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PERSUADING CUSTOMERS VIA CHATBOT REMINDERS:THE EFFECT OF MESSAGES

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Abstract

This study focuses on funeral cover products sold via chatbots and the challenge of customer disengagement during the purchasing process. The research conducts Randomized Control Trials (RCTs) by sending reminders at various times, using two types of informative messages as reminder types. Results indicate that all reminders significantly increase the likelihood of users resuming insurance quotes. However, no significant effect on sales transactions is observed. In summary, this study provides insights into re-engaging users in the funeral cover purchase process using reminders but questions their effectiveness in driving sales.

Keywords

Chatbot, insurance, reminder, statistical message, narrative message

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I. INTRODUCTION

The financial sector is witnessing a growing trend in steadily replacing face-to-face interactions with digital and virtual channels (Bagus et al. 2020). Technological advancements and changes in expectations and preferences of the digitally influenced younger generation exert considerable pressure on companies to adjust (Barrett et al. 2015). To remain competitive and innovative, companies in the financial sector must embrace digital transformations throughout their value chain. This includes restructuring their business models to engage with customers in new and innovative ways, as highlighted by Barrett et al. (2015).

In this financial sector, customers often find themselves overwhelmed by various product offerings, creating a challenging environment to navigate (McShane et al. 2017). Simultaneously, financial enterprises such as insurance companies constantly struggle to attract and retain their customers' attention, recognizing the importance of regular and sustained customer engagement initiatives (Ahmed 2021; Gravert 2021). Within their promotional strategies, businesses can seamlessly integrate the practice of sending product reminders to their customer base. There is extensive literature on optimizing customer engagement (Schadler and McCarthy 2012) via online reminders (Du et al. 2020; Reinartz, Wiegand, and Imschloss 2019). Particularly in the finance sector, the utilization of text reminders has demonstrated increased loan repayments (Du et al. 2020) and microloan deposits (Karlan, Morten, and Zinman 2016), indicating elevated customer engagement.

Chatbots present a viable solution to streamline complex processes to retarget customers (Rodriguez Cardona et al. 2019; Singh et al. 2019; and Koetter et al. 2019). Chatbots, often called ‘conversational agents’, are automated yet personalized virtual assistants that leverage the power of natural language processing and machine learning to communicate seamlessly

with humans (Rodriguez Cardona et al. 2019; Tsai, Liu, and Chuan 2019). They serve as valuable business tools, facilitating connections with potential customers and elevating overall customer satisfaction. The interactive nature of chatbots fosters deeper customer engagement, proving to be remarkably cost-efficient compared to traditional communication methods. Chatbots are available 24/7, providing real-time responses to consumers' inquiries, eliminating the need for long waiting times on the phone or delays in email exchanges (Tsai, Liu, and Chuan 2019; Nuruzzaman and Hussain 2020). By automating responses to more than 70% of daily inquiries that are related to insurance account information, claim status, and simple policy-related questions (Singh et al. 2019), chatbots can provide constant support. The three crucial processes within the insurance value chain are marketing, sales, customer contracts, and claim management, which traditionally involve significant paperwork (Koetter et al. 2019).

As a part of FinTech, which refers to technological innovations and development in the financial sector, InsurTech focuses on challenges and opportunities in the insurance industry (PwC 2016). InsurTechs are modern market players providing the technological component to insurance products or services, aiming to increase efficiency (OECD 2017). With technology facilitating the dissemination of information directly to customers (Erasmus 2023), InsurTechs can drastically enhance access to financial products among individuals (Tanguy et al. 2017). Mostly, InsurTechs play the role of brokers that facilitate the distribution of financial products (Erasmus 2023). Consequently, they support traditional providers by streamlining and digitizing processes along the value chain. Engaging in partnerships unlocks opportunities for both sides. Incumbents can expedite their response to the digitalization occurring in the insurance sector by collaborating with tech-savvy start-ups. In turn, InsurTechs gain access to a more extensive existing customer base that they can cultivate (Koprivica 2018).

This study is conducted in cooperation with the South African InsurTech RatherChat, headquartered in Cape Town. Its chatbot technology helps to ease the sales processes for insurance companies that primarily sell funeral, life, and health cover products within the South African insurance sector. The messenger-based chatbot provides automated guidance, generates quotes, and addresses customer inquiries throughout the purchasing process. Potential customers are acquired by spreading advertisements for specific insurance products by various providers via social media platforms. Customers click on the link and are led through the guided conversation. Individuals can personalize their optimal funeral quote, selecting the desired number of family members for coverage and specifying the coverage level. Towards the end of the process, customers are asked whether they wish to proceed with the purchase based on their personalized quote.

This study solely focuses on funeral cover products. A major hurdle in this purchasing process is the loss of numerous customers who disengage from the conversation, resulting in missed sales opportunities. Internal data from RatherChat reveal that merely 5% of acquired customers complete the sales process, with the majority dropping out at various stages throughout the interaction. Distractions, disinterest, or interrupted data coverage are potential reasons for this occurrence. While the company has already started attempts to lower attrition, it still needs to be determined what strategy to retarget users works best.

An extensive body of literature has worked on how to best re-engage customers by retargeting them in a certain way. Customer retention is critical, prompting the strategic implementation of reminders as a solid instrument to direct customers toward embracing specific actions (Gravert 2021). Other studies, such as Li et al. (2022) and Goic, Rojas, and Saavedra (2021), reinforce the efficacy of targeted reminders in a B2C context. This sheds light on the vital role of digital

communication channels in fostering interactions between customers and brands. Within their studies, customers who have been inactive for an extended period are reminded of their incomplete transactions. Given the yet still novel field of a chatbot taking over the sales agent role, the existing literature offers limited insights into addressing the optimal retargeting strategy. Consequently, this research aims to explore the potential of reminders as a potent promotional tool for re-engaging users via chatbot, encouraging them to continue with insurance quote inquiries and ultimately boosting sales of funeral cover products.

When configuring reminders to retarget users that interrupted a specific sales process, two questions are central: When is the most effective time to dispatch reminders, and how can they be optimally designed? Considering the timing component, valuable insights can be obtained from academic studies that have explored the impact of timing on survey response rates. Lindgren et al. (2020), Faught, Whitten, and Green Jr. (2004), and Lewis and Hess (2017) conduct research in related fields, aiming to identify the “best time” during the day for sending survey invitations to maximize response rates. One option of reminder design involves sending a persuasive text message outlining compelling reasons for the potential customer to continue with the purchasing process. Studies that evaluate the content that a message should contain typically examine the design of statistical and narrative statements and compare them in their effectiveness (Allen and Preiss 1997; Baesler and Burgoon 1994; De Wit, Das, and Vet 2008; Hornikx 2018; Kopfman et al., 1998; Zebregs et al. 2015). Statistical messages are characterized by presenting quantitative information and primarily factual content (Hornikx 2018). In contrast, narrative messages tell a story by sharing experiences, actions, and outcomes related to specific topics from another person's perspective, offering a more personal approach (De Wit, Das, and Vet 2008; Kopfman et al. 1998).

While several studies investigate the optimal timing for sending survey invites, there is a notable gap in the literature when assessing various reminder dispatch times throughout the day within chatbots. Many studies are focusing on sending various message types (De Wit, Das, and Vet 2008; Kopfman et al. 1998) but none of them focuses on designing reminders used in chatbots. Consequently, the objective of this study is twofold: not only to assess the efficacy of sending reminders at various times throughout the day but also to investigate how the impact varies solely based on the reminder type, i.e., statistical and narrative message, sent.

To answer the first part of the research question, reminders are sent out to the 95% of chatbot users who dropped out of conversation at three distinct times throughout the day. Recipients are randomly allocated to a morning, noon, or evening dispatch. Considering the second part of the research question, the study employs two message types sent out after users stop communicating with the chatbot. The key difference in the messages is how they are presented: they can either be based on statistical facts or crafted as a narrative emphasizing emotions. Following the randomization of timing and message type, the experiment allows the execution of several randomized control trials (RCTs). Recognizing the diversity of official languages in South Africa, a subsample analysis is undertaken, comparing English speakers and those who indicate other home languages. Given the random dispatch of reminders at three distinct times during the day, the sample can additionally be categorized based on the time elapsed between the initial end of the conversation and the assigned treatment time. Lastly, the impact across a younger and an older age cohort is assessed.

Existing literature demonstrates that reminders positively impact customer engagement (Gravert 2021; Li et al. 2022; Goic, Rojas, and Saavedra 2021), effectively directing attention to decision-making processes (Gravert 2021). The study partly aligns with these findings,

confirming that reminders effectively re-engage users within the chatbot purchasing process, boosting quote continuation. However, contrary to Goic, Rojas, and Saavedra's (2021) conclusion that reminders increase overall sales, the research suggests that reminders do not affect sales in this study context. The contribution to the literature highlights the nuanced effects of reminders in different contexts and underscores the need to explore further their effectiveness in driving sales. This null result regarding the effectiveness of reminders on sales opens a discussion of whether they are a sufficient promotional instrument in other study setups.

Existing literature studies the impact of sending out reminders at different times (Faught, Whitten, and Green Jr. 2004; Lewis and Hess, 2017; Lindgren et al. 2020). Although Faught, Whitten, and Green Jr. (2004) and Lewis and Hess (2017) find that specific weekdays and hours of the day are most effective in evoking a positive response, the significant effects that are found by Lindgren et al. (2020) diminish gradually along the study period. The results highlight positive significant results for all three times but do not show significant differences across the three predetermined time slots throughout the day. The study contributes to the literature on timing as it provides insights into an industry previously not covered by such research.

When examining the two message types, reminders effectively boost quote continuation. However, neither message type significantly influences overall sales transactions, indicating suboptimal effectiveness within the context. The findings align with literature like Du et al. (2020) and Gravert (2021), suggesting that reminders conveying negative connotations, as in the case with funeral cover, have no positive effect on sales. The contribution highlights the limited efficacy of negative-themed reminders in achieving sales objectives. In the literature, De Wit, Das, and Vet (2008) and Baesler and Burgoon (1994) suggest that narrative evidence tends to be more effective due to its ability to convey memorable information and evoke

personal engagement. In contrast, Kopfman et al. (1998) and Allen and Preiss (1997) find statistical evidence to trigger systematic processing, leading to heightened cognitive heuristics. However, some studies, like Zebregs et al. (2015), have failed to reach a clear consensus, with results indicating that the impact of statistical and narrative evidence can vary. The study results align with the findings of Zebregs et al. (2015), as no significant differences in the effectiveness of statistical and narrative messages are found. While both effectively increase customer engagement, considering the entire sample, they have no significant impact. The variability in findings between this study and the existing literature underscores the complexity of determining the superior effectiveness between the two message types.

