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Key Drivers of Contact Success in Digital Active Sourcing Processes

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Abstract (English)

Active sourcing is a prominent recruitment trend, presenting a strategic opportunity for recruiters to reach highly qualified, hard-to-find candidates in an increasingly competitive labor market. By tailoring strategies to specific target groups and optimizing outreach methods, active sourcing can enhance the recruitment process to attract these hard-to-find talents. This master's thesis addresses a notable research gap by investigating factors possibly enhancing contact success in digital active sourcing approaches. Employing a quantitative research approach, data was collected through an online survey targeted at HR professionals in the DACH region to capture their perceptions of successful active sourcing practices. The study explores whether candidate characteristics like gender, age and tenure, along with message personalization and follow-up frequency, positively influence response rates. Additionally, the thesis analyzes whether the use of AI moderates the personalization of active sourcing messages and therefore enhances contact success. Multiple linear regression analysis shows that age, personalization and the use of AI are key determinants influencing response rates, while other factors have limited impact. These results suggest that recruiters can improve contact success by considering a candidate's age and personalizing their active sourcing messages. However, the observed negative effect of AI use when personalizing messages suggests that current AI-tools are not yet fully embraced by recruiters, possibly due to their limitations in capturing the human touch. This highlights the need for more fine-tuned AI-tools that are better suited for practical application. Despite these challenges, the study offers practical recommendations to optimize active sourcing techniques and leverage digital tools to improve talent acquisition. The insights not only contribute to theoretical knowledge but also provide applicable guidance for recruiters and HR professionals seeking to optimize their active sourcing processes.

Keywords: active sourcing, digital recruiting, response rates, candidate response, talent acquisition, talent attraction, human resources (HR)

Abstract (Deutsch)

Active Sourcing ist ein bedeutender Rekrutierungstrend, der es Recruiter*innen ermöglicht, in einem zunehmend wettbewerbsintensiven Arbeitsmarkt hochqualifizierte, jedoch schwer erreichbare Kandidat*innen zu identifizieren. Durch die gezielte Anpassung von Strategien an spezifische Zielgruppen und die Optimierung der Ansprachemethoden kann Active Sourcing den Rekrutierungsprozess verbessern, um diese Talente effizient anzusprechen. Die Masterarbeit schließt eine wichtige Forschungslücke, indem sie Faktoren untersucht, die den Erfolg der Kontaktaufnahme im digitalen Active Sourcing steigern können. Hierfür wurde im Rahmen eines quantitativen Forschungsansatzes Daten durch eine Online-Umfrage unter HR-Fachkräfte aus der DACH-Region erhoben, um deren Einschätzungen zu erfolgreichen Active Sourcing Praktiken zu erfassen. Die Studie untersucht insbesondere, ob Kandidat*innenmerkmale wie Geschlecht, Alter und Betriebszugehörigkeit sowie die Personalisierung von Nachrichten und die Häufigkeit von Follow-up-Nachrichten die Antwortquoten positiv beeinflussen. Zudem wird analysiert, ob der Einsatz von KI die Personalisierung moderiert und somit den Erfolg der Kontaktaufnahme erhöht. Multiple lineare Regressionsanalyse zeigt, dass Alter, Personalisierung und der Einsatz von KI wesentliche Einflussfaktoren sind, während andere Aspekte nur begrenzte Auswirkungen zeigten. Diese Ergebnisse deuten darauf hin, dass Recruiter*innen ihre Erfolgsquoten steigern können, indem sie das Alter der Kandidat*innen berücksichtigen und ihre Nachrichten stärker personalisieren. Allerdings weist der beobachtete negative Effekt des KI-Einsatzes bei der Personalisierung darauf hin, dass aktuelle KI-Tools von Recruiter*innen noch nicht vollständig akzeptiert werden, möglicherweise aufgrund ihrer Einschränkungen, eine menschliche Note authentisch zu vermitteln. Dies unterstreicht die Notwendigkeit, KI-Tools weiterzuentwickeln, um eine verbesserte Praxistauglichkeit zu erreichen. Trotz dieser Herausforderungen bietet die Studie praktische Empfehlungen zur Optimierung von Active Sourcing Techniken und zum Einsatz digitaler Tools zur Verbesserung der Talentgewinnung. Die Erkenntnisse tragen nicht nur zur theoretischen Forschung bei, sondern liefern auch praxisnahe Leitlinien für Recruiter*innen und HR-Fachkräfte, um ihre Active Sourcing Prozesse zu optimieren.

Keywords: Active Sourcing, aktive Kandidat*innenansprache digitales Recruiting, Antwortquoten, Talentakquise, Talentgewinnung, Personalwesen (HR)

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List of abbreviations

AI	Artificial Intelligence
CV	Curriculum Vitae
DACH	Germany, Austria, Switzerland
FUP	Follow-Up
HR	Human Resources
IT	Information Technology
KPI	Key Performance Indicator
VIF	Variance Inflation Factor

1. Introduction

“People went from cogs in the wheel of tangible assets to the engines driving value” (Black and van Esch, 2020, p. 215). This statement underscores the modern importance of HR departments, emphasizing their focus on employees and the critical task of finding the best-suited talents. Within today’s business landscape where the war for talents is still present (Michaels, Handfield-Jones and Axelrod, 2001; Dickson and Nusair, 2010; Hansen and Hauff, 2019; Werding, 2019), it is often hard to find those “engines driving value[s]” which is why recruitment initiatives are particularly important and currently evolving to attract highly qualified talents. Companies focus more on the quality than the quantity of new hires driving them to adapt their recruitment strategies to find the best qualified personnel (Melanthiou, Pavlou and Constantinou, 2015; Phillips and Gully, 2015; Vardarlier and Özşahin, 2017; Villeda and McCamey, 2019; Black, Hasan and Koning, 2024; *LinkedIn*, 2024). In line with this shift, today’s recruitment trends emphasize the use of AI technology to streamline hiring processes, the strengthening of employer branding strategies to position companies as attractive employers, and the adaptation of active sourcing methods to tailor candidate searches on highly qualified but often hard-to-find talents (Weitzel *et al.*, 2020; Randstad and ifo, 2022; *LinkedIn*, 2024).

Active sourcing as a proactive recruitment approach to identify and engage potential candidates is increasingly important as qualified talents become harder to find (Tallgauer, Festing and Fleischmann, 2020; Kroll, Veit and Ziegler, 2021; Black, Hasan and Koning, 2024). Within active sourcing, modern social media platforms and especially professional social networking sites such as LinkedIn or XING play a crucial role (Caers and Castelyns, 2011; Subhani *et al.*, 2012; Zide, Elman and Shahani-Denning, 2014; Pavlíček and Novák, 2018; Davis *et al.*, 2020; Kroll, Veit and Ziegler, 2021). Although there is extensive research on social media in recruitment (Melanthiou, Pavlou and Constantinou, 2015; Roulin and Levashina, 2019; Woods *et al.*, 2020; Rehman *et al.*, 2022), especially on platforms like LinkedIn and XING (Basak and Calisir, 2014; Davis *et al.*, 2020), there is only limited focus on active sourcing itself and its practical application (Roulin and Levashina, 2019), particularly in understanding the factors influencing candidate response rates. While studies like Peltokorpi’s (2021, 2023) address candidates’ characteristics in headhunter searches, they largely view active sourcing as a specialized practice for headhunters rather than a widespread strategy. Given, however, the growing adoption of active sourcing across various companies and industries as well as its streamlined integration into in-house recruitment (Coverdill and Finlay, 2017; Weitzel *et al.*, 2020), this study aims to bridge the research gap by exploring effective strategies to improve response rates, providing valuable insights for recruiters and HR professionals.

The objective of the thesis is to answer the research question: "What are the key determinants influencing contact success in digital active sourcing processes?" The study seeks to fill a gap in existing literature by examining factors that may improve response rates in active sourcing, focusing on the elements gender, age, tenure, personalization, follow-up frequency and the role of AI. The goal is to assess these factors, identified from prior research, as truly influential and understand their impact on response rates. Additionally, given the limited research on the effectiveness of different social media platforms for recruitment (Golovko and Schumann, 2019), the current thesis also seeks to explore which tools and platforms are most commonly used by professionals to identify and contact potential candidates, contributing to the broader discussion on optimizing active sourcing strategies.

The study employs a quantitative research approach, analyzing data collected through an online survey targeted at recruiters and HR professionals to capture their assessments of active sourcing and its influencing factors. To analyze the data and identify significant effects on response rates, multiple linear regression analysis was conducted.

The thesis is organized to first introduce active sourcing, its key components, and motivations for this research, providing the theoretical foundation. It then presents relevant digital tools and platforms used in active sourcing and explores determinants influencing contact success. After establishing this groundwork, the research model, the hypotheses, and the employed methodology are introduced. The results from survey analysis and regression models are then described and analyzed in detail, followed by a discussion of findings, practical implications, and limitations of the study. The thesis concludes with summarizing remarks and an overview of the literature referenced throughout the paper.

2. Current trends and challenges in recruitment

Before delving into the topic of active sourcing more deeply, it is important to identify current trends and challenges in recruitment. The following chapter, therefore, provides insights into the current state of recruitment strategies and practices and serves as a motivating factor for writing this thesis.

Even though some researchers already pointed out the importance of recruitment and selection strategies more than 50 years ago (Rees, 1966), it was only in the last 20-30 years that companies widely changed their view on human resources and employees' value, putting people at the center of a company's assets and defining them as "engines driving value" (Black and van Esch, 2020, p. 215). This led to new developments and a shift within the HR department that now has more focus on recruiting activities.

Even though recruiting is at the center of HR activities, recent surveys show that global hiring declined from 2022 to 2023 and that companies are hiring at a more cautious pace, meaning that they adjust their recruitment strategies to make sure to select only the best fits for the firm (*LinkedIn: Global Talent Trends*, 2023). In addition to more cautious recruiting measures, HR departments in the German-speaking DACH region are prioritizing improvements to the employee experience, strengthening talent management, optimizing recruitment processes, and emphasizing employer branding (*Mercer*, 2023). These trends are also supported on a global scale by a study combining LinkedIn data with a survey including almost 2000 HR professionals from 23 different countries that set up a total of six recruitment trends. Leading those trends is the use and implementation of AI within recruitment strategies. Within this context, digital recruiting tools, partly based on AI, are perceived as relevant as they offer ways for recruiters to more easily pinpoint suitable candidates. A further trend is the focus on quality instead of quantity of new personnel, which supports the prior mentioned trend of more cautious recruiting strategies (*LinkedIn*, 2024). This is also supported by Phillips and Gully (2015), who point out that hiring costs decrease the longer new employees remain with the company, as this prevents the need to restart the entire recruitment process. Therefore, focusing on good quality hires can decrease hiring costs due to lower turnover rates. This proves to be beneficial, as high efforts are invested into the process to ensure finding good fit candidates who are willing to stay within the company. Other than that, further trends include a clear focus on flexibility and adaptability in recruitment, remote working and again, employer branding is pointed out as relevant factor, underscoring the importance of companies' images and employer brands (*LinkedIn*, 2024). This was also demonstrated in a study conducted in Germany, which found that if recruiters had more budget and time available, they would mainly invest in employer branding and personnel marketing activities as well as active sourcing, hiring of recruiting specialists for active sourcing and technologies such as AI. Within the context of active sourcing the study also shows that every second candidate would rather want to be approached by firms than actively look for a job, showing the high potential of active sourcing (Weitzel *et al.*, 2020). Similar results can be found in other studies that show that candidates are getting frustrated of long application processes (Tallgauer, Festing and Fleischmann, 2020;

Verhoeven, 2020). This also presents an opportunity for active sourcing, as candidates might appreciate not having to extensively search through job offers, but they value recruiters reaching out to them and providing all relevant job information directly.

In addition to the trends described above, the war for talents, a keyword that was defined already in the late 1990s (Michaels, Handfield-Jones and Axelrod, 2001), is still a main term in today's recruitment. Within this context, talents can be described as "individuals who are highly skilled and highly sought after on the labor market" (Lassleben and Hofmann, 2023, p. 546). In order to poach these rare talents, many companies are forced to adjust their recruitment strategies. Besides enhancing employer branding and asking companies to position themselves as attractive employers to appeal to qualified personnel (Lassleben and Hofmann, 2023), a shift from a purely post-and-pray approach to a more active one can be seen within companies, which again supports the trend towards more flexibility in recruitment and explains the focus on active sourcing processes as a hiring strategy (Dannhäuser, 2017; Black and van Esch, 2020; Tallgauer, Festing and Fleischmann, 2020). Furthermore, the war for talents forces firms to look beyond national borders and attract skilled workers internationally. Within this context digital tools and active sourcing are key factors for successfully attracting international personnel (Dickson and Nusair, 2010; Hansen and Hauff, 2019; Werding, 2019).

Even though various trend forecasts and studies show the importance of adjusting recruitment strategies and the adoption of active sourcing in hiring (Weitzel *et al.*, 2020; *Mercer*, 2023; *LinkedIn*, 2024), a survey conducted by Randstad and the ifo Institute in 2022 shows that 35% of respondents have never tried active sourcing, and in general, it is perceived to be rather done by bigger companies. Even though active sourcing is not yet widely used for recruitment processes, the study also shows that those companies who tried it have discovered its potential (Randstad and ifo, 2022). This aligns with similar findings from Caers and Castelyns (2011), stating that only frequent users of LinkedIn are aware of its potential.

All these studies show the current trends in recruitment with developments around AI, employer branding and active sourcing being the main drivers within recruitment departments. However, as Roulin and Levashina (2019) point out, there is still a gap between the practical implementation of active sourcing and academic research, meaning even though the potential of active sourcing has been recognized, academic research within this area still lags behind. This is why the current thesis aims to contribute to the research field of recruitment by focusing on active sourcing as one of the current dominant trends.

Furthermore, in today's digital world, where activities and interactions increasingly take place online, active sourcing is also widely conducted through digital platforms which is why the current study focuses on digital active sourcing approaches and aims to find out how recruiters can successfully engage in this process. Therefore, the study aims to identify which factors influence response rates in digital active sourcing.

3. Theoretical foundation and existing research

To provide a comprehensive understanding of the paper and its subject matter, the following chapter offers an overview of existing literature essential for the topic, which was used as the basis for identifying hypotheses that were then statistically tested.

3.1. Recruitment processes

As active sourcing is a component of recruitment, firstly, the main concept of recruiting will briefly be introduced. The recruitment or staffing process within the HR department can be defined as "the process of attracting, screening, selecting, and hiring the best employee based on skill, experience, and organization fit" (Melanthiou, Pavlou and Constantinou, 2015, p. 33) and is said to be among the most important areas of HR departments (Orlitzky, 2008; Phillips and Gully, 2015). In order to efficiently find the best fit employees, companies need to design an appropriate recruitment strategy, which must answer the questions whom, where and when to recruit as well as which sources to use and what message to communicate to potential candidates (Orlitzky, 2008; Villeda and McCamey, 2019). It is then essential that this recruitment strategy strongly aligns with the overall business strategy in order to achieve organizational effectiveness and productivity (Phillips and Gully, 2015).

Looking at the historical development of recruitment, we are currently experiencing digital recruiting 3.0, which refers to the field of recruiting that started to be developed in 2010 and is characterized by the implementation of AI recruitment tools. Digital recruiting 3.0 developed from so-called analog recruiting (until the end of the 1990s) through two key stages: digital recruiting 1.0, driven by the rise of online job boards, and digital recruiting 2.0, marked by the emergence of platforms like Indeed and LinkedIn in the early 2000s. While the importance of job ads in print media steadily declines, since 2012 the internet has been the main source for job ads and finding candidates (Villeda and McCamey, 2019; Black and van Esch, 2020).

The recruitment process then consists of various steps and is usually quite a long process (Subhani *et al.*, 2012; Melanthiou, Pavlou and Constantinou, 2015). It starts by analyzing the requirements for the job, defining the necessary qualifications and competencies of potential new employees, as well as selecting target groups. According to the defined target group, adequate strategies for finding and approaching possible talents need to be identified. This can involve passive methods such as the post-and-pray approach, meaning to post job ads and waiting for candidates to apply (Vardarlier and Özşahin, 2017), or more proactive ones such as active sourcing. Nowadays relevant platforms for finding and approaching candidates mainly consist of a variety of online job boards and social media websites. However, depending on the industry, some companies still use newspapers or offline advertisements to announce their job openings. Active, as well as passive, strategies ideally lead to the formation of a candidate pool from which adequate candidates are picked for further interviews. This step might be followed by another round of assessments and background checks on applicants to narrow down the number of possible employees before a final assessment is made concluding with the decision of which candidate to hire (Melanthiou, Pavlou and Constantinou, 2015).

This whole process can be very time-consuming and cost-intensive. However, as mentioned above, it has undergone relevant changes due to digitalization and the development of technology and innovations. This shift from offline to online job advertising and the usage of social media and social networking platforms for recruitment is often referred to as "e-recruitment" (Subhani *et al.*, 2012; Melanthiou, Pavlou and Constantinou, 2015), where especially social networking platforms such as LinkedIn have revolutionized recruitment all over the world and forced companies to adapt their recruitment strategies in order to stay competitive on the labor market (Pavlíček and Novák, 2018).

Various researchers point out that e-recruitment and the integration of social media into recruitment processes have the potential to lower hiring costs, reduce the time-to-hire and improve the quality of candidates (Melanthiou, Pavlou and Constantinou, 2015; Vardarlier and Özşahin, 2017; Villeda and McCamey, 2019; Rehman *et al.*, 2022). The reduced costs thanks to e-recruitment come from the fact that companies use online job boards to post vacancies instead of expensive offline advertisements. Additionally, they reduce their costs by conducting interviews and screening candidates online (Melanthiou, Pavlou and Constantinou, 2015). When considering active sourcing, however, researchers argue that the activity itself as well as the process of developing an adequate strategy is quite time-consuming and therefore cost-intensive, which is why it is still often outsourced to specialized agencies (Melanthiou, Pavlou and Constantinou, 2015; Kroll, Veit and Ziegler, 2021). Therefore, when talking about cost and time reduction thanks to e-recruitment it is important to distinguish between using those technologies and social media platforms for screening and interviewing candidates, and on the other hand, for active sourcing and approaching candidates which will in more detail be explained in Chapter 113.2.3.

In general, the recruitment process has undoubtedly undergone major changes within the last years due to technological innovations and the emergence of digital platforms and social media sites, resulting in new ways to hire and forcing companies to adopt in order to gain a competitive advantage.

3.2. Active sourcing

Active sourcing is one of the leading trends in recruitment with platforms such as LinkedIn revolutionizing the field. This is why it has been chosen as the research focus for the current study. The following chapter aims to describe the concept of active sourcing, the difference between active and passive candidates, the distinction between and comparison of active sourcing and social media recruitment as well as the relationship between active sourcing and employer branding.

3.2.1. Concept of active sourcing

Active sourcing in general describes the proactive identification and contacting of possible candidates by recruiters. While the most commonly used term for this strategy is active sourcing, some authors also refer to it as “outbound recruiting” (Black, Hasan and Koning, 2024) as well as “poaching” or “talent raiding” (Nikolaou, 2014). For the present study, only the term active sourcing will be used.

Active sourcing can come in various forms, online as well as offline. While the most common methods of active sourcing include the use of social media or career networking platforms as well as recommendations from existing employees to find possible candidates, there are also notable offline strategies such as collaborations with schools and universities or the attendance at career fairs (Weitzel *et al.*, 2020; Randstad and ifo, 2022). As the goal of this thesis is to evaluate key drivers of digital active sourcing approaches, the paper will focus on online strategies such as the use of social media and professional networking platforms for active sourcing.

Active sourcing is mostly done when there are not enough or no suitable candidates who apply for a job. This is when recruiters start actively searching for candidates and reaching out to them instead of waiting for candidates to apply. This approach is important in times when qualified employees are hard to find and recruiters need to be proactive, convey a favorable employer brand and try to bind possible candidates to the company at an early stage. This is why active sourcing is especially relevant within the previously mentioned war for talents (Tallgauer, Festing and Fleischmann, 2020; Kroll, Veit and Ziegler, 2021; Lassleben and Hofmann, 2023).

The concept of active sourcing can in a way be seen as a modern term for the widely known practice of headhunting. Since the 1980s the concept of headhunting by external recruitment firms has been a popular strategy for firms (Peltokorpi, 2023). Headhunters or executive search firms are intermediaries between firms and the labor market and play the role of a "matchmaker" to locate and hire hard-to-find personnel for their customers, using active sourcing approaches to identify these individuals (Bonet, Cappelli and Hamori, 2013). In other words, the concept of active sourcing was originally done mainly by headhunting firms due to the significant time and effort required (Peltokorpi, 2023). However, due to technological advancements and the broad access to passive candidates via social media and social networking platforms, active sourcing is no longer exclusively done by specialized headhunters but became more accessible to all firms. Unlike headhunting, traditionally used for executive-level positions and usually accompanied by high fees, active sourcing is now used for all types of job groups and has the potential to be more cost-effective than hiring outside agencies (Villeda and McCamey, 2019; Kroll, Veit and Ziegler, 2021).

Prior research has shown that firms engage in active sourcing processes more intensely if the costs of approaching passive candidates are relatively lower than for finding candidates through traditional strategies. This is usually the case when looking for high-skilled and hard-to-find candidates (Black, Hasan and Koning, 2024). Even though Black, Hasan and Koning (2020) did their research for the USA, they show the high potential of active sourcing as in the USA almost 18% of employees were hired in 2020 through active sourcing while this number was only around 4% in 1991. Interestingly, when looking only at Silicon Valley, this number is much higher, namely 25% of employees that were recruited by active sourcing. This highlights the assumption that active sourcing is more relevant in highly skilled areas. Furthermore, their results showed that from the percentage of candidates being actively approached, roughly 13% were approached by in-house recruiters while only around 5% were approached by external headhunters (Black, Hasan and Koning, 2024). Even though other researchers point out that active sourcing is still often outsourced to specialized agencies (Kroll, Veit and Ziegler, 2021), their results indicate that active sourcing processes are getting easier for internal recruiters to conduct and are increasingly being integrated into in-house recruitment strategies. This was also shown in a study conducted by the Centre of Human Resources Information Systems (CHRIS) at the University of Bamberg and Friedrich-Alexander University Erlangen-Nuremberg that revealed that firms want to prioritize their in-house recruitment departments over outsourcing it to external service companies (Weitzel *et al.*, 2020). Furthermore, Black, Hasan and Koning (2020) state that there was a significant rise in the proportion of HR roles focusing on recruiting, noting that in 2010 about 30% of jobs within HR included recruiting, while in 2020 this number rose to nearly 50%. This is not only the case for recruiting skills but also skills regarding the use of social media are increasingly in demand for HR professionals, showcasing the growing importance of in-house recruitment and especially active sourcing skills (Black, Hasan and Koning, 2024).

Taking all those points into consideration, Coverdill and Finlay (2017) argue that social media and social networking platforms such as LinkedIn radically transformed in-house recruitment and improved "the ease, speed, and breath of extensive search" (Coverdill and Finlay, 2017, p. 14). However, their argument applies only to extensive search, originally defined by Rees (1966), meaning that a large number of possible candidates can be rather quickly identified via social networking sites. This task of extensive search can now more easily be done by recruiters. "Intensive" search on the other hand involves thorough research and in-depth screening of candidates, which still takes up a significant amount of time. Some companies therefore adjust job roles within HR, defining differentiated roles for "researchers" and "recruiters" (Coverdill and Finlay, 2017). This shows that active sourcing is still a time-consuming process requiring specialized skills and expertise to be successful. This is why even though there is a trend toward more in-house recruiting and active sourcing, headhunting firms still take up a valuable role as they are specialized within this area, have better information about the external labor market and are performing those extensive as well as intensive searches on a daily basis (Peltokorpi, 2021).

As mentioned above, within the context of active sourcing, social media platforms such as LinkedIn and XING, but also Facebook or X (former Twitter) play a significant role and are typically used for so-called "profile mining" in active sourcing (Tallgauer, Festing and Fleischmann, 2020). Profile mining is the most popular method used for active sourcing and describes the process of identifying possible candidates on social media and professional social networking sites by scanning through their profiles. In addition to profile mining on social media platforms, searching internal or external CV databases or existing talent networks are other forms of digital active sourcing (Dannhäuser and Braehmer, 2017).

In summary, the concept of active sourcing, previously performed exclusively by specialized headhunting firms, has now been adopted by internal HR departments, mainly thanks to advancements in technology and social networking sites providing access to large candidate pools. However, due to the time-consuming nature of active sourcing, it is still primarily used for candidates possessing specialized skills and who are rare to find on the labor market.

