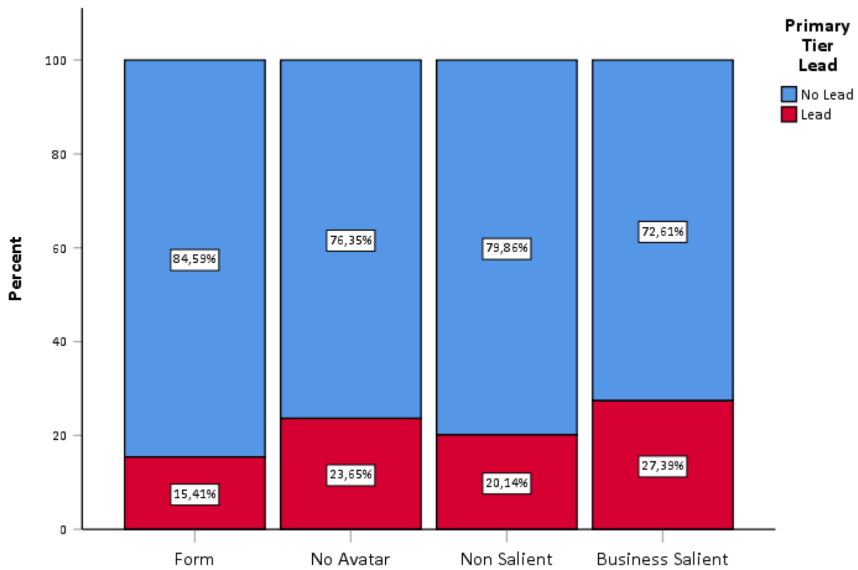

Figure 10 (Primary Tier Lead)

4.3.2 Secondary Tier Information

For the secondary tier information ($n = 165$) similar results were obtained as with the primary tier information for the visitors (23.3). In support of *H2*, significantly more secondary tier information was disclosed from the visitors of the *bot* conditions (26.5%) in comparison to visitors of the *form* (15.8%), $\chi^2(1) = 11.813$, $p < .001$. No significant difference was found for the visitors from within the *bot* conditions, $\chi^2(2) = 1{,}250$, $p = .535$. Therefore, there is insufficient evidence for the support of *H8* or *H14*. The results are displayed in Figure 11:

Figure 11 (Secondary Tier Lead)

4.3.3 Third Tier Information

In support of *H3*, significantly more third tier information was disclosed with the *bot* condition (33.2%), compared to the *form* (23.3%), $\chi^2(1) = 8.369$, $p = .004$. Additionally, in support of *H9* and *H15*, within the *bot* conditions, the *business-salient bot* yielded significantly more third tier information (44.6%) than the *no avatar* condition (29.7%), $\chi^2(1) = 7.184$, $p = .007$ (corrected $p = .014$); and the *non-salient* condition (24.3%), $\chi^2(1) = 13.600$, $p < .001$ (corrected $p < .003$).. Additionally, due to the open-ended questions of the third-tier information, a word count comparison between the *form* and *bot* as well as within the *bot* condition was conducted. Not in support of hypotheses *H4*, *H10* or *H16*, no significant difference was found between the *bot* and *form*, $U = 4962.5$, $z = -0.241$, $p = .809$; nor within the *bot* conditions, $H(2) = 1.276$, $p = .528$. It is worth mentioning that for the question about the Hometown of the secondary tier information, significantly more words by generated by the *bot* than the *form*, $U = 9435$, $z = -2.368$, $p = .018$. The results are displayed in Figure 12 and in Table 10:

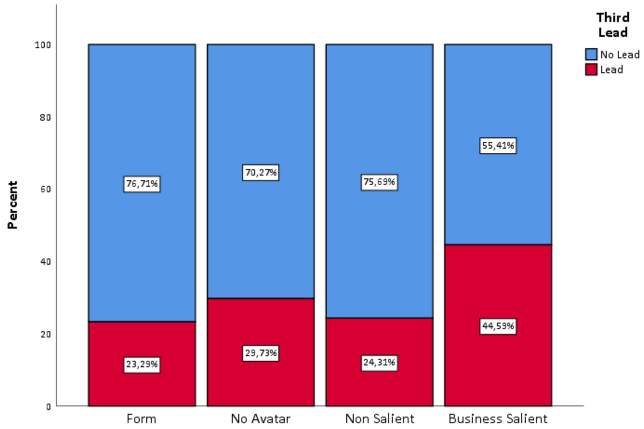

Figure 12 (Third Tier Lead)

Table 10 (Survey Completion)

Parameter		Form	No Avatar	Non Salient	Business Salient	Statistical Test
Visitors **n = 741**		292	148	144	157	
Respondents **n = 396**		81 (27.7)	114 (77)	76 (52.7)	122 (77.7)	**form vs bot:** $\chi^2(1) = 127.937, p < .001$ **within bots:** $\chi^2(2) = 30.821, p < .001$ **no avatar – non salient:** $\chi^2(1) = 18.882, p < .002$ [a] **no avatar – business:** $\chi^2(1) = 0.302, p = .583$ [a] **non salient – business:** $\chi^2(1) = 24.389, p < .002$ [a]
Fully Com-pleted **n = 82**		26 (8.9)	14 (9.5)	16 (11.1)	26 (16.6)	**form vs bot:** $\chi^2(1) = 2.556, p = .556$ **within bots:** $\chi^2(2) = 3.617, p = .164$
Primary Tier **n = 152**		45 (15.4)	35 (23.6)	29 (20.1)	43 (27.4)	**form vs bot:** $\chi^2(1) = 7.693, p = .006$ **within bots:** $\chi^2(2) = 2.179, p = .336$
Secondary Tier **n = 165**		46 (15.8)	35 (23.6)	38 (26.4)	46 (29.3)	**form vs bot:** $\chi^2(1) = 11.813, p < .001$ **within bots:** $\chi^2(2) = 1.250, p = .535$
Third Tier **n = 217**		68 (23.3)	44 (29.7)	35 (24.3)	70 (44.6)	**form vs bot:** $\chi^2(1) = 8.369, p = .004$ **within bots:** $\chi^2(2) = 15.121, p = .001$ **no avatar – non salient:** $\chi^2(1) = 1.088, p = .297$ [a] **no avatar – business:** $\chi^2(1) = 7.184, p = .014$ [a] **non salient – business:** $\chi^2(1) = 13.600, p < .003$ [a]
Third Tier Word Count						
	Md	178	166.5	198	149	**form vs bot:**
	IQR	189.25	181.25	252	143.75	$U = 4962.5, z = -0.241, p = .809$
	Min	32	39	15	41	
	Max	923	856	1938	490	**within bots:** $H(2) = 1.276, p = .528$