Some research has raised concerns that sending reminders in the form of messages could have a negative impact on customer behavior. Du et al. (2020) and Gravert (2021) suggest that including health-related information in reminders may trigger negative emotions and irritation among readers. In a subgroup analysis focusing on different age groups, as mall but highly significant negative coefficients on sales for individuals aged above 45 are observed. This study adds to the literature by shedding light on the potential adverse effects of message reminders, particularly among older users.

The study begins by providing the contextual background for the experiment in Section II. Section III outlines the specific designs of the treatments, followed by Section IV, covering the methodology. Section V presents the empirical results, which will be thoroughly discussed in Section VI. Finally, the study culminates in Section VIII, where conclusions are drawn based on the findings and insights into potential areas for further research are offered.

II. BACKGROUND

The experimental study is conducted within the dynamic landscape of South Africa, a country facing significant challenges related to financial and digital inclusion. This environment has led to a notable disparity between a small wealthy and a sizeable underprivileged population. According to a study by Deloitte (2017), economically disadvantaged households at the bottom of the pyramid without accessible and reasonably priced options for insurance find themselves defenseless against undesirable events such as unemployment, illness, or death. Limited financial knowledge and constraints attributed to this population group may challenge insurance providers to serve them adequately. In response to the lack of accessible insurance products, there is a growing demand for cost-efficient solutions. One of South Africa's prominent insurance products is funeral cover, deeply rooted in cultural traditions.

2.1 Financial and Digital Inclusion in South Africa

A significant segment of the South African population has relatively low levels of financial literacy. Roberts et al. (2021) conduct a baseline survey on financial literacy in South Africa from 2015 to 2020. The analysis involves a comprehensive financial quiz encompassing financial control, planning, and product selection. Results reveal a significant gap in financial literacy across various income groups. South Africa has a large income gap between population groups, exhibiting one of the highest inequality rates globally, with a Gini coefficient[1] of 0.67 in 2018 (OECD 2022). Over the past few decades, South Africa has witnessed advancements in financial services, revolutionizing the landscape of products (FSCA n.d.). Financial inclusion

[1] The Gini coefficient assesses income distribution within a specific population, ranging from 0 to 1. As the coefficient increases, so does the level of inequality. In other words, a higher Gini coefficient indicates that a small portion of the population is receiving a significant proportion of the total income for that population. (Source: Investopedia, 2023)

is essential for developing an equitable society as it provides primarily underserved or excluded individuals with access to affordable financial services (National Treasury n.d.).

In line with the low coefficient of equality, digital inclusion remains a second factor that differs largely between rich and poor. Using the definition of Adedokun and Zulu (2022), digital inclusion explains the possession of adequate internet literacy skills and access to a computer or mobile phone, enabling individuals to navigate digital platforms effectively. This entails possessing a certain level of technical proficiency and the capability to access the necessary digital services when required. South Africa has one of the continent's highest mobile phone penetration rates, with an impressive 90% of the adult population owning a mobile phone and 69% of that being smartphones (Genesis Analytics 2019). Despite this encouraging statistic, the persistence of the digital divide remains a significant hurdle, preventing marginalized segments of the population from actively participating in the transformative wave of digitization. High mobile data costs further fuel the digital divide. Data is needed to ensure an internet connection. With the price of one gigabyte (ZAR 85~ four EUR) equivalent to four hours of wage for an individual earning minimum wage, South Africa queues into one of the countries with the most expensive data prices in Sub-Saharan Africa (World Economic Forum 2022).

2.2. The South African Insurance Market

Pre-Covid estimates suggested promising economic growth expectations for Africa. Combined with a largely underdeveloped insurance market, the continent was ranked the second-fastest growing region for insurance after Latin America worldwide (Bagus et al. 2020). Before the pandemic, the insurance industry in Africa was ranked the 8th largest globally, with a value of

roughly $68 billion in gross written premium (GWP)[2]. Across the African continent, South Africa accounts for just above 70% of the overall GWP, followed by North Africa, including Morocco, Algeria, Tunisia, Libya, Egypt, and Sudan, with almost 13% (Bagus et al. 2020). Figures from 2021 show that the greatest insurance uptake is dedicated to funeral cover, with 42% of the South African population insured, followed by 10% of adults covered by life insurance. Health insurance uptake comes last, with only 8% of adults insured (FSCA 2022). The South African government's attempt to offer state-managed universal funeral insurance, considering it one of the most widely held insurance products, has failed and has been postponed to a distant future (Milliman 2023). Internal political structures overshadowed by corruption, patronage, and mismanagement are relevant aspects posing a barrier to its implementation (Khasoane 2019). The prevailing poverty and inequality in South Africa create a high barrier to intergenerational mobility, exacerbating low employment rates and a significant proportion of individuals engaged in the informal sector. This underscores the unfortunate reality that society's most vulnerable members often lack the financial means to adequately protect themselves against unforeseen financial threats (UN 2020).

2.3 The Relevance of Funeral Cover

According to Berg (2011), funeral insurance is recognized as one of the earliest forms of insurance. The high uptake of funeral insurance in South Africa is embedded in a cultural context. According to Olupona (2015), a professor of Indigenous African Religions at Harvard Divinity School, ancestors are considered to exist in a realm of presence superior to that of humans in several African cultures. They are thought to hold the power to determine the fate of

[2] Gross Written Premium (GWP) is the revenue source of an insurance company composed of the total sum of insurance premiums written or issued by an insurance company during a specific period (Liberto 2020).

their descendants, thereby having the ability to grant blessings or inflict illness upon them. Hence, proper death rituals in the form of dignified farewells ensure that the deceased person rests in peace and becomes a spirit that watches over the descendants. According to Dercon et al. (2006), death has a strong social and psychological presence among many African cultures. Funerals are regarded as communal occasions that unite families and affirm a family's status within the community. The importance of funeral cover can be traced back to the development of funeral associations, as Berg (2011) describes. The key objective of so-called stokvels is to pool risk among its members. Members can receive funds through individual contributions regularly or as a transaction upon death to organize and pay for funerals. As funeral associations are mainly formed within communities among friends, colleagues, or relatives, they go beyond simply covering funeral expenses by providing emotional support and spiritual counsel. Further, burial societies are autonomous, trust-based, and member-governed funeral associations with informal agreements and fines for non-compliance. However, the absence of formal regulation increases the risk of abuse. In South Africa, many households simultaneously hold formal and informal funeral insurance due to the social significance and high cost of funerals (Bester et al. 2005). According to Writer (2020), OECD Better Life Index Data shows that average funerals cost around ZAR26,875 (ZAR20 ~ one Euro). Internal company data reveal that most chatbot users inquiring about funeral cover have a monthly income between ZAR3,500 - ZAR10,000. This indicates that an average funeral costs between 33% and 64% of annual income. Given these circumstances, relatively high funeral costs and high poverty levels create financial risks for family members.

2.4 RatherChat

RatherChat is an InsurTech with a technological approach to enhance the holistic insurance purchasing experience. Their chatbot solution lets customers obtain insurance coverage without

phone calls or face-to-face interactions. Thereby, the necessity for a middleman, such as a broker, between the insurance provider and the customer is eliminated. The startup extends its services to insurance providers in South Africa, delivering an average reduction of 80% in the cost per purchase compared to transactions conducted through the insurers' websites. RatherChat leverages the popularity of WhatsApp as its primary messenger service to engage with customers. WhatsApp's widespread dominance on the African continent is evident from Global Web Index's 2020 Flagship Report statistics, showing massive penetration rates in Kenya at 97%, followed by South Africa at 96%, and Nigeria at 95%. In analyzing the effectiveness of communication channels, RatherChat's research discovered that email encounters a 17% open rate, while WhatsApp messages raise this rate to 95%. Similarly, response rates via email range from 2-5%, while WhatsApp achieves a rate as high as 20-50%. These findings firmly establish WhatsApp as more effective than emails for sales processes.

2.5 Chatbot Technology

Employing a messenger-based chatbot solution presents insurance companies with numerous opportunities. Firstly, it addresses the growing trend highlighted by Gartner (2015) that the frequency of app downloads stagnates. With users becoming reluctant to download additional apps on their smartphones, InsurTechs relying on separate app installations or website interfaces may experience lower adoption rates than chatbot technologies. Chatbots are accessible via messaging apps that most smartphone users use daily (Koetter et al. 2019), offering a more appealing and convenient option. Secondly, chatbots eliminate the need for customers to familiarize themselves with a new interface or navigate through information-heavy websites, reducing barriers often encountered with conventional applications. Chatbots can efficiently narrow down the information relevant to the customer right from the beginning

of the conversation (Koetter et al. 2019), making the experience more seamless and user-friendly.

Despite chatbots finding widespread application in retail and e-commerce markets, as indicated by Paraskevi and Saprikis (2022), their adoption in the insurance industry has been relatively limited. One potential explanation, as highlighted by Koetter et al. (2019), is the presence of heterogeneous IT infrastructures within many insurance companies, making it challenging to implement universal data-driven AI solutions. Moreover, the authors explain that the insurance sector faces the complexities of adhering to various legacy regulations and managing high volumes of sensitive data. Ensuring the secure processing of customer data and protecting their privacy throughout the process is crucial for chatbots in this context. The study by Rodriguez Cardona (2019) reveals that customers may not yet fully trust chatbot solutions to handle insurance-related decisions without human interaction, leading them to prefer a hybrid customer interface.

III. TREATMENT DESIGN

The main challenge in chatbot communications is customer dropouts, often caused by distraction, product uncertainty, or limited financial understanding. This leads to potential customer loss due to external distractions and financial literacy issues, representing missed sales opportunities. Re-engaging customers through the chatbot by sending reminders can address these issues by providing additional information, overcoming interruptions, and gaining insights into customer preferences. Successful retargeting can result in increased sales and higher customer satisfaction.

The primary objective of the study is to understand to what extent sending reminders as a promotional strategy effectively persuades customers to buy funeral insurance. To achieve this goal, the analysis is split into two parts. Firstly, to examine the overall effectiveness of reminders, they are sent at three different time slots during the day. Secondly, the reminders are distinguished by message type and aim to urge customers to continue their funeral purchasing process. The aim is to determine whether a message incorporating various statistical measures is more effective than an emotionally engaging narrative that resonates with the customer. The overarching research question that is aimed to be answered is: Are reminders an effective tool to retarget customers, and if they are, when is the optimal time to dispatch them, and how are they best designed?