3.2.2. Active and passive candidates

Those hard-to-find candidates are often passive candidates, who must be distinguished from active ones. Active candidates are defined as people who are looking for new job opportunities and therefore actively check job offers. Passive candidates, on the other hand, are not actively seeking a new job (Bonsón and Bednarova, 2013; Villeda and McCamey, 2019; Ernst, 2021). Prior research has shown that these passive candidates are considered to be very valuable due to their experience and skills (Melanthiou, Pavlou and Constantinou, 2015; Villeda and McCamey, 2019; Chen, 2023). Within this context, Black and Van Esch (2020) point out that "the number of passive candidates is roughly three times larger than active candidates" (Black and van Esch, 2020, p. 219). Even though those passive candidates are not actively looking for jobs, about 80% would be willing to leave their current job if being offered a better one (Nikolaou, 2014; Black and van Esch, 2020). Within this context, Cappelli (2019) however highlights that on average only 11% of positions are filled by passive candidates and points out the importance of analyzing existing hiring data and creating a good mix of active and passive approaches depending on the firm's needs. Nevertheless, whether classified as active or passive candidates, various studies indicate that the majority of candidates are interested in receiving job offers to explore potential opportunities and can be convinced to change jobs when the right opportunity arises (Bonet, Cappelli and Hamori, 2013; Dannhäuser, 2017). This again underscores the significance of active sourcing, as recruiters are informing potential candidates about job opportunities without them needing to actively perform extensive job searches. One way of doing so is by using social media platforms as for example LinkedIn, Facebook, X (formerly Twitter) or Instagram, with LinkedIn being one of the most important platforms nowadays (Nikolaou, 2014; Black and van Esch, 2020). However, when using those platforms, there is a distinction between making passive candidates aware of job openings or actively reaching out to them with specific job offers. Making passive candidates aware of a job can be done, for example, by posting job campaigns on social media. When employing an active sourcing approach, on the other hand, recruiters proactively reach out to individuals. This distinction between active sourcing and social media recruiting will be explored in more detail within the next chapter.

While active sourcing is most commonly seen as a strategy for reaching out to passive candidates, Peltokorpi (2023) within his study does not differ between active and passive candidates, but instead found that headhunters most often target "easy-to-contact and easy-to-move" candidates (Peltokorpi, 2023, p. 716). This highlights that within active sourcing, the decision to contact a candidate should not be based only on their activity level but recruiters must assess whether it is worth investing time in reaching out and whether a candidate is expected to reply. This is why the current thesis wants to explore this issue in more depth and focus on the factors influencing response rates in active sourcing.

3.2.3. Active sourcing and social media recruiting

Prior literature often addresses the use of social media within recruitment but emphasizes the use of these platforms more as screening or advertising than as selection tools (Melanthiou, Pavlou and Constantinou, 2015; Roulin and Levashina, 2019; Woods *et al.*, 2020). The following chapter aims to provide a better understanding of how active sourcing differs from the more general term of social media recruitment.

As already established earlier, companies over the last years largely discovered the potential of social media when it comes to recruitment. It can be seen as an "authentic and reliable medium for talent hunting" (Rehman *et al.*, 2022, p. 2) and has the potential to increase quality as well a quantity of candidates (Vardarlier and Özşahin, 2017; Rehman *et al.*, 2022). However, it is important to distinguish between social media recruitment in general and active sourcing.

First of all, active sourcing does not solely rely on the use of social media platforms but can come in various forms, online as well as offline (Dannhäuser and Braehmer, 2017; Weitzel *et al.*, 2020; Randstad and ifo, 2022). When talking about using social media in recruitment, most researchers refer to it as the use of social media platforms for screening and conducting background checks on their candidates (Melanthiou, Pavlou and Constantinou, 2015; Roulin and Levashina, 2019), while only some point out the various function, including their use for active sourcing (Kroll, Veit and Ziegler, 2021; Rehman *et al.*, 2022). While screening means searching for candidates and checking their social media profiles to see whether they are a good fit for a job, active sourcing includes more steps, starting at identifying possible candidates, followed by screening them, and actively getting in touch with them (Villeda and McCamey, 2019; Kroll, Veit and Ziegler, 2021). Screening therefore might be part of the active sourcing process but is not solely limited to that. This distinction is also shown in a study from Vardarlier and Özşahin (2017) that indicates that 61,5% of recruiters use social media platforms like LinkedIn for reference checks, while only 30,2% use them for recruitment purposes which emphasizes the use of social media for both screening and recruitment, including active sourcing activities.

Subhani *et al.* (2012) also emphasizes within this context the importance of platforms like LinkedIn, Facebook, and X (formerly Twitter). While Facebook and X are, however, primarily used for posting job openings, LinkedIn is more frequently utilized as a tool for actively identifying possible candidates. This distinction introduces a broader discussion about the definition of social media versus social networking sites. While some researchers do not differentiate between the two (Bonsón and Bednarova, 2013), others highlight the difference, preferring the phrase "social networking sites" when referring to digital networks whose main purpose is for users to connect and communicate (Zide, Elman and Shahani-Denning, 2014; Villeda and McCamey, 2019). Accordingly, Villeda and McCamey (2019) define social media as a broad term, with social networking sites considered a subcategory (Kim, Kim and Nam, 2014; Villeda and McCamey, 2019). More specifically, LinkedIn as well as XING are categorized as professional social networking sites, emphasizing users' professional backgrounds and experiences (Caers and Castelyns, 2011). This highlights the need to distinguish active sourcing from social media recruitment, as active sourcing leverages social media platforms for candidate searches whereas social media recruitment includes a wider range of tools and strategies beyond just candidate searches.

However, as Subhani *et al.* (2012) point out, besides screening and the active identification of candidates, social media in general plays a significant role in enhancing a firm's employer brand and personnel marketing, whether it is by publishing posts, running campaigns or writing to potential candidates. This shows the difficulty of separating its various uses, as they are tightly interconnected and collectively contribute to recruitment success and hiring the best-fit candidates.

3.2.4. Active sourcing and employer branding

As discussed in the previous chapter, distinguishing between active sourcing and social media recruiting is not straightforward. At the same time, both concepts are closely connected to the principle of employer branding. Employer branding reflects how employees perceive a company and is considered a significant factor in candidates' decisions about which firm to join (Lassleben and Hofmann, 2023). Numerous researchers point out the importance of employer branding strategies for efficient recruiting (Allen, Mahto and Otondo, 2007; Dannhäuser and Braehmer, 2017; Golovko and Schumann, 2019; Tallgauer, Festing and Fleischmann, 2020). However, to ensure consistency, all personnel marketing strategies should be aligned with the company's overall marketing approach, as a positive employer brand is said to be critical for successful active sourcing and attracting the wanted talents (Allen, Mahto and Otondo, 2007; Dannhäuser and Braehmer, 2017; Golovko and Schumann, 2019; Tallgauer, Festing and Fleischmann, 2020). In general, successfully communicating an employer brand can lead to a bigger and better qualified applicant pool which contributes to gaining a competitive advantage in the market (Phillips and Gully, 2015).

The importance of employer branding was also shown in a study introduced earlier which was conducted in 2019 in Germany and evaluated what recruiters would do if they had one million euros additional budget or one hour per day of additional working time. While the one additional hour would mainly be used for active sourcing or strategical analysis, the majority would invest the additional budget in employer branding activities followed by personnel marketing and AI-technologies (Weitzel *et al.*, 2020). Similar results were shown by LinkedIn (2024), which reports that 67% of HR professionals in the DACH region anticipate increased employer branding expenses over the next year to meet the evolving demands (*LinkedIn*, 2024). This demonstrates the significance of employer branding in today's business landscape where especially social media channels were revealed to be effective in enhancing a firm's reputation. This can be achieved not only through large employer branding campaigns but also by creating a favorable candidate experience as candidates' impressions during the entire recruiting process influence the overall perception of an employer. This is why the concept of employer branding is tightly connected with active sourcing and indicates that employer branding on the one hand affects active sourcing but at the same time, the way recruiters engage with possible candidates vice versa affects the employer brand (Melanthiou, Pavlou and Constantinou, 2015; Golovko and Schumann, 2019; Villeda and McCamey, 2019; Black and van Esch, 2020).

Hausknecht, Day and Thomas (2004) furthermore highlight the importance of choosing the right selection methods in recruitment. Approaching candidates in an unsuitable manner can harm the company's image, and as a result make candidates less likely to accept job offers or recommend the employer to others (Hausknecht, Day and Thomas, 2004). This further underscores the connection between active sourcing and employer branding and consequently suggests that the way recruiters engage with talents also affects response rates. At the same time, Phillips and Gully (2015) demonstrate that when brand awareness is already high, recruitment messages can be less detailed and specific. In contrast, when an employer is fairly unknown, more information should be conveyed to persuade possible applicants. This again reflects the importance of employer branding and indicates that within active sourcing, different approaches depending on the employer branding strategy should be realized.

3.3. Digital active sourcing tools

One very important aspect within active sourcing is to thoroughly select the platforms for candidate search depending on the target group, as picking the wrong platform might lead to receiving unsuitable applicants (Melanthiou, Pavlou and Constantinou, 2015; Bernauer, 2019; Rehman *et al.*, 2022). The following chapter, therefore, aims to give an overview of the most relevant digital tools when talking about active sourcing.

Various researchers investigated the use of different social media platforms within recruitment in general, where most frequently the platforms LinkedIn, XING, Facebook and X (formerly Twitter) were evaluated and are said to be most frequently used by recruiters (Caers and Castelyns, 2011; Subhani *et al.*, 2012; Pavlíček and Novák, 2018; Kroll, Veit and Ziegler, 2021). However, as discussed in previous chapters, many studies focus on the general use of social media platforms for recruitment rather than specifically for active sourcing. Platforms like Facebook or X are therefore most frequently mentioned in the context of social media recruiting, but their role in active sourcing is rarely addressed, which is why they will not be further considered in this study. Within this context, a survey conducted by Monster (2020) also shows that ten years from now, there will be a clearer distinction between private and professional social media platforms, and candidates will rather use professional career networks for work-related matters than private social media platforms (Weitzel *et al.*, 2020). This is supported by example by Zide, Elman and Shahani-Denning (2014) as well as Davis *et al.* (2020) who highlight the importance of social media channels such as Facebook or X but point out that LinkedIn clearly dominates within a professional context and is rated as the most relevant one. This was also supported by Nikolaou (2014), whose study shows that LinkedIn compared to Facebook is more relevant for recruiters, as well as Subhani *et al.* (2012), who note that even though Facebook has more active users, within a professional context LinkedIn is more frequently used. This also demonstrates that LinkedIn clearly stands out on a global scale, while the similar platform XING can be considered an important competitor only within the German-speaking DACH region (Zide, Elman and Shahani-Denning, 2014; Roulin and Levashina, 2019; Davis *et al.*, 2020; Ruparel *et al.*, 2020). As both, LinkedIn and XING, however, offer talent acquisition solutions for recruiters, they can be considered valuable platforms for active sourcing, which is why they are explored in more detail in the next chapters.

3.3.1. LinkedIn

As many researchers mention, within a professional context and as a recruitment and selection tool, LinkedIn stands out as the most relevant one (Zide, Elman and Shahani-Denning, 2014; Coverdill and Finlay, 2017; Roulin and Levashina, 2019; Davis *et al.*, 2020; Ruparel *et al.*, 2020). The professional networking platform is widely used by applicants to search and actively apply for jobs, which also makes it interesting for recruiters who gain access to those possible candidates. A study from 2017 evaluated that after traditional career pages, LinkedIn is the second most preferred channel for applicants to look for jobs, showing its enormous potential (Verhoeven, 2020). Similar results were found by Peltokorpi (2021), who shows that headhunters prefer using LinkedIn over traditional online job boards as the platform has high potential to find highly skilled and qualified candidates. At the same time however, as all headhunters and recruiters have recognized LinkedIn's potential, this means that there is a large number of recruiters hunting on LinkedIn leading to the fact that "LinkedIn is thus a resource for searching candidates, but also a source of competition between recruiters" (Peltokorpi, 2021, p. 651), which is why recruiters should not solely rely on LinkedIn as a source for active sourcing.

LinkedIn was launched in 2003 and by that time was a unique platform by providing users the opportunity to upload CVs and use the platform for purely professional reasons (Villeda and McCamey, 2019). While originally LinkedIn was created to offer users a forum to exchange information on a professional scale, the site was soon recognized as having high potential for recruiting processes due to the transparency of users who add professional information to their profiles. As the number of users increases and more people adjust their profiles with relevant skills and expertise, these platforms provide the opportunity to create a large pool of possible candidates through Boolean searches (using operators like "and", "or" or "not" to connect keywords), which recruiters can access for talent sourcing (Coverdill and Finlay, 2017; Pavlíček and Novák, 2018; Tifferet and Vilnai-Yavetz, 2018; Ruparel *et al.*, 2020).

Since its launch, LinkedIn has grown into the largest and fastest-growing professional networking platform worldwide, with more than one billion members in 2023. The company has a diversified business model, including talent, as well as marketing and sales solutions. Besides that, LinkedIn provides an AI-assisted job board that identifies passive candidates and matches open jobs with the best-suited candidates. From the one billion users, more than 22 million are in the DACH region (Bonsón and Bednarova, 2013; Black and van Esch, 2020; *LinkedIn: Info*, 2024; *LinkedIn: About Us*, 2024). Those numbers grew rapidly over the last decade and at the same time it has to be mentioned that LinkedIn is particularly popular within the HR community (Caers and Castelyns, 2011). This is also supported by a quote from a recruiter used within Archambault and Grudin (2012) who states: "I can't recall how I did this job without LinkedIn" (Archambault and Grudin, 2012, p. 2747), as well as a study done by Black, Hasan and Koning (2024) who show that individuals utilizing LinkedIn are more frequently targeted by recruiters compared to those who do not utilize the platform.

As mentioned above, LinkedIn offers a specified tool for talent recruiting called LinkedIn Recruiter, which allows recruiters to find qualified talent, build connections with possible candidates, and manage talent acquisition within a recruiting team. Recruiters use Boolean keyword searches and can set more than 40 filters to narrow down their search and find the ideal candidate. Once a list of suitable candidates has been created, the LinkedIn Recruiter allows recruiters to connect with talents by sending InMails. The tool also offers various KPIs among which are the number of InMails sent, average response rates as well as the number of accepted and declined InMails. The relatively easy to use tool offers recruiters the possibility to create candidate pipelines "in a matter of minutes, not days or weeks" (Coverdill and Finlay, 2017, p. 97) (Coverdill and Finlay, 2017; Pavlíček and Novák, 2018; *LinkedIn Recruiter*, 2024).

As professional information on LinkedIn profiles is added by users themselves, it raises the question of how trustworthy the information is for recruiters. When it comes to the reliability and validity of information on LinkedIn, one advantage is that profiles do not only consist of information added by the users themselves, but LinkedIn allows other users to add or confirm people's skills making the profile information more reliable (Alavi *et al.*, 2014). Even though it has been shown that hiring managers perceive the skills and abilities listed on LinkedIn profiles as slightly less reliable compared to classical resumes (Roulin and Levashina, 2019), studies also show that LinkedIn, compared to Facebook, is seen as a trustworthy platform within a professional context (Caers and Castelyns, 2011; Melanthiou, Pavlou and

Constantinou, 2015). Roulin and Levashina (2019) also show that the accuracy of competences listed on LinkedIn depends on the nature of the skills as soft skills are rather difficult to detect on LinkedIn profiles (Roulin and Levashina, 2019). Those should rather be evaluated by recruiters, for example, during a phone call or an interview with the candidate (Coverdill and Finlay, 2017). The combination of self-entered skills and skills added or confirmed by other users, however, leads to quite accurate descriptions of people's expertise. When looking for highly skilled and highly qualified employees, LinkedIn therefore offers a suitable tool to narrow down the number of possible candidates and find the best fit (Pavlíček and Novák, 2018; Ruparel *et al.*, 2020).

Clearly, LinkedIn is not only a tool to connect with professional contacts and stay up to date on colleagues' career journeys but plays a vital role for recruitment. However, as Caers and Castelyns (2011) as well as Randstad and ifo (2022) point out, the success in active sourcing via LinkedIn heavily depends on the frequency and the intensity in which recruiters use the tool because "frequent users appear to have discovered this opportunity, while occasional users may not use their accounts sufficiently enough to experience or create the benefit" (Caers and Castelyns, 2011, p. 442).

3.3.2. XING

While LinkedIn clearly dominates on a global scale, within the DACH region, XING can be considered the closest competitor to LinkedIn, with roughly the same number of users in Germany, Austria and Switzerland (Dannhäuser and Chikato, 2015; Rehman *et al.*, 2022; *Workwise*, 2024; *XING*, 2024).

Very similar to the LinkedIn Recruiter, XING offers an active sourcing license called the XING TalentManager. The tool offers recruiters the ability to identify and contact potential candidates that have profiles on XING. By using Boolean keyword searches and filtering specific skills, demographics, und experiences, recruiters can work together on projects and set up a talent pipeline of potential candidates. These candidates can then be reached out to, even if the recruiter is not yet connected with them. The filters based on Boolean searches can hereby either be identified automatically according to the entered key points or by the recruiters themselves. Similar to the LinkedIn Recruiter, the XING TalentManager uses AI to create personalized messages tailored at candidates' profile information (Dannhäuser and Chikato, 2015; *XING*, 2024).

Besides the active sourcing tool, XING offers a job posting section where jobs can be advertised and discovered by candidates actively searching for opportunities. Besides those features, XING provides two more key tools for enhancing recruitment processes. The first one is “onlyfy one”, an application tracking system designed to optimize the recruiting process. The second one is “Kununu”, a platforms that helps companies to strengthen their employer branding by allowing employees to post reviews and give feedback on the workplace (Dannhäuser and Chikato, 2015). XING also provides an additional TalentPoolManager where potential candidates initially contacted via the TalentManager can be organized to maintain the relationships with them in case recruiters want to contact them again at a later point in time (*Workwise*, 2024).

3.3.3. Additional active sourcing platforms

Besides LinkedIn and XING, there are various other, often country specific, tools that might be used for active sourcing. Dannhäuser and Braehmer (2017) give a list of possible tools for active sourcing which includes the XING TalentManager, the LinkedIn Recruiter, Talentwunder, TalentBin, Open Web, Stack Overflow Talent, Textkernel as well as CV databases from Monster, Experteer or StepStone.

Monster as well as Talentwunder can be considered important recruitment platforms. While Monster offers more traditional job posting tools with match functions and a CV-center for recruiters, Talentwunder specializes on sourcing tools that systematically search through candidate profiles on social networking platforms including LinkedIn and XING. While Monster operates globally, Talentwunder is more specialized in the DACH region (Zide, Elman and Shahani-Denning, 2014; Gärtner, 2020; *Monster*, 2024; *Talentwunder*, 2024). Similar to the Monster CV-center, the platforms StepStone as well as Experteer offer CV-databases where possible candidates upload their CVs and recruiters can systematically search through them, identify suitable candidates and easily get in touch with them (*StepStone*, 2024; *Experteer*, 2024). Textkernel offers similar services, where not only social networking platforms are searched, but with the integration into applicant tracking (ATS) or customer relationship management systems (CRM), it is also possible to systematically scan internal CV databases for suitable candidates (Gärtner, 2020; *Textkernel*, 2024). Dice as well as Stack Overflow focus their talent searches on IT personnel and offer solutions to attract and connect with qualified tech talents. (*Dice*, 2024; *Stack Overflow*, 2024)

As there are a variety of tools to choose from when considering active sourcing, the current study also aims to contribute to the research field and determine which tools are most frequently and most successfully used for active sourcing purposes.

3.4. Definition of "success" in active sourcing

To adequately address the research question and define the key drivers for contact success in digital active sourcing processes, it is important to note how to define "success" within active sourcing. Existing studies evaluate positive as well as negative response rates from active sourcing activities indicating that half of the contacted candidates reply, while only around 28% positively reply (Weitzel *et al.*, 2020). The question, however, remains whether only positive replies should be considered a success. For the current thesis, social network theory and the research on strong versus weak ties, originally studied by Granovetter (1973), serve as the foundation for exploring this concept.

Granovetter (1973) distinguishes between strong and weak ties where the strength of a tie can be explained as "a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie" (Granovetter, 1973, p. 1361). In his studies, he states that weak ties are more crucial than strong ones when it comes to job referrals. His research shows that the majority of respondents found their job through referrals from weak ties, meaning they were only in touch with these contacts occasionally or rarely. Often these contacts were former colleagues from university or work (Granovetter, 1973). This might suggest that recruiters can form weak ties with candidates by connecting with them via social networking platforms, improving the likelihood for them to reply to possible job offers.

However, previous studies indicate that one should "not just [...] apply social network theories (or any other theories) blindly to social media, but [...] carefully consider whether the features of these technologies conform to the assumptions on which these theories are based" (Alavi *et al.*, 2014, p. 298). One relevant distinction, for example between classical and social media networks lies in its structure. While traditional networks often pose challenges in this regard, social media platforms offer visualization and navigation tools in order for users to understand their network and its structure (Boyd and Ellison, 2007; Alavi *et al.*, 2014). This is significant for recruiters, as it enables them to transparently manage candidate pools. Furthermore, a larger variety of tie types needs to be considered for digital social networks, as factors such as the frequency and depth of interactions or the effects of positive or negative ties are not considered in traditional theory. Moreover, social media networks are associated with more complexity and are more dynamic than traditional ones (Alavi *et al.*, 2014). This aspect also carries important implications for recruiters and HR professionals, as it enables them to easily establish and oversee complex networks consisting of potential candidates. Furthermore, the more connections and the more ties recruiters have via social networking sites, the greater is their social capital which is a crucial factor within recruitment as it can enhance the process of identifying suitable candidates (Shi *et al.*, 2023).

The topic of informal networks was also studied by Rees (1966). Even though he focuses on referrals coming from already existing employees, the author highlights the importance of informal networks when recruiting new personnel. When looking at the phenomenon of active sourcing, social networking sites offer a way to create those weak ties and informal networks (Archambault and Grudin, 2012; Pavlíček and Novák, 2018; Davis *et al.*, 2020). This is further supported by Peltokorpi (2021), whose study on headhunters highlights that one of the most valuable sources for headhunters is their personal database. Similarly, Coverdill and Finlay (2017) point out the importance of recruiters' LinkedIn networks and state that "on occasion, a connection quickly becomes a candidate" (Coverdill and Finlay, 2017, p. 95). Furthermore, this assumption is picked up by Phillips and Gully (2015) who point out that creating connections to possible candidates at an earlier point in time can have positives effects on the recruitment success later on, and is supported by the concept of the candidate journey which is an approach that aims to create numerous touchpoints with candidates, making them interested in the company and fostering some kind of connection to the firm (Schrader, 2020; Verhoeven, 2020). When combined with social network theory, emphasizing the importance of weak ties in recruitment, this suggests that even negative responses can be seen as a form of success in active sourcing. While typically success is defined by identifying a suitable candidate who shows immediate interest in the job offer or applies promptly, recruiters may, however, also perceive a negative response as a meaningful outcome. This is because even in such cases, they receive feedback, engage with candidates, and potentially maintain connections as weak ties for future targeting.

3.5. Target industries for active sourcing

Various studies indicate that industry type has a relevant impact on the use of social networking sites (Kim, Kim and Nam, 2014; Zide, Elman and Shahani-Denning, 2014; Melanthiou, Pavlou and Constantinou, 2015; Ruparel *et al.*, 2020; Black, Hasan and Koning, 2024). While some evaluate the overall use of social media within companies (Kim, Kim and Nam, 2014), some focus on the use of social networking sites for talent attraction or screening purposes (Melanthiou, Pavlou and Constantinou, 2015; Ruparel *et al.*, 2020) and others evaluate which industries are mainly targeted through active sourcing processes on specific platforms (Zide, Elman and Shahani-Denning, 2014; Black, Hasan and Koning, 2024). However, only few clearly assess whether candidates from certain industries are more receptive to digital active sourcing approaches and which platforms would need to be used to increase the likelihood of response.

When considering the influence of industry type on LinkedIn usage for example, Bonsón and Bednarova (2013) show that companies from industries such as technology and telecommunication, travel and leisure followed by the oil and gas industry have the highest percentages of corporate LinkedIn accounts. Kim, Kim and Nam (2014), on the other hand, identified financial businesses as the industry with the most use of LinkedIn compared to manufacturing, communication, wholesale, retail, and service. Both studies, however, did not investigate LinkedIn usage on an employee level but took into consideration corporate usage only. Candidate-level use was included in a study by Zide, Elman and Shahani-Denning (2014) who show that LinkedIn is mostly used to search for candidates in the fields of sales, marketing, and HR. Other than specific LinkedIn usage, prior studies indicate that active sourcing is used most frequently in STEM industries (science, technology, engineering, and mathematics), health and medicine as well as business. More specifically, the paper by Black, Hasan and Koning (2024) indicates that individuals who completed their studies in these fields are more likely to be approached by recruiters compared to those with majors in social science or education. This is also reflected in a study by Ng *et al.* (2007) who note that IT professionals are more frequently switching employers and might therefore be more often targeted by recruiters, as well as in the study from Bonet, Cappelli and Hamori (2013) mentioning that headhunters and labor market intermediaries are especially often used within the technology sector. Similar results were mentioned in a 2020 study on current active sourcing trends, where researchers differentiated between top-1000 firms and top-300 IT companies in Germany. Their results show that active sourcing in general is more popular within the IT sector and digital active sourcing approaches via career networking sites are more often used by IT- firms than the top-1000 companies (Weitzel *et al.*, 2020).