[a] Bonferroni-Holm-correction

4.3.4 Qualitative Ratings of Responses

As mentioned before, the content of the responses was rated for a level of lead quality on a scale from 0-10. The average quality of the responses was about 6 with a standard deviation of between 2.10 and 2.61. Ratings below 1 (outliers) were excluded from the analysis due to a skew in the data. No difference was found for content quality between the *Form* and *Bot*, $U = 9602.5$, $z = -0.218$, $p = .827$; nor within the *Bot* conditions, $H(2) = 1.660$, $p = .436$. These results are shown in Figure 13.

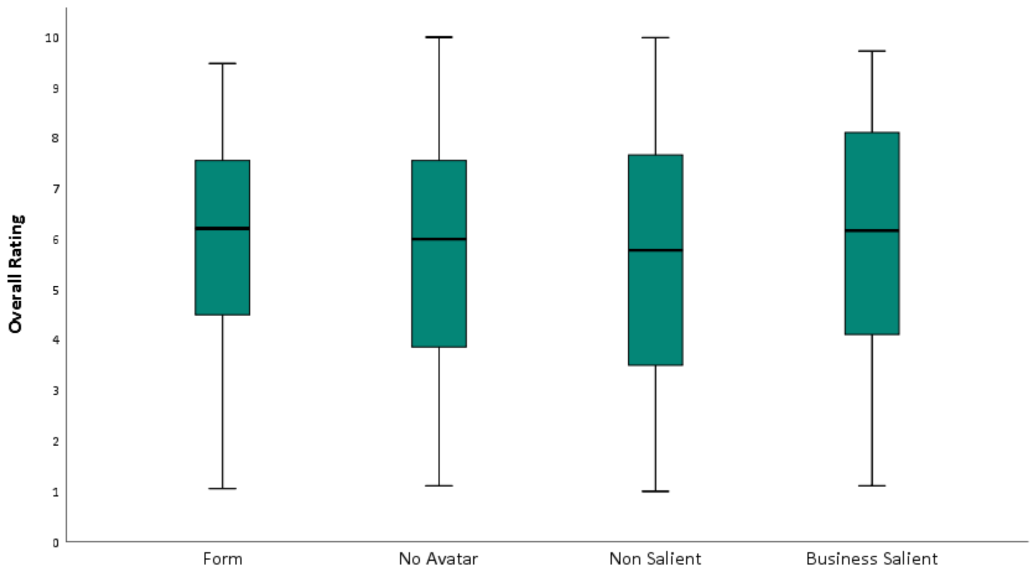

Figure 13 (Quality Ratings Within Conditions)

Taking into consideration the standard level of lead content quality, the ratings in this study that are considered of adequate quality are those that were rated above 6, which approximately corresponds to the mean and median. Additionally, the ratings considered of excellent lead content quality are those that were rated above 8, which correspond to the top 25% of respondent ratings. In real B2B lead generation campaigns, ss single leads have a potential of possessing very high lifetime values (LTV), the level of quality of the lead is of higher importance than the volume of leads. Subsequently, B2B leads are typically much more costly than B2C leads. Therefore, the leads with ratings above 8 were screened in analogy to real-world cases. A significant difference was found between the *Form* and *Bot* for adequate lead content quality (>6) and excellent lead content quality (>8), $\chi^2(3) = 11.453$,

p = .010. Moreover, the excellently rated leads of the *Bot* were rated higher than the excellently rated leads of the *Form*, U = 254.5, z = -2.893, p = .004. Within the *Bot* conditions, no difference was found for adequate and excellent lead content quality, $H(2)$ = 1.801, p = .406. These results are displayed in Figure 14 and **Error! Reference source not found.**.

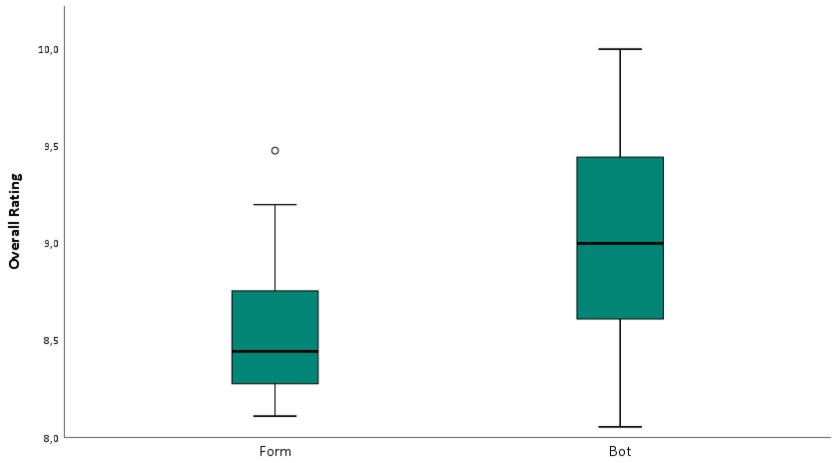

Figure 14 (Adequate & Excellent Lead Quality)

4.3.5 Time Persistence of Respondents

In addition to the other analyzed lead parameters, the *Time* persistence of respondents in their condition was analyzed as well. The outliers of extreme *Time* values of the top and bottom ranges were excluded from the analysis. These represented the top 5% and bottom 5% of the values. No significant difference was found between the *Form* and *Bot*, U = 4607, z = -0.427, p = .669 nor within the *Bot* conditions, $H(2)$ = 3.265, p = .195. A further *Time* analysis was done with the excellently rated leads due to interest whether higher quality responses require more time in one of the conditions. Similar results were obtained; no significant difference was found between the conditions (p > .05). The results are displayed in **Error! Reference source not found.**.