3.1 Timing of Reminders

To determine the most efficient timing for the treatments, the research relies on valuable insights from academic studies exploring the impact of timing on survey response rates. Lindgren et al. (2020) conduct a study on the optimal time for survey invitations sent via email during the day. The authors highlight the presence of inconvenient periods during the day when survey invitations are more likely to be forgotten or ignored. With the advancement of technology enabling a shift towards digital communication methods, researchers face the challenge of being unable to control when potential participants read their messages despite having control over the dispatch time. This emphasizes the critical role of timing in effectively engaging individuals, according to Faught, Whitten, and Green Jr. (2004). The authors focus on identifying the "best time" during a specific day of the week, sending surveys at various times throughout the day. Building upon these three studies mentioned above, the research aims to investigate whether there is an optimal time during the day when the chosen treatments yield the highest interaction rates and may ultimately lead to a higher sales rate.

RahterChat internal data, see Appendix, reveals the total number of first interactions and total sales throughout the day for funeral insurance. Several noteworthy observations emerge from this data. Firstly, sales peak between 9 am and 10 am. This peak can be attributed to incomplete sales from the previous days and sales occurring within zero to three hours after the initial interaction. As depicted by the internal data (see Appendix), the latter is the spectrum in which most sales are converted after the first interaction. Hence, the first treatment is initiated at 6 am for the study design. The target group likely faces extended commuting times to their workplaces, necessitating an early start to their day. By sending out treatments at 6 am, it is ensured that individuals with time during their morning commute can actively engage in the sales process. Secondly, as the number of interactions remains relatively stable around noon, the second treatment is sent at 12 pm to re-engage customers during their lunch break. This approach ensures that both early and late lunch breakers receive some form of treatment, maximizing the chances of re-engagement. Lastly, the global maximum of interactions occurs between 6 pm and 7 pm. During this time, many potential customers are likely finishing their workday, allowing them to dedicate time to go through the chatbot process. Moreover, they may be able to discuss important insurance-related matters with family members. Thus, the final treatment is sent out at 6 pm to take the most out of this peak engagement period. No treatments are sent during nighttime to avoid inconvenience (Lindgren et al. 2020).

3.2 Message Reminders (Louisa)

By sending the two message reminders it is aimed to investigate the effectiveness of different sub-treatments of messages in influencing potential customers to purchase funeral insurance when re-engaging with them. Drawing inspiration from McCroskey's seminal work from 1969, two distinct approaches to communication a speaker employs when attempting to convince others are explored. The first approach involves relying on statistical evidence obtained from

external sources, emphasizing the available objective data. The second approach involves leveraging other individuals' experiences and opinions and utilizing personal narratives to engage the audience. Both methods aim to enhance the speaker's persuasiveness by presenting compelling arguments. Commonly, the inclusion of supporting material, such as evidence or proof, is believed to bolster the cogency of the information presented (Allen and Preiss 1997). Building upon this assumption, the research examines whether including facts and numerical information in the message, i.e., statistical evidence, effectively influences the audience's decision-making process. Alternatively, the potential power of anecdotal stories, i.e., narrative evidence, in shaping customer attitudes and behaviors is explored. By investigating the comparative impact of these two sub-treatments, statistical messaging and narrative messaging, the experiment aims to shed light on the most effective and persuasive approach to promote the purchase of funeral insurance by fostering re-engagement. Through the comprehensive analysis, it is sought to provide valuable insights that can inform future communication strategies for chatbot applications.

As a persuasive tool, statistical evidence encompasses quantitative information that relies on substantial data points (Hornikx 2018). This approach employs numerical measures to convince the message receiver. To illustrate the efficiency of statistical evidence, De Wit, Das, and Vet (2008) conduct a comparative study to raise awareness among homosexual men about the risk associated with hepatitis B virus infection. The researchers examined the impact of two distinct messages, with one emphasizing statistical evidence. They focused on communicating the increase in infection cases and risk levels using numeric measures. Similarly, Kopfman et al. (1998) explore how different message types could increase the number of individuals filling out organ donor cards. Their statistical message emphasizes the urgency of committing to organ donation by presenting factual information and statistics. This method offers the advantage of

applicability across a broader range of populations, as the information is grounded in extensive case data (Allen and Preiss 1997). However, it is important to note that statistical information can be prone to misunderstandings, particularly when individuals lack sufficient education and knowledge on interpreting such measures.

In contrast to statistical evidence, narrative evidence relies on concrete stories typically narrated from the perspective of one or a few protagonists (De Wit, Das, and Vet 2008; Kopfman et al. 1998). These anecdotes aim to share specific experiences, actions, and outcomes related to the topic at hand, intending to persuade the message receiver. De Wit, Das, and Vet (2008) exemplify the use of narrative evidence in their study by introducing a fictitious character named Remco, who describes his journey of hepatitis B virus infection in a first-person quote. This narrative message emphasizes the urgency of receiving vaccination for protection. Similarly, Kopfman et al. (1998) created fictitious scenarios based on real-life cases for their narrative messages. They vividly portrayed a college student who, after his death, saved numerous lives through organ donation. These narratives aim to engage the message receiver by being relatable and easily understood (Allen and Preiss 1997). One key advantage of narrative evidence is its ability to convey significant information using concise storytelling techniques (Kopfman et al., 1998). De Wit, Das, and Vet (2008) further elaborate that the persuasive effect of narrative evidence is based on the psychological principle of heuristics. Vividly presented information that resonates with the message receiver's circumstances can trigger strong emotional reactions and enable vivid imagination. This facilitates easier recall of the shared information and promotes active message processing. However, it is important to note that narrative evidence often consists of a single case (Hornikx 2018), reducing the probability of the message receiver relating to the scenario. In some cases, the feeling of

dissimilarity may even lead the message receiver to conclude that the issue does not affect them personally (Baesler and Burgoon 1994).

Sending out such treatments via chatbot requires careful consideration in designing them. Previous research indicates that many customers are skeptical of chatbot communication due to the absence of interaction with real humans (Adam, Wessel, and Benlian 2021). Chatbot technology faces the challenge of lower social presence (Konya-Baumbach, Billa, and von Janda 2023; Araujo 2018) as it lacks non-verbal cues like facial expressions, gestures, and vocal cues that are facilitated through physical appearance (Gunawardena and Zittle 1997). However, studies have demonstrated that chatbots can enhance social presence by applying anthropomorphism. Biocca (1997) defines social presence as the perception of one individual that the other instance it is communicating with is real and present. The concept of social presence traces back to Short, William, and Christie's (1976) discussions on telecommunication in social psychology. They developed a theory that social presence depends on a system's ability to convey information through verbal and non-verbal cues. Konya-Baumbach, Billa, and von Janda (2023) suggest that chatbots can increase social presence by incorporating anthropomorphic elements, such as names, profile pictures, emoticons, and human-like language. Anthropomorphism refers to attributing human-like characteristics, motivations, intentions, and emotions to non-human entities like chatbots (Epley, Waytz, and Cacioppo 2007). Considering the significance of social presence and the potential for anthropomorphism to enhance chatbot interactions, it becomes imperative to incorporate these concepts when designing the two message types within the context of chatbot communication. By infusing emotional narratives and utilizing the appropriate social cues and anthropomorphic elements, chatbot messages can be created that foster social presence, establish a sense of human-like interaction, and ultimately enhance user engagement and persuasion.

To date, the literature has not explored the relative effectiveness of statistical and narrative evidence when communicated via a chatbot, particularly within the context of the insurance purchase process. Therefore, this study aim to fill this research gap by drawing insights from existing studies and conducting a new experiment to determine which message type via chatbot is more effective.

The statistical message is carefully configured to encourage customers to continue purchasing. By distinguishing it from the narrative message in terms of social presence, it is designed to be worded in a straightforward manner, showing few emotions. The message begins with a general introduction, acknowledging that the chatbot has noticed the individual's pause in the funeral cover purchase. Subsequently, three relevant facts are presented: Firstly, the message highlights the substantial costs typically associated with funerals in South Africa, drawing data from a national news site (Moonstone 2022). It emphasizes how funeral insurance can cover these expenses, underscoring the financial protection it offers. Secondly, the message provides information regarding the number of adults in South Africa who already possess funeral cover, establishing the prevalence and acceptance of such insurance among the population (FSCA 2022). This statistic aims to create a sense of reassurance and comfort, implying that acquiring funeral insurance is a common and prudent decision. Lastly, the message emphasizes the increasing trend of individuals completing insurance purchases via WhatsApp. By highlighting this convenient and familiar mode of transaction, the message aims to instill confidence and a sense of ease in continuing the purchasing process immediately:

"Hey, we noticed that you did not finish the funeral cover purchase. 🤌 *Did you know that a typical funeral can cost between* ***R15,000 and R100,000?*** *Hence, many families need to take*

out loans to finance the funeral of family members. A funeral cover can relieve the financial burden as it covers costs up to ***R100,000.***

In South Africa, ***42% of adults already have funeral cover.*** *Become one of them to avoid financial distress in the future. It is as easy as it sounds:* ***85% of all sales are fully completed right here in WhatsApp, no phone call needed.***

Do you want to get a funeral cover now? Just click "Continue Quote“ and you will be guided through the process.”

Recognizing the significance of social presence in chatbot interactions, the narrative message is crafted to evoke emotions, employing carefully selected emojis. It begins by acknowledging the pause in the funeral insurance purchase, mirroring the introductory approach of the statistical message. However, the narrative message takes a different approach by incorporating a first-person quote from a fictitious customer who has personally experienced the financial burden of funeral costs following the loss of a loved one. This quote humanizes the message and makes it more relatable, allowing the audience to empathize with the challenges individuals face in similar situations. Through the use of emotionally charged words such as “touching story", “life-changing decision”, and “relieved”, the narrative message aims to elicit a strong emotional response from the recipient. As the narrative unfolds, the first-person quote provides a personal perspective that allows the audience to immerse themselves in the story, fostering empathy and a deeper understanding of the need for adequate coverage.

“Hey, we noticed that you did not finish the funeral insurance purchase. We want to share with you a touching story from a recent CompariSure customer who made a life-changing decision :

🌰*"After unexpectedly losing a beloved family member, I faced an impossible task: providing a dignified farewell while shouldering the heavy burden of funeral costs alone. I don't want this to happen to me or my loved ones again. CompariSure was easily able to help me purchase a funeral cover policy. I am now very relieved that my family won't have the added stress of funding my funeral."* ♥

Join the countless individuals who have turned their personal experiences into life-changing decisions. Do you want to get a funeral cover now? Just click "Continue Quote" and you will be guided through the process. 🌟"

In line with the overarching goal, both messages conclude by inviting the recipient to consider continuing the quote. Posing this question, encourages the individual to take the next step in the funeral insurance purchase process, motivated by the emotional impact of the shared experience and the desire to avoid a similar burden.