The suggestion that active sourcing and industry type are tightly connected, and that the choice of platforms heavily depends on the target group, was also picked up by Ernst (2021), who points out the importance of active sourcing in the care industry but emphasizes that candidates are not expected to frequently use LinkedIn or XING. This is why recruiters should preferably use Facebook, Instagram or special blogs and forums for actively sourcing care personnel. Similarly, Phillips and Gully (2015) state that recruitment for IT professionals might also differ from “regular” recruitment strategies as specialized platforms, forums or websites are used to approach IT talents. This underscores a crucial point in active sourcing, previously mentioned in Chapter 3.3, that the selection of platforms and sources heavily depends on the target group and where they are most active. While certain industries are more present on specific social networking sites or forums, it is always important to identify the target group and design recruitment strategies according to their behavior in order to determine the most efficient methods (Phillips and Gully, 2015).

In general, existing literature establishes a connection between industry type and active sourcing or LinkedIn usage. However, comparing these studies is challenging as the examined industries as well as user types in relation to LinkedIn vary across different studies. Furthermore, few studies clearly identify which sources are most successful for specific industries and which factors influence contact success depending on the candidates’ industry sector.

3.6. Candidates’ demographics in active sourcing

As the current thesis seeks to identify key determinants affecting response rates in active sourcing, candidate demographics were identified as potentially influencing factors. The following chapter therefore provides an overview of current studies suggesting that demographics such as gender, age and tenure may impact response rates in active sourcing.

This research field is mainly dominated by findings from Peltokorpi (2023) who answered the question “What are the characteristics that make headhunters more likely to contact candidates?” Even though his study focuses on subsidiaries in Japan and headhunters recruiting host country national employees, the research question is comparable to the one in this thesis. Overall within his study six factors were identified that influence headhunters’ willingness to contact candidates: age, gender, education level, English proficiency, tenure and prior placement by headhunters (Peltokorpi, 2023). For the current study, and within the context of active sourcing, gender, age, as well as tenure, were identified as relevant and possibly influencing response rates, which is why they are discussed in more detail within the following chapters.

3.6.1. Gender

Various studies look into whether specific groups of people are being left out or discriminated against within the recruitment process in general and active sourcing processes in particular (Caers and Castelyns, 2011; Stoilkovska, Ilieva and Gjakovski, 2015; Kroll, Veit and Ziegler, 2021) and what leads to the fact that women are underrepresented in numerous positions and industries (Fernandez-Mateo, Rubineau and Kuppuswamy, 2023). Peltokorpi (2023) in particular suggests that women are more inclined than men to accept job offers when they are presented. However, none of the existing studies define whether gender in general has an impact on response rates in the context of active sourcing.

Gender is one factor among many others such as age, sexual orientation, race, religion, disabilities, appearance, nationality or names that are often influencing screening and selecting processes and have been intensively investigated in scientific research papers (Caers and Castelyns, 2011; Melanthiou, Pavlou and Constantinou, 2015; Stoilkovska, Ilieva and Gjakovski, 2015; Gärtner, 2020). The effects of gender within recruitment processes were already the subject of studies almost 40 years ago when, for example, Powell (1987) studied how sex and gender impact recruitment processes and found that gender often influences recruitment decisions. Also, various newer studies show that women are still underrepresented in talent pipelines for various reasons. For jobs or industries dominated by men, women are more likely to be left out during screening processes. Women tend not to apply for jobs traditionally dominated by men and there is a higher drop-out-rate of women from candidate pools and during application processes (Fernandez-Mateo, Rubineau and Kuppuswamy, 2023). Therefore, companies try to increase the number of female candidates within their talent pool to eventually raise the number of female employees. However, current studies also show that women tend to shy away from reapplying for jobs after having been rejected at an earlier point in time. As a consequence, if there are more women in the candidate pool this suggests that you lose more than you gain by having to reject most of them (Fernandez-Mateo, Rubineau and Kuppuswamy, 2023). As active sourcing however involves targeting potential candidates in a highly specific and streamlined manner, this might present an opportunity, as women may be more likely to respond positively when being approached by recruiters rather than actively applying for a job themselves.

Within the context of active sourcing, Kroll, Veit and Ziegler (2021), however, show that female employees are approached significantly less than male ones. Their research reveals that female employees are 45% less likely to be contacted by a recruiter. Black, Hasan and Koning (2024) support the expectation that gender affects the possibility of being actively sourced. Within their study they show that almost 19% of men got their current job thanks to recruiters actively reaching out to them while this number is only 16% for women. Similar studies show that men present themselves differently on LinkedIn than women, as they are for example more likely to add more professional and status-related information to their profiles, making it easier for recruiters to find them (Zide, Elman and Shahani-Denning, 2014; Tifferet and Vilnai-Yavetz, 2018). Similarly, Tifferet and Vilnai-Yavetz (2018) show that more men than women have a premium account on LinkedIn where, according to LinkedIn, this gives you "4x more profile views than non-Premium members" (*LinkedIn: Premuim*, 2024), suggesting that men are more visible to recruiters than women.

While those studies show that men tend to be approached more frequently than women during active sourcing, Peltokorpi (2023) highlights that female candidates are more inclined to accept job offers than men. In contrast to this, Ng, Huang and Young (2019) indicate that male employees are more likely to switch jobs when seeing an opportunity. However, their study does not focus on active sourcing, but on voluntary turnover after mergers or acquisitions. These discrepancies in literature, however, raise the question whether female or male candidates are more perceptive to digital active sourcing approaches. Although there are various studies on the effects of gender within recruitment, none of them investigate its influence on response rates in active sourcing, which is why the current study wants to add to this topic.

3.6.2. Age

As previously noted, age is frequently discussed in the context of recruitment and according to Peltokorpi (2023) also influences headhunters' decisions on whether to contact a candidate or not, which is why it is also included in the current thesis.

A thorough review of the literature on this topic reveals that studies on the influence of age in active sourcing processes yield varying results. Kroll, Veit and Ziegler (2021) for example show that older employees are 22% less likely than younger ones to receive active sourcing messages from a recruiter. Similarly, a study from Villeda and McCamey (2019) indicates that younger generations might be more available and reachable via social networking platforms than generation X or baby boomers, making them a more convenient target group for recruiters. In contrast to this, Archambault and Grudin (2012) investigated the use of social networking sites among different age groups and found that LinkedIn usage among Microsoft employees was the highest for employees between the age of 46-55 years. This was also supported by Nikolaou (2014) who states that older candidates use professional social networking sites such as LinkedIn more often than younger ones who tend to use Facebook instead. However, since these papers were published in 2012 and 2014, it is likely that platform usage among different generations has changed over the past decade. What Nikolaou (2014) nonetheless points out is that younger people in general spend more time on social media platforms which is expected to hold true also for today.

Within the context of active sourcing, Black, Hasan and Koning (2024) observed that no age group is more likely to be recruited by actively sourcing recruiters than others. In contrast, Peltokorpi (2023) shows that among headhunters, candidates in their 30s and 40s are in the highest demand and, therefore, more frequently approached. Even though not directly linked to active sourcing, various studies state that younger generations (millennials, Gen Z) are more engaged in so-called "job-hopping", meaning they switch to new jobs more frequently when an employer offers higher pay or better conditions (Vela, 2022). This result was also shown by Rubenstein *et al.* (2018) who indicate that younger employees change their job more frequently than older ones.

Given the various findings in existing literature concerning the relationship between active sourcing approaches and candidates' age alongside evidence indicating that young generations are in general switching jobs more frequently and are more present on social media platforms, the current study wants to evaluate whether there is a relationship between a candidate's age and the likelihood of a response within digital active sourcing.

3.6.3. Tenure

As mentioned above, tenure is also expected to influence a candidate's willingness to switch jobs and, therefore, might affect response rates in active sourcing. Tenure can be defined as the "time employed with one's current organization" (Rubenstein *et al.*, 2018, p. 28) and is said to affect an employee's likelihood of changing jobs as those with longer tenure, often associated with a higher salary or well-established workplace connections, are generally less willing to leave their job but rather remain with their current employer (Benson, Finegold and Mohrman, 2004; Rubenstein *et al.*, 2018).

In general, the topic of job mobility has been widely discussed in existing literature, indicating that employees tend to switch jobs more often than they did some decades ago (Ng *et al.*, 2007).

When defining job mobility, Ng *et al.* (2007) specifically distinguish between six types: internal-upward, external-upward, internal-lateral, external-lateral, internal-downward, and external-downward. When considering job changes due to active sourcing, only external types, more specifically external-upward and external-lateral are relevant as they explain the change of employers. External-upwards means that employees take promotions from a new employer, external-lateral is switching to a new employer but staying at the same hierarchy level. These two are expected to be relevant for active sourcing, as employees are expected to be willing to switch jobs only when offered higher positions or better conditions. According to Ng *et al.* (2007) IT professionals often engage in external-lateral job changes which is consistent with study results presented above, emphasizing that active sourcing is frequently done within the technology and IT sector (Bonet, Cappelli and Hamori, 2013; Black, Hasan and Koning, 2024). Ng *et al.* (2007) also indicate that the willingness to switch jobs heavily depends on personality traits. For example, extroverts, enterprising or in general open-minded people are more likely to engage in lateral job mobility and external mobility in general as they are more eager to gain new experiences.

When considering tenure within the active sourcing process, however, Peltokorpi (2023) shows that headhunters tend to avoid contacting candidates who have held one job for an extended period, as they are less likely to change their position. Within an earlier study, Peltokorpi (2021) however also points out that possible candidates with very short tenures can be considered “job hoppers” defined by very frequently switching employers. Even though they might be easier to convince to leave their current employer, they are not favorable candidates as they are expected to move on to another employer soon after. This suggests that recruiters engaging in active sourcing must find a balance. On the one hand, candidates with very long tenure might be reluctant to leave their current employer. On the other hand, candidates with very short tenure might quickly move on to another job, leaving the employer with an open position once again.

As existing literature shows that longer tenure is typically connected with a smaller likelihood to switch employers (Benson, Finegold and Mohrman, 2004; Rubenstein *et al.*, 2018) and that headhunters are more likely to approach candidates with shorter tenures (Peltokorpi, 2021, 2023), the current study wants to find out whether candidates with shorter tenures tend to reply more often to active sourcing messages than those who have already been working in the same company for an extended period.

3.7. Personalization of active sourcing messages

Prior research shows that personalization within active sourcing messages is relevant and perceived by possible candidates as more appealing (Dannhäuser and Chikato, 2015; Ernst, 2021). This effect of personalized messages on response rates has also been shown within other areas of research, especially when trying to increase response rates for web-based surveys or emails (Heerwegh *et al.*, 2005; Dillman, 2007; Trespalacios and Perkins, 2016). This is clearly stated by Heerwegh et al. (2005) saying that "by personalizing correspondence, one increases the degree to which recipients perceive the importance and value attached to them" (Heerwegh *et al.*, 2005, p. 86). However, studies from Trespalacios and Perkins (2016) as well as Heerwegh *et al.* (2005) investigate the degree of personalization only according to whether recipients are addressed by their names rather than anonymously and focus their study on response rates for surveys and email invitations not considering active sourcing messages. Dannhäuser and Chikato (2015) on the other hand concentrated their study on active sourcing and emphasized that personalizing messages is essential to be successful. They define personalization as more than just personally addressing the candidate by name, but state that it involves building a connection, for example by referencing keywords or skills mentioned in the candidate's social networking profile. When doing this, however, it is important to find the balance between appearing professional and including only relevant information but at the same time including enough so that the message is perceived as individualized, enabling talents to be successfully attracted and added to the candidate pool (Brickwedde, 2017; Dannhäuser and Braehmer, 2017; Weitzel *et al.*, 2020).

Highlighting the importance of personalized messages, a survey conducted on behalf of Monster revealed that one in ten candidates finds active sourcing approaches irritating or annoying, primarily because they perceive them uninteresting or the messages seem impersonalized and standardized (Weitzel *et al.*, 2020). This underscores the importance for recruiters to engage with and review potential candidates' profiles and their most recent posts to assess if a job offer aligns with their interests (Ernst, 2021). Subsequently sourcing messages can then be based on the candidate's skills, rather than just sending generic, mass messages. However, it is crucial to filter out which information is relevant to each candidate and design a message tailored to them to ensure it seems credible and appealing. Furthermore, the message should include streamlined information about the job and the employer as established by Allen, Mahto and Otondo (2007) who state that "recruitment messages and materials that provide more information about job and organization characteristics should positively influence applicant attraction to the organization" (Allen, Mahto and Otondo, 2007, p. 1698). While their research is focused on recruitment messages on companies' websites and does not focus on active sourcing messages, similar results were found by Golovko and Schumann (2019), who focus their study on the effectiveness of personnel marketing on Facebook and found that posts that contain more detailed information about jobs result in an increased number of applications.

In addition to personalizing messages based on candidates' experiences and skills as well as addressing them by name, another level of personalization is writing the message in the candidate's native language. This is especially relevant, as several researchers highlight the increasing competition for talent and the need to attract talent internationally (Dannhäuser, 2017; Werding, 2019). Hansen and Hauff (2019) dig deeper into the globalization of the war for talents and establish brain drain as the loss of skilled workers, while brain gain describes the attraction of skilled workers from abroad. The war for talents therefore forces recruiters and HR professionals to attract the best qualified personnel beyond national borders, where active sourcing and the use of social networking platforms offer a comparatively cheap option compared to hiring third-party agencies to search for talent internationally (Hansen and Hauff, 2019; Villeda and McCamey, 2019). Language stands out as a key factor in the context of international recruitment and is an important aspect of the personalization of active sourcing messages, possibly influencing response rates and candidates' likelihood of replying.

In summary, within existing literature personalization has been established as a factor which positively influences response rates. The referral to skills and experiences, the personal salutations as well as the composition of the active sourcing message in a candidate's native language have been identified as possible levels of personalization (Dannhäuser and Chikato, 2015; Dannhäuser and Braehmer, 2017; Weitzel *et al.*, 2020). While there are studies in the context of survey design showing that personalization might increase response rates (Heerwegh *et al.*, 2005; Trespalacios and Perkins, 2016), there are only a few existing studies clearly indicating this for active sourcing message. This is why the current study aims to add to this topic by finding out whether recruiters expect more personalized messages to positively influence response rates.

3.8. Follow-up frequency in active sourcing

Similar to other research areas such as survey design or sales strategies, response rates in active sourcing are expected to improve when reminder or follow-up messages are sent to potential candidates. Within the area of survey response rates, existing research shows that contacting participants more than just once can significantly increase response rates, with Dillman (2007) stating that even several follow-ups are needed, which can then lead to 20-40% higher response rates (Dillman, 2007; Trespalacios and Perkins, 2016). Dannhäuser and Chikato (2015) within this context specifically refer to active sourcing and note that sending reminder messages about one week after the initial contact can increase response rates by 10-25%. At the same time, however, existing studies show that candidates are to some extent annoyed by active sourcing messages (Weitzel *et al.*, 2020). This means that recruiters must find a balance between sending enough reminders for candidates to respond successfully without irritating them.

Sending follow-ups is important not only for individual recruiting projects but also plays a relevant role throughout the entire candidate journey. Various studies in this regard (Enaux, 2019; Gärtner, 2020; Schrader, 2020) highlight the importance of talent or candidate relationship management and the regular contact with talents from the candidate pools. This concept is similar to the well-known customer relationship management and has the goal to set up long-term commitments between talents and the company (Enaux, 2019). Recruiters should therefore regularly engage with talents to establish a sense of connection between the recruiter and the possible candidate. This practice relates to the previously mentioned social network theory, with weak ties being relevant for recruitment processes, and is closely linked to the concept of employer branding, which aims to create a favorable impression of the employer in a candidate's mind. By regularly staying in contact with potential talents, recruiters can foster favorable connotations with the company which might lead to higher response rates when reaching out at a later point in time again (Enaux, 2019). Similarly, candidate journey is a major keyword within this context describing the entire process from the first touchpoint of a possible candidate with a company to eventually an application of the candidate. Engaging with candidates along the candidate journey can range from passive approaches such as social media advertisements to proactive ones during active sourcing or in-person events like career fairs. The overall objective, however, is to create numerous touchpoints to foster positive associations and encourage candidates to apply for jobs or accept active sourcing offers, which is why follow-up messages in active sourcing are expected to add to those touchpoints (Gärtner, 2020; Schrader, 2020).

In summary, existing literature within various fields of research suggests that follow-up messages can increase response rates (Dillman, 2007; Dannhäuser and Chikato, 2015; Trespalacios and Perkins, 2016). With the addition, that more touchpoints along the candidate journey might increase possible candidates' positive associations with an employer (Gärtner, 2020; Schrader, 2020), it is expected that follow-up messages positively influence response rates in active sourcing processes which is why the current study wants to add to this topic.

3.9. The use of AI in active sourcing

As mentioned earlier recruiting practices are highly impacted by the use and implementation of AI. However, according to Böhmer and Schinnenburg (2023) there is still a gap between technological maturity and practical application when it comes to the use of AI within recruitment as well as a lack of case studies within existing literature showing successful real-world implications. Similarly, Black and van Esch (2020) point out that "for the majority of companies today, AI-enabled recruiting systems are new and unfamiliar" (Black and van Esch, 2020, p. 223). This is also supported by a recent LinkedIn study, indicating that 65% of HR professionals within the DACH region consider AI to be a helpful tool for the future of recruitment, while only 5% actively include AI tools in their daily work. AI is mainly considered a tool that automates routine tasks, improves wording and graphics in job postings, and optimizes the identification and contact of potential candidates, which should help HR professionals dedicate more time to valuable communicative tasks with possible candidates (*LinkedIn*, 2024). Other AI-assisted tools that are already integrated into HR professionals' workflows include AI-based recommendation tools to match candidates and CVs with job offers. The use of such tools however is expected to still be rapidly growing within the next years (Dickson and Nusair, 2010; Laumer, Weitzel and Luzar, 2019; Gärtner, 2020).

Without a doubt, the use of various active sourcing tools, especially when combined with optimized AI-based algorithms, can ease the search for employees (Ruparel *et al.*, 2020). While at the same time, AI tools facilitate the analysis of profiles and the selection of possible candidates, social competencies such as networking skills, creative thinking and the ability to interpret and recognize socio-cultural backgrounds gain relevance and are key factors for active sourcing (Gärtner, 2020; Böhmer and Schinnenburg, 2023). This assumption is also supported by Orlitzky (2008) as well as Phillips and Gully (2015) who emphasize that when reaching out to possible candidates, not only strategic thinking but also recruiters' interpersonal and social skills are relevant, as these significantly influence candidates' decisions on whether to take a job offer or not. While recruiters must not only generate candidate pools with the help of AI-assisted tools, they also need to analyze candidates' preferences, their values, how they want to be approached and what might trigger a positive response. Therefore, soft skills and tailored communication strategies gain greater importance in the presence of AI.

In addition to automating routine tasks and the matchmaking functions for candidates and job offers, another way AI is already widely used in recruitment is to design and formulate job ads. Especially when recruiting internationally and personalizing messages according to candidates' native language, AI can support recruiters by translating and formulating texts in various languages within just seconds (Chen, 2023). This feature is expected to heavily influence active sourcing strategies as messages can be personalized according to a candidate's native language by just one click.

In 2024 LinkedIn already announced various AI features that are now integrated in their recruiter tool. One of them is the automated creation of personalized InMails in various languages. To generate those messages, the integrated AI tool adds personalized information according to candidates' LinkedIn profiles and merges it with the job-related details that recruiters include in their project. While so far this feature is only available in German, English, French, Italian, Portuguese and Spanish, it offers a simple way to approach possible candidates internationally and in a personalized way. Furthermore, LinkedIn offers the AI-automated creation of candidate pools as well as a function to automatically send follow-up messages when candidates are not replying (*LinkedIn: AI-assisted messages*, 2024; *LinkedIn: Follow-up*, 2024). The tool also integrates KPIs to determine whether AI-generated InMails perform better than individually created ones. These insights will provide users with valuable guidance, enabling them to adjust their active sourcing strategies for optimal efficiency (*LinkedIn: InMail*, 2024).

Even though in literature there is still a lot of discussion whether AI imposes an opportunity or a threat for recruiters, the above-mentioned features are expected to make active sourcing more easy, reducing the importance of time and cost as AI offers a more time-efficient way to do active sourcing (Melanthiou, Pavlou and Constantinou, 2015; Gärtner, 2020). By just communicating with a chatbot, candidate searches can be created and only several clicks are needed to reach out to possible candidates in a personalized manner. Therefore, AI will take over administrative tasks and support recruiters in sourcing and screening processes, allowing them more time to engage in strategic HR activities and focus on interpersonal matters involving employees and applicants (Gärtner, 2020; Chen, 2023).

Given the high potential of AI and its integration into various active sourcing tools, it offers a way to facilitate the degree of personalization in active sourcing messages. Especially the fact that messages can be personalized with the help of AI and translated into various languages by just one click leads to the expectation that the use of AI effects the degree of personalization and thereby indirectly improves response rates.

4. Research model and hypotheses

Drawing from an extensive review of literature on active sourcing and recognizing the gap in research regarding response rates and their influencing factors, this thesis seeks to address the following research question:

> *What are the key determinants influencing contact success in digital active sourcing processes?*

As established within previous chapters, there are only a few existing studies focusing on the factors that influence response rates in active sourcing processes. Peltokorpi's studies (2021, 2023), investigating factors affecting headhunters' decision to contact possible candidates, are most closely related to the subject of this thesis and provide valuable insights for developing the proposed hypotheses. Among others, candidates' characteristics such as age, gender and tenure were analyzed by Peltokorpi which is why those three factors are also used as independent variables within the current thesis (Peltokorpi, 2021, 2023). Alongside with further literature suggesting that gender influences active sourcing approaches (Zide, Elman and Shahani-Denning, 2014; Tifferet and Vilnai-Yavetz, 2018; Black and van Esch, 2020; Kroll, Veit and Ziegler, 2021; Peltokorpi, 2023), as well as younger candidates (Rubenstein *et al.*, 2018; Villeda and McCamey, 2019; Kroll, Veit and Ziegler, 2021; Peltokorpi, 2023) or candidates with shorter tenure possibly being more likely to respond to active sourcing messages (Benson, Finegold and Mohrman, 2004; Ng *et al.*, 2007; Rubenstein *et al.*, 2018; Peltokorpi, 2023), the following hypotheses were designed for the current study:

> ***Hypothesis 1:*** *Female candidates are more likely to respond to digital active sourcing messages than male ones.*
>
> ***Hypothesis 2:*** *Younger candidates are more likely to respond to digital active sourcing messages than older ones.*
>
> ***Hypothesis 3:*** *Candidates with shorter tenure are more likely to respond to digital active sourcing messages than those with longer tenure.*

Furthermore, it has been established that more personalized messages might lead to higher response rates since possible candidates may be discouraged when receiving standardized and impersonalized messages (Heerwegh *et al.*, 2005; Dannhäuser and Chikato, 2015; Trespalacios and Perkins, 2016; Dannhäuser and Braehmer, 2017; Weitzel *et al.*, 2020). This leads to the following hypothesis:

> ***Hypothesis 4:*** *Candidates are more likely to respond to digital active sourcing message if these are more personalized (e.g. written in a candidate's native language, include references to candidates' skills or experiences).*

Furthermore, various studies indicate that writing follow-up messages can increase response rates in various settings (Dillman, 2007; Dannhäuser and Chikato, 2015; Trespalacios and Perkins, 2016), which is why it is expected that reminder messages also stimulate candidates' likelihood of a response in active sourcing approaches leading to the fifth hypothesis:

> ***Hypothesis 5:*** *Candidates are more likely to respond to digital active sourcing messages when contacted more than once.*

Finally, as established in Chapter 3.9, AI is being incrementally included in many active sourcing tools making the process easier and less time-consuming. AI can write personalized messages within just seconds giving recruiters the opportunity to streamline their active sourcing approaches by creating more personalized messages in a shorter time (Laumer, Weitzel and Luzar, 2019; Gärtner, 2020; Ruparel *et al.*, 2020; Böhmer and Schinnenburg, 2023; Chen, 2023). This is why AI is included in the current thesis as a moderating factor. Moderation hereby refers to the situation where the effect of an independent on a dependent variable shifts based on the value of a moderator (Memon *et al.*, 2019). Given that AI is expected to affect the variable of personalization by offering solutions that automatically personalize active sourcing messages, it is expected that AI positively influences the variable of personalization and therefore might lead to higher response rates. This is why the last hypothesis is stated as follows:

> ***Hypothesis 6:*** *The influence of personalization of active sourcing messages on response rates is expected to be positively moderated by the use of AI-assisted tools.*

The following graphic summarizes the proposed hypotheses and showcases the model for the current study with response rate being the dependent variable. Gender, age, tenure, personalization and follow-up can be considered independent variables while the use of AI is expected to positively moderate the influence of personalization on response rates.