Table 11 (Quality & Time)

Parameter	Form	No Avatar	Non Salient	Business Salient	Statistical Test
Quality Rating					
M	5.92	5.69	5.60	6.10	**form vs bot:**
Md	6.21	6.00	5.78	6.17	U = 9602.5, z = -0.218, p = .827
SD	2.10	2.50	2.61	2.28	
Min	1	1	1	1	**within bots:**
Max	9	10	10	10	$H(2)$ = 1.660, p = .436
High Quality Ratings > 8					
M	8.56	9.16	8.97	8.90	**form vs bot:**
Md	8.44	9.33	9.00	8.89	U = 254.5, z = -2.893, p = .004
SD	0.41	0.64	0.59	0.42	
Min	8	8	8	8	**within bots:**
Max	9	10	10	10	$H(2)$ = 1.801, p = .406
n	17	15	17	24	
Times (Rating > 8)					
M	36.18	33.93	32.47	30.04	**form vs bot:**
Md	32.00	26.00	25.00	28.50	U = 399.5, z = -0.999, p = .318
SD	19.76	21.54	17.71	11.21	
Min	17.00	11.00	14.00	14.00	**within bots:**
Max	104.00	87.00	87.00	51.00	$H(2)$ = 0.001, p = .999

4.3.6 Digital Nudging Effect

In the Bot conditions, as mentioned earlier, digital nudges were programmed to elicit more information from respondents. The amount of information was operationalized with the number of words. Within the Bot conditions, the nudges elicited 62 additional words on average (Md = 45) compared to 68 average words prior to the nudges (Md = 44), thereby almost doubling the amount of information. However, the nudges did not elicit a significantly different word count for the Bot respondents than the Form respondents in total. The nudge effect was similar between the three bot conditions, H(2) = 1.020, p = .600. Even when analyzing the percentage increase in words, relative to the initial response prior to the nudge, no difference between the Bot conditions was found, H(2) = 2.496, p = .287. The results are shown in Table 12 and Figure 15.

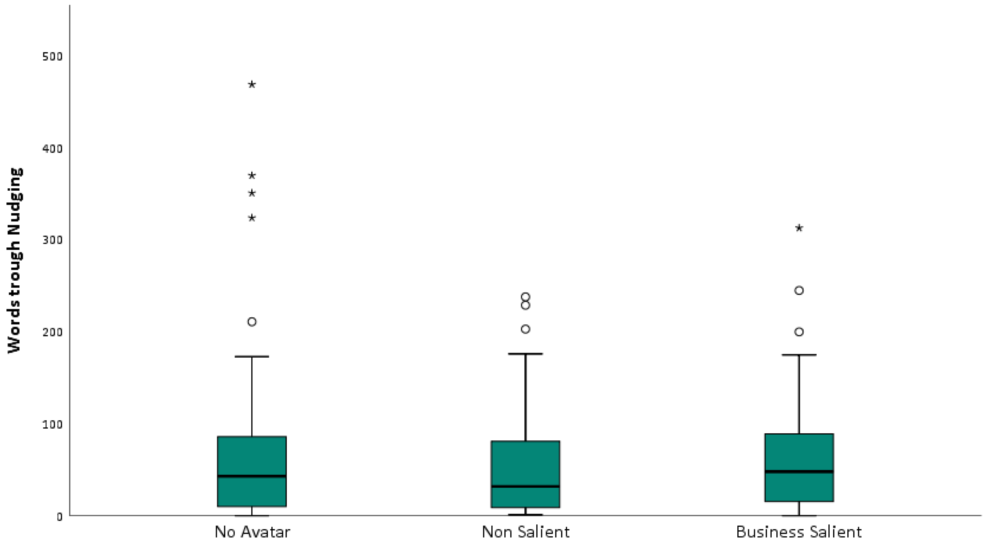

Figure 15 (Nudge Word Increase)

Table 12 (Nudge Word Increase)

Parameter	No Avatar	Non Salient	Business Salient	Statistical Test
Words without nudge				
M	62.55	81.30	67.02	**within bots:**
Md	34.00	40.00	48.00	$H(2) = 1.279, p = .528$
SD	85.64	97.64	70.99	
Min	0.00	0.00	0.00	
Max	481.00	394.00	342.00	
Words through nudge				
M	62.55	61.70	61.50	**within bots:**
Md	43.00	32.00	48.00	$H(2) = 1.020, p = .600$
SD	81.84	70.22	57.69	
Min	0.00	1.00	0.00	
Max	469.00	238.00	313.00	
Percentage Increase in Word Count				
M	279.64	294.85	272.95	**within bots:**
Md	220.26	252.08	231.51	$H(2) = 2.496, p = .287$
SD	284.74	142.85	247.04	
Min	128.57	163.16	45.10	
Max	2320.00	766.67	2383.33	

4.3.7 Further Indicators of Performance

Following the completion of the survey, participants were asked to rate their experience with the form or the bot on a scale from 0 (worst) to 10 (best). No significant difference was found for the subjective experience of respondents between the *form* and *bot*, $U = 6900.5$, $z = -0.757$, $p = .449$; as well as within the *bot* conditions, $H(2) = 0.003$, $p = .999$. However, the word count for the explanation of the rating was significantly higher for the *bot* ($M = 29.9$, $Md = 26$) compared to the *form* ($M = 20.6$, $Md = 15.5$), $U = 4730$, $z = -3.658$, < .001. The word count comparisons for the subjective rating of experience are depicted in Figure 16:

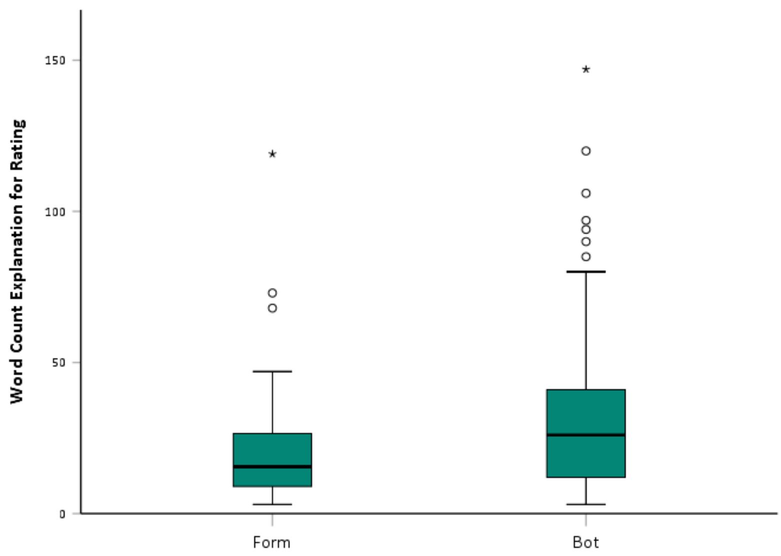

Figure 16 (Rating Explanation Word Count)

The number of questions answered was counted for the respondents and was compared between the conditions. A significant difference was found between the *form* and *bot*. Respondents of the *form* answered significantly more questions than the *bot*, $U = 7202.5$, $z = -6.113$, $p < .001$. No significant difference was found within the *bot* conditions. It is noteworthy mentioning that unlike in the *bot* participants of the *form* condition immediately saw the whole questionnaire and had the choice to answer questions by preference without any mandatory order. Furthermore, more significantly participants bounced from the *form* in an earlier stage. The results are illustrated in Table 13:

Table 13 (Survey Completion Time & Experience)

Parameter		Form	No Avatar	Non Salient	Business Salient	Statistical Test
Rating of Experience						
	M	7.95	8.00	8.13	8.22	**form vs bot:**
	Md	8.00	8.50	8.00	8.00	$U = 6900.5$, $z = -0.757$, $p = .449$
	IQR	1.90	2.18	1.87	1.63	**within bots:** $H(2) = 0.003$, $p = .999$
	Min	2	1	2	4	
	Max	10	10	10	10	
Mean Time		7 Min 16 Sec	10 Min 32 Sec	12 Min 36 Sec	17 Min 13 Sec	
Number of Questions						**form vs bot:**
	Md	16	14	14	15	$U = 7202.5$, $z = -6.113$, $p < .001$
	IQR	2	9	10	9	**within bots:** $H(2) = 2{,}449$, $p = .294$
	Min	6	2	2	2	
	Max	17	17	17	17	

Note. Numbers are absolute values (percentages). Chi-Square Test for two categorical variables, U-Test for two samples, Kruskal-Wallis-H-Test for >2 samples

5 Conclusion

The following section will begin with the discussion of the results in light of the theory discussed in the literature review. Following, practical implications for real B2B lead generation campaigns will be deduced from the results. Thereafter, some limitations to the study will be discussed with suggestions for further research in the future.

5.1 Discussion

In line with *H1*, *H2* and *H3*, the bots were able to generate significantly more leads than the form. This was true for the primary, secondary and third tier lead information. Furthermore, the bounce rate was significantly lower for the bots than for the form. A few reasons may provide explanation for these results. Firstly, upon reaching the assigned condition (*Form* or *Bot*), the respondents saw either a full-length questionnaire or a greeting by the bot. Differently from the bot, the length of the form was immediately disclosed, and the participant was able to view all the questions before beginning the survey. While this may provide several advantages for the participant namely the possibility to choose the order in which he/she responds to the questions, and the ability to estimate the time necessary to complete the survey; this proved to be largely a disadvantage as the length of the survey and its content is likely what drove away participants before beginning the survey. The bot asked the questions one by one without possibility to skip forward or move backward thereby stimulating an element of curiosity in the participants. Additionally, the two-way communication aspect of the bot which both possessed a name and identity, as well as addressed the participants by their names; likely provoked a sense of responsibility and courteousness in the participants to respond and continue with the conversation being held. Differently from the form where the participant was accountable for him/herself to both choose whether or not to fill out the answers, when to do so and to which level of quality; the bot nudged the participants to both answer and provide more quality answers in the time frame of the conversation.

From a technical standpoint, the bot possessed advantages that were impossible to implement with the industry-standard form that was used in this study. Specifically, the bot instantly saved and sent to a server the responses of each question of the survey. This was done automatically when the participant pressed the “Enter” key to continue the chat. Differently, the form could only save the responses when the user clicked “Submit”, and therefore potentially lost participants that answered a few questions before deciding to bounce without clicking “Submit”. However, participants had no required questions in either of the conditions. Therefore, in the form condition where the participant had access to the entirety of the questions beforehand, it could be argued that the participant would not have started to answer the form if he/she initially did not like one of the questions, was short of time/patience or for any other reason. Although, despite the bot saving the information of bounced participants, this information is likely not highly operational, as the practice of B2B lead generation depends on highly interested and compliant prospects. If a prospect bounced, it is often not worthwhile to attempt to convert him/her into a client/customer as opposed to investing time, effort and capital into converting highly interested and compliant prospects that completed the survey, or at least decided to submit a few of the answers he/she decided to answer. Nonetheless, the data of the bounced participants are still valuable.

In line with the research of Zumstein and Hundertmark (2017, pp.96-109), it can be argued that the two-way personalized communication created a form of rapport and a relationship with the participants, that subsequently increased the likelihood of disclosing private information. Some supporting examples include the participants speaking with the bot in a personal manner: “you know…”, “what would you like to know?”, “you are funny”. Moreover, the bot was programmed to respond with a delay while displaying “typing…” to simulate the action of thinking as in a real virtual chat conversation. Contrarily, it can be argued that there is a higher resistance of people to share information with a static form and a dramatic “Submit” button.