IV. METHODOLOGY

4.1 Data Collection

The primary objective is to address the core research question of whether reminders can effectively retarget customers who initiated the funeral purchasing process via chatbot but discontinued before concluding a sales transaction. To collect data for the study, RatherChat's chatbot is utilized and employs four automatic reminders dispatched at three times during the day. A condition is implemented to ensure that individuals who halted the process shortly before a threshold time do not receive a reminder immediately after. According to this, the earliest reminder can be sent out two hours after their last interaction with the chatbot. For instance, if a customer stops the process at 11.30 am, the earliest possible reminder they could receive

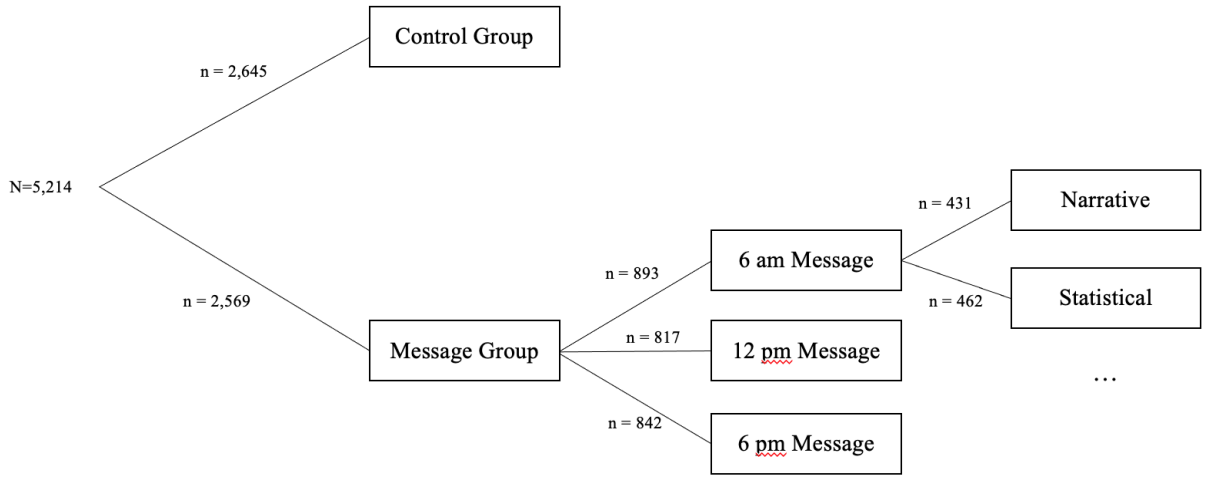
would hence be at 6 pm. The sample includes 5,214 observations collected over a total period of eight weeks.

A customer receives either none or one of the two messages after the conversation has been interrupted. In that case, she or he will be given the option to continue the quote or indicate their disinterest by selecting ‘not now’. Once the customer chooses to proceed by clicking ‘continue quote’, they are guided back to their last interaction with the chatbot, which reflects the previous interaction's dropout. They are prompted to provide relevant information required for completing the funeral insurance purchase. Throughout this process, various interaction events are tracked, such as the moment the initial conversation pauses, the timing of reminder dispatch, and the end of the conversation after re-engagement. These data points are subsequently compiled into a comprehensive dataset.

4.2 Randomization

Each individual within the sample of 5,214 observations is randomly allocated to a specific group. Firstly, roughly one-third (n = 2,645) is assigned to the control group, where the observations are excluded from any intervention. This group serves as a benchmark with which the actual effect of the treatments can be determined. Another third is allocated to the message group (n = 2,569), as shown in Figure 1 below. Participants receive a statistical or a narrative message when allocated to the message group. Simultaneously, each treated participant randomly receives the reminder at one of the three preselected time slots. For instance, 431 participants receive the narrative and 462 the statistical message at 6 am. Further, it allows to accumulate over the specific time slots, irrespectively of which reminder type has been sent. This results in a sample size of n = 1,813 for participants receiving any reminder in the morning, n = 1,638 at noon, and n = 1,727 in the evening.

Figure 1: Randomization of the sample



4.3 Dependent Variables

To effectively measure reminders are an effective tool to retarget customers who have interrupted the purchasing process, two outcome variables are specified. Firstly, a binary variable can take on a value of one if the chatbot user engages in the conversation after receiving one of the four sub-treatments at one of the three times of the day. If users continue the quote, it is considered successful retargeting, allowing them to proceed with the funeral insurance purchasing process. Secondly, the outcome variable sale is also designed as a binary variable, taking on a value of one if a sale occurs and zero if otherwise. From a marketing strategy perspective, the ultimate goal of sending reminders is to increase sales. Hence, this outcome variable is core to the analysis with the goal to test the effectiveness of reminders.

4.4 Independent and Control Variables

Throughout collecting data, a range of variables that can serve as explanatory factors in this analysis are gathered. The treatment variables are of particular importance, which indicate the specific reminder each customer received and the corresponding time of day when the treatment

was administered. Moreover, data on various interaction moments are captured, such as when the initial conversation and the conversation after re-targeting ended. In addition to these interaction-related variables, various socio-economic data such as number of children, language spoken at home[3], and the number of policy members are collected. Additionally, conducting a subsample analysis with the variable age is only possible. Throughout the chatbot conversation the users are not asked to provide their age until shortly before finalizing the policy contract. The dataset does not contain the variable gender, as it is not required for generating a quote on funeral cover and hence not asked for throughout the process within the chatbot conversation. For a comprehensive list of variables, their corresponding names in Stata, and detailed descriptions, please refer to the Appendix.

4.5 Hypotheses

The hypothesis testing is split into two sections, Panel A and Panel B. The objective of Panel A is to investigate the effectiveness of sending reminders on the two outcome variables, continue quote and sale. In the analysis, the three preselected time slots - morning (6 am), noon (12 pm), and evening (6 pm) - are considered to further explore the optimal timing of sending reminders. To test the optimal time of dispatch, all reminders regardless of their type are accumulated. The guiding hypothesis states:

A) H1: Reminders are an effective tool to retarget customers at the most successful time of the day, irrespective of the type of reminder sent.

[3] South Africa has eleven official languages, namely English, Afrikaans, isiNdebele, isiXhosa, isiZulu, Sesotho, Sepedi, Setswana, siSwati, Tshivenda, Xitsonga. English serves as the common language of communication (Alexander 2023).

Panel B builds upon the previous Panel by further investigating how the reminders should be designed to successfully retarget chatbot users. This section's timing component is neglected as it solely examines the optimal design of reminders. For this purpose, Panel B.i) explores the effectiveness of the predefined designs for messages in general. While in a second step, in Panel B.ii) these broad types are specified into their subgroups: statistical and narrative message. The hypothesis states:

B) H1: Regardless of the time of the day, an effective reminder design exists to re-engage customers who abandoned the purchasing process.

4.6 Empirical Specification

Panel A of the empirical testing aims to identify the optimal timing to re-engage with customers who had previously stopped their purchase process of funeral cover. Based on the two key outcome variables (*outcome*) the effectiveness of each time slot is evaluated: continue quote (*cont_quote*) and sale (*sale*). Several linear regression models to analyze the impact of these time slots on each outcome variable. In these models, the coefficients β_1, β_2, and β_3 represent the influence of receiving a reminder at 6 am (*morning*), 12 pm (*noon*), and 6 pm (*evening*), respectively. The error term *e* in the equation measures the disparity between the actual outcome variable value and the predicted value generated by the model calculations. The linear regression model is given by Equation 1:

$$1) \quad outcome = \beta_0 + \beta_1 \times morning + \beta_2 \times noon + \beta_3 \times evening + e$$

Panel B compares the impact of receiving a message on the outcome variables in general. In a second specification, the effect of narrative vs. statistical message on the three outcome

variables, regardless of timing considerations is examined. Equation 2 measures the effect of the reminder type on the dependent variables. Similarly, Equation 3 illustrates the linear regression model for measuring the effect of the specific sub-treatments.

2) $outcome = \beta_0 + \beta_1 \times message + e$

3) $outcome = \beta_0 + \beta_1 \times narrative + \beta_2 \times statistical + e$

V. RESULTS

5.1 Empirical Results

Table 1 presents Panel A and B results using the dataset with 5,214 observations. In Panel A, highly significant results regarding the effectiveness of reminders are observed. Based on this finding, the null hypothesis regarding quote continuation can be confidently rejected, indicating that reminders effectively retarget customers, thereby supporting the alternative hypothesis. For instance, sending out reminders at noon, irrespective of their type, leads to an approximately 15% increase in the likelihood of users continuing the quote. The difference in the coefficients of the three day times is smaller than the standard errors between them, indicating that it cannot be said with certainty which time is most effective for quote continuation. Albeit promising significant effects on the uptake of further conversation after receiving a reminder, none of the three time slots reveals a positive effect on completed sales transactions. This result indicates that the null hypothesis cannot be rejected regarding sales, implying that sending reminders does not necessarily lead to increased completed transactions. Reminders serve as a valuable tool to retarget customers but fail to evoke a positive influence on sales.

Table 1: Overall results of RCTs

	(1) Continue quote	(2) Sale
Panel A. Direct impact of timing		
Morning (6 am)	0.112	-0.002
	(0.017)***	(0003)
Noon (12 pm)	0.121	0.001
	(0.017)***	(0.004)
Evening (6 pm)	0.117	0.000
	(0.017)***	(0.004)
R - squared	0.1	0.01
Observations	5,214	5,214
Panel B. i) Direct impact of reminder type		
Message	0.115	-0.001
	(0.012)***	(0.003)
R squared	0.1	0.01
Observations	5,214	5,214
Panel B. ii) Direct impact of sub-reminder type		
Narrative message	0.103	-0.001
	(0.015)***	(0.004)
Statistical message	0.127	0.000
	(0.015)***	(0.004)
R - squared	0.1	0.01
Observations	5,214	5,214

Note: *** p<0.01, ** p<0.05, * p<0.1. Reminders increase the likelihood of quote continuation but have no impact on sales. The unit of observation is a chatbot user. Panel A reports the result when reminders are dispatched at three times during the day. Panel B.i. shows results for general reminder types, Panel B.ii. represents findings splitted by subcategories of reminders. Column 1 and 2 present results regarding two outcome variables, quote continuation, and sales transactions. Controls include the difference between the end of the initial conversation and receipt of the reminder, the number of members insured under the policy, the language spoken at home, and the number of children. The robust standard errors are reported in parentheses.

Panel B.i) indicates a strongly positive impact for messages on the probability of users continuing the quotation within the chatbot conversation as they exhibit an average increase of 12%. This result favors the alternative hypothesis, emphasizing the effectiveness of the

reminder design when retargeting chatbot users. Considering the impact of the two reminders on sales, the results fail to reject the null hypothesis for the second outcome variable. Like findings in Panel A, sending such reminders does not yield higher sales transactions. While approximately one-third of total sales in the sample is completed by the control group, two-thirds are almost equally distributed among the two reminder groups, as shown in Table 2. Hence, the findings support that the impact of reminders on sales approaches zero.