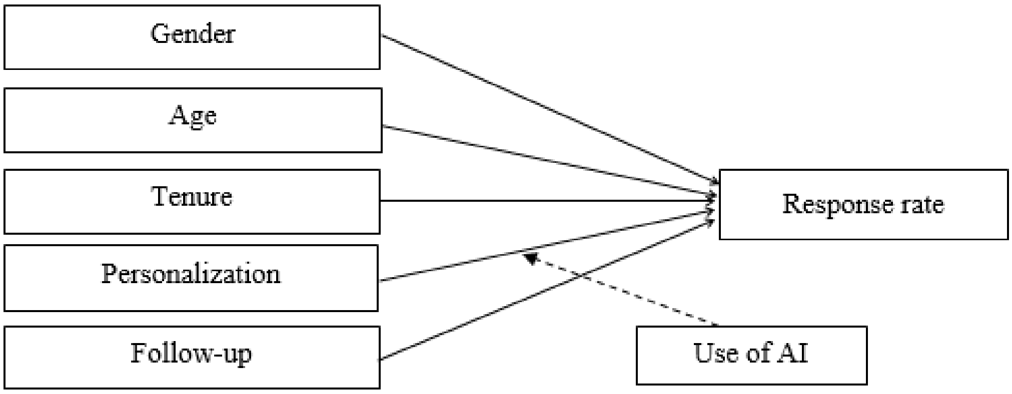

Figure 1. Conceptual model

In addition to the proposed hypotheses, the current thesis wants to add to the discussion of successful active sourcing tools. The study aims to identify which tools are most frequently used by HR and recruiting professionals to provide the basis for further research within this field.

5. Methodology

The following chapter outlines the research design used in the current study. It elaborates on the quantitative nature of the research and in detail explains the sampling method, the online-survey design, its distribution and the method for analyzing the collected data.

5.1. Research method and survey design

In general, the current study follows a quantitative research approach. Quantitative research can be described as an approach that wants "to measure and/or count social phenomena and the relationship between them" (Bryman, Bell and Harley, 2019, p. 163) and follows a deductive research approach which means that the thesis is based on solid theory from which hypotheses are deducted and then statistically tested (Bryman, Bell and Harley, 2019).

To collect the quantitative data, a self-completion, web-based questionnaire was used. Respondents hereby completed the survey online and independently, without any assistance from the researcher. Therefore, it was important to ensure clarity and understandability of the questions beforehand. The survey approach was chosen because HR professionals were expected to have limited time available, making a brief questionnaire a more practical and suitable approach than time-intensive interviews. Furthermore, a larger number of possible respondents could be reached by distributing an online survey compared to conducting interviews (Bryman, Bell and Harley, 2019). To encourage busy HR professionals and recruiters to participate in the survey and to prevent "respondent fatigue" (Bryman, Bell and Harley, 2019, p. 23), the questionnaire was kept short and could be completed within just five minutes (Dillman, 2007). However, this naturally reduced the number of questions, which limited the depth of the insights gathered. To further ensure the usability of the online questionnaire, only closed questions were used within the survey except for open text fields, where respondents could provide additional options not listed in the multiple-choice answers.

The questionnaire was administered in English and was designed as a web-based survey using SosciSurvey which offers a free software specifically designed for scientific research and projects (Leiner, 2024). As suggested by Bryman, Bell and Harley (2019) the questionnaire was designed including an introduction stating why respondents were picked for answering the questionnaire, what the goal of the survey was and ensuring respondents' confidentiality. The questionnaire further consisted of various sections starting with basic questions about the use of active sourcing and its tools, following six sections each designed to evaluate the proposed hypotheses. Among those were two additional questions about the frequency of AI use in active sourcing as well as the number of follow-up messages that are sent. The last section of the survey asked respondents about demographics such as their current position, country of employment and the industry they work in. While questions about the use of active sourcing, its tools and the respondents' demographics were asked as single or multiple choice questions, the questions designed to evaluate the proposed hypotheses could be answered with a 5-point Likert scale (1= "strongly disagree" to 5= "strongly agree"). The complete questionnaire is provided in Appendix A.

To further ensure the usability of the survey tool and the comprehensibility of the questions, pre-tests were done prior to sending the survey to the target group (Bryman, Bell and Harley, 2019). The pre-test was sent to six people of which two were part of the target group. The pre-test was successful, and only small adjustments were made before distributing the survey among the target group. One key adjustment was to exclude the word "tenure" from the questionnaire as it appeared to cause confusion during the pre-test. The original question "Candidates with shorter tenure are more likely to respond to digital active sourcing messages" was therefore adjusted to "Candidates who have worked fewer years in the same company are more likely to respond to digital active sourcing messages." Furthermore, the question about the number of follow-up messages as well as the question about the industry in which the company operates were slightly adjusted to ensure clarity.

5.2. Data collection and sampling

To distribute the survey among the target group, a convenience sampling method was applied. In general, this kind of non-probability sampling method is not ideal since findings are hard to generalize (Bryman, Bell and Harley, 2019). However, it was applied in the current study as the target group of HR professionals engaging in active sourcing is very specified and it was expected to be difficult to find enough respondents. Since the researcher at the time of the study was employed in an Austrian personnel management firm, it granted access to recruiters who were engaging in active sourcing and willing to participate in the survey. As it was not expected to reach that many recruiters only by distributing the survey online, the convenience sample offered an opportunity to collect sufficient responses to do statistical analysis.

Due to the researcher's connections that are mainly limited to HR professionals within the German-speaking region as well as the general similarity of Germany, Austria and Switzerland, it has been decided to focus the research on the DACH region.

Firstly, the survey was directly distributed within the Austrian personnel management firm that the researcher worked in, where approximately 30 employees were working in the area of active sourcing. Each possible respondent was reached by mail. Additionally, the survey was sent by mail and WhatsApp to the researcher's personal contacts asking them to distribute the survey within their companies which also included firms specializing in personnel management. Furthermore, the survey was sent to approximately 270 recruiters and HR professionals via LinkedIn within the researchers' own LinkedIn network as well as employees from major personnel management firms within the DACH region. In addition to the personal network, the Sales Navigator license on LinkedIn was used to contact LinkedIn users not yet connected with the researcher. Moreover, the link to the survey was posted on LinkedIn and shared by various colleagues and other HR professionals to reach an even broader audience.

The survey was initially available between 10^{th} of July until 10^{th} of August 2024. Due to an insufficient number of responses, the survey was extended another week until the 17^{th} of August 2024. In addition to reminder messages, more potentially relevant respondents were identified and contacted via LinkedIn. After this five-week period, a total number of approximately 315 people personally received the link to the survey and a sample size of $N = 167$ could be reached.

The dataset was cleaned by excluding those respondents that did not fully finish the survey, reducing the sample size to $N = 136$ observations. Three observations that did not fully complete the survey were kept for the analysis as they filled out the whole questionnaire except for the last page asking about the industry. As this was the only information missing, it was decided to retain those datasets for further analysis. One more observation was excluded since the respondent was employed outside of the DACH region, thereby reducing the sample to N = 135. Furthermore, the dataset was filtered to only include those respondents who actively engage in active sourcing, indicated by answering "Yes" to the question "Do you use active sourcing for recruitment purposes?" This reduced the dataset by another 26 observations, leaving a final sample size of N = 109.

A simple rule of thumb often used in statistical research is to have at least ten observations per variable (Backhaus *et al.*, 2021). As the current study has one dependent variable, five independent ones as well as one moderating variable, a sample size of N = 70 could be considered enough. For the current study a more accurate rule-of-thumb by Green (1991) was considered who suggests that the minimum number of observations should be $N \geq 50 + 8m$, with m being the number of independent variables. Considering that there are six hypotheses that want to be checked within the current study, a sample size of N = 98 would be a reasonable number to do statistical tests. As there are N = 109 observations, there are sufficient responses to conduct further statistical tests.

5.3. Data analysis

To test the influence of the defined independent variables and the moderating effect of AI on the dependent one, multiple linear regression analysis was chosen as structure-testing method. This method is suitable when there is more than one independent variable that wants to be tested on their effect on the dependent variable, and when all variables are metric (Eckstein, 2016; Backhaus *et al.*, 2021; Planing, 2022). As the dependent variable, which is the estimated response rate (in percent), as well as the independent variables (gender, age, tenure, personalization and follow-up), which were evaluated using Likert scales, can be considered metric, regression analysis is a valid method to test the proposed hypotheses (Eckstein, 2016; Backhaus *et al.*, 2021; Planing, 2022).

To analyze the dataset, do statistical tests and perform the regression analysis, the data analysis program IBM SPSS Statistics 29 was used.

6. Analysis and results

Within the next chapter, the findings from the online survey and the results of the statistical analysis are presented. The suggested hypotheses were tested using regression analysis to evaluate the relationships between the variables. Key results and outcomes of the regression models are summarized to provide a clear understanding and basis for further interpretations within Chapter 7.

6.1. Reliability

To test the reliability of measures within a survey, Cronbach's alpha is usually computed, which is used to test internal reliability and to check the coherence of multiple-item measures (Bryman, Bell and Harley, 2019). As the survey for this study did not include multiple items and the variables gender, age, tenure and personalization were all checked by only one survey question, it is not necessary to calculate Cronbach's alpha. Only for the questions about follow-up frequency as well as the use and contribution of AI there were two separate questions in the survey. However, since the two questions address different aspects, they cannot be combined within one variable and therefore Cronbach's alpha was deemed unsuitable and not computed within the current study.

6.2. Descriptive statistics

Prior to conducting the regression analysis, a detailed analysis of the descriptive statistics was performed to provide an overview of the data distribution and key characteristics of the sample. Before outlining the descriptive statistic, it is important to clarify that some tables distinguish between "percent" and "valid percent" due to missing responses in the questionnaire. To get an accurate representation of the frequencies, the analysis utilizes "valid percent" (Eckstein, 2016).

When looking at the distribution of where respondents were employed at the time of the survey, Table 1 shows that most of them worked in Austria (46,8%) and Germany (44,0%), whereas only 9,2% of respondents were employed in Switzerland.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Austria	51	46,8	46,8	46,8
	Germany	48	44,0	44,0	90,8
	Switzerland	10	9,2	9,2	100,0
	Total	109	100,0	100,0	

Table 1. Frequencies: Country of employment

To find out which industry the respondents work in, the survey included the question "Which industry sector best represents the primary focus of your company", where 25,5% indicated to work in consulting services. This is not surprising given the fact that the contacted respondents via LinkedIn were often working in specialized personnel management or personnel consulting services, which were expected to use active sourcing in their daily business. Other than that, what stands out is that 22,6% of respondents work in the IT or technology sector and 12,3% could not identify with any given sectors. Other sectors, not listed in the survey, that were additionally mentioned by respondents are: life science, staffing industry, telecommunication, insurance, TIC (Testing, Inspection, and Certification), architecture, venture capital/fonds and e-commerce.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Construction/Real Estate	6	5,5	5,7	5,7
	Consulting Services	27	24,8	25,5	31,1
	Energy/Utilities	4	3,7	3,8	34,9
	Finance/Banking	8	7,3	7,5	42,5
	Healthcare/Medical	6	5,5	5,7	48,1
	Hospitality/Travel	1	,9	,9	49,1
	Manufacturing/Engineering	9	8,3	8,5	57,5
	Media/Entertainment	1	,9	,9	58,5
	Retail/Consumer Goods	7	6,4	6,6	65,1
	Technology/IT	24	22,0	22,6	87,7
	Other (please specify):	13	11,9	12,3	100,0
	Total	106	97,2	100,0	
Missing	no answer	3	2,8		
Total		109	100,0		

Table 2. Frequencies: Industry

Table 3 shows the position or job title of respondents at the time of the survey. The majority (43,1%) indicated to work as recruiters or recruitment specialists. 16,5% at the time of the survey worked as recruiting consultants and 14,7% as talent acquisition managers. 9,2% were head of HR or recruiting, 8,3% HR business partner, 4,6% HR manager or director and 3,7%

chose “Other” which was more clearly specified as being the owner of personnel consulting services, head of talent acquisition, people manager and specialist talent acquisition.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Recruiter/Recruitment Specialist	47	43,1	43,1	43,1
	Talent Acquisition Manager	16	14,7	14,7	57,8
	HR Business Partner	9	8,3	8,3	66,1
	HR Manager/Director	5	4,6	4,6	70,6
	Head of HR/Recruiting	10	9,2	9,2	79,8
	Recruiting Consultant	18	16,5	16,5	96,3
	Other (please specify):	4	3,7	3,7	100,0
	Total	109	100,0	100,0	

Table 3. Frequencies: Current position

Table 4 shows how many years of experience survey participants have in their working field. Most of the respondents (26,6%) have worked in their current field for 3-5 years and 21,1% for 6-10 years. While 18,3% worked in the business for only 1-2 years, there are quite a lot of respondents with a large amount of experience, working in the current field for 11-15 years (16,5%) or even more than 15 years (13,8%).

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 1 year	4	3,7	3,7	3,7
	1-2 years	20	18,3	18,3	22,0
	3-5 years	29	26,6	26,6	48,6
	6-10 years	23	21,1	21,1	69,7
	11-15 years	18	16,5	16,5	86,2
	More than 15 years	15	13,8	13,8	100,0
	Total	109	100,0	100,0	

Table 4. Frequencies: Experience

On average respondents selected 2,14 active sourcing tools that they most frequently use for active sourcing with 30,3% using only one tool, 38,5% two tools and 22,9% three tools. Only 8,3% used more than three different tools for active sourcing purposes. To analyze the multiple-choice question from the survey and combine the various dichotomous variables, a variable set was created and analyzed for frequencies shown in Table 6 (Eckstein, 2016). LinkedIn clearly stands out as the most relevant tool with 99,1% of respondents using it for active sourcing. Even though the respondents were all working in the DACH region, the XING TalentManager was only used by 45,9%. Textkernel Search seems to be a quite relevant tool as well with 20,2% of respondents using it, as well as the StepStone CV-center with 17,4%. All other tools

(Open web, Stack Overflow Talent, Monster Lebenslaufdatenbank, Experteer Lebenslaufdatenbank) were used by less than 5% whereas Talentwunder and TalentBin were not used by respondents at all. In addition to the options provided in the survey, there was a large number of respondents (20,2%) using other platforms not listed in the multiple-choice options. Among those were: personal networks and internal databases, databases from the federal employment agency, Google, Indeed, karriere.at databases, FreelancerMap and Freelance.de, Hireez, Meetup and GitHub.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	33	30,3	30,3	30,3
	2	42	38,5	38,5	68,8
	3	25	22,9	22,9	91,7
	4	5	4,6	4,6	96,3
	5	3	2,8	2,8	99,1
	6	1	,9	,9	100,0
	Total	109	100,0	100,0	

Table 5. Frequencies: Number of active sourcing tools

		Responses		Percent of Cases
		N	Percent	
Auswahl Active Souricng Tools[a]	LinkedIn Recruiter	108	46,4%	99,1%
	XING TalentManager	50	21,5%	45,9%
	Stack Overflow Talent	4	1,7%	3,7%
	Textkernel Search	22	9,4%	20,2%
	Monster Lebenslaufdatenbank	5	2,1%	4,6%
	Experteer Lebenslaufdatenbank	3	1,3%	2,8%
	StepStone CV-Center	19	8,2%	17,4%
	Others	22	9,4%	20,2%
Total		233	100,0%	213,8%

a. Dichotomy group tabulated at value 1.

Table 6. Frequencies: Active sourcing tools

Within the survey there were three questions asking respondents to estimate: "About how many active sourcing messages do you send to potential candidates per month? What is your estimated overall response rate (negative + positive) to your active sourcing messages? What is your estimated positive response rate?" Tables 7 and 8 present descriptive statistics for the answers to those questions. Notably, there is a wide range in the data as for instance, the average number of active sourcing messages varies from a minimum of 5 to a maximum of 2000. Given the expectation of outliers impacting these statistics, outliers for all three variables were detected using boxplots as well as a Stem-and-Leaf plots (Eckstein, 2016; Backhaus *et al.*, 2021). The analysis detected eight extreme values for the number of messages sent and five for estimated positives response rates (see Figure B. 1, Figure B. 2 and Figure B. 3 in Appendix B). To get a better picture, those outliers were excluded, and revised descriptive statistics are presented in Table 8. These adjusted figures show that HR professionals on average send 110,31 active sourcing messages monthly with a standard deviation of 101,14. The overall response rate, combining positive and negative replies, averages 39,67% with a standard deviation of 21,32. For only positive responds, the average is 18,01% with a standard deviation of 13,05.

	N	Minimum	Maximum	Mean	Std. Deviation
Number of active sourcing messages (monthly)	109	5	2000	177,06	282,818
Estimated positive + negative response rate	109	1	95	40,05	22,171
Estimated positive response rate	109	0	80	19,92	17,084
Valid N (listwise)	109				

Table 7. Descriptive statistics: Active sourcing messages and response rates (including outliers)

	N	Minimum	Maximum	Mean	Std. Deviation
Number of active sourcing messages (monthly)	96	5	400	110,31	101,138
Estimated positive + negative response rate	96	1	95	39,67	21,316
Estimated positive response rate	96	0	50	18,01	13,048
Valid N (listwise)	96				

Table 8. Descriptive statistics: Active sourcing messages and response rates (excluding outliers)

Furthermore, the answers from Likert scale questions that are related to the independent variables were analyzed in more detail and shown in Tables 9-14. For a more visual display of the results, bar charts of the following analyses are displayed in Appendix B (see Figure B. 4 – Figure B. 9).

When looking at the frequencies of responses to the question whether women are more likely to answer to digital active souring messages, 57,8% answered with neutral, 25,6% disagree or strongly disagree and only 16,6% agree or strongly agree with women answering more often. When considering age, while 45,8% agree or strongly agree with the statement that younger candidates are more likely to respond to active sourcing messages, only 21,1% disagree or strongly disagree. For tenure, 47,7% (strongly) agree that candidates with shorter tenure are more likely to respond, while 17,4% (strongly) disagree. Furthermore, 56,9% (strongly) agree that sending reminder messages increases the chance of responses, while 22,9% (strongly) disagree. The clearest picture can be seen for personalization where 59,6% strongly agree and 33,9% agree that personalization enhances response rates. Only 3,7% disagree while no respondents strongly disagree. For the moderating effect of AI, frequency analysis shows while 40,3% (strongly) agree that AI enhances personalization and can therefore increase response rates, 22,0% (strongly) disagree with this statement.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	strongly disagree	8	7,3	7,3	7,3
	disagree	20	18,3	18,3	25,7
	neutral	63	57,8	57,8	83,5
	agree	15	13,8	13,8	97,2
	strongly agree	3	2,8	2,8	100,0
	Total	109	100,0	100,0	

Table 9. Frequencies: Likert Scale Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	strongly disagree	2	1,8	1,8	1,8
	disagree	21	19,3	19,3	21,1
	neutral	36	33,0	33,0	54,1
	agree	42	38,5	38,5	92,7
	strongly agree	8	7,3	7,3	100,0
	Total	109	100,0	100,0	

Table 10. Frequencies: Likert Scale Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	strongly disagree	1	,9	,9	,9
	disagree	18	16,5	16,5	17,4
	neutral	38	34,9	34,9	52,3
	agree	44	40,4	40,4	92,7
	strongly agree	8	7,3	7,3	100,0
	Total	109	100,0	100,0	

Table 11. Frequencies: Likert Scale Tenure

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	disagree	4	3,7	3,7	3,7
	neutral	3	2,8	2,8	6,4
	agree	37	33,9	33,9	40,4
	strongly agree	65	59,6	59,6	100,0
	Total	109	100,0	100,0	

Table 12. Frequencies: Likert Scale Personalization

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	strongly disagree	5	4,6	4,6	4,6
	disagree	20	18,3	18,3	22,9
	neutral	22	20,2	20,2	43,1
	agree	44	40,4	40,4	83,5
	strongly agree	18	16,5	16,5	100,0
	Total	109	100,0	100,0	

Table 13. Frequencies: Likert Scale FUP

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	strongly disagree	6	5,5	5,5	5,5
	disagree	18	16,5	16,5	22,0
	neutral	41	37,6	37,6	59,6
	agree	36	33,0	33,0	92,7
	strongly agree	8	7,3	7,3	100,0
	Total	109	100,0	100,0	

Table 14. Frequencies: Likert Scale Moderating effect AI

Table 15 shows the number of follow-up messages that respondents send, where more than half of the respondents (52,3%) send one reminder message to possible candidates. 19,3% send two reminder messages, 5,5% three and only 0,9% more than three. However, almost one quarter (22,0%) of respondents do not send follow-ups at all. Similarly, looking at frequencies of answers to the question “To what extent do you use AI-assistance for personalizing your active sourcing messages”, 33,6% only rarely use AI-assistance and 21,5% do not use it at all. This means that more than half of the respondents do not extensively engage in the use of AI assistance to personalize their messages. 25,2% indicate using it sometimes, while only 13,1% often and 6,5% always use the help of AI for personalization.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Never	24	22,0	22,0	22,0
	1 time	57	52,3	52,3	74,3
	2 times	21	19,3	19,3	93,6
	3 times	6	5,5	5,5	99,1
	More than 3 times	1	,9	,9	100,0
	Total	109	100,0	100,0	

Table 15. Frequencies: Number of FUPs

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Always	7	6,4	6,5	6,5
	Often	14	12,8	13,1	19,6
	Sometimes	27	24,8	25,2	44,9
	Rarely	36	33,0	33,6	78,5
	Not at all	23	21,1	21,5	100,0
	Total	107	98,2	100,0	
Missing	no answer	2	1,8		
Total		109	100,0		

Table 16. Frequencies: Use of AI

6.3. Multiple linear regression analysis

Multiple linear regression analysis was performed to analyze the influence of the independent variables (gender, age, tenure, personalization, follow-up and AI) on the response rates in active sourcing and test the proposed hypotheses. The following chapter presents the results of this analysis.

As established in the literature review, the primary dependent variable for the current study is the overall response rate in active sourcing including positive as well as negative responses. Additionally, the questionnaire asked respondents to state their estimated positive response rate which has also been incorporated in the analysis. Given furthermore that hypothesis 6 aims to test a moderating effect, various regression models were created. The following models therefore account for all relevant factors and their results will be presented in the subsequent chapter:

- **Model 1:** Dependent variable – overall response rate (positive + negative responses) excluding moderating effect
- **Model 2:** Dependent variable – overall response rate (positive + negative responses) including moderating effect

- **Model 3:** Dependent variable – positive response rate excluding moderating effect
- **Model 4:** Dependent variable – positive response rate including moderating effect

Chapter 6.3.1 starts with analyzing the influence of the independent variables as well as the moderating one on the dependent variable of overall response rate. To test whether there is a difference between the influence on overall compared to only the positive response rate, the same regressions were performed on positive response rate and results are displayed in Chapter 6.3.2

In line with common practice in scientific research, for all further analyses an error probability of $\alpha = 5\%$ for statistical analysis was used (Backhaus *et al.*, 2021).

6.3.1. Model 1 and 2: Dependent variable – overall response rate

To be able to perform a multiple regression analysis, there are several requirements that need to be met. Firstly, all variables must be metric which is the case for the dependent variable "response rate" as well as for all independent ones that were analyzed using Likert scales which can be counted as metric scales (Planing, 2022). Further requirements that were tested are linearity, homoscedasticity, autocorrelation, normal distribution and multicollinearity (Field, 2018; Backhaus *et al.*, 2021; Planing, 2022). All tables and graphs computed for these tests can be found in Appendix C.

To test whether there is linearity between the dependent and independent variables, scatterplots plotting the residuals against the fitted y-values were used. As the scatterplot does not show any pattern and the residuals are distributed randomly, linearity can be assumed (Field, 2018; Backhaus *et al.*, 2021). Autocorrelation was tested using the Durbin-Watson test, checking the correlation between residuals. Field (2018) hereby indicates that values smaller than one may cause problems. Backhaus *et al.* (2021) propose that a score between 1,5 and 2,5 suggests an absence of autocorrelation. As the Durbin-Watson test shows a value of 1,707, both requirements are met and there are no issues with autocorrelation. The homoscedasticity requirement was tested using the Levene test to check whether the variance for error terms is constant. The test shows insignificant values ($p > 0{,}050$) for all variables, indicating that the variances are not significantly different from each other and the homoscedasticity requirement is met (Field, 2018; Backhaus *et al.*, 2021; Planing, 2022). To test for normal distribution, Planing (2022) as well as Backhaus *et al.* (2021) state that normal distribution can be assumed when there is a sufficient number of responses ($N > 40$). Furthermore, the requirement was also tested plotting the residuals in a histogram as well as checking the Q-Q plot and P-P plot. The histogram indicates that the residuals are approximately normally distributed. Furthermore, the P-P and Q-Q plots show that the residuals are scattered approximately along the linear line, supporting the assumption of normality (Field, 2018; Backhaus *et al.*, 2021). Finally, to be able to perform a linear multiple regression, there should not be a linear relationship among the independent variables. For the current study, the VIF (variance inflation factor) was used to check for multicollinearity which should ideally show values smaller than five (Eckstein, 2016; Field, 2018; Backhaus *et al.*, 2021; Planing, 2022). As for all variables VIF was slightly above one, this suggests that the variables are not linearly correlated with each other and the requirement is met. In addition to the VIF test, the correlation between the variables was examined and presented in a correlation matrix displaying the Pearson correlation coefficient. The matrix in Table 17 shows that only tenure and gender are correlated (0,231). However, according to Backhaus *et al.* (2021) values smaller than 0,3 can be considered a weak correlation and should therefore not disturb further testing.