Not in support of *H4*, the bots did not collect more words from respondents than the form. Similarly, to a real virtual chat, responses in the bot condition were not initially long and were therefore incomparable to the length of the responses in the form condition. An explanation for this is that 2-way conversations tend to comprise of shorter exchanges between the conversing pair. We may see this in day-to-day chats, consisting of jargon that shortens words and aims at reducing the time to produce a message. Perhaps the participants felt that the bot is waiting on them for a response, thus creating time-pressure for the participant to answer quickly. The bot imitated a real conversational partner as it displayed the text “typing” as it was asking questions. This time pressure does not exist in forms where the participant has as much time as desired to complete it. Additionally, the text area of the bot was smaller than that of the form. Thus, solely with the effect of the digital nudges that continually pressed and motivated the respondents to write and share more, did the bot produce similarly long answers as did the form. More precisely, without the nudges, the answers in the bot condition were approximately half in length. Not in line with *H10*, *H4* and *H16*, no final difference in word count between the conditions results in the conclusion that nudges are essential in the implementation of lead generation bots. Additionally, the word count was highly correlated with the content quality, supporting the essentiality of nudges in the bot. Thereafter, including the nudges, the content quality was similar for both the form and the bot; implicating that without the nudges, the form would have yielded higher quality responses than the bot. This was not in line with *H6* which expected higher quality results in the bot condition. The overall mean and median quality of the responses of both the form and the bot was 6/10, which reflects high operational value of the leads. Therefore, despite no significant difference between the quality of the responses between the form and bot, the fact that significantly more people bounced from the form condition suggests that the bot was more effective than the form. A significantly higher percentage of visitors in the bot condition responded to the questions than visitors in the form condition. This signifies higher costs per lead and higher total costs in a B2B context for the form than the bot; as the advertiser pays for the traffic and clicks rather than just the completed surveys, thereby including the costs of the bounced visitors. Precisely, in a real business context, the results of this study suggest that leads from a form would be 2.5 times more costly than leads from a bot, with the same quality outcome. In addition, not in line with *H12* and *H17*, no difference in quality rating for the responses was found within the bot conditions. The hypotheses were generated based on a business B2B setting. This study only simulated a B2B setting and therefore, the business-salient avatar was probably not appropriate in producing a behavioral confirmation effect amongst these participants. While in the constellation of this study there was not enough evidence in support of a behavioral confirmation effect to the business-salient bot, further studies could retest this hypothesis in either a real B2B setting, or with a clean B2B sample.

Age showed to have a negative relationship with the disclosure of information with the bot. The older the participant, the less likely of disclosing primary, secondary and third tier information the participant was. This was also in line with the disclosure of age itself in the survey, as it was significantly less disclosed in the bot condition than in the form. Additionally, the origin of the targeted participant showed a tendency of influencing the response rate. Particularly, Europeans tended to prefer the form over the bot in comparison to non-European participants. This suggests that in practice, an older or European audience should perhaps be targeted with a form rather than with a bot.

In the study conducted by Peña (2011, pp.150-168), participants that operated elderly avatars selected elderly-related products more often than participants that operated young avatars. Somewhat conversely, in this experiment, the non-salient avatar showed significantly higher bounce rates than the business-salient and no avatar conditions. Additionally, respondents of the non-salient condition were significantly younger and had lower incomes than respondents of the business-salient and no avatar conditions. This result suggests that older and/or higher income participants likely bounced when encountering the younger and informal character of the non-salient bot. This can be argued because of the randomization of the allocation to the treatments. Not in support of *H7*, *H8*, *H13*, and *H14*; for the primary and secondary tier information, the avatars showed no difference in generating leads. However, in line with *H9* and *H15* the business-salient avatar elicited significantly more third tier (detailed) information compared to the non-salient and no avatar bots. Furthermore, European respondents significantly less often bounced from the business-salient bot compared to the other bots, to the extent that the bounce rate of the Europeans was similar to the bounce rate of the European respondents in the form. Although respondents in the business-salient condition were not older and did not have higher incomes than respondents in the no avatar condition, the business-salient bot was more successful overall in generating high-quality leads than the other avatar conditions. There is evidence to support the business-salient bot over the other bots in B2B lead generation campaigns. The non-salient bot was risky and showed disadvantages of use with an older and higher-income target group, which are typically the ideal prospect group in B2B contexts. Peña (2011, pp.150-168) contented that avatars have priming effects that can induce cognitive, emotional and behavioral influence. Correspondingly, the results of this study indicate a social priming effect of the avatars.

Another measure of rating of experience was tested in this study between the four conditions. Due to the nature of the bot as a conversational agent providing dynamic feedback to the conversational opponent, rather than a static form; it was hypothesized that the bot will induce higher subjective experience ratings from the participants. Additionally, it was hypothesized that the business-salient bot will induce higher subjective experience ratings than those produced by the no avatar bot. No evidence in support of *H5* and *H11* was found in the study. For all the four conditions, the ratings were very high at around 8 on a scale of 1-10 on average. A follow-up question was asked of the participants to explain their ratings. One weakness possibly skewing these ratings was found as a vast number of participants thoroughly enjoyed the questions, feeling great enjoyment and enlightenment answering the personal questions. Evoking these feelings from participants was unintentional as the questions served the purpose of solely simulating B2B lead generation questions. This enjoyment was identical for all four conditions and led the participants to rating the survey's questions rather than the experience with the form, bot and bot avatars.