Table 2: Distribution of completed sales among reminder types

	Control Group	Message Receiver
Sale	32	29
No Sale	2,613	2,540
Observations	2,645	2,569

Note: Table shows equal distribution of sales among the control group and the two treatment groups, message receiver and quiz receiver. Total observations sum up to 7,755.

According to the results in Panel B.i), message reminders successfully convince users to take up the quotation where they left off. In more detail, this form of reminder is further split into statistical and narrative messages in Panel B.ii), both being highly significant. Both messages increase the likelihood of continued conversation by 12% on average, providing evidence favoring the alternative hypothesis. It cannot be said with certainty that either of the two messages is statistically more powerful to convince recipients to continue the conversation. As expected, considering the results in Panel B.i), both message types have no significant effects on sales. Hence, the findings fail to reject the null hypothesis regarding the second outcome variable.

5.2 Subsample Analysis

In the diverse regional landscape of South Africa, a variety of eleven official languages exist, all of which are represented in the sample. Approximately 60% of the individuals in the study disclose English as their primary language spoken at home. It is important to note that many South African citizens are bilingual, with English as a common language for communication. Hence, some individuals may indicate English as their first language but also speak one of the other ten languages at home. Following English, the second-largest group in the dataset comprises isiXhosa speakers (9.35%), followed by those who identify themselves with the Zulu language (8.72%). The distribution of the eleven languages within the dataset is shown in the Appendix.

Table 3: Panel A results clustered by language spoken at home

	(1)	(2)	
i) Continue Quote	English	Other	Prob > F
Morning (6 am)	0.109	0.118	0.768
	(0.021)***	(0.029)***	
Noon (12 pm)	0.13	0.111	0.5206
	(0.021)***	(0.029)***	
Evening (6 pm)	0.122	0.113	0.772
	(0.022)***	(0.03)***	
R squared	0.13	0.05	
Observations	3,086	2,128	
ii) Sale			
Morning (6 am)	-0.002	000.0	0.957
	(0.004)	(0.007)	
Noon (12 pm)	-0.001	0.004	0.534
	(0.005)	(0.008)	
Evening (6 pm)	-0.001	0.001	0.761
	(0.005)	(0.008)	
R squared	0.02	0.01	
Observations	3,086	2,128	

Note: *** p<0.01, ** p<0.05, * p<0.1. When split by language spoken at home, reminders increase the likelihood of quote continuation but have no impact on sales. The unit of observation is a chatbot user.

Column 1 and 2 present results regarding the two subgroups, English and any other language. Controls include the difference between the end of the initial conversation and receipt of the reminder, number of members insured under the policy, language spoken at home, and number of children. The robust standard errors are reported in parentheses.

To draw further conclusions on Panel A, the sample is subdivided into an English-speaking group and one containing all other languages. As shown in Table 3, the coefficients describing the relationship between timing and the likelihood of chatbot users continuing the quote exhibit significance across all three time slots for the English subgroup and all other languages. Consistent with the initial results, the reminders have no significant impact on funeral insurance sales. When employing a Wald test to investigate whether the coefficients between the two groups have significant differences, it is proven that they are consistently equal. Thus, it cannot be concluded that there are major differences among language groups when retargeting chatbot users.

To obtain more intricate findings for Panel B.i.), subcategories are established by examining the time interval between the conclusion of the initial conversation and the moment of the reminder dispatch. These subgroups are categorized into four segments, each representing a specific time interval in hours. The first group, in which reminders are sent within the first five hours after the initial interaction stops, is a reference to which all other groups are compared. Results are shown in the Appendix. Conducting the Wald test, it is discover that all coefficients in the subgroups are not statistically different from those in the reference group. Hence, no recommended time interval between the end of the initial conversation and dispatching reminders can be derived. Further, these results reveal consistency with those found in Panel B.i).

5.3 Robustness Check

Considering the age distribution regarding sales, as shown in the Appendix, it is shown that most sales occur within the middle-aged population until age 45. Knowing this, it is useful to investigate if the effect of the reminders differs when the sample is categorized into two age groups. This analysis requires age as the determining factor of categorization, which reduces the sample size to 2,950 as the dataset does not entail the variable age for all 5,214 observations. Still, when observing the results on quote continuation in Table 5, no major differences in the coefficients compared to the general analysis are observed. In contrast to previous findings for the second outcome variable sale, this subsample analysis reveals significant results for the age group older than 45. Looking into the distribution of sales among the control group and two reminder groups, the data show a fairly equal distribution across the age group younger than 45, as shown in Table 4. Contrastly, almost all sales in the second sub-group, aged above 45 years, are attributed to the control group, with only one purchase being made after receiving a message reminder.

Table 4: Distribution of completed sales among control group and reminder types clustered by age

Age <= 45	Control Group	Message Receiver
Sale	20	28
No Sale	1.015	970
Observations	1.035	998

Age > 45	Control Group	Message Receiver
Sale	12	1
No Sale	447	457
Observations	459	458

Note: Equal distribution of sales among the control group and the message group for chatbot users aged below 45. Almost zero sales under message receivers when aged above 45. Total observations sum up to 4,379.

These findings are mirrored in the results in Table 5 as coefficients for the second group even partially take on negative values. This implies that receiving a message reminder seems to impact the purchasing behavior of people older than 45 negatively. Given several unobservable external factors, this finding can only be vaguely interpreted. It may be that users above a certain age threshold are turned away from this form of marketing, even resulting in a backlash effect of message reminders. Firstly, older people could be simply annoyed by receiving additional and relatively long messages. Secondly, a message about the urgency of purchasing a funeral cover may trigger anxiety and death-related thoughts. These two reasons may lead to a lower willingness to deal with such a topic, resulting in close to zero sales transactions. No significant negative effect is found for quiz reminders on retargeting users, elevating the negative impact of message reminders for people above 45.

Table 5: Overall results categorized by users aged below and above 45 years

	i) Continue Quote			*ii) Sale*		
	(1)	(2)		(1)	(2)	
	Age <=45	Age > 45	Prob > F	Age <=45	Age > 45	Prob > F
Panel A. Direct impact of timing						
Morning (6 am)	0.106	0.097	0.846	0.006	-0.025	0.000
	(0.029)***	(0.044)***		(0.009)	(0.007)***	
Noon (12 pm)	0.156	0.09	0.16	0.014	-0.025	0.000
	(0.031)***	(0.045)***		(0.011)	(0.007)***	
Evening (6 pm)	0.14	0.1	0.388	0.009	-0.021	0.001
	(0.031)***	(0.046)***		(0.010)	(0.01)**	
R squared	0.06	0.05		0.01	0.01	
Observations	2,033	917		2,033	917	
Panel B.i). Direct impact of reminder type						
Message	0.132	0.094	0.219	0.009	-0.023	0.000
	(0.021)***	(0.031)***		(0.007)	(0.008)***	
R squared	0.06	0.05		0.01	0.01	
Observations	2,033	917		2,033	917	
Panel B. ii) Direct impact of sub-reminder type						
Narrative	0.127	0.077	0.184	0.01	-0.025	0.000
	(0.026)***	(0.038)***		(0.009)	(0.007)***	
Statistical	0.137	0.112	0.513	0.008	-0.022	0.001
	(0.025)***	(0.038)***		(0.008)	(0.009)**	
R squared	0.06	0.05		0.01	0.01	
Observations	2,033	917		2,033	917	

Note: *** p<0.01, ** p<0.05, * p<0.1. Robustness check. Reminders increase the likelihood of quote continuation, irrespective of age group. In the form of messages, they negatively impact sales in the group of users above 45. No other impact on sales. The unit of observation is a chatbot user. Panel A reports the result when reminders are dispatched at three distinct times during the day. Panel B.i. shows results for general reminder types, Panel B.ii. represents findings splitted by subcategories of reminders. Column 1 and 2 present results regarding the two subgroups, age below 45 and above 45, respectively. Controls include the difference between the end of the initial conversation and the receipt of the reminder, number of members insured under the policy, language spoken at home, and number of children. The robust standard errors are reported in parentheses.

VI. DISCUSSION

6.1 Overall Results

Many of the existing studies in the literature have consistently demonstrated that reminders positively impact driving customer engagement (Gravert 2021; Li et al. 2022; Goic, Rojas, and Saavedra 2021). Reminders can embrace specific behavioral action, effectively directing attention toward critical decision-making processes (Gravert 2021). Li et al. (2022) reinforce the effectiveness of reminders as e-coupons on retargeting customers. The implementation of targeted reminders for coupons significantly boosts the coupon redemption rate. Additionally, Goic, Rojas, and Saavedra (2021) focus on reminding customers about incomplete transactions or rekindling engagement with those inactive on websites for extended periods. Their study yields significant outcomes, particularly regarding the effectiveness of such reminders in increasing revenues through online channels. The findings of this research support the notion that users can be effectively retargeted through reminders within the chatbot purchasing process. A significant positive coefficient on quote continuation is observed, regardless of the treatments applied to different subgroups. Hence, the findings align with Gravert (2021) and Li et al. (2022), indicating that engagement can be enhanced when using reminders as promotional tools. However, the conclusion put forth by Goic, Rojas, and Saavedra (2021) that reminders

can increase overall sales cannot be supported. On the contrary, reminders appear to have no positive effect on sales.

In the study context, reminders effectively persuade users to continue the quotation. However, despite this positive effect on quote continuation, neither design – narrative nor statistical - sufficiently influences overall sales transactions. This suggests that both designs may not be optimal within this specific study context. The findings align with literature, such as Du et al. (2020) and Gravert (2021), which indicate that reminders conveying the likelihood of an undesirable situation may have no effect or even a negative impact on the desired outcome. The contribution to the literature underscores the limited effectiveness of reminders with negative connotations in achieving sales objectives, corroborating findings from related studies.