		Estimated positive + negative response rate	Gender	Age	Tenure	Personalization	FUPs	Moderating effect AI
Estimated positive + negative response rate	Pearson Correlation	1	-,046	-,157	,041	,081	,048	,012
	Sig. (2-tailed)		,637	,102	,669	,405	,620	,899
	N	109	109	109	109	109	109	109
Gender	Pearson Correlation	-,046	1	-,017	,231*	,006	,068	,145
	Sig. (2-tailed)	,637		,859	,016	,947	,482	,134
	N	109	109	109	109	109	109	109
Age	Pearson Correlation	-,157	-,017	1	,033	-,073	,080	-,017
	Sig. (2-tailed)	,102	,859		,735	,449	,410	,863
	N	109	109	109	109	109	109	109
Tenure	Pearson Correlation	,041	,231*	,033	1	,061	,120	,180
	Sig. (2-tailed)	,669	,016	,735		,532	,213	,060
	N	109	109	109	109	109	109	109
Personalization	Pearson Correlation	,081	,006	-,073	,061	1	,003	-,024
	Sig. (2-tailed)	,405	,947	,449	,532		,978	,801
	N	109	109	109	109	109	109	109
FUPs	Pearson Correlation	,048	,068	,080	,120	,003	1	-,110
	Sig. (2-tailed)	,620	,482	,410	,213	,978		,253
	N	109	109	109	109	109	109	109
Moderating effect AI	Pearson Correlation	,012	,145	-,017	,180	-,024	-,110	1
	Sig. (2-tailed)	,899	,134	,863	,060	,801	,253	
	N	109	109	109	109	109	109	109

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

Table 17. Correlation matrix 1

Furthermore, before performing the regression, outliers possibly influencing the regression results were detected by looking at leverage values as well as the Cook's distance (Backhaus *et al.*, 2021; Planing, 2022). As suggested by Backhaus *et al.* (2021), the cut-off value 4/N (4/109) for Cook's distance was used, resulting in an upper threshold of 0,037 (approximated from 0,03669725). Accordingly, all observations with a Cook's distance greater than this were excluded for the regression model, which applied to four observations. For graphical display, the Cook's distance and the leverage values were displayed in a scatterplot clearly showing these outliers (see Figure C. 5 in Appendix C). When examining the scatterplot, case 210 also appears to be an outlier with a high leverage value. However, this observation was not excluded as high leverage alone does not necessarily mean that the observation is affecting the regression. It becomes problematic when a data point significantly influences the regression line and at the same time has a large deviation from the predicted value. This is usually only the case for observations with high Cook's distance (Planing, 2022). Excluding those four observations leads to a sample size of N = 104 that was included in the regression analysis below.

After checking all requirements and excluding outliers, a multiple regression analysis was performed for Model 1 and displayed in Tables 18, 19 and 20, including overall response rate as dependent variable and gender, age, tenure, personalization and follow-up as independent ones.

To check for effects, both the significance values and the unstandardized B coefficients were carefully examined (Backhaus *et al.*, 2021). Table 20 shows that gender is not a significant predictor of overall response rate (B = -1,405; p = 0,608) meaning hypothesis 1 is rejected. Age is the only independent variable that shows significant results in Model 1 (B = -5,525; p = 0,015) with B = -5,525 indicating that age has a significant negative effect on response rate meaning that younger candidates are perceived to be more likely to respond to active sourcing messages, supporting hypothesis 2. The variable tenure with B = -1,240 indicates that shorter tenure might lead to higher response rates. However, this is not statistically significant (p = 0,621) which is why hypothesis 3 is rejected. Similarly, the regression shows that personalization (B = 2,818; p = 0,318) and follow-up (B = 2,473; p = 0,211) may have positive effects on response rates. Nevertheless, both effects are statistically insignificant which is why hypotheses 4 and 5 are also rejected. This means that according to Model 1, out of the hypotheses 1-5, only hypothesis 2 is supported.

In general, however, it must be noted that the ANOVA analysis (see Table 19) shows a p-value of 0,125 which means that the overall regression model is not statistically significant, suggesting the need for further research. To further test the goodness-of-fit for the current model, R-squared (R^2) was used which is "the proportion of total variation in Y that is explained by the independent variables" (Backhaus *et al.*, 2021, p. 78). However, as the regular R^2 does not account for sample size and the number of independent variables, adjusted R^2 was used as a more accurate measure within the current study (Chatterjee and Hadi, 2006; Backhaus *et al.*, 2021). The model summary in Tabel 18 shows an adjusted R^2 of 0,036 which means that the independent variables gender, age, tenure, personalization and follow-up explain only 3,6% of the variance of the overall response rate.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,287[a]	,082	,036	20,932

a. Predictors: (Constant), FUPs, Gender, Personalization, Age, Tenure

Table 18. Summary: Regression Model 1

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3892,951	5	778,590	1,777	,125[b]
	Residual	43377,240	99	438,154		
	Total	47270,190	104			

a. Dependent Variable: Estimated positive + negative response rate

b. Predictors: (Constant), FUPs, Gender, Personalization, Age, Tenure

Table 19. ANOVA Model 1

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	44,446	18,109		2,454	,016
	Gender	-1,405	2,730	-,051	-,514	,608
	Age	-5,525	2,236	-,240	-2,471	,015
	Tenure	-1,240	2,501	-,050	-,496	,621
	Personalization	2,818	2,808	,097	1,003	,318
	FUPs	2,437	1,937	,124	1,258	,211

a. Dependent Variable: Estimated positive + negative response rate

Table 20. Regression coefficients Model 1

To enhance the model and test hypothesis 6 with the moderating effect of AI on personalization and response rates, Model 2 was created following the product-indicator approach (Memon *et al.*, 2019). According to this approach, in addition to the original independent variables, the moderating variable as well as an interaction term consisting of the variable personalization multiplied with the moderating variable of AI were included in the regression model.

As Model 2 includes new variables, Cook's distance was again computed, and seven outliers were identified exceeding the Cook's distance cut-off value of 0,037 (see Figure C. 6 in Appendix C). Those observations were excluded meaning that there were N = 102 observations included in the following regression analysis.

As within Model 1, the second regression in Table 23 also shows insignificant value for the variables gender (B = -1,082; p = 0,682), tenure (B = -0,742; p = 0,761) and follow-up (B = 2,045; p = 0,296) meaning that according to Model 2, hypotheses 1, 3 and 5 are rejected. Age is again significant (B = -5,603; p = 0,014) and shows a negative effect on overall response rate, supporting hypothesis 2 that younger candidates tend to reply more often to active sourcing messages. The additional variable of the moderating effect of AI shows a p-value slightly over 5% (p = 0,068) whereas B = 29,880 would indicate that the use of AI enhances personalization and leads to higher response rates, however, this is not statistically significant. Other than Model 1, Model 2 shows significant values for personalization (B = 24,496; p = 0,039) with B = 24,496 indicating that personalization has a strongly positive effect on response rates, supporting hypothesis 4. The interaction term also shows significant values (B = -6,989; p = 0,048). However, the results show that the positive impact of personalization on response rates is reduced by the use of AI, indicating that AI moderates the effect of personalization but in a negative way (B = -6,989). Since hypothesis 6 expected that this effect would be positive, hypothesis 6 also needs to be rejected.

Nevertheless, the ANOVA analysis in Table 22 again shows that the regression model is not significant (p = 0,076). However, compared to Model 1 (p = 0,125) it improved and is now closer to being significant. Furthermore, adjusted R^2 improved to 0,059 meaning that the independent variables including the moderating effect explain 5,9% of the variance of the overall response rate (see Table 21).

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,353[a]	,125	,059	19,920

a. Predictors: (Constant), Interaction Term Personalization * AI, Age, FUPs, Gender, Tenure, Personalization, Moderating effect AI

Table 21. Summary: Regression Model 2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5312,963	7	758,995	1,913	,076[b]
	Residual	37298,851	94	396,796		
	Total	42611,814	101			

a. Dependent Variable: Estimated positive + negative response rate

b. Predictors: (Constant), Interaction Term Personalization * AI, Age, FUPs, Gender, Tenure, Personalization, Moderating effect AI

Table 22. ANOVA Model 2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-49,127	55,354		-,887	,377
	Gender	-1,082	2,629	-,041	-,411	,682
	Age	-5,603	2,239	-,248	-2,502	,014
	Tenure	-,742	2,434	-,031	-,305	,761
	Personalization	24,496	11,730	,835	2,088	,039
	FUPs	2,045	1,946	,106	1,051	,296
	Moderating effect AI	29,880	16,168	1,410	1,848	,068
	Interaction Term Personalization * AI	-6,989	3,494	-1,713	-2,000	,048

a. Dependent Variable: Estimated positive + negative response rate

Table 23. Regression coefficients Model 2

6.3.2. Model 3 and 4: Dependent variable – positive response rate

As mentioned earlier, within the survey the overall response rates for active sourcing as well as only the positive response rates were evaluated. Therefore, to compare those two, there were additional regression analyses performed with only positive response rate as dependent variable.

As done for the prior regressions, outliers exceeding a Cook's distance of 0,037 were excluded from the regression which was the case for five observations. Furthermore, all requirements (linearity, homoscedasticity, autocorrelation, normal distribution and multicollinearity) were again checked and displayed in Appendix C (Field, 2018; Backhaus *et al.*, 2021; Planing, 2022). Even though the scatterplot displaying residuals and fitted y-values shows some points clustering in the middle-lower part of the scatterplot, it does not show any clear pattern which is why linearity can be assumed. The Durbin-Watson test shows a value of 2,040, indicating that there is no problem with autocorrelation. The Levene test for homoscedasticity shows insignificant values for the variables gender, tenure, personalization, follow-up and the moderating effect of AI, indicating that the variances are not significantly different from each other. However, the variable age shows a p-value of 0,026 indicating that there might be a problem with heteroscedasticity. To check whether this is the case, in addition to the Levene test, the Breusch-Pagan test was undertaken which shows a p-value of 0,947 indicating that the homoscedasticity requirement is nevertheless met (Field, 2018). A histogram plotting the residuals shows that the error terms are approximately normally distributed. Furthermore, the P-P and the Q-Q plots show that the residuals are roughly following the linear line which means that the requirement for normal distribution is met. Furthermore, the VIF shows values slightly above one, indicating that there is no problem with multicollinearity (Eckstein, 2016; Field, 2018; Backhaus *et al.*, 2021; Planing, 2022). The Pearson correlation matrix below again displays the correlation among all variables (Backhaus *et al.*, 2021). As seen within the previous models, only tenure and gender weakly correlate (0,231).

		Estimated positive response rate	Gender	Age	Tenure	Personalization	FUPs	Moderating effect AI
Estimated positive response rate	Pearson Correlation	1	-,023	-,132	,034	,040	-,026	-,084
	Sig. (2-tailed)		,810	,173	,725	,681	,790	,385
	N	109	109	109	109	109	109	109
Gender	Pearson Correlation	-,023	1	-,017	,231*	,006	,068	,145
	Sig. (2-tailed)	,810		,859	,016	,947	,482	,134
	N	109	109	109	109	109	109	109
Age	Pearson Correlation	-,132	-,017	1	,033	-,073	,080	-,017
	Sig. (2-tailed)	,173	,859		,735	,449	,410	,863
	N	109	109	109	109	109	109	109
Tenure	Pearson Correlation	,034	,231*	,033	1	,061	,120	,180
	Sig. (2-tailed)	,725	,016	,735		,532	,213	,060
	N	109	109	109	109	109	109	109
Personalization	Pearson Correlation	,040	,006	-,073	,061	1	,003	-,024
	Sig. (2-tailed)	,681	,947	,449	,532		,978	,801
	N	109	109	109	109	109	109	109
FUPs	Pearson Correlation	-,026	,068	,080	,120	,003	1	-,110
	Sig. (2-tailed)	,790	,482	,410	,213	,978		,253
	N	109	109	109	109	109	109	109
Moderating effect AI	Pearson Correlation	-,084	,145	-,017	,180	-,024	-,110	1
	Sig. (2-tailed)	,385	,134	,863	,060	,801	,253	
	N	109	109	109	109	109	109	109

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

Table 24. Correlation matrix 2

As all requirements for a multiple linear regression analysis were met, the regression for Model 3 could be computed. The following tables show the regression analysis excluding exceeding Cook's distance values.

The coefficients table in Table 27 shows very similar results to the regression in Model 1. Other than in Model 1, gender (B = 0,534; p = 0,750) and tenure (B = 0,591; p = 0,704) seem to have a positive effect on response rates. However, both effects are not statistically significant meaning that hypotheses 1 and 3 are rejected according to Model 3. Similarly, personalization (B = 0,046; p = 0,980) and follow-up (B = 0,990; p = 0,413) indicate weaker positive effects than in Model 1. However, those effects are also not statistically significant, which is why hypotheses 4 and 5 are again rejected. Like within Model 1, age is the only variable that is statistically significant (B = -3,358; p = 0,025), with B = -3,358 indicating that younger candidates tend to more often positively reply, supporting hypothesis 2.

Just like the previous models, the ANOVA analysis shows that the regression model in general is not significant with a p-value of 0,298 (see Table 26). Additionally, adjusted R^2 in Table 25 shows that only 1,1% of the variance of the positive response rate can be explained by the variables gender, age, tenure, personalization and follow-up which indicates that there is high potential to improve Model 3 (Backhaus *et al.*, 2021).

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,244[a]	,059	,011	13,407

a. Predictors: (Constant), FUPs, Gender, Personalization, Age, Tenure

Table 25. Summary: Regression Model 3

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1110,449	5	222,090	1,236	,298[b]
	Residual	17614,388	98	179,739		
	Total	18724,837	103			

a. Dependent Variable: Estimated positive response rate

b. Predictors: (Constant), FUPs, Gender, Personalization, Age, Tenure

Table 26. ANOVA Model 3

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	21,478	11,767		1,825	,071
	Gender	,534	1,670	,032	,320	,750
	Age	-3,358	1,474	-,224	-2,279	,025
	Tenure	,591	1,552	,039	,381	,704
	Personalization	,046	1,801	,002	,025	,980
	FUPs	,990	1,203	,081	,823	,413

a. Dependent Variable: Estimated positive response rate

Table 27. Regression coefficients Model 3

To enhance the model and test the moderating effect of AI on the positive response rate, an interaction term was again computed and added to the regression following the product-indicator approach (Memon *et al.*, 2019). As the model hereby changes, the dataset was again checked for outliers, and six observations exceeding the upper Cook's distance threshold were excluded from the regression (see Figure C. 12 in Appendix C). The following tables therefore show the regression with N = 103.

Other than Model 2 with overall response rate as dependent variable, Model 4 with only positive response rate does not show significant effects with either the interaction term (B = -4,061; p = 0,066), nor the independent variable of personalization (B = 13,821; p = 0,070) or the variable of the moderating effect (B = 15,832; p = 0,120). As within all prior models, the variables gender (B = 0,967; p = 0,557), tenure (B = 0,853; p = 0,580) and follow-up (B = 0,317; p = 0,797) stayed not significant. Even the variable age is within Model 4 slightly above the significance level (B = -2,863; p = 0,051). This means that according to Model 4, all hypotheses must be rejected. However, as within all previous models, the ANOVA analysis (see Table 29) shows an insignificant p-value for the whole regression model (p = 0,083). Adjusted R^2 also indicates that only 5,6% of the variance of the positive response rate are explained by the variables gender, age, tenure, personalization, follow-up as well as the moderating effect of AI. This indicates an improvement to Model 3 (adjusted $R^2 = 0{,}011$) but shows that Model 4 still performs less well than Model 2 (adjusted $R^2 = 0{,}059$).

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,348[a]	,121	,056	13,064

a. Predictors: (Constant), Interaction term Personalization * AI, Age, Gender, FUPs, Tenure, Personalization, Moderating effect AI

Table 28. Summary: Model 4

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2233,247	7	319,035	1,869	,083[b]
	Residual	16213,161	95	170,665		
	Total	18446,408	102			

a. Dependent Variable: Estimated positive response rate

b. Predictors: (Constant), Interaction term Personalization * AI, Age, Gender, FUPs, Tenure, Personalization, Moderating effect AI

Table 29. ANOVA Model 4

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-33,910	35,850		-,946	,347
	Gender	,967	1,641	,059	,589	,557
	Age	-2,863	1,451	-,192	-1,973	,051
	Tenure	,853	1,539	,056	,555	,580
	Personalization	13,821	7,553	,760	1,830	,070
	FUPs	,317	1,229	,026	,258	,797
	Moderating effect AI	15,832	10,095	1,150	1,568	,120
	Interaction term Personalization * AI	-4,061	2,187	-1,552	-1,857	,066

a. Dependent Variable: Estimated positive response rate

Table 30. Regression coefficients Model 4

In summary, Table 31 presents all four regression models, comparing the p-values for each variable, the adjusted R^2 as an indicator for the goodness-of-fit, and the p-value for the overall regression model. Model 2 shows the best adjusted R^2, explaining 5,9% of the variance of the dependent variable through the independent and moderating variables. Even though it is still insignificant, Model 2 is only slightly above the significance threshold (p = 0,076) and includes two variables (age, personalization) as well as the interaction term that are significant at a 5% level.

	Model 1	Model 2	Model 3	Model 4
	p-values	p-values	p-values	p-values
Gender	0,608	0,682	0,750	0,557
Age	**0,015**	**0,014**	**0,025**	0,051
Tenure	0,621	0,761	0,704	0,580
Personalization	0,318	**0,039**	0,980	0,070
Follow-up	0,211	0,296	0,413	0,797
Moderating effect of AI	-	0,068	-	0,120
Interaction term	-	**0,048**	-	0,066
ANOVA	0,125	0,076	0,298	0,083
Adjusted R^2	0,036	0,059	0,011	0,056

Table 31. Comparison regression models

Furthermore, Table 32 summarizes the outcomes of hypotheses testing and states which hypotheses were accepted or rejected depending on the model used for testing.

	Model 1	Model 2	Model 3	Model 4
Hypothesis 1	rejected	rejected	rejected	rejected
Hypothesis 2	**accepted**	**accepted**	**accepted**	rejected
Hypothesis 3	rejected	rejected	rejected	rejected
Hypothesis 4	rejected	**accepted**	rejected	rejected
Hypothesis 5	rejected	rejected	rejected	rejected
Hypothesis 6	-	rejected	-	rejected

Table 32. Summary hypotheses testing

Taking all results into consideration, with an adjusted R^2 of 5,9% and a p-value close to significance (0,076), Model 2 can be considered the model that best describes the variation of response rate in active sourcing. According to this model, hypotheses 2 and 4 were accepted and hypotheses 1, 3, 5 and 6 rejected. For hypothesis 6 it must be mentioned that the interaction term is statistically significant, confirming a moderating effect of AI on personalization. However, contrary to the hypothesis, this effect is negative, leading to the rejection of hypothesis 6.

6.4. Robustness and statistical limitations

To assess the robustness of the computed regressions, additional analyses were conducted to better understand and interpret the results.

Firstly, the relationship between tool usage and industry type was assessed. To analyze this, crosstabs were created and Chi-square tests were performed to evaluate the strength and significance of the relationship (Eckstein, 2016; Planing, 2022). The analysis shows that only the use of the LinkedIn Recruiter ($p = 0{,}002$) and Textkernel ($p < 0{,}001$) have a statistically significant relationship with the industry in which recruiters work (see Table D. 1 and Table D. 2). All other tests did not show significant results. Furthermore, crosstabs then reveal that the LinkedIn Recruiter is most frequently used by recruiters in consulting services (25,7%) and technology/IT (22,9%). Similarly, Textkernel is primarily used in consulting services (71,4%) and technology/IT (23,8%). All corresponding tables can be found in Appendix D. However, these findings are explored in more detail in Chapter 7, as their validity must be considered in the context of the sample's composition.

Furthermore, within the context of work experience, further analysis was undertaken to test whether HR professionals with more experience achieve higher response rates. This analysis aimed to uncover any potential advantage experienced recruiters might have in comparison to less experienced HR professionals. However, simple regression analysis shows that work experience does not have a statistically significant effect on response rates (both overall and positive response rates). Corresponding regression coefficient tables can again be found in Appendix D.

In addition to the regression models presented in Chapter 6.3, where outliers were excluded according to a Cook's distance threshold, all regressions were also computed without excluding these outliers and are presented in Appendix D. These alternative regression models did not produce any significant results and show higher p-values for the overall model constructions. Moreover, R^2 and adjusted R^2 as a measure for the goodness-of-fit yield notably lower values compared to the regression models presented in Chapter 6.3. This is why it can be assumed that the outliers, identified by Cook's distance, indeed affect the results and the robustness of the models, emphasizing the importance of dealing with influential data points to ensure the reliability of outcomes.

7. Discussion

Within this chapter, the results from the previously described analyses will be discussed and interpreted as well as compared to existing literature.

7.1.1. Theoretical implications

The results from regression analysis show that with overall response rate as dependent variable, age has a significant negative effect indicating that HR professionals perceive that younger candidates reply to digital active sourcing approaches more often than older ones. This is also reflected in the analysis of the direct question for participants to rate how strongly they agree with the fact that younger candidates are more likely to reply, where almost half (45,8%) agreed or strongly agreed with the statement. This supports findings from prior literature suggesting that age plays a significant role in active sourcing (Kroll, Veit and Ziegler, 2021; Peltokorpi, 2023) and younger candidates are more available and better accessible via social media (Villeda and McCamey, 2019). When comparing the different regression models with varying dependent variables, it stands out that in Model 4, the variable of age became statistically insignificant. Although the p-value was only slightly above significance level ($p = 0{,}051$), it suggests that age is no longer a significant predictor for positive response rate when adding the moderating effect. The inclusion of the moderating effect therefore appears to weaken the influence of age on positive responses. This means, while younger candidates overall are perceived to answer more often, their likelihood of giving positive responses seems to be less connected to their age.

For the variable of tenure, prior literature suggests that candidates with higher tenure are less willing to switch jobs and therefore tend not to answer to active sourcing messages (Benson, Finegold and Mohrman, 2004; Rubenstein *et al.*, 2018; Peltokorpi, 2023). With the additional information that job mobility is said to have increased in general (Ng *et al.*, 2007), it was expected that candidates with shorter tenure more often reply. In contrast to existing literature and prior expectations, within this study tenure was not a significant factor influencing response rates. This, however, was not so clearly reflected in respondents' direct answers where more than half (47,7%) agreed or strongly agreed with the hypothesis that candidates with shorter tenure are more likely to respond. This discrepancy suggests that even though many recruiters and HR professionals believe that candidates with shorter tenure are more likely to reply, its actual influence is less significant than expected and might be overestimated. Furthermore, the overall rise in job mobility may suggest that tenure can no longer be seen as a reliable indicator of a candidate's willingness to switch jobs and as a result is not reflected as a factor significantly influencing response rates.

The influence of gender, where female candidates were expected to respond more often than male ones (Peltokorpi, 2023), showed similar outcomes with insignificant results across all regression models. This was also supported by survey participants' direct answers stating that only 16,6% (strongly) agreed with the statement that women tend to answer more often. This clearly contrasts with findings from Peltokorpi (2023) but one could rather assume that this supports results from Ng, Huang and Young (2019), indicating that male employees are more likely to switch jobs when seeing an opportunity. However, the current study only tested for the effect of female candidates. The opposite effect of male candidates replying more often cannot automatically be assumed but would need to be tested in further studies.

Within the context of follow-up messages, various researchers suggest that response rates within different settings can be increased by sending reminder messages (Dillman, 2007; Dannhäuser and Chikato, 2015; Trespalacios and Perkins, 2016) and highlight the importance of creating more touchpoints with candidates in general (Gärtner, 2020; Schrader, 2020). The results from the regression analysis, however, lead to the rejection of hypothesis 5 meaning that sending follow-up messages has not been shown to significantly increase response rates. Interestingly, the analysis of the direct question to rate whether "candidates are more likely to respond to digital active sourcing messages after receiving reminder or follow-up messages" shows that 56,9% (strongly) agree with this statement. Nevertheless, when asking respondents how often they send reminder messages, almost one quarter (22,0%) states to not send follow-ups at all. This shows a discrepancy between what recruiters and HR professionals believe about follow-up messages and how they actually implement them in practice. The results suggest that many respondents have not yet effectively attempted to send follow-up messages, which could explain why this is not evident in their response rates and why the regression models yield insignificant results. Future research could evaluate why a large portion of active sourcing professionals avoids sending reminder messages. This might be due to time constraints, in which case, however, AI and automated follow-ups could offer a time-efficient alternative. Alternatively, recruiters might perceive an excessive number of reminders as too pushy and overly persistent, which could damage the employer brand. Moreover, they may believe that candidates find them more annoying than helpful in increasing response rates.

Interesting results were shown for personalization as determinant for contact success. Prior literature clearly suggests that more personalized messages can lead to higher response rates in active sourcing (Dannhäuser and Chikato, 2015; Dannhäuser and Braehmer, 2017; Weitzel *et al.*, 2020; Ernst, 2021), particularly when recruiting internationally (Hansen and Hauff, 2019; Villeda and McCamey, 2019). This suggestion was strongly supported when analyzing respondents' direct answers, where 93,5% (strongly) agreed that personalization enhances response rates. However, this was not as clearly reflected in the regression analyses. While Model 1, 3 and 4 all show insignificant results leading to a rejection of hypothesis 4, only Model 2 with overall response rates and including the moderating effect of AI shows a significant effect of personalization on overall response rate. At the same time, an unstandardized B-value of 24,496 indicates that personalization has a strongly positive effect on overall response rate. However, the fact that the variable only shows statistical significance in Model 2 indicates that personalization might only be a significant predictor in combination with AI. Interestingly, Model 4, which includes AI and positive response rates, does not show a significant effect of personalization. This suggests that while personalization might increase response rates overall, it does not necessarily yield more positive responses.