5.2 Practical Implications

The results obtained from this study give practical insight into best practices for B2B lead generation campaigns, as well as for B2C lead generation campaigns. Overall, bots proved to be less costly than forms, producing leads of the same quality for a significantly lower cost per lead (CPL). The bots showed a cost advantage over the form, producing leads with a CPL that is 2.5 times cheaper than the CPL of the form. However, the nudging techniques of the bot were indispensable for producing these results; and most likely, the bots would have performed much less strongly than the form without these nudges. While the business-salient avatar showed some advantages compared to the non-salient and no avatar conditions, the overall advantages were mixed and inconclusive. Additionally, the avatars were shown to have been risky. On the one hand, the business-salient bot yielded more third-tier information, and less European and older individuals bounced. On the other hand, the opposite was the case for the non-salient avatar. This shows that while a socially salient avatar can be used to yield higher quality leads from a specific demographic, it must be precisely tailored to the attributes of the target group. As the benefits of avatars fail to outweigh the risks involved with using them, it is likely best to implement a no avatar bot in such lead generation campaigns. However, socially framed avatars can be used as a form of a prequalifying method of prospects; as it can be used to attract only a specified group that fits the desired prospect criteria of the campaign-authoring firm, while it diverts prospects that do not identify with such criteria. Split testing various socially framed avatars in a bot against a no avatar bot, should be used if attempting to prequalify prospects in such a manner in lead generation campaigns. For the use in a specific target group, companies should invest in preliminary testing initially to be later used long-term with the same target group in on-going campaigns. Additionally, an avatar can be used for brand-building and can establish long-term rapport, comfort and a relationship with the targeted prospects. As a particular avatar becomes more known, it is likely that the familiarity of the prospects with the character, as well as the character's perceived associated qualities, would lead to an increase in lead quantity and quality in the long run. For example, if a B2B company uses a business-framed avatar with the company logo to attract its targeted audience, it can build a serious business personality in the avatar character that will prime prospects to provide serious leads.

5.3 Limitations & Suggestions for Further Research

The present study had a few limitations to be discussed. The theme of this study and the research questions were derived from the practical experience of the author; and motivated by the attempt to gain practical insight into best practices in online B2B lead generation campaigns. However, the design of the study was such that it was absent of a product or service offering, and absent of real interested prospects or customers/clients. Additionally, no funds were spent on advertising in relevant industry networks that are typically used for online B2B lead generation. These conditions were simulated through the design of this study; using the chance of winning gift cards as the motivating medium in exchange for the lead information and using simulating questions instead of B2B-relevant questions. It is not ascertained though that the chance of winning gift cards evokes the same motivation in participants as would a real B2B offering. The value offering simulation with the gift cards still highly resembles situations in real B2B lead generation campaigns. For example, many industry campaigns include the demand of lead information in the form of an application, for the chance in qualifying to work with the company or participate in a program. Moreover, the avatars used in this study were males, and therefore did not test for gender effects of the avatars. Despite the possible shortcomings of this web-based experimental study, its implications are still of high external validity due to its high resemblance to real-world scenarios.

In light of the discussed results and limitations, suggestions for further research to expand on the topic are proposed. Due to the ambiguity of the results of the priming of the avatars used, studies should aim to further understand the priming potential of avatars in online lead generation and online/digital marketing in general. Preferences of individuals to specific avatars in the context of marketing campaigns is still unclear. Further research should address this issue in a digital marketing context. Avatars can be adapted to suit the prospect in communication. For example, a senior avatar can be matched to a senior, a male for a male, female for a female etc. Additionally, this study should be similarly replicated to a real B2B digital marketing campaign with a real value exchange and a real business professional audience.

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7 Appendix A

Master Thesis Research

Please be so kind and fill in this survey that only takes around 15 minutes to complete!

I need 300 respondents at least so I am super appreciative of your support!

The more questions you answer, the more points you get and the higher your chance in winning 1 of the 3 prizes!

The 3rd place prize is an Amazon Gift Card of €15

The 2nd place prize is an Amazon Gift Card of €30

The 1st place prize is an Amazon Gift Card of €55!

THE WINNERS WILL BE CONTACTED BY EMAIL IN THE END OF JUNE

All the information you provide will be used for the purpose of this research paper ONLY and will NOT be used for any marketing, or other purposes.

You will NOT be added to any mailing list!

All your data will remain anonymous!

The answers that you provide in this survey will be deleted immediately after the analysis for this research paper.

You will be contacted by email (if you provide it) ONLY if you win one of the prizes! If not, you will NOT be contacted and your email address will be DELETED.

GET STARTED

The survey takes around 15 minutes to complete. Your answers will be highly valuable for the research I am conducting!

If you have any questions or concerns, you may write an email to the researcher at: ben.tochner@lbs.ac.at

8 Appendix B

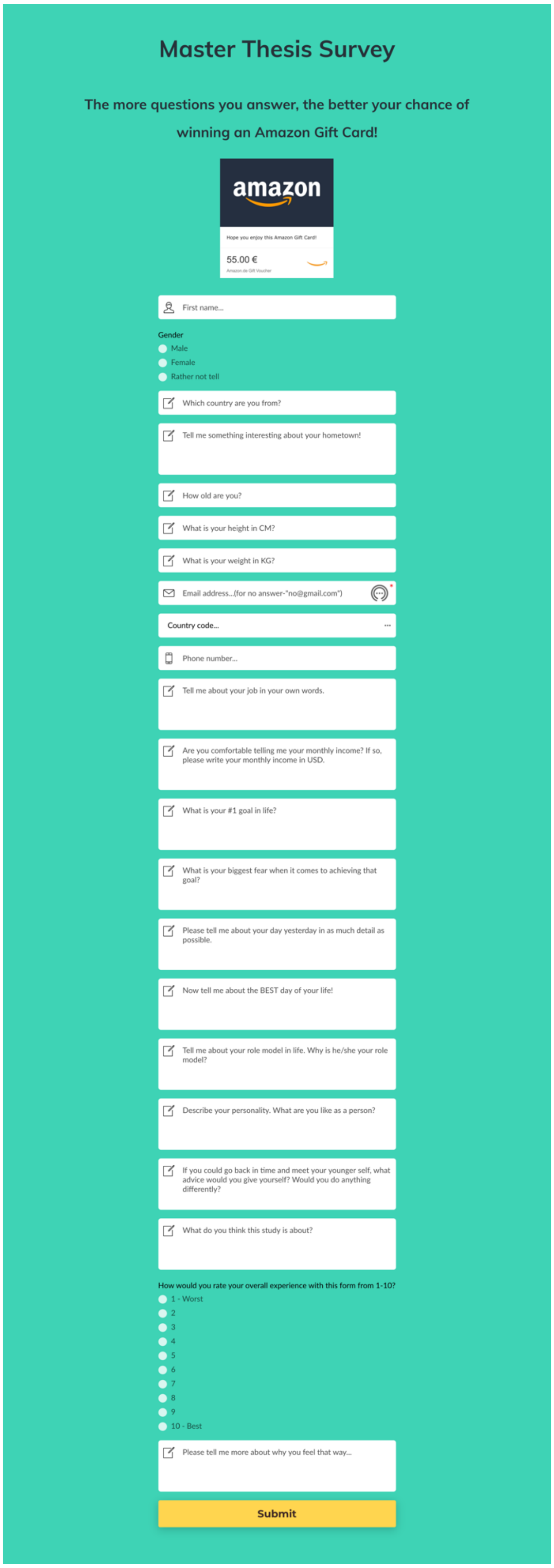
Thank You So Much For Participating!