As previously outlined, several external factors may hinder the completion of the purchase of funeral cover. Firstly, a product requiring a stable income may not be affordable to many retargeted chatbot users. Even though quotes start as low as ZAR20 (~ one EUR), this might still be beyond possible for individuals with sporadic employment. Secondly, many people interacting with the chatbot might use the service to compare different product offerings to seek the best quotation. Consequently, retargeted customers may be interested in obtaining a personalized quotation and not proceed with the purchase transaction. Thirdly, once the purchasing process reaches a stage in which personal details must be shared such as the provision of identification, bank provider, and account details, they may be deterred by the administrative effort and prefer to stop the process. Fourthly, external distractions may make it impossible for users to continue the conversation. Such distractions could be due to work or family-related obligations, other push notifications on the phone resulting in a loss of attention, or a network disconnection. Fifthly, as section two of this paper describes, funeral associations play an important role in South African communities. Despite the higher risk of

mismanagement and corruption of informal means of funeral cover, many citizens may not be inclined to enter contracts with formal insurance providers. The latter lacks the emotional support and spiritual counsel that funeral associations can offer. Sixthly, as previously mentioned, the cost of data can also result in a hindrance, as it is relatively expensive in South Africa and thus an exclusive resource for some users. Finally, achieving successful contract completion may hinge on two critical factors: a comprehensive grasp of the product's financial scope and a proficient use of digital devices. These factors can potentially deter individuals from fully understanding the complexity of the product or feeling overwhelmed using chatbot technology for purchasing activity. Users may lack trust in this novel technology when handling sensitive information, leading users to hesitate and thus fully engage in the digital purchasing process.

The contribution to the literature opens a significant avenue for discussion. Considering that marketing is a well-established sector in most companies with substantial resources allocated to crafting promising promotional strategies, it is intriguing to encounter a robust null result regarding the effectiveness of reminders. While this study does not intend to cast doubt on marketing as a whole, it is wished to emphasize that sending reminders does not contribute to increasing sales in the specific case of this study. This represents only a small contribution to the broader topic. However, further research examining whether these results hold in regional markets or for various products could be insightful.

6.2 Timing

To the best of the authors' knowledge, no existing literature specifically examines the impact of sending reminders at various times throughout the day on the continuation of a conversation via chatbot and subsequent sales transaction. Academic studies on the optimal timing of sending

survey invitations reveal that certain time slots can be more effective regarding response rates. For instance, Lindgren et al. (2020) find significant short-term effects, suggesting that sending surveys on weekdays between noon and evening is optimal in their study context. Nevertheless, as the study period advances, these effects gradually diminish. Faught, Whitten, and Green Jr. (2004) demonstrate that Wednesday mornings yield the highest response rates. This finding aligns with the results by Lewis and Hess (2017), who conclude that sending invitations during the early hours of the day is more effective in eliciting responses. This research does not uncover such significant differences in quote continuation among the three predetermined time slots during the day. This implies that communication timing with users may not be as critical within messenger-based chatbot technology. WhatsApp, which enjoys extensive popularity in South Africa, is a platform where users are generally receptive to frequent messages since they can access and read them conveniently. Many users may even appreciate regular contact, as WhatsApp is a platform where people enjoy spending their time and receiving messages is an integral part of the experience.

6.3 Message

The effectiveness of both message types in persuading the audience toward a particular matter remains a topic of debate in the literature, with mixed findings. According to De Wit, Das, and Vet (2008) statistical evidence is often deemed less effective than narratives due to its lack of memorable information. The authors find that participants perceived a higher personal risk of hepatitis B infection when exposed to narrative evidence. They propose that narratives more effectively highlight personal risk by evading defensive message processing. Additional studies, such as that conducted by Baesler and Burgoon (1994), support the notion that narrative evidence is more effective in conveying specific information. In contrast, Kopfman et al. (1998) discover that sharing statistical evidence about organ donation had a greater impact on systematic information processing, leading to heightened cognitive heuristics. Allen and Preiss

(1997) substantiate these findings by comparing both types of messages. It is worth noting that some studies have failed to yield a clear consensus on which message type is more effective. For instance, Zebregs et al. (2015) find that while statistical evidence strongly influenced beliefs and attitudes, anecdotal evidence had a greater impact on intentions. The findings of this study contribute to Zebregs et al. (2015) conclusion as no significant differences in the effectiveness of statistical and narrative messages could be found. These varying results of the findings of this study and those from the literature highlight the complexity of determining the superior effectiveness between statistical and narrative evidence.

Some research suggests that sending reminders in the form of messages may not only have no positive effect but could potentially backfire, resulting in a negative impact on customer behavior. Gravert (2021) highlights this challenge and indicates that when health-related information is included in a reminder, readers might experience negative emotions and become irritated by the message. Upon analyzing the entire sample in this study, this research does not find any significant results for sales. However, in the subgroup analysis focusing on different age groups, small but highly significant negative coefficients on sales for the subsample aged above 45 is found. This suggests that individuals over 45 may react negatively when receiving a reminder as a message due to an unobservable factor. Since message reminders contain information about funeral cover, which is closely associated with death, they may evoke feelings of threat among older chatbot users, leading to this adverse response.

What implications does this have for configuring optimal reminders in the form of message dispatch? It likely suggests that the same design principles employed in this study remain applicable. Still, great attention needs to be paid regarding the content, given its sensible topic that may trigger anxiety. It would be intriguing to explore whether concealing certain

information, such as funeral and death-related aspects, could be more effective. Instead, the message could emphasize the advantages and create a positive connotation, such as funeral cover policies being attractive alternatives to savings accounts. As previously described, chatbot technology lacks the presence of a real human. Social presence in this context plays an enormous role and adding additional anthropomorphism elements may result in different results regarding the effectiveness of such reminders.

VII. FINAL REMARKS

This study addresses a critical challenge in chatbot communications: the high customer attrition rate during purchasing. The research aims to investigate the effectiveness of re-engaging these customers through the chatbot to overcome interruptions. It examines the impact of different daily dispatch times and distinct reminder designs on quote continuation and sales transactions. The findings contribute to the broader literature on chatbot interactions and customer engagement. They highlight the complexities of re-engagement strategies and the importance of tailoring them to specific contexts. While reminders prove effective in keeping customers interested, their influence on sales remains limited.

As the financial industry continues to embrace digital solutions, the role of chatbot technology becomes increasingly vital. Conducting additional research to assess strategies for promoting specific products could provide valuable insights into the argument that traditional marketing methods may no longer be adequate in this evolving technological landscape.

REFERENCES

Adam, Martin, Michael Wessel, and Alexander Benlian. 2021. "AI-based chatbots in customer service and their effects on user compliance." *Electronic Markets* 31, no. 2: 427-445.

Adedokun, Theophilus Adedayo, and Sylvia Phiwani Zulu. 2022. "Towards digital inclusion in South Africa: the role of public libraries and the way forward." *Interdisciplinary Journal of Economics and Business Law; Vol. 11, Issue 4*.

Ahmed, Kabir. 2021. "Digital Revolution and Insurance Industry: Some Important Issues for India." *Issue 3 Int'l JL Mgmt. & Human.* 4: 4194.

Alexander, Mary. 2023. “The 11 languages of South Africa”. *South Africa Gateway*. April, 1, 2023.
https://southafrica-info.com/arts-culture/11-languages-south-africa/.

Allen, Mike, and Raymond W. Preiss. 1997. "Comparing the persuasiveness of narrative and statistical evidence using meta-analysis." *Communication research reports* 14, no. 2: 125-131.

Araujo, Theo. 2018. "Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions." *Computers in Human Behavior* 85: 183-189.

Baesler, E. James, and Judee K. Burgoon. "The temporal effects of story and statistical evidence on belief change." *Communication research* 21, no. 5 (1994): 582-602.

Bagus, Umar, Clayton Hall, Uzayr Jeenah and Gökhan Sari. 2020. “Beyond COVID-19: Charting the road to recovery for South African insurers.” *McKinsey*, November 2, 2017. https://www.mckinsey.com/featured-insights/middle-east-and-africa/beyond-covid-19-charting-the-road-to-recovery-for-south-african-insurers

Barrett, Michael, Elizabeth Davidson, Jaideep Prabhu, and Stephen L. Vargo. 2015. "Service innovation in the digital age." *MIS Quarterly* 39, no. 1: 135-154.

Berg, Erlend. 2011. “Funeral insurance.” CSAE Working Paper, Centre for the Study of African Economies, University of Oxford, England.

Bester, Hennie, Doubell Chamberlain, Ryan Short, and Richard Walker. 2005. “A Regulatory Review of Formal and Informal Funeral Insurance Markets in South Africa.” Genesis Analytics.

Biocca, Frank. 1997. "The cyborg's dilemma: Progressive embodiment in virtual environments." *Journal of computer-mediated communication* 3, no. 2: JCMC324.

Catlin, Tanguy, Johannes-Tobias Lorenz, Björn Münstermann, and Valentino Ricciardi. 2017. "Insurtech-the Threat That Inspires." *McKinsey, March 1, 2017.* https://www.mckinsey.com/industries/financial-services/our-insights/insurtech-the-threat-that-inspires

De Wit, John BF, Enny Das, and Raymond Vet. 2008. "What works best: objective statistics or a personal testimonial? An assessment of the persuasive effects of different types of message evidence on risk perception." *Health Psychology* 27, no. 1: 110.

Deloitte. 2017. "*Unlocking New Markets Digital Innovation in Africa's Insurance Industry*." https://www2.deloitte.com/za/en/pages/financial-services/articles/digital-innovation-in-africa-insurance-industry.html

Dercon, Stefan, Joachim De Weerdt, Tessa Bold, and Alula Pankhurst. 2006. "Group-based funeral insurance in Ethiopia and Tanzania." *World development* 34, no. 4: 685-703.

Deutskens, Elisabeth, Ko De Ruyter, Martin Wetzels, and Paul Oosterveld. 2004. "Response rate and response quality of internet-based surveys: An experimental study." *Marketing letters* 15: 21-36.

Du, Ninghua, Lingfang Li, Tian Lu, and Xianghua Lu. 2020. "Prosocial compliance in P2P lending: A natural field experiment." *Management Science* 66, no. 1: 315-333.

Epley, Nicholas, Adam Waytz, and John T. Cacioppo. 2007. "On seeing human: a three-factor theory of anthropomorphism." *Psychological review* 114, no. 4: 864.

Faught, Kent S., Dwayne Whitten, and Kenneth W. Green Jr. 2004."Doing survey research on the internet: Yes, timing does matter." *Journal of Computer Information Systems* 44, no. 3: 26-34.

FSCA. 2022. "*Financial Sector Outlook Study*." https://www.fsca.co.za/Documents/FSCA%20Financial%20Sector%20Outlook%20Study%202022.pdf

FSCA. n.d. " *FSCA Financial Inclusion Strategy*." https://www.fsca.co.za/Documents/FSCA%20Financial%20Inclusion%20Strategy.pdf

Gatzioufa, Paraskevi, and Vaggelis Saprikis. 2022. "A literature review on users' behavioral intention toward chatbots' adoption." *Applied Computing and Informatics* ahead-of-print.