Building on this, the moderating effect of AI was tested, where the interaction term (moderating effect of AI * with personalization) only shows significant results in Model 2. While prior literature suggests that AI might have a positive effect on personalization (Laumer, Weitzel and Luzar, 2019; Gärtner, 2020; Böhmer and Schinnenburg, 2023), the current study does not support this hypothesis. In fact, the regression analysis reveals that the interaction between AI and personalization has a negative moderating effect (B = -6,989). This means that recruiters and HR professionals perceive that the use of AI negatively moderates personalization and response rates. Nevertheless, the frequency analysis of responses to the question whether AI can enhance response rates by improving personalization reveals that 40,3% (strongly) agree with the statement. Despite this, more than half of the respondents (55,1%) indicate to only rarely or not at all use AI assistance to personalize their messages. This shows that AI usage is still infrequent, limiting its practical impact on response rates, and indicating that infrequent users may not have fully discovered its potential. This was also suggested in prior literature concerning the use of LinkedIn, where only frequent users are said to have discovered its full potential (Caers and Castelyns, 2011; Randstad and ifo, 2022). The negative moderation of AI, however, might also reflect a concern of recruiters and HR professionals that creating messages with AI could be perceived by candidates as less personal, leading to lower response rates. This could be because AI technologies integrated into active sourcing tools are not yet advanced enough to create personalized messages that are identical to those written by human recruiters. This implies that AI may need to be more fine-tuned or more strategically applied to preserve the impact of truly personalized messages.

The aim of this thesis was to identify key drivers of contact success in digital active sourcing processes. While the variables gender, age, tenure, personalization and follow-up were expected to influence response rates in active sourcing, the use of AI was expected to positively moderate the influence of personalization on contact success. Considering Model 2 as most useful in illustrating the influence of the independent variables on the dependent one, the analysis of survey data reveals only two significant drivers for contact success: age and personalization. This means that younger candidates are perceived to be more likely to respond to digital active sourcing approaches and messages that are more personalized are expected to yield higher response rates. Significant effects of gender, tenure and follow-up could not be confirmed within this study. Furthermore, the use of AI has been shown to influence personalization, however, contrary to expectations, this effect was negative.

In general, even though this chapter provides discussion and interpretations around the results, it must be highlighted that none of the four regression models show significant values for the entire model and adjusted R^2 values between 1-6% reflect that there are factors missing that significantly influence contact success. However, the literature review already shows that the concept of active sourcing tightly interacts with various other research fields such as employer branding, personnel marketing as well as the industry that candidates work in. The models therefore should be further improved to be able to give more valuable statements about determinants for contact success in active sourcing.

Besides determining influencing factors for contact success, the current thesis wants to add to the topic of successful active sourcing tools. As expected from existing literature (Subhani *et al.*, 2012; Nikolaou, 2014; Zide, Elman and Shahani-Denning, 2014; Davis *et al.*, 2020; Ruparel *et al.*, 2020), LinkedIn clearly stands out as the most relevant tool as almost all respondents (99,1%) indicated to frequently use it for active sourcing. Even though the current thesis focused on the DACH region, the XING TalentManager was only used by 45,9% of survey participants, demonstrating the dominance of LinkedIn not only on a global scale, but also within the DACH region. Furthermore, Textkernel Search appears to be a relevant tool with 20,2% of respondents using it as well as the StepStone CV-center used by 17,4%. The study also examines the choice of active sourcing tools in relation to the industries in which recruiters and HR professionals work. Crosstabs in combination with Chi-square tests show that the LinkedIn Recruiter as well as the Textkernel tool are most frequently used by recruiters in consulting services as well as technology/IT. Those results, however, must be interpreted with caution as descriptive analysis reveals an unevenly distributed sample with a large proportion (25,5%) of survey respondents working in consulting services and 22,6% in the technology and IT industry. This uneven sample distribution might indicate that the observed relationship between the use of LinkedIn Recruiter and Textkernel Search is influenced by the sample composition. Therefore, for a more accurate picture, further research within this area is needed.

7.1.2. Practical implications

Based on the results from the current thesis, there are some practical implications that can be considered by recruiters and HR professionals in active sourcing.

Survey results show that sending follow-ups is not yet universally implemented within active sourcing routines, although various studies indicate its success regarding the increase of response rates (Dillman, 2007; Dannhäuser and Chikato, 2015; Trespalacios and Perkins, 2016) and even survey participants themselves widely agreed with the statement that sending reminders can improve response rates. This is why the current study suggests recruiters and HR professionals to introduce follow-up messages into their active sourcing routine. This is expected to be more easily implementable with the help of automated and AI-assisted follow-ups that are integrated, for example, in the widely used LinkedIn Recruiter tool. Accordingly, the study suggests that recruiters and HR professionals should consider incorporating AI technologies into their active sourcing strategies, not only for automated follow-ups, but also for crafting personalized messages. Survey results reveal that the majority of respondents have not yet adopted AI for personalizing active sourcing messages, possibly due to concerns that AI-generated messages may seem less trustworthy or can be recognized by candidates as not being written by a human recruiter. Nonetheless, existing literature suggests that AI holds significant potential in the recruitment field (Laumer, Weitzel and Luzar, 2019; Gärtner, 2020; Böhmer and Schinnenburg, 2023; Chen, 2023). Furthermore, the latest version of the LinkedIn Recruiter offers KPIs showing whether AI-generated messages or personally crafted messages perform better in active sourcing (*LinkedIn: InMail*, 2024). Therefore, the current thesis recommends recruiters to make use of this function and test for themselves how AI-crafted messages are perceived by possible candidates and whether it should be more actively integrated into their active sourcing approach.

Furthermore, the thesis highlights that LinkedIn, XING, and the StepStone CV-Center are the most commonly used digital platforms for active sourcing. Additionally, Textkernel Search is utilized for systematically analyzing internal CV-databases. These platforms are anticipated to be effective and could therefore be trialed by recruiters for active sourcing purposes. However, HR professionals should also consider that they might face significant competition on these platforms, meaning that candidates are likely to receive numerous active sourcing messages as lots of recruiters use them. This suggests that while recruiters should leverage these popular platforms, it may also be beneficial to explore less crowded alternatives that are specifically tailored to the intended target group.

In general, the thesis recommends recruiters and HR professionals to experiment with various active sourcing strategies and then implement a data-driven approach rather than relying on intuitions. KPIs should be measured and analyzed, and response rates should be evaluated and compared across different strategies to evaluate which approaches are most effective and yield higher response rates.

7.1.3. Limitations and future research

Although this study provides important insights into active sourcing and its main drivers of contact success, there are several limitations that may affect the scope of the findings, going hand in hand with suggestions for future research on the topic.

The survey sample in this study was limited to a specific group of HR professionals and recruiters involved in active sourcing. Anticipating a low response rate, the researcher utilized her professional network to reach potential participants, resulting in what is known as a convenience sample. As pointed out by Bryman, Bell and Harley (2019) this leads to the fact, that the findings are hard to generalize since many respondents are likely to come from the same organization with similar active sourcing practices. This unevenly distributed sample also limited further insights into whether industry type has an effect on the choice of tools used for active sourcing. Future researchers should therefore attempt to use different sampling methods to reach a wider range of HR professionals, enhance the generalizability of the results and achieve a more evenly distributed sample. However, given that very limited research has been conducted in this specific area so far, the findings of the current study offer valuable insights and initial directions for future research.

Moreover, it can be assumed that there is a potential data collection error arising from ambiguity in the questions of the self-completion survey. For example, the question regarding the industry in which the company operates, may have caused confusion, as some participants responded based on the industry from which they were actively sourcing candidates or left the question unanswered altogether. This might have been the case for respondents that are part of a consulting or staffing service that operates across multiple sectors while searching for employees. However, the question was meant to determine the general industry of the firm, not the specific industry from which recruiters are actively sourcing candidates. Future studies should therefore clarify this distinction to obtain more accurate insights. Furthermore, the survey only included one question per hypothesis to keep it brief and encourage HR professionals to participate. Adding multiple items to assess each variable could, however, enhance the accuracy of the findings and should be considered for future research.

Even though this current study offers discussion and interpretations around the results, it must be highlighted that none of the regression models produced significant values for the entire model. While Model 2 was closest to significance, it still indicates that the chosen independent variables collectively do not explain the variance in response rates very well. As a consequence, the models need to be further improved to be able to give more valuable statements about determinants for contact success. Future research should therefore evaluate further factors possibly influencing response rates and include them to improve the proposed models.

A further limitation to the study is that despite theoretically having a sufficient number of survey responses, the sample was still relatively small with N = 109 observations. Given the number of hypotheses, larger samples are expected to yield clearer and more generalizable results. Therefore, future researchers should aim to use a larger sample that includes respondents from diverse industries to achieve more broadly applicable findings. This would also allow the inclusion of further independent variables possibly influencing contact success, thereby enhancing the existing models. Existing literature suggests that factors such as industry, employer branding or personnel marketing in general could also affect response rates, incorporating these into future models could lead to deeper insights.

Further research should also investigate the effectiveness and success of different active sourcing tools across various industries. Prior literature suggests that both the industry and the specific characteristics of the target group are crucial for assessing the most effective tools and platforms for active sourcing. For instance, within the area of technology and IT, there are numerous blogs and niche sites that are utilized more frequently than platforms like LinkedIn (Davis *et al.*, 2020). Therefore, future studies should evaluate the significance of various sites and their potential as active sourcing tools as well as their effectiveness in relation to specific target groups. The current thesis tried to establish a relationship between various active sourcing tools and industry types. However, as previously mentioned, the analysis did not yield particularly meaningful results due to the uneven distribution of the survey sample. Further research should analyze a more diverse sample to provide better recommendations for successful platforms based on industry type. Furthermore, survey respondents indicated to use a variety of other platforms that have not been originally included in the survey such as databases from the federal employment agency, Google, Indeed, karriere.at databases, FreelancerMap and Freelance.de, Hireez, Meetup and GitHub. Their effectiveness could be evaluated in more depth in future research.

Finally, this study assessed contact success from the perspectives of recruiters and HR professionals. However, future research should consider the candidates' perspective and examine how potential candidates perceive active sourcing approaches and what motivates them to respond. This could include evaluating follow-up messages and determining whether candidates perceive them as spam or find them annoying, which might be a reason for recruiters to not use them. Additionally, future studies could assess whether candidates can distinguish AI-crafted messages from human-crafted ones, and how they perceive each type. Furthermore, future researchers could explore the connection between personality traits and the likelihood of response in active sourcing which was already attempted by Davis *et al.* (2020) as well as Ng *et al.* (2007) in the area of LinkedIn usage and the general willingness to switch jobs. Such research could provide deeper insight into factors that positively influence response rates and help recruiters to identify the most effective strategies.

8. Conclusion

The adoption of active sourcing has widely emerged as a necessary recruitment tool to find best qualified but hard-to-find personnel. Besides the integration of AI-technologies in recruitment and the streamlined focus on employer branding, active sourcing is among the most frequently mentioned recruiting trends in the current business landscape. Quality research yet lags behind which is why the current thesis seeks to address a gap in existing literature by identifying factors influencing contact success in digital active sourcing processes. The study specifically assessed the impact of candidates' gender, age and tenure as well as the degree of personalization in active sourcing messages and the frequency of follow-ups as factors influencing response rates. Additionally, it examined the role of AI as a moderating factor on personalization.

The thesis shows that age as well as personalization are influential determinants for improved response rates. Younger candidates are perceived to more often reply to digital active sourcing approaches and messages that are more personalized are recognized to be more successful. However, a candidate's gender as well as tenure did not show significant effects on response rates, nor did follow-ups show significant positive impact. Nevertheless, given that respondents have not widely adopted the strategy of sending reminders, the current study suggests trying this strategy to evaluate whether increased response rates can be achieved. Interestingly, AI has been shown to have a moderating effect on personalization, but contrary to prior expectations, this effect was negative meaning that respondents appear to believe that using AI to personalize messages reduces response rates. However, the limited adoption of AI use by survey respondents may have influenced this outcome which is why the current thesis recommends implementing AI-technologies into active sourcing strategies to better evaluate its potential impact on response rates.

Even though the current study does not find significant results for all proposed factors, it contributes valuable insights to the research field and offers numerous directions for further exploration. Future researchers are encouraged to refine the proposed models to define influential factors with greater clarity and depth. The study therefore serves as an entry point into an evolving research area where further research is suggested to establish effective strategies and ultimately help recruiters and HR professionals in developing successful active sourcing practices to efficiently reach highly qualified, hard-to-find candidates.

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Appendices

Appendix A: Questionnaire

Introduction

Dear participant,

I am a Master´s student at the University of Vienna. As part of my Master´s thesis, **"Key Drivers of Contact Success in Digital Active Sourcing Processes,"** I have developed an online survey to gather insights on the factors that influence response rates in active sourcing.

The survey will take approximately **5 minutes** to complete and is aimed at recruiters and HR professionals involved in active sourcing. To ensure the success of this study, I kindly ask you to complete all the questions.

All information will be treated confidentially and anonymously and will be used exclusively for scientific purposes.

Thank you very much for participating!

In case of questions, please feel free to contact me via email (a11848941@unet.univie.ac.at).

Best regards
Annika Gari

This questionnaire focuses on **active sourcing**.

Active sourcing is the process of proactive identification and contacting of possible candidates by recruiters. This approach involves using various digital tools to find and connect with candidates who may not be actively looking for a new job but possess the skills and experience needed for specific roles.

Please proceed with the survey and answer the questions based on your own experiences and practices in active sourcing.

Do you use active sourcing for recruitment purposes?

- ◯ Yes.
- ◯ No.

Which digital tools do you most frequently use for active sourcing?

- ☐ LinkedIn Recruiter
- ☐ Onlyfy TalentManager by XING
- ☐ Talentwunder
- ☐ TalentBin by Monster
- ☐ Open Web by Dice
- ☐ Stack Overflow Talent
- ☐ Textkernel Search!
- ☐ Monster Lebenslaufdatenbank
- ☐ Experteer Lebenslaufdatenbank
- ☐ StepStone CV-Center
- ☐ Others (please specify): ______

For the following questions, please give estimations based on your own experience:

About how many active sourcing messages do you send to potential candidates per month?

Please estimate in numbers.

What is your estimated overall response rate (negative + positive) to your active sourcing messages?

Please estimate in percentage (%) and type in only the numbers.

What is your estimated positive response rate?

Please estimate in percentage (%) and type in only the numbers.

In your experience with digital active sourcing, to what extent do you agree with the following statements:

	strongly agree	agree	neutral	disagree	strongly disagree
Female candidates are more likely to respond to digital active sourcing messages.	○	○	○	○	○
Younger candidates are more likely to respond to digital active sourcing messages.	○	○	○	○	○
Candidates who have spent less time in the same company are more likely to respond to digital active sourcing messages.	○	○	○	○	○

To what extent do you agree with the following statement:

	strongly agree	agree	neutral	disagree	strongly disagree
Candidates are more likely to respond to digital active sourcing attempts when the messages are more personalized. (e.g., written in a candidate´s native language, including personalized greetings or referring to a candidate´s skills or experiences).	○	○	○	○	○

To what extent do you agree with the following statement:

	strongly agree	agree	neutral	disagree	strongly disagree
Candidates are more likely to respond to digital active sourcing messages after receiving reminder or follow-up messages.	○	○	○	○	○

How often do you typically send reminder or follow-up messages to the same candidate in your active sourcing process?

- ○ Never
- ○ 1 time
- ○ 2 times
- ○ 3 times
- ○ More than 3 times

Tools that include AI-assistance can create automated messages based on candidates´ profile information or automatically formulate messages in their native language.

To what extent do you agree with the following statement:

	strongly agree	agree	neutral	disagree	strongly disagree
AI-assistance enhances the personalization of active sourcing messages and improves response rates.	○	○	○	○	○

To what extent do you use AI-assistance for personalizing your active sourcing messages?

- ○ Always
- ○ Often
- ○ Sometimes
- ○ Rarely
- ○ Not at all

Where are you currently employed:

- ○ Austria
- ○ Germany
- ○ Switzerland
- ○ Other

What is your current position:

- ○ Recruiter/Recruitment Specialist
- ○ Talent Acquisition Manager
- ○ HR Business Partner
- ○ HR Manager/Director
- ○ Head of HR/Recruiting
- ○ Recruiting Consultant
- ○ Other (please specify):

How many years of experience do you have in your current field of work?

- ○ Less than 1 year
- ○ 1-2 years
- ○ 3-5 years
- ○ 6-10 years
- ○ 11-15 years
- ○ More than 15 years

Which industry sector best represents the primary focus of your company?

- ◯ Construction/Real Estate
- ◯ Consulting Services
- ◯ Education
- ◯ Energy/Utilities
- ◯ Finance/Banking
- ◯ Government/Public Sector
- ◯ Healthcare/Medical
- ◯ Hospitality/Travel
- ◯ Manufacturing/Engineering
- ◯ Media/Entertainment
- ◯ Retail/Consumer Goods
- ◯ Technology/IT
- ◯ Other (please specify):

Thank you for completing this questionnaire!

Your contribution to the study on "Key Drivers of Contact Success in Digital Active Sourcing Processes" is very valuable. If you have any further questions about the research, do not hesitate to contact me via email (a11848941@unet.univie.ac.at).

Your answers were transmitted, you may close the browser window or tab now.