You have successfully completed the survey.

Feel free to share the link and help me complete my research!

http://www.masterthesis.site

9 Appendix C



Master Thesis Survey

The more questions you answer, the better your chance of winning an Amazon Gift Card!

amazon

Hope you enjoy this Amazon Gift Card!

55.00 €

Amazon.de Gift Voucher

First name...

Gender
- Male
- Female
- Rather not tell

Which country are you from?

Tell me something interesting about your hometown!

How old are you?

What is your height in CM?

What is your weight in KG?

Email address...(for no answer-"no@gmail.com")

Country code...

Phone number...

Tell me about your job in your own words.

Are you comfortable telling me your monthly income? If so, please write your monthly income in USD.

What is your #1 goal in life?

What is your biggest fear when it comes to achieving that goal?

Please tell me about your day yesterday in as much detail as possible.

Now tell me about the BEST day of your life!

Tell me about your role model in life. Why is he/she your role model?

Describe your personality. What are you like as a person?

If you could go back in time and meet your younger self, what advice would you give yourself? Would you do anything differently?

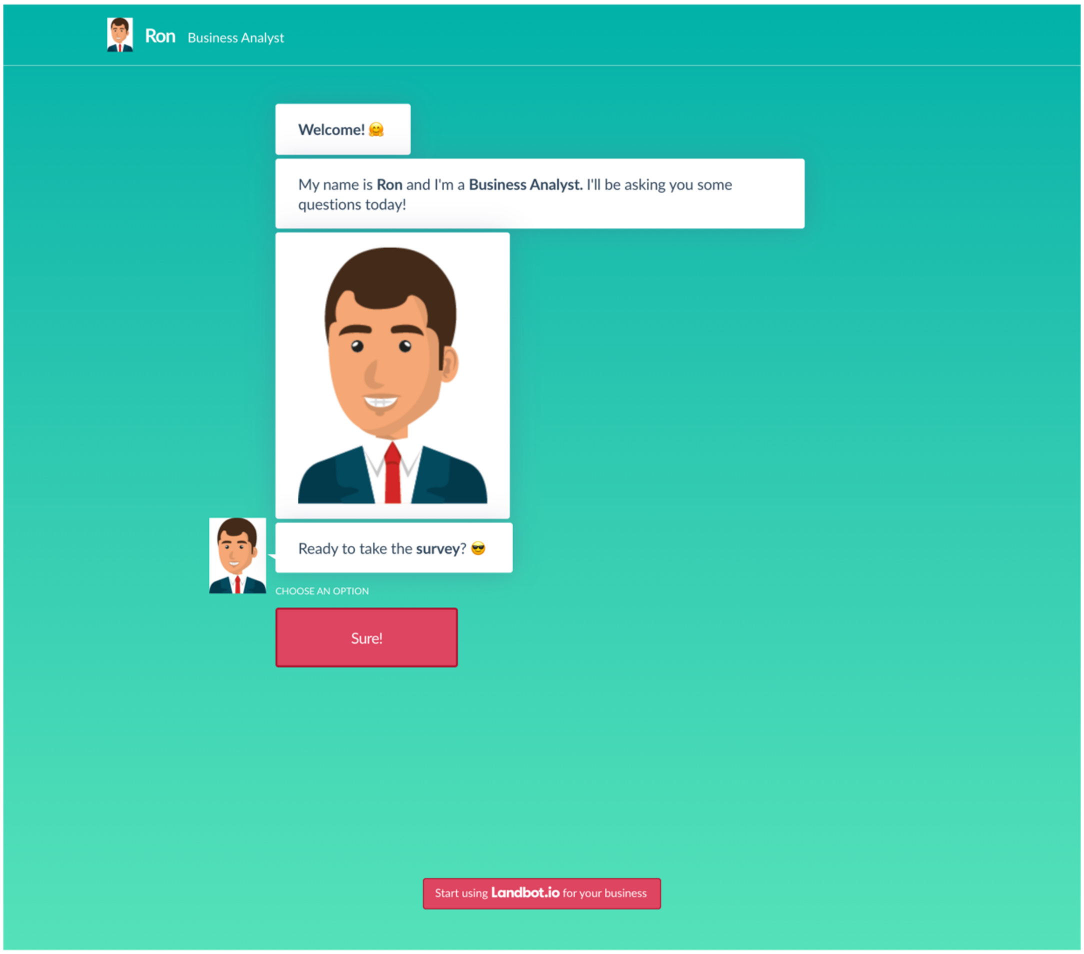
What do you think this study is about?

How would you rate your overall experience with this form from 1-10?
- 1 - Worst
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10 - Best