Genesis Analytics. 2019. "*Fintech Scoping in South Africa*." https://www.treasury.gov.za/comm_media/press/2020/WB081_Fintech%20Scoping%20in%20SA_20191127_final%20(002).pdf

Global World Index. 2020. “GlobalWebIndex’s flagship report on the latest trends in social media.”
https://www.gwi.com/hubfs/Social%20Media%20Trends%20Report.pdf?sbrc=1gdn8hbD-aDjRiBvV1JM-hg%3D%3D%248MqYz9TUB2uNPV6Ao0lV_w%3D%3D

Goic, Marcel, Andrea Rojas, and Ignacio Saavedra. 2021. "The effectiveness of triggered email marketing in addressing browse abandonments." *Journal of Interactive Marketing* 55, no. 1: 118-145.

Gravert, Christina Annette. 2021. "Reminders as a tool for behavior change." *A version of this article is in Mazar N and Soman D.(in press), Behavioral Science in the Wild, Toronto, Canada: University of Toronto Press, Forthcoming*.

Gunawardena, Charlotte N., and Frank J. Zittle. 1997."Social presence as a predictor of satisfaction within a computer-mediated conferencing environment." *American Journal of Distance Education* 11, no. 3: 8-26.

Hornikx, Jos. 2018. "Combining anecdotal and statistical evidence in real-life discourse: Comprehension and persuasiveness." *Discourse Processes* 55, no. 3: 324-336.
https://www.fsca.co.za/Documents/FSCA%20Financial%20Sector%20Outlook%20Study%202022.pdf

Jacques Erasmus. 2023. “The Changing Landscape in Life Insurance Presents an Opportunity for SA’s Long Term Insurers.” *FANEWS*. March 17, 2023.
https://www.fanews.co.za/article/life-insurance/9/general/1202/the-changing-landscape-in-life-insurance-presents-an-opportunity-for-sa-s-long-term-insurers/36637

Karlan, Dean, Melanie Morten, and Jonathan Zinman.2015. "A personal touch in text messaging can improve microloan repayment." *Behavioral Science & Policy* 1, no. 2 (2015): 25-31.

Khasoane, Napo Claudius. 2019. "Corruption and patronage in post-colonial Sub-Saharan Africa: an Afrocentric ethical critique." PhD diss.

Koetter, Falko, Matthias Blohm, Jens Drawehn, Monika Kochanowski, Joscha Goetzer, Daniel Graziotin, and Stefan Wagner. 2019. "Conversational agents for insurance companies: from theory to practice." In *Agents and Artificial Intelligence: 11th International Conference, ICAART 2019, Prague, Czech Republic, February 19–21, 2019, Revised Selected Papers 11*, pp. 338-362. Springer International Publishing.

Konya-Baumbach, Elisa, Miriam Biller, and Sergej von Janda. 2023. "Someone out there? A study on the social presence of anthropomorphized chatbots." *Computers in Human Behavior* 139: 107513.

Kopfman, Jenifer E., Sandi W. Smith, James K. Ah Yun, and Annemarie Hodges. 1998."Affective and cognitive reactions to narrative versus statistical evidence organ donation messages.": 279-300.

Koprivica, Marija. 2018. "Insurtech: Challenges and opportunities for the insurance sector." In *2nd International Scientific Conference ITEMA*, pp. 619-625.

Kotecha, Shivani. 2023. "Learnings from our WhatsApp chatbot survey platform – A lightweight, digital research tool that meets the customers where they are." *BFA Global*, June 19, 2023. https://bfaglobal.com/idc/insights/learnings-from-our-whatsapp-chatbot-survey-platform-a-lightweight-digital-research-tool-that-meets-the-customers-where-they-are/#:~:text=In%20South%20Africa%2C%2095%25%20of,of%20WhatsApp%20on%20the%20continent.

Lewis, Taylor, and Karl Hess. 2017. "The effect of alternative e-mail contact timing strategies on response rates in a self-administered web survey." *Field Methods* 29, no. 4: 351-364.

Li, Li, Xiaotong Li, Wenmin Qi, Yue Zhang, and Wensheng Yang. 2022. "Targeted reminders of electronic coupons: using predictive analytics to facilitate coupon marketing." *Electronic Commerce Research*: 1-30.

Liberto, Daniel. 2022. "What Is a Written Premium in the Insurance Industry?" Investopedia, November 29, 2020. https://www.investopedia.com/terms/w/written-premium.asp#:~:text=Key%20Takeaways,a%20specific%20period%20of%20time.

Lindgren, Elina, Elias Markstedt, Johan Martinsson, and Maria Andreasson. 2020."Invitation timing and participation rates in online panels: Findings from two survey experiments." *Social Science Computer Review* 38, no. 2: 225-244.

Lusardi, Annamaria, and Olivia S. Mitchell. 2011. "Financial literacy and retirement planning in the United States." *Journal of pension economics & finance* 10, no. 4: 509-525.

McCroskey, James C. 1969. "A summary of experimental research on the effects of evidence in persuasive communication." *Quarterly Journal of Speech* 55, no. 2: 169-176.

McLeod, Caroline C., Carrie N. Klabunde, Gordon B. Willis, and Debra Stark. 2013. "Health care provider surveys in the United States, 2000–2010: a review." *Evaluation & the health professions* 36, no. 1: 106-126.

McShane, Blakely B. et al. 2017. "When Are Consumers Most Likely To Feel Overwhelmed By Their Options?" *KellogInsight*, October 3, 2017. https://insight.kellogg.northwestern.edu/article/what-predicts-consumer-choice-overload

Miller, Andrew D., Jessica Pater, and Elizabeth D. Mynatt. 2013."Design strategies for youth-focused pervasive social health games." In *2013 7th international conference on pervasive computing technologies for healthcare and workshops*, pp. 9-16. IEEE.

Milliman. 2023. "*South Africa: Insurance Industry Update*." https://za.milliman.com/-/media/milliman/pdfs/2023-articles/2-10-23-sa-insurance-industry-update.ashx

Moonstone. 2022. "Funeral Insurance – a Product for the Poor, or Is It?" *Moonstone,* 4 November, 2022. https://www.moonstone.co.za/funeral-insurance-a-product-for-the-poor-or-is-it/.

National Treasury. n.d. " *An Inclusive Financial Sector for All.*" https://www.treasury.gov.za/comm_media/press/2020/Financial%20Inclusion%20Policy%20-%20An%20Inclusive%20Financial%20Sector%20For%20All.pdf

Nuruzzaman, Mohammad, and Omar Khadeer Hussain. 2020. "IntelliBot: A Dialogue-based chatbot for the insurance industry." *Knowledge-Based Systems* 196: 105810.
OECD. 2017. "*Technology and innovation in the insurance sector*." https://www.oecd.org/pensions/Technology-and-innovation-in-the-insurance-sector.pdf

OECD. 2022. "In Southern Africa, Leveling the Playing Field at Birth Critical to Reducing Inequality, Intergenerational Poverty." *OECD*, March 14, 2022. https://www.worldbank.org/en/region/afr/publication/in-southern-africa-leveling-the-playing-field-at-birth-critical-to-reducing-inequality-intergenerational-poverty

Olupona, Jacob. 2015. "The Spirituality of Africa." *The Harvard Gazette*, October 6, 2015. https://news.harvard.edu/gazette/story/2015/10/the-spirituality-of-africa/#:~:text=The%20defining%20line%20between%20deities,illness%20upon%20their%20living%20descendants

PwC. 2016. "*Opportunities await: How InsurTech is reshaping insurance.* Global FinTech Survey."https://www.pwc.com/gx/en/industries/financial-services/fintech-survey/insurtech.html

Reinartz, Werner, Nico Wiegand, and Monika Imschloss. 2019. "The impact of digital transformation on the retailing value chain." *International Journal of Research in Marketing* 36, no. 3: 350-366.

Roberts, Benjamin, Jarè Struwig, Steven Gordon, and Thobeka Zondi. 2021. "*Financial Literacy in South Africa: Results from the 2020 Baseline Survey*." Human Sciences Research Council (HSRC)
https://www.fscamymoney.co.za/Research%20Documents/Financial%20Literacy%20in%20South%20Africa%20Results%20from%20the%202020%20Baseline%20Survey.pdf

Robertson, Jane, Emily J. Walkom, and Patricia McGettigan. 2005. "Response rates and representativeness: a lottery incentive improves physician survey return rates." *Pharmacoepidemiology and drug safety* 14, no. 8: 571-577.

Rodríguez Cardona, Davinia, Oliver Werth, Svenja Schönborn, and Michael H. Breitner. 2019. "A mixed methods analysis of the adoption and diffusion of Chatbot Technology in the German insurance sector.".

Schadler, Ted, and John C. McCarthy. 2020. "Mobile is the new face of engagement." *Forrester Research* 13: 1-30.

Singh, Abhishek, Karthik Ramasubramanian, and Shrey Shivam. 2019. *Building an enterprise chatbot: Work with protected enterprise data using open source frameworks*. New York: Apress.

Tsai, Wan-Hsiu Sunny, Yu Liu, and Ching-Hua Chuan. 2021. "How chatbots' social presence communication enhances consumer engagement: the mediating role of parasocial interaction and dialogue." *Journal of Research in Interactive Marketing* 15, no. 3: 460-482.

United Nations. Department of Economic and Social Affairs. 2020. "*World social report 2020: Inequality in a rapidly changing world*." https://www.un.org/development/desa/dspd/wp-content/uploads/sites/22/2020/02/World-Social-Report2020-FullReport.pdf

van der Meulen, Rob, Janessa Rivera. 2015. "Gartner Says Mobile App Adoption Is Maturing As Usage Mellows." *Gartner, March 31, 2015. https://www.gartner.com/en/newsroom/press-releases/2015-03-31-gartner-says-mobile-app-adoption-is-maturing-as-usage-mellows#:~:text=User%20interest%20in%20apps%20has,more%20apps%20in%20the%20future.*

VanGeest, Jonathan B., Timothy P. Johnson, and Verna L. Welch. 2007. "Methodologies for improving response rates in surveys of physicians: a systematic review." *Evaluation & the health professions* 30, no. 4: 303-321.