Appendix B: Descriptive statistics

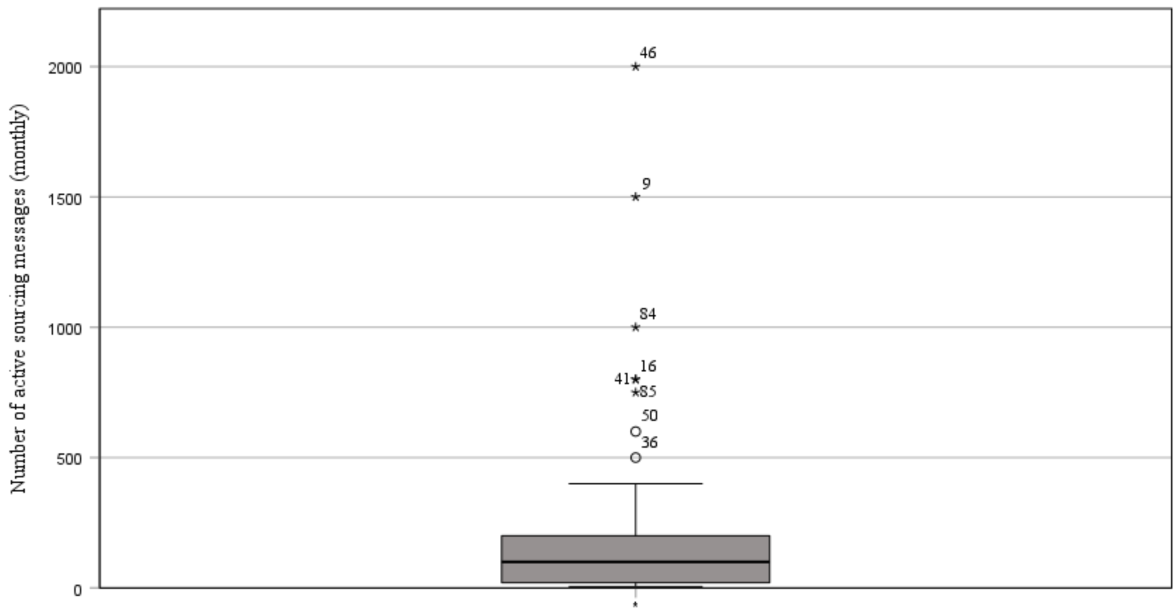

Figure B. 1. Boxplot: Number of active sourcing messages

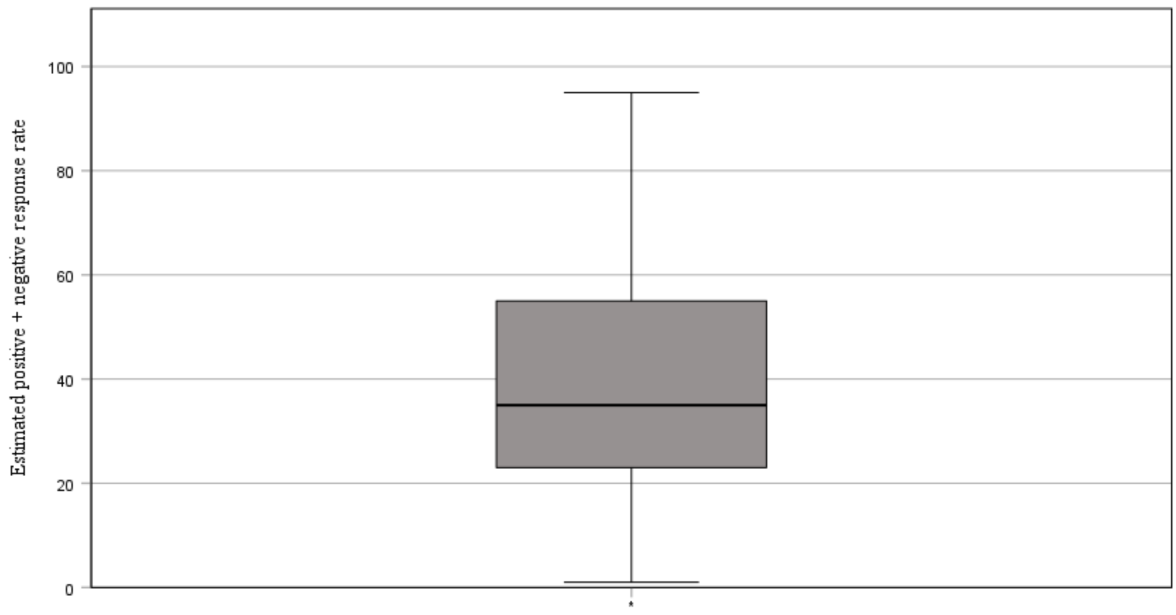

Figure B. 2. Boxplot: Overall response rate

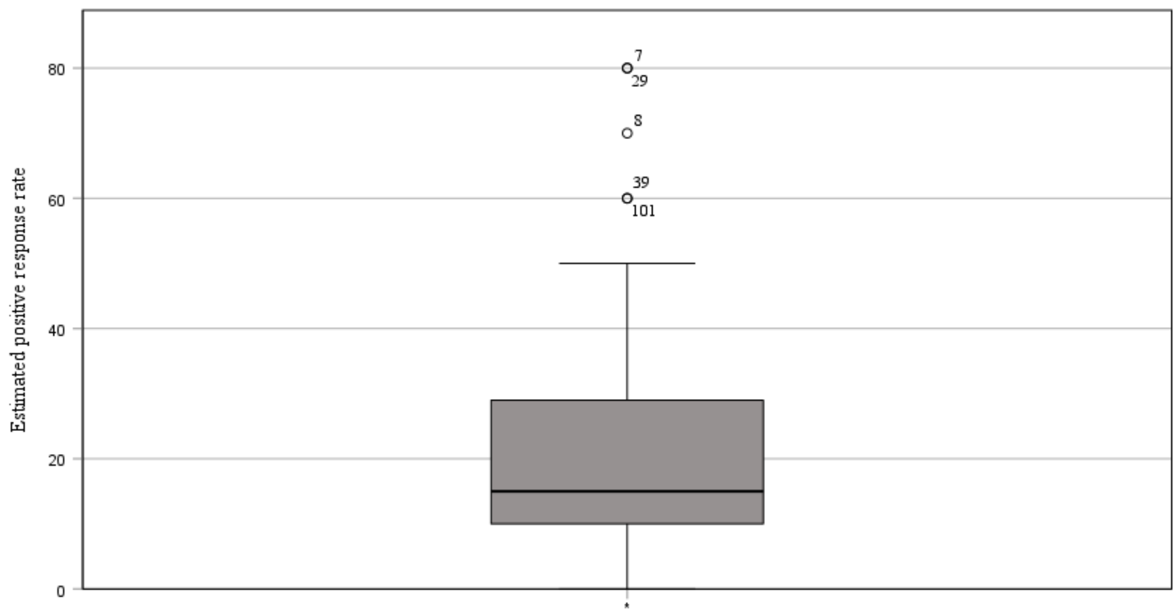

Figure B. 3. Boxplot: Positive response rate

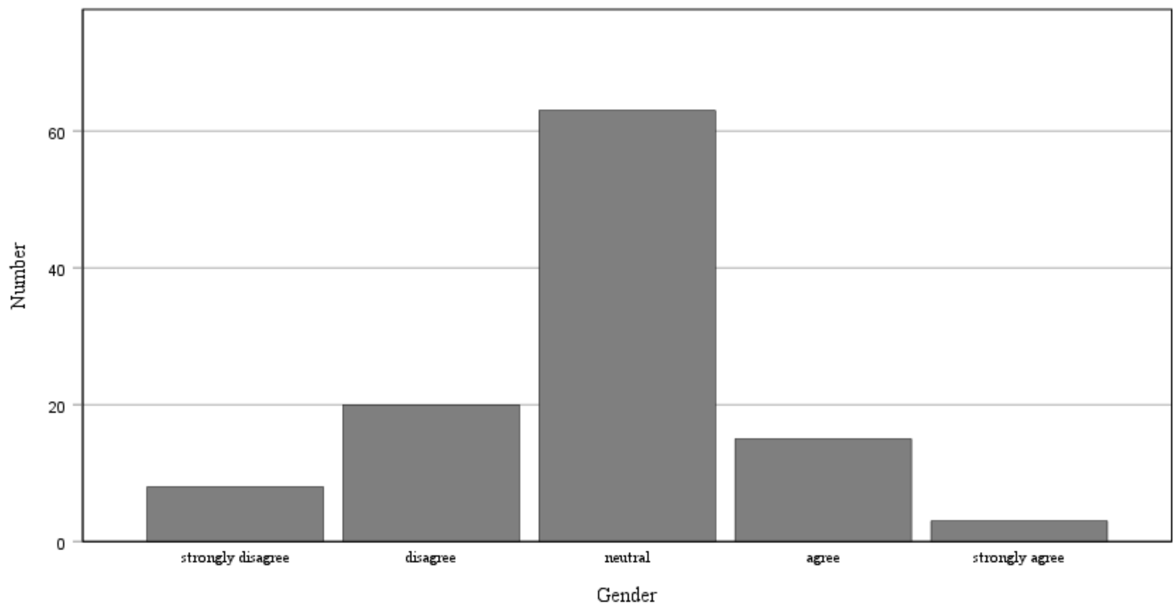

Figure B. 4. Bar chart: Frequencies Gender

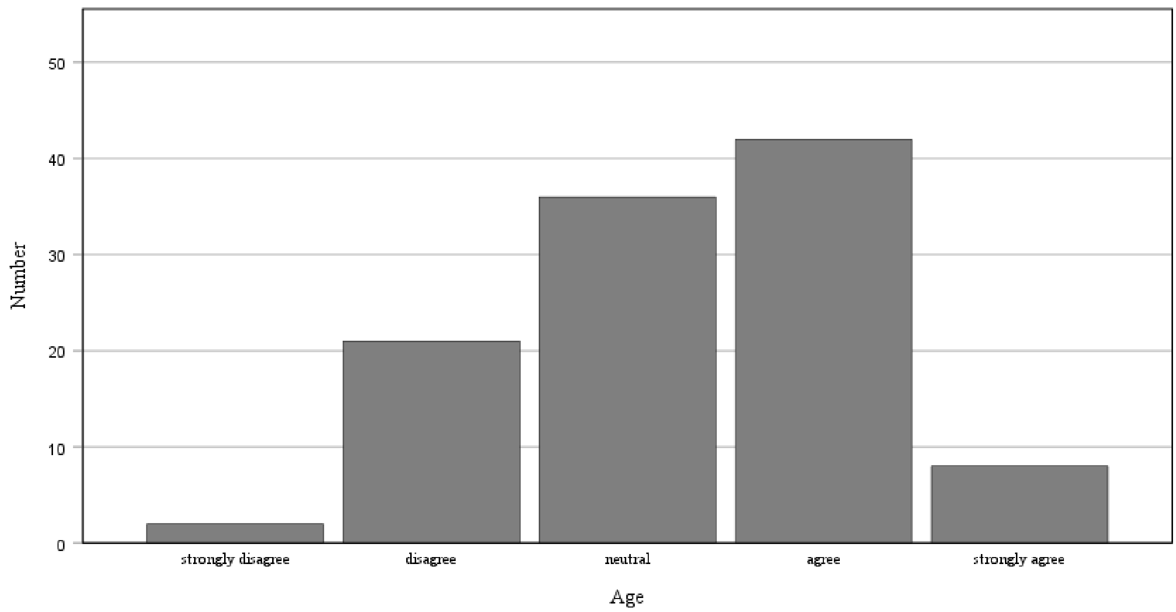

Figure B. 5. Bar chart: Frequencies Age

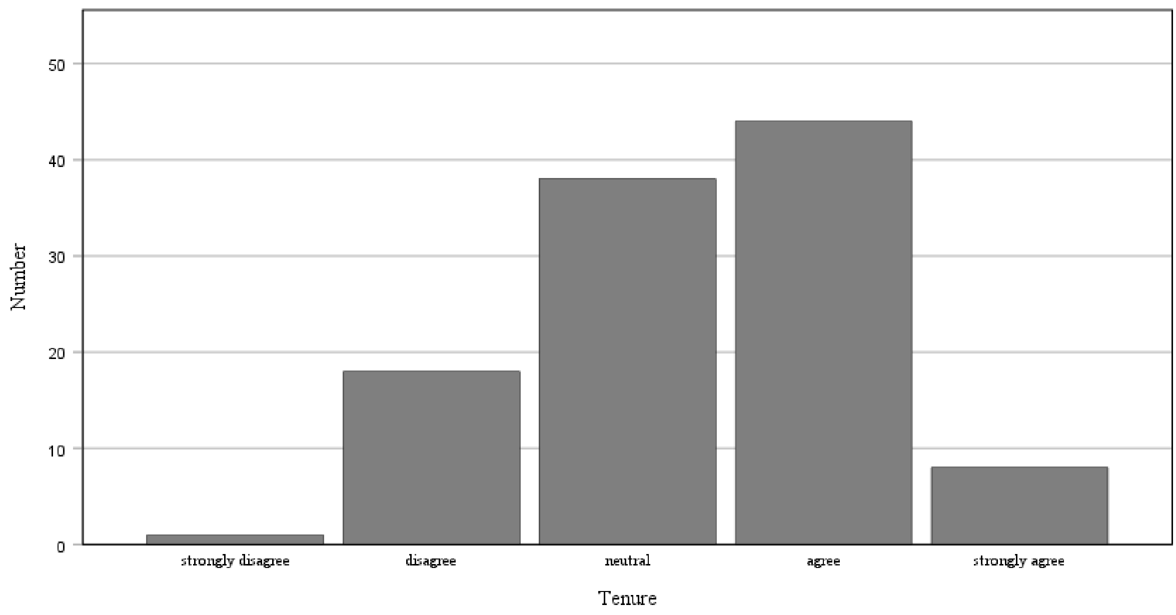

Figure B. 6. Bar chart: Frequencies Tenure

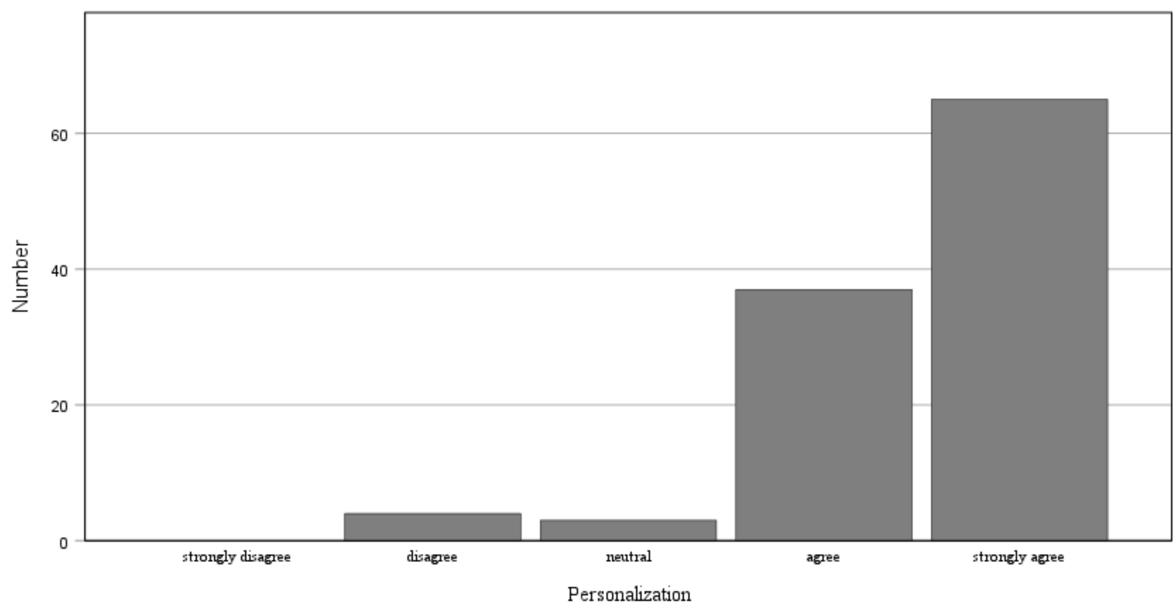

Figure B. 7. Bar chart: Frequencies Personalization

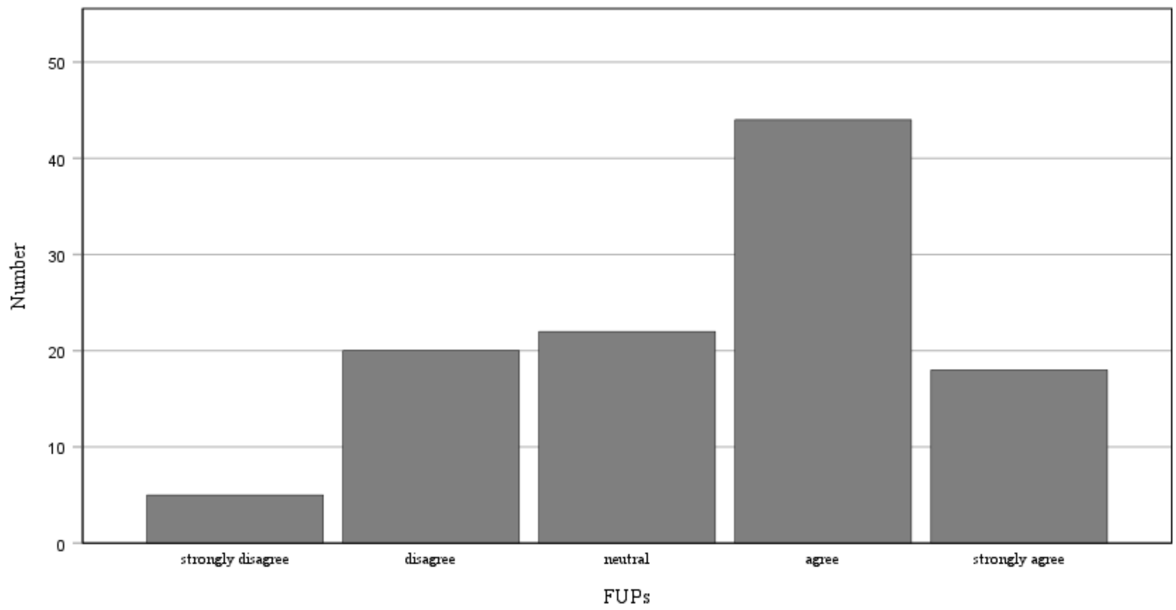

Figure B. 8. Bar chart: Frequencies FUP

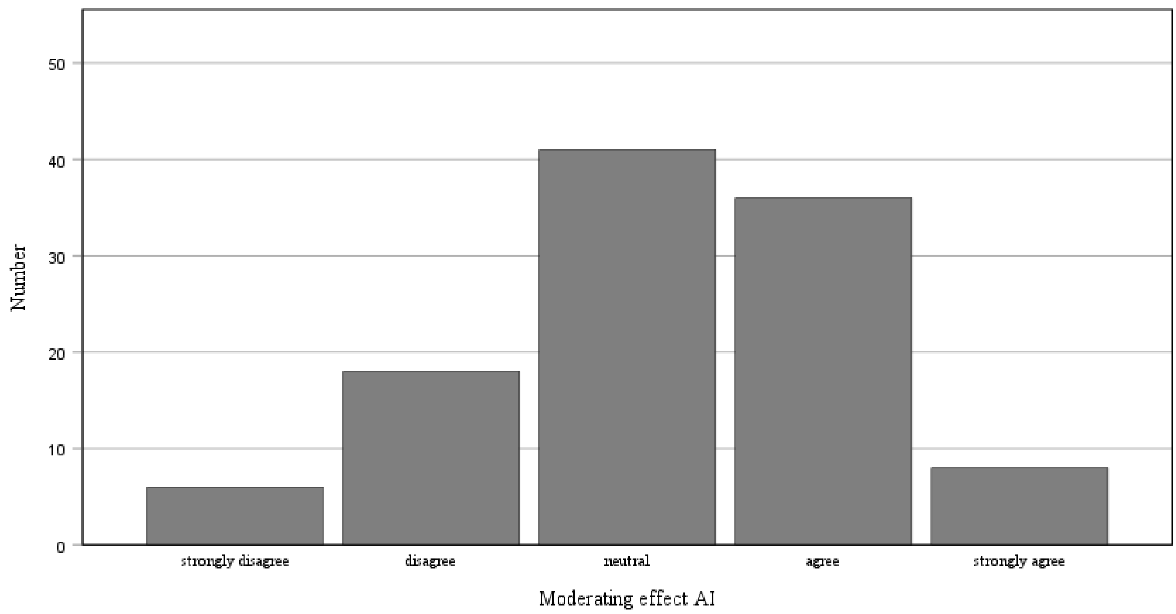

Figure B. 9. Bar chart: Frequencies Moderating effect of AI

Appendix C: Requirements regression analyses

Model 1 and 2:

Scatterplot
Dependent variable: Estimated positive + negative response rate

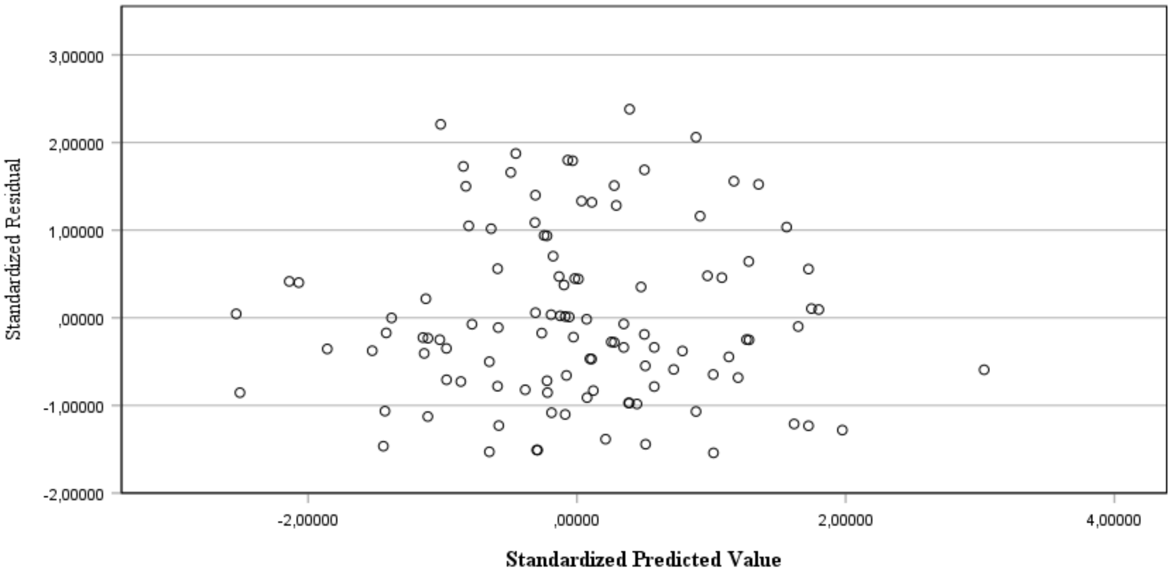

Figure C. 1. Linearity Scatterplot 1

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,197[a]	,039	-,018	22,368	1,707

a. Predictors: (Constant), Moderating effect AI, Age, Personalization, FUPs, Gender, Tenure

b. Dependent Variable: Estimated positive + negative response rate

Table C. 1. Autocorrelation Durbin-Watson 1

		Levene Statistic	df1	df2	Sig.
Estimated positive + negative response rate	Based on Mean	,763	4	104	,552
	Based on Median	,629	4	104	,643
	Based on Median and with adjusted df	,629	4	102,428	,643
	Based on trimmed mean	,757	4	104	,556

Table C. 2. Test of Homogeneity of Variances Gender 1

		Levene Statistic	df1	df2	Sig.
Estimated positive + negative response rate	Based on Mean	,631	4	104	,641
	Based on Median	,521	4	104	,721
	Based on Median and with adjusted df	,521	4	100,535	,721
	Based on trimmed mean	,626	4	104	,645

Table C. 3. Test of Homogeneity of Variances Age 1

		Levene Statistic	df1	df2	Sig.
Estimated positive + negative response rate	Based on Mean	1,343	3	104	,265
	Based on Median	1,117	3	104	,346
	Based on Median and with adjusted df	1,117	3	97,063	,346
	Based on trimmed mean	1,279	3	104	,286

Table C. 4. Test of Homogeneity of Variances Tenure 1

		Levene Statistic	df1	df2	Sig.
Estimated positive + negative response rate	Based on Mean	2,297	3	105	,082
	Based on Median	1,652	3	105	,182
	Based on Median and with adjusted df	1,652	3	101,637	,182
	Based on trimmed mean	2,264	3	105	,085

Table C. 5. Test of Homogeneity of Variances Personalization 1

		Levene Statistic	df1	df2	Sig.
Estimated positive + negative response rate	Based on Mean	1,107	4	104	,357
	Based on Median	,718	4	104	,581
	Based on Median and with adjusted df	,718	4	95,454	,582
	Based on trimmed mean	1,070	4	104	,375

Table C. 6. Test of Homogeneity of Variances FUP 1

		Levene Statistic	df1	df2	Sig.
Estimated positive + negative response rate	Based on Mean	1,672	4	104	,162
	Based on Median	,737	4	104	,569
	Based on Median and with adjusted df	,737	4	85,589	,569
	Based on trimmed mean	1,551	4	104	,193

Table C. 7. Test of Homogeneity of Variances Moderating effect of AI 1

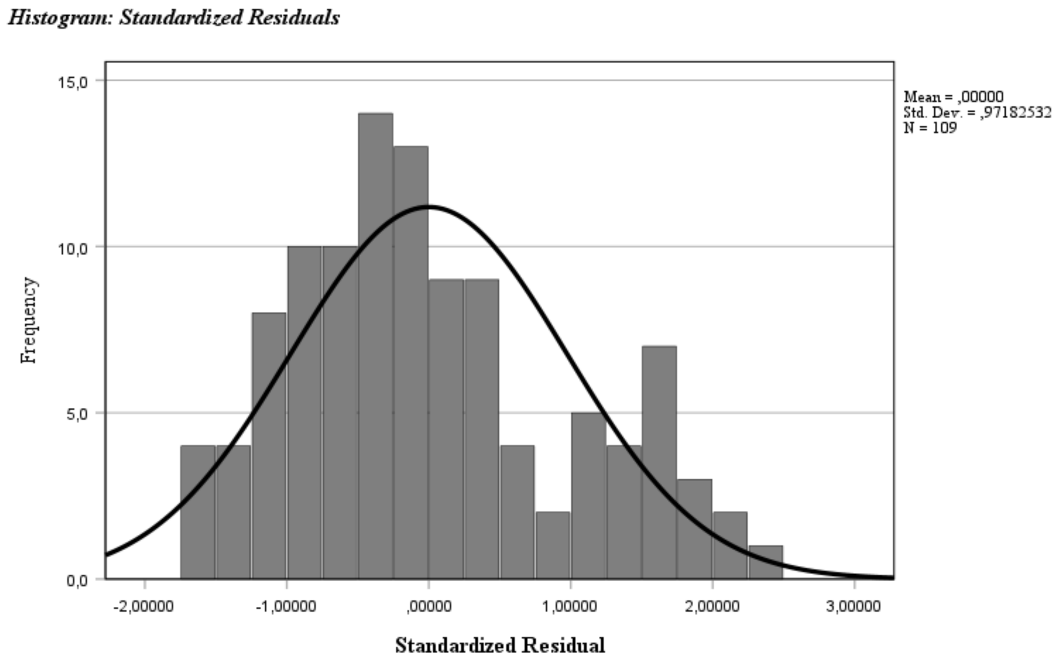

Figure C. 2. Histogram Normal Distribution 1

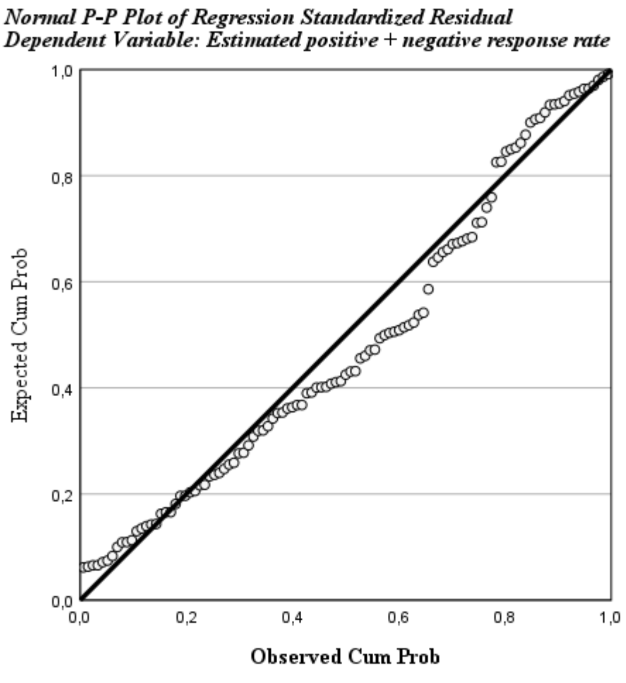

Figure C. 3. Normal P-P Plot Regression Standardized Residual 1

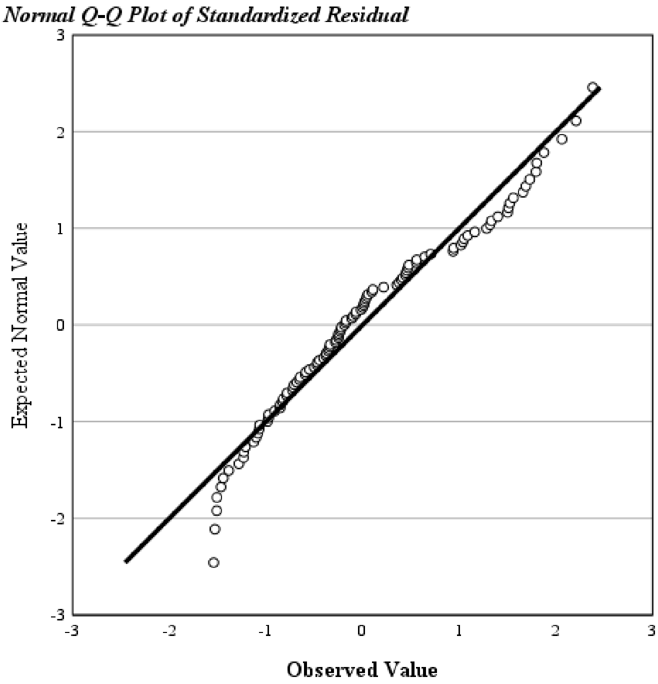

Figure C. 4. Normal Q-Q Plot Standardized Residual 1

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	Gender	,932	1,073
	Age	,986	1,014
	Tenure	,904	1,106
	Personalization	,989	1,011
	FUPs	,959	1,043
	Moderating effect AI	,936	1,068

a. Dependent Variable: Estimated positive + negative response rate

Table C. 8. Multicollinearity VIF 1

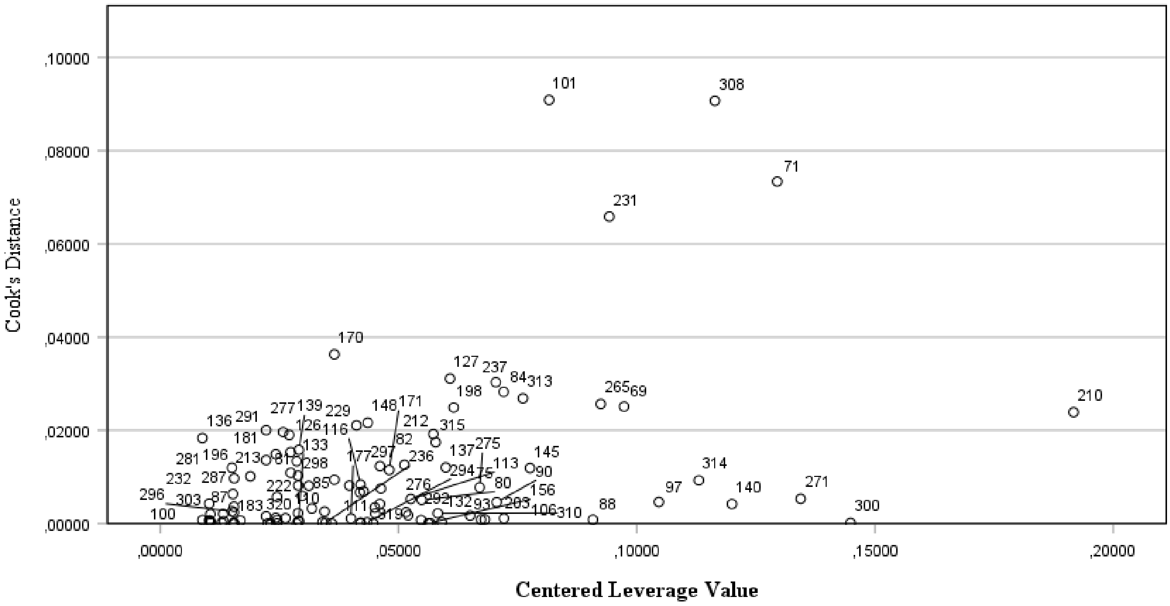

Figure C. 5. Scatterplot Cook's Distance vs. Centered Leverage Value (Model 1)