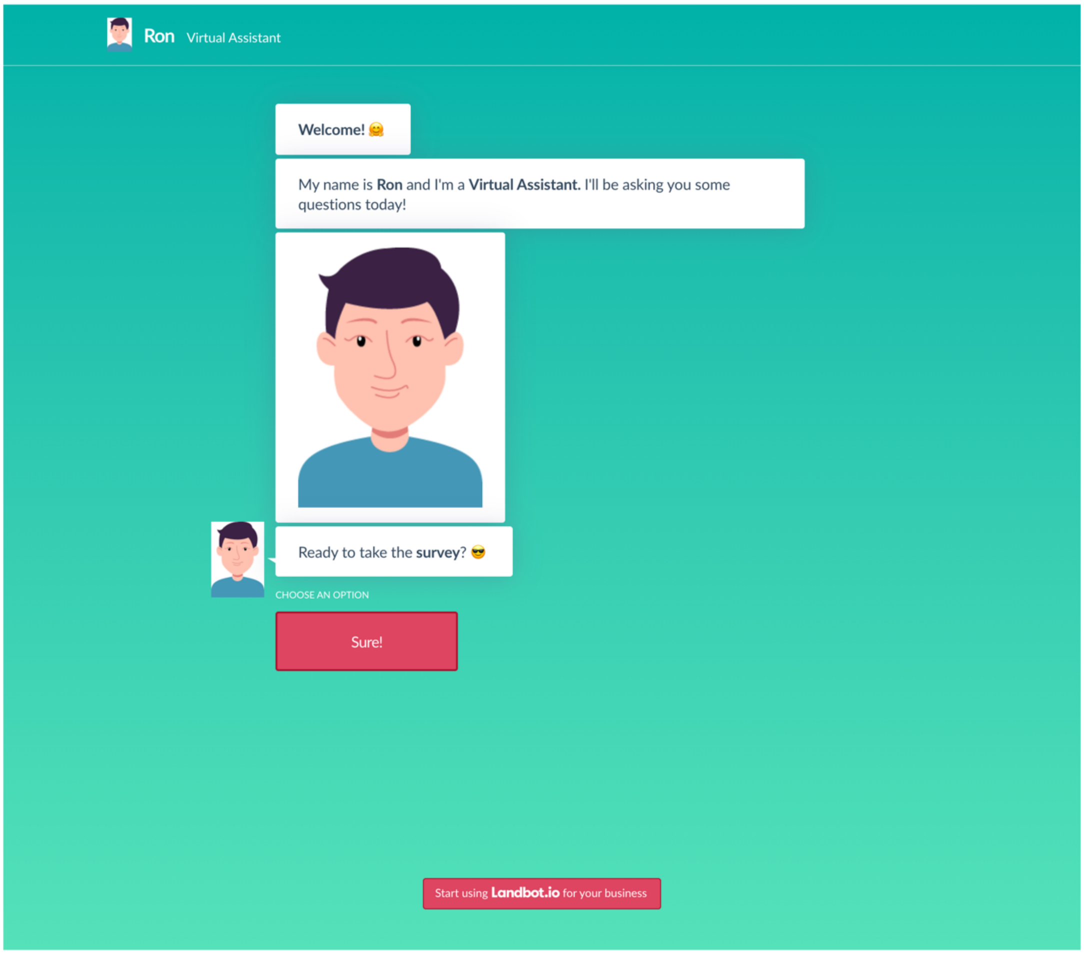
Please tell me more about why you feel that way...

Submit

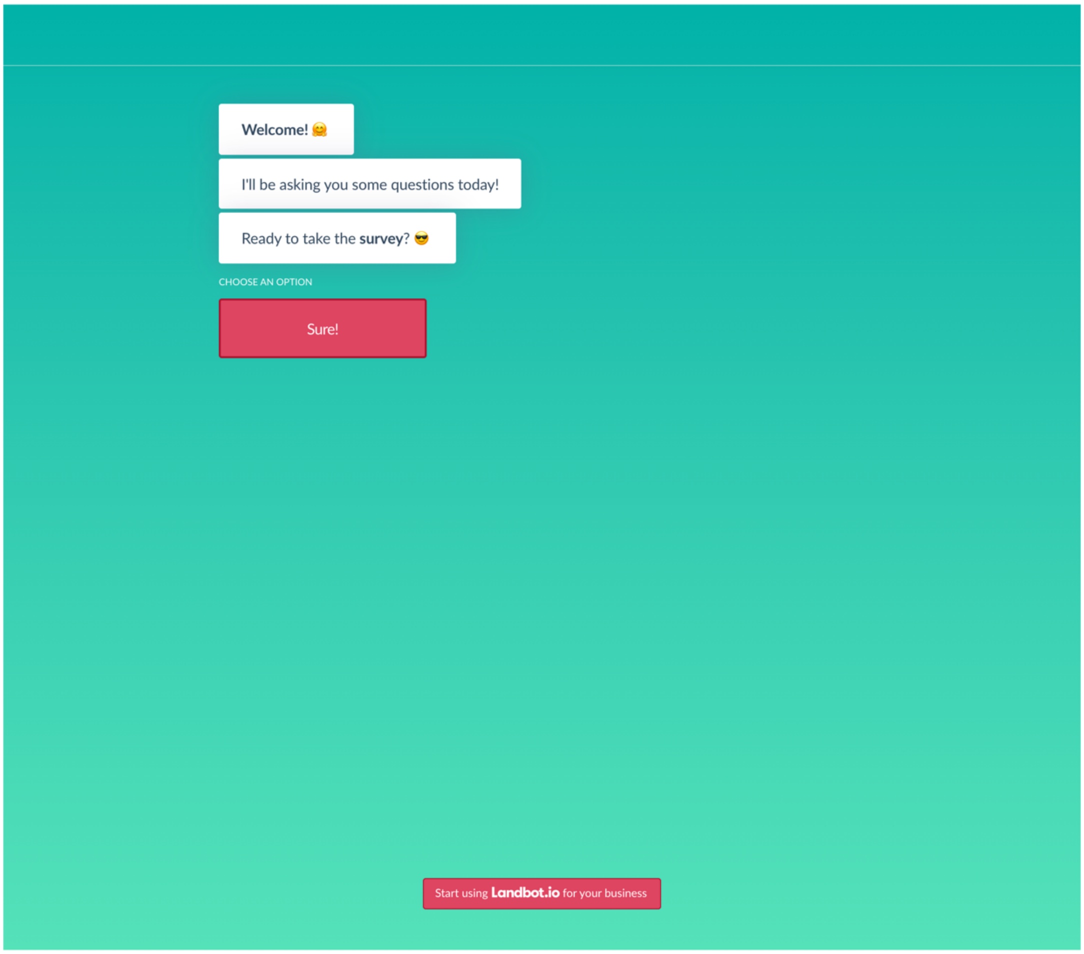
10 Appendix D



11 Appendix E



12 Appendix F



13 Appendix G