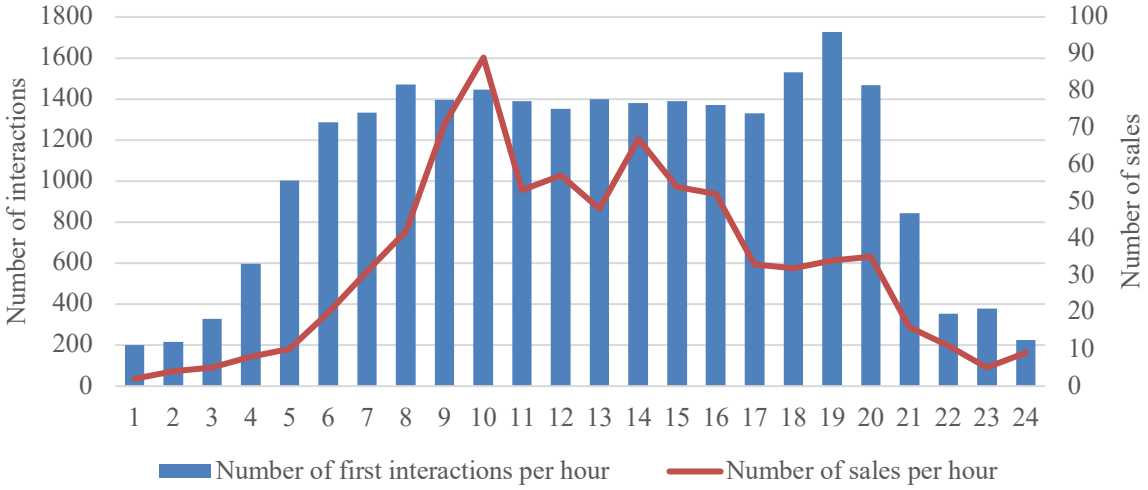
World Economic Forum. 2022. "As young Africans push to be online, data cost stands in the way." *World Economic Forum*, June 21, 2022. https://www.weforum.org/agenda/2022/06/as-young-africans-push-to-be-online-data-cost-stands-in-the-way/

Writer, Staff. 2020. "The Cost of Dying in South Africa vs the World." *Businesstech*, August 22, 2020. https://businesstech.co.za/news/trending/426402/the-cost-of-dying-in-south-africa-vs-the-world/

Zebregs, Simon, Bas van den Putte, Peter Neijens, and Anneke de Graaf. 2015. "The differential impact of statistical and narrative evidence on beliefs, attitude, and intention: A meta-analysis." *Health communication* 30, no. 3: 282-289.

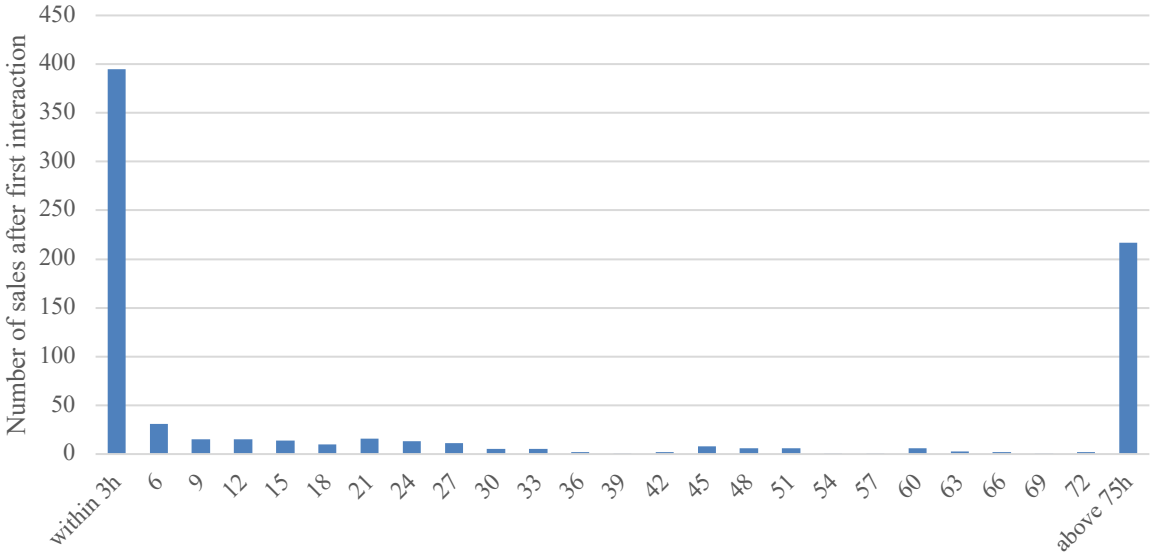
APPENDIX

Figure A.1: Number of first interactions and total sales throughout the day.



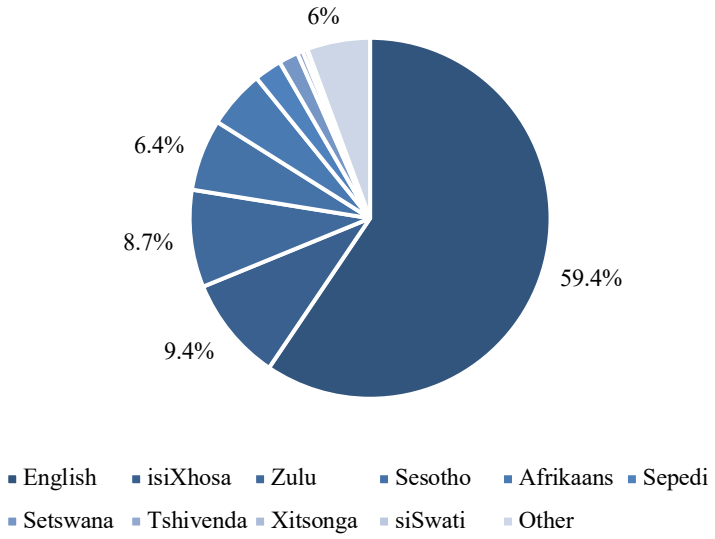
Note: Blue bars represent the number of first interactions during the day. The red line shows sales in absolute numbers. While the first interactions peak between 6 and 7 pm, sales are highest between 9 and 10 am. Source: Internal RatherChat data, based on 25,410 observations.

Figure A.2: Number of sales by hours from the first interaction.



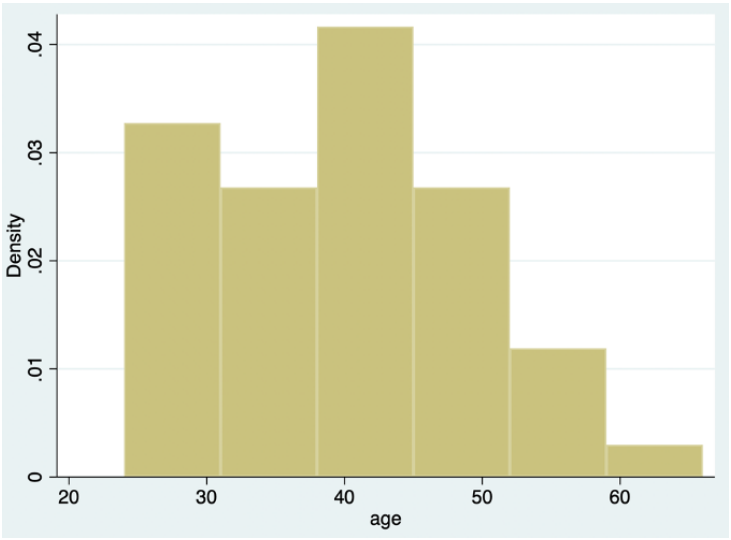
Note: Blue bars represent the number of sales categorized on hours between the first interaction and the actual sales transaction. Sales peak between zero and three hours after the first interaction with chatbot users. Source: Internal RatherChat data, based on 25,410 observations.

Figure A.3: Distribution of languages spoken at home in the overall sample.



Note: English-speaking users represent the majority, followed by isiXhosa and Zulu. Most South African citizens choose English as the common language of communication.

Figure A.4: Distribution of completed sales with respect to age.



Note: The highest density of sales falls within the age of approximately 40 and 45. It decreases with increasing age. Data for age is available for 4,379 observations.

Table A.1: Panel B results of the direct impact of reminder type clustered by the time between the end of the initial conversation and the reminder dispatch.

i) Continue Quote

	(1) Within 5 hours	(2) Between 5 & 10 hours	Prob > F
Panel B. i) Direct impact of reminder type			
Message	0.117	0.11	0.824
	(0.026)***	(0.023)***	
R squared	0.1	0.1	
Observations	1,231	1,433	
	(1) Within 5 hours	(3) Between 10 & 15 hours	Prob > F
Panel B. i) Direct impact of reminder type			
Message	0.117	0.098	0.467
	(0.026)***	(0.026)***	
R squared	0.1	0.08	
Observations	1,231	1,049	
	(1) Within 5 hours	(4) After 15 hours	Prob > F
Panel B. i) Direct impact of reminder type			
Message	0.117	0.126	0.649
	(0.026)***	(0.022)***	
R squared	0.1	0.1	
Observations	1,231	1,501	

Note: *** p<0.01, ** p<0.05, * p<0.1. Reminders increase the likelihood of quote continuation, independently of the time between the initial conversation ended and the reminder dispatch. The unit of observation is a chatbot user. Panel B.i. shows results for general reminder types. Results are compared to Column 1, representing the results for reminders sent within the first five hours. Column 2 shows results for reminders sent between 5 and 10 hours, Column 3 between 10 and 15 hours, and Column 4 after 15 hours. Controls include the difference between the end of initial conversation and receival of reminder, number of members insured under the policy, language spoken at home, and number of children. The robust standard errors are reported in parentheses.

List of Variables:

Stata Variable	**Description**
cont_quote	Dummy variable indicating whether a chatbot user continued quote (=1) or not (=0)
clicked_cont_quote	Dummy variable indicating whether a chatbot user clicked on 'continue quote' (=1) or not (=0)
sale	Dummy variable indicating whether individual completed a sale (=1) or not (=0)

duration	Duration of interaction after assigned time. If positive, re-engagement has been successful
message	Dummy variable indicating whether a chatbot user received any kind of message (=1) or not (=0)
narrative	Dummy variable whether individual received the narrative message (=1) or not (=0)
statistical	Dummy variable whether individual received the statistical message (=1) or not (=0)
group	Categorical variable indicating whether a chatbot user is assigned to the control group (=0), the narrative message group (=1), the statistical message group (=2), the incentivized quiz group (=3), or the non-incentivized quiz group (=4)
time	Categorical variable indicating whether a chatbot user is assigned to the morning (=1), the noon (=2), or the evening (=3) group
morning	Dummy variable equal to 1 if user is assigned to morning slot
noon	Dummy variable equal to 1 if user is assigned to noon slot
evening	Dummy variable equal to 1 if user is assigned to evening slot
age	Age of chatbot user (available for 4,379 observations)
language	Categorical variable indicating the language of chatbot user spoken at home: 1 = English; 2 = Afrikaans; 3 = Zulu; 4 = Sepedi; 5 = Sesotho; 6 = Xitsonga; 7 = isiXhosa; 8 = Tshivenda; 9 = Setswana; 10 = siSwati; 11 = isiNdebele; 12 = Other
language_t	Language of chatbot user spoken at home
children	Number of children a chatbot user has
holder_num	Total number of individuals covered by funeral cover policy
pre_time	Time difference (measured in days) between the end of the initial conversation and the assigned time slot
pre_time_hour	Time difference (measured in hours) between the end of the initial conversation and the assigned time slot