MASTERARBEIT | MASTER'S THESIS

Titel | Title

Professionally polarized: Examining Group Polarization on LinkedIn through the lenses of Social Identity and Information Sharing

verfasst von | submitted by

Andreea-Simina Fernea BSc

angestrebter akademischer Grad | in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien | Vienna, 2024

Studienkennzahl lt. Studienblatt | Degree programme code as it appears on the student record sheet:	UA 066 915
Studienrichtung lt. Studienblatt | Degree programme as it appears on the student record sheet:	Masterstudium Betriebswirtschaft
Betreut von | Supervisor:	Assoz. Prof. Steffen Keck PhD

Acknowledgements

The acknowledgements of this thesis go to all the people who played an important role throughout my writing journey.

First, I would like to express my gratitude to my supervisor, Assoc. Prof. Steffen Keck, PhD, for offering me the opportunity to write my thesis in the Strategic Management Subject Area, and for his support and feedback throughout the past year.

Second, special thanks go to all my study participants, without whom the sample of this thesis would not have been achieved. Also, to my colleagues who participated in the master's thesis conservatory, thank you for the nice exchange we had during the course.

I would like to also thank some people close to my heart, who provided emotional support throughout the past year. I am grateful to my family, especially to my parents, who made it possible for me to study in Vienna, and for encouraging me to pursue my dreams guided by their unconditional love and support. To my partner and friends, thank you for your understanding, patience, and always having a kind word and an open ear. Thank you for the unconditional support, for believing in me and pushing me to do a bit more, even when I was doubting myself.

I would like to dedicate this thesis to my grandfather, Stefan, who was always curious and eager to listen to what I have learned in university whenever I visited home on breaks. Although he is no longer with us, his stories ignited my curiosity, and his unconditional love shaped me to the person I am today.

Finally, my gratitude goes to everyone who crossed my path and whose names may not be mentioned, but whose exchanges and encouragements have played a role in this academic journey.

Abstract

With digitalization and social media platforms playing an important role in today's society, one can barely avoid its effects on how identities are shaped by it in both personal and professional aspects of our lives. The present thesis explores the dimensions of group polarization within professional groups on LinkedIn, a social media platform that displays one's professional self. Social Identity and Sharing Behavior are identified as two key factors that play a role in this complex interplay.

The thesis follows a quantitative research design for collecting first-hand data from professionals active on LinkedIn, but it also presents a significant literature review as a base. The findings emphasize the importance of Sharing Behavior in promoting active engagement, as well as the multifaceted influence of social identity on user interaction, which contributes to the emergence of polarization within professional online groups.

The presented theoretical implications contribute to the existing academic body of literature on the impact of digital platforms on professional identities and group dynamics, while the provided practical insights present valuable strategies for professionals and organizations seeking to cultivate more diverse and less polarized discussions on LinkedIn.

Zusammenfassung

In einer Gesellschaft, in der Digitalisierung und Social-Media-Plattformen eine immer wichtigere Rolle spielen, kann man sich den Auswirkungen auf die Gestaltung von Identitäten sowohl im privaten als auch im beruflichen Bereich kaum noch entziehen. Die vorliegende Masterarbeit untersucht die Dimensionen der Gruppenpolarisierung innerhalb von professionellen Gruppen auf LinkedIn, einer Social-Media Plattform, die das eigene berufliche Selbst darstellt. Soziale Identität und Sharing-Verhalten werden als zwei Schlüsselfaktoren identifiziert, die in diesem komplexen Zusammenspiel eine wichtige Rolle spielen.

Die Arbeit verwendet ein quantitatives Forschungsdesign, um Daten aus erster Hand von Professionals, die auf LinkedIn aktiv sind, zu sammeln. Als Basis wird jedoch auch eine umfangreiche Literaturübersicht präsentiert. Die Ergebnisse bestätigen die Bedeutung von Sharing-Verhalten für die Förderung eines aktiven Engagements sowie den facettenreichen Einfluss der sozialen Identität auf die Interaktion der Nutzer, der zur Entstehung von Polarisierung innerhalb professioneller Online-Gruppen beiträgt.

Die in der Arbeit vorgestellten theoretischen Implikationen tragen zur bestehenden akademischen Literatur über die Auswirkungen digitaler Plattformen auf berufliche Identitäten und Gruppendynamik bei, während die bereitgestellten praktischen Erkenntnisse wertvolle Strategien für Fachleute und Organisationen darstellen, die versuchen, vielfältigere und weniger polarisierte Diskussionen auf LinkedIn zu kultivieren.

Table of Contents

List of Abbreviations

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
CV	Control Variable
DV	Dependent Variable
EFA	Exploratory Factor Analysis
GP	Group Polarization
IV	Independent Variable
gologit2	Generalized