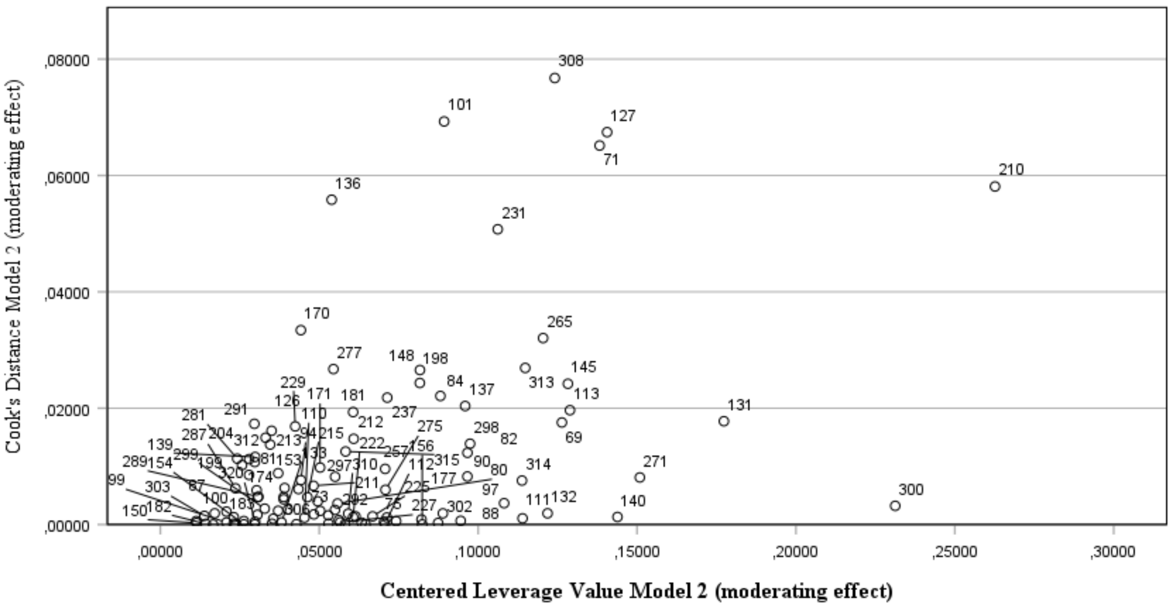

Figure C. 6. Scatterplot Cook's Distance vs. Centered Leverage Value (Model 2)

Model 3 and 4:

Scatterplot
Dependent variable: Estimated positive response rate

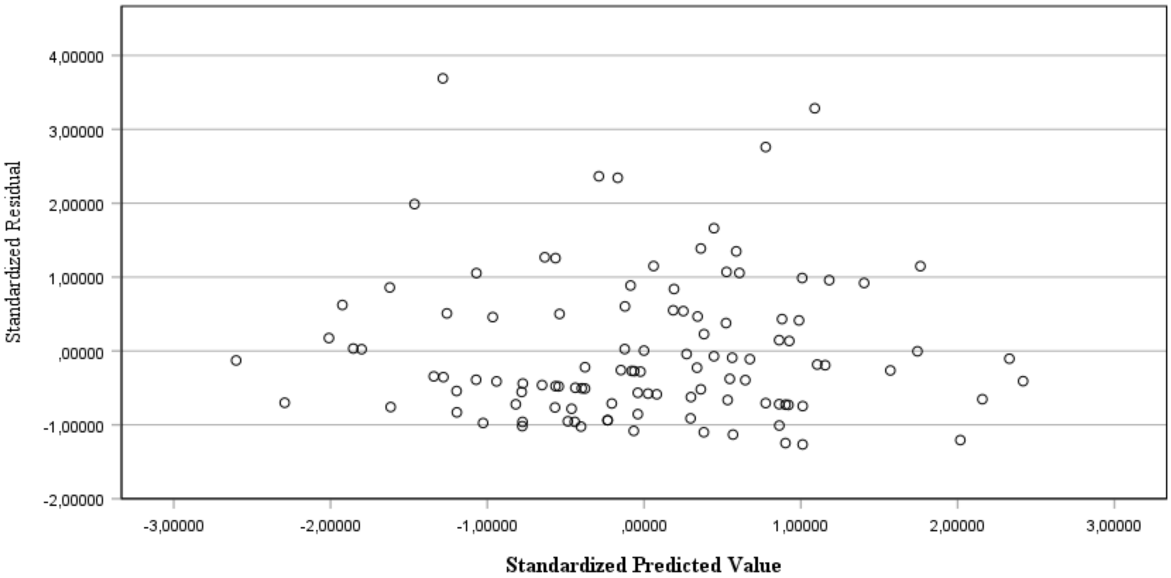

Figure C. 7. Linearity Scatterplot 2

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,173[a]	,030	-,027	17,313	2,040

a. Predictors: (Constant), Moderating effect AI, Age, Personalization, FUPs, Gender, Tenure

b. Dependent Variable: Estimated positive response rate

Table C. 9. Autocorrelation Durbin-Watson 2

		Levene Statistic	df1	df2	Sig.
Estimated positive response rate	Based on Mean	1,175	4	104	,326
	Based on Median	,539	4	104	,707
	Based on Median and with adjusted df	,539	4	74,882	,707

Table C. 10. Test of Homogeneity of Variances Gender 2

		Levene Statistic	df1	df2	Sig.
Estimated positive response rate	Based on Mean	2,874	4	104	,026
	Based on Median	1,733	4	104	,148
	Based on Median and with adjusted df	1,733	4	77,377	,151
	Based on trimmed mean	2,477	4	104	,049

Table C. 11. Test of Homogeneity of Variances Age 2

		Levene Statistic	df1	df2	Sig.
Estimated positive response rate	Based on Mean	,430	3	104	,732
	Based on Median	,344	3	104	,793
	Based on Median and with adjusted df	,344	3	96,807	,793
	Based on trimmed mean	,339	3	104	,797

Table C. 12. Test of Homogeneity of Variances Tenure 2

		Levene Statistic	df1	df2	Sig.
Estimated positive response rate	Based on Mean	,513	3	105	,674
	Based on Median	,331	3	105	,803
	Based on Median and with adjusted df	,331	3	102,502	,803
	Based on trimmed mean	,444	3	105	,722

Table C. 13. Test of Homogeneity of Variances Personalization 2

		Levene Statistic	df1	df2	Sig.
Estimated positive response rate	Based on Mean	,984	4	104	,420
	Based on Median	,357	4	104	,839
	Based on Median and with adjusted df	,357	4	70,355	,839
	Based on trimmed mean	,763	4	104	,551

Table C. 14. Test of Homogeneity of Variances FUP 2

		Levene Statistic	df1	df2	Sig.
Estimated positive response rate	Based on Mean	,780	4	104	,541
	Based on Median	,422	4	104	,792
	Based on Median and with adjusted df	,422	4	94,221	,792
	Based on trimmed mean	,612	4	104	,655

Table C. 15. Test of Homogeneity of Variances Moderating effect of AI 2

Breusch-Pagan Test for Heteroskedasticity[a,b,c]

Chi-Square	df	Sig.
,004	1	,947

a. Dependent variable: Estimated positive response rate

b. Tests the null hypothesis that the variance of the errors does not depend on the values of the independent variables.

c. Predicted values from design: Intercept + Q6_Gender + Q7_Age + Q8_Tenure + Q9_Personalization + Q10_FUP + Q12_AI

Table C. 16. Homoscedasticity Breusch-Pagan

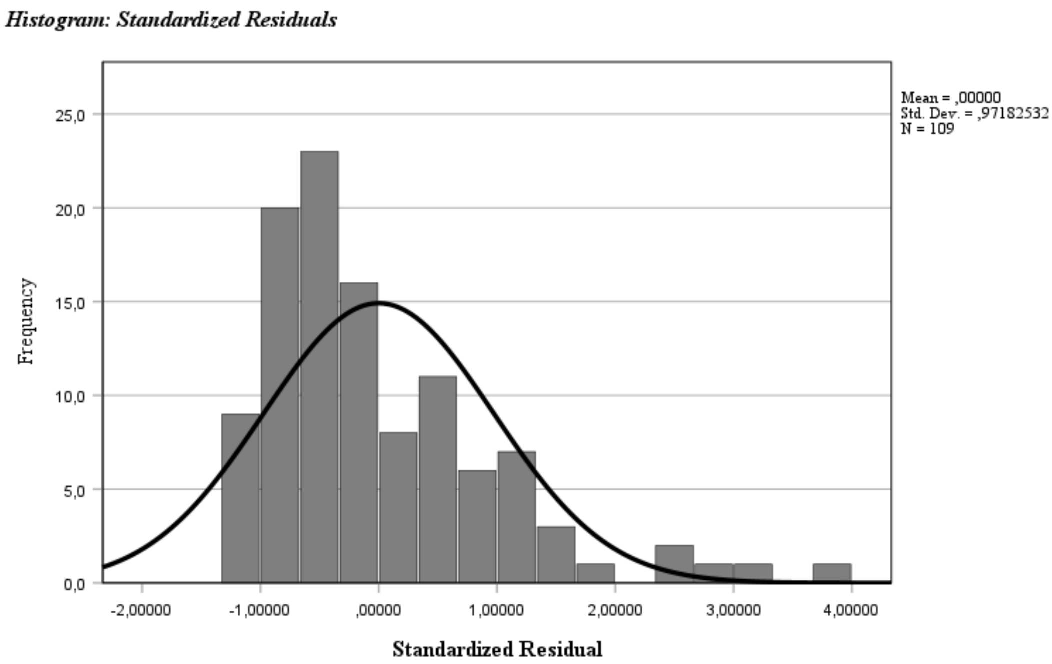

Figure C. 8. Histogram Normal Distribution 2

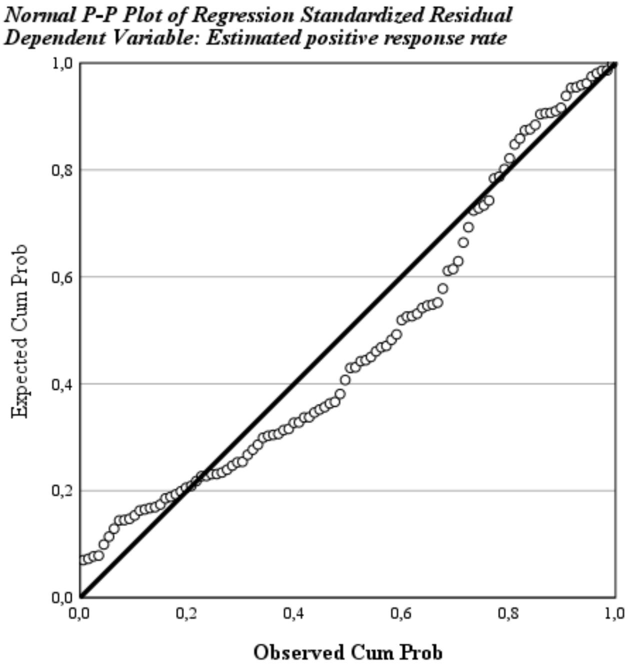

Figure C. 9. Normal P-P Plot Regression Standardized Residual 2

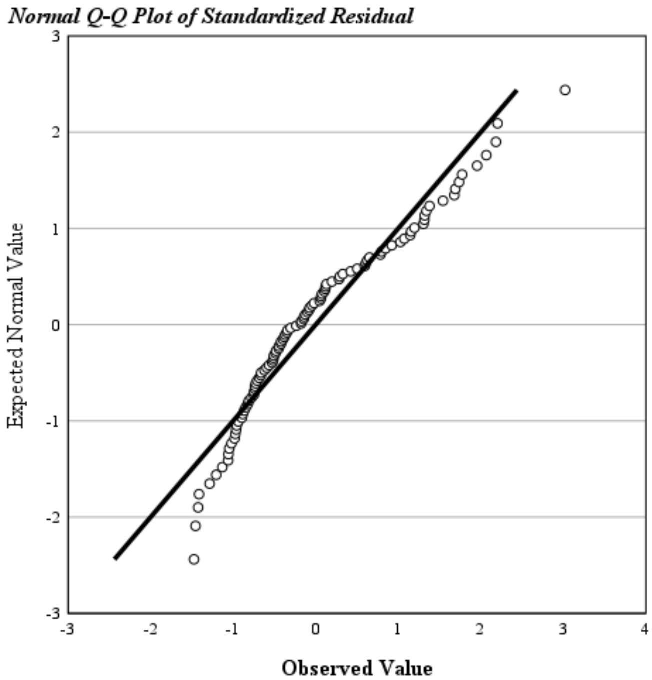

Figure C. 10. Normal Q-Q Plot Standardized Residual 2

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	Gender	,932	1,073
	Age	,986	1,014
	Tenure	,904	1,106
	Personalization	,989	1,011
	FUPs	,959	1,043
	Moderating effect AI	,936	1,068

a. Dependent Variable: Estimated positive response rate

Table C. 17. Multicollinearity VIF 2

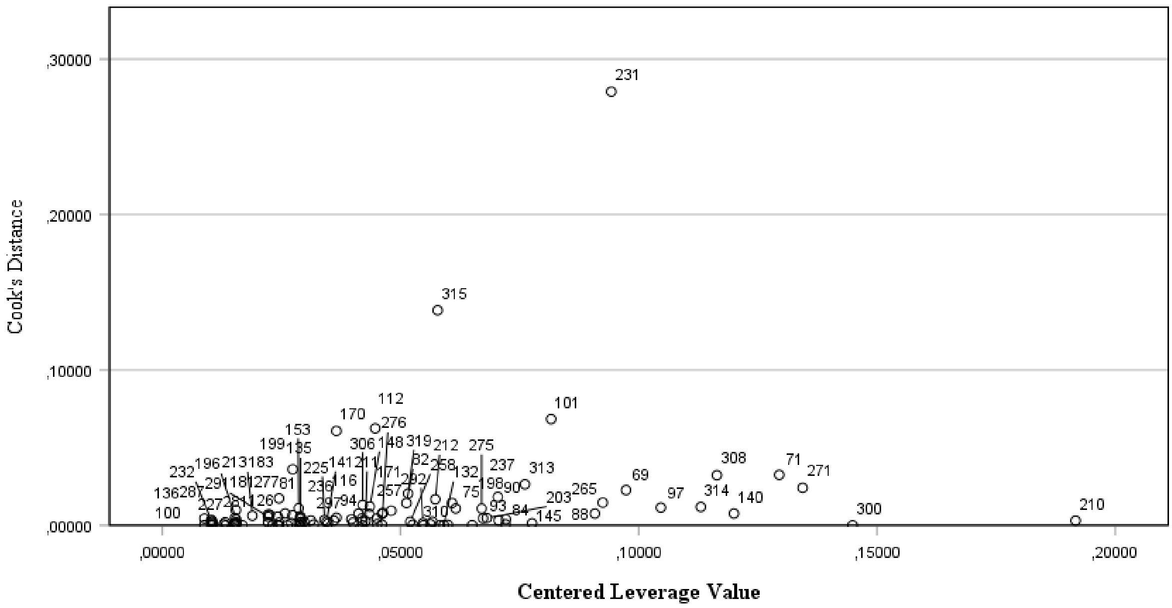

Figure C. 11. Scatterplot Cook's Distance vs. Centered Leverage Value (Model 3)

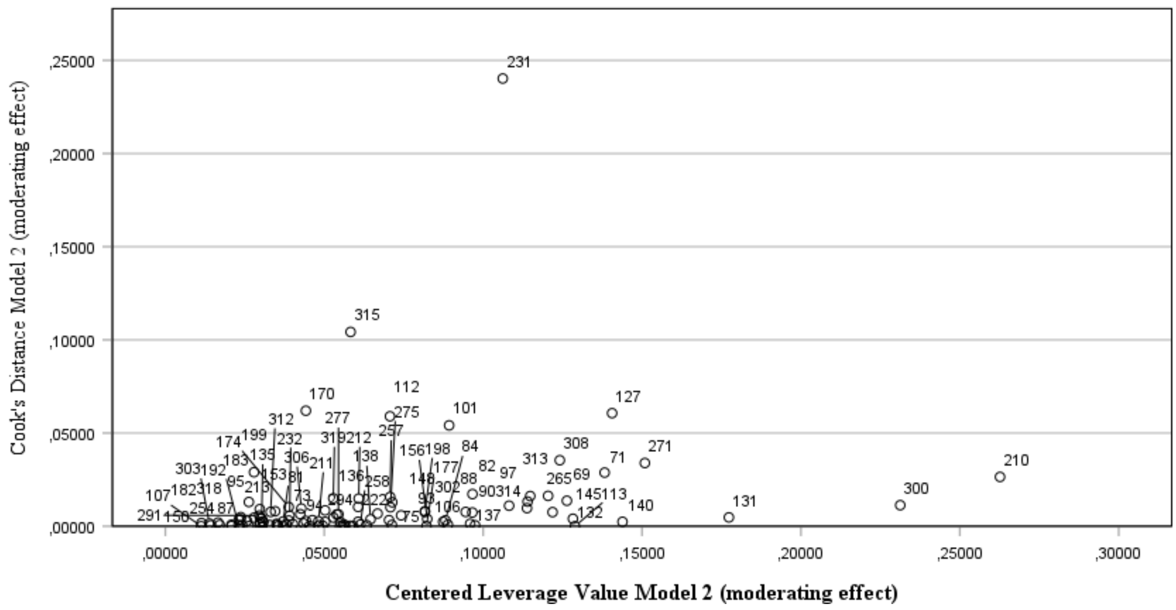

Figure C. 12. Scatterplot Cook's distance vs. Centered Leverage Value (Model 4)

Appendix D: Additional analyses

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	28,435[a]	10	,002
Likelihood Ratio	19,274	10	,037
Linear-by-Linear Association	,218	1	,641
N of Valid Cases	110		

[a]. 14 cells (63,6%) have expected count less than 5. The minimum expected count is ,05.

*Table D. 1. Chi-square tests: Industry * LinkedIn Recruiter*

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	35,237[a]	10	<,001
Likelihood Ratio	38,548	10	<,001
Linear-by-Linear Association	8,730	1	,003
N of Valid Cases	110		

[a]. 14 cells (63,6%) have expected count less than 5. The minimum expected count is ,19.

*Table D. 2. Chi-square tests: Industry * Textkernel*

		LinkedIn Recruiter				Total	
		not selected		selected			
		N	%	N	%	N	%
Industry	Construction/Real Estate	0	0,0%	6	5,7%	6	5,5%
	Consulting Services	0	0,0%	27	25,7%	27	24,5%
	Energy/Utilities	0	0,0%	4	3,8%	4	3,6%
	Finance/Banking	0	0,0%	8	7,6%	8	7,3%
	Healthcare/Medical	1	20,0%	6	5,7%	7	6,4%
	Hospitality/Travel	1	20,0%	1	1,0%	2	1,8%
	Manufacturing/Engineering	3	60,0%	8	7,6%	11	10,0%
	Media/Entertainment	0	0,0%	1	1,0%	1	0,9%
	Retail/Consumer Goods	0	0,0%	7	6,7%	7	6,4%
	Technology/IT	0	0,0%	24	22,9%	24	21,8%
	Other (please specify):	0	0,0%	13	12,4%	13	11,8%
Total		5	100,0%	105	100,0%	110	100,0%

*Table D. 3. Crosstab: Industry * LinkedIn Recruiter*

		Textkernel Search				Total	
		not selected		selected			
		N	%	N	%	N	%
Industry	Construction/Real Estate	6	6,7%	0	0,0%	6	5,5%
	Consulting Services	12	13,5%	15	71,4%	27	24,5%
	Energy/Utilities	4	4,5%	0	0,0%	4	3,6%
	Finance/Banking	8	9,0%	0	0,0%	8	7,3%
	Healthcare/Medical	7	7,9%	0	0,0%	7	6,4%
	Hospitality/Travel	2	2,2%	0	0,0%	2	1,8%
	Manufacturing/Engineering	11	12,4%	0	0,0%	11	10,0%
	Media/Entertainment	1	1,1%	0	0,0%	1	0,9%
	Retail/Consumer Goods	7	7,9%	0	0,0%	7	6,4%
	Technology/IT	19	21,3%	5	23,8%	24	21,8%
	Other (please specify):	12	13,5%	1	4,8%	13	11,8%
Total		89	100,0%	21	100,0%	110	100,0%

*Table D. 4. Crosstab: Industry * Textkernel*

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	36,999	6,024		6,142	<,001
	Experience (years)	,824	1,524	,052	,541	,590

a. Dependent Variable: Estimated positive + negative response rate

*Table D. 5. Regression coefficients: Overall response rate * experience*

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	19,149	4,648		4,120	<,001
	Experience (years)	,208	1,176	,017	,177	,860

a. Dependent Variable: Estimated positive response rate

*Table D. 6. Regression coefficients: Positive response rate * experience*

Regression Model 1:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,196[a]	,038	-,008	22,263

a. Predictors: (Constant), FUPs, Personalization, Gender, Age, Tenure

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2036,152	5	407,230	,822	,537[b]
	Residual	51052,619	103	495,656		
	Total	53088,771	108			

a. Dependent Variable: Estimated positive + negative response rate

b. Predictors: (Constant), FUPs, Personalization, Gender, Age, Tenure

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	40,105	19,040		2,106	,038
	Gender	-1,696	2,612	-,065	-,649	,518
	Age	-3,820	2,324	-,160	-1,644	,103
	Tenure	1,275	2,528	,051	,505	,615
	Personalization	2,013	2,956	,066	,681	,498
	FUPs	1,177	1,952	,059	,603	,548

a. Dependent Variable: Estimated positive + negative response rate

Table D. 7. Regression N = 109 (Model 1)

Model 2:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,221[a]	,049	-,017	22,361

a. Predictors: (Constant), Interaction Term Personalization * AI, Age, FUPs, Gender, Tenure, Personalization, Moderating effect AI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2588,958	7	369,851	,740	,639[b]
	Residual	50499,812	101	499,998		
	Total	53088,771	108			

a. Dependent Variable: Estimated positive + negative response rate

b. Predictors: (Constant), Interaction Term Personalization * AI, Age, FUPs, Gender, Tenure, Personalization, Moderating effect AI

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-19,390	59,854		-,324	,747
	Gender	-1,792	2,641	-,068	-,679	,499
	Age	-3,694	2,337	-,155	-1,580	,117
	Tenure	,948	2,587	,038	,366	,715
	Personalization	14,695	12,600	,483	1,166	,246
	FUPs	1,380	1,985	,069	,695	,488
	Moderating effect AI	17,819	16,967	,795	1,050	,296
	Interaction Term Personalization * AI	-3,778	3,654	-,874	-1,034	,304

a. Dependent Variable: Estimated positive + negative response rate

Table D. 8. Regression N = 109 (Model 2)

Model 3:

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,145[a]	,021	-,026	17,308

a. Predictors: (Constant), FUPs, Personalization, Gender, Age, Tenure

b. Dependent Variable: Estimated positive response rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	666,567	5	133,313	,445	,816[b]
	Residual	30853,689	103	299,550		
	Total	31520,257	108			

a. Dependent Variable: Estimated positive response rate

b. Predictors: (Constant), FUPs, Personalization, Gender, Age, Tenure

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	24,873	14,802		1,680	,096
	Gender	-,715	2,031	-,035	-,352	,726
	Age	-2,397	1,807	-,130	-1,327	,188
	Tenure	,917	1,965	,047	,467	,642
	Personalization	,649	2,298	,028	,283	,778
	FUPs	-,289	1,517	-,019	-,191	,849

a. Dependent Variable: Estimated positive response rate

Table D. 9. Regression N = 109 (Model 3)

Model 4:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,242[a]	,059	-,007	17,139

a. Predictors: (Constant), Interaction term Personalization * AI, Age, FUPs, Gender, Tenure, Personalization, Moderating effect AI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1850,737	7	264,391	,900	,510[b]
	Residual	29669,520	101	293,758		
	Total	31520,257	108			

a. Dependent Variable: Estimated positive response rate

b. Predictors: (Constant), Interaction term Personalization * AI, Age, FUPs, Gender, Tenure, Personalization, Moderating effect AI

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-46,174	45,878		-1,006	,317
	Gender	-,542	2,024	-,027	-,268	,790
	Age	-2,261	1,792	-,123	-1,262	,210
	Tenure	,927	1,983	,048	,467	,641
	Personalization	17,045	9,658	,726	1,765	,081
	FUPs	-,300	1,521	-,019	-,197	,844
	Moderating effect AI	20,952	13,005	1,213	1,611	,110
	Interaction term Personalization * AI	-4,917	2,800	-1,476	-1,756	,082

a. Dependent Variable: Estimated positive response rate

Table D. 10. Regression N = 109 (Model 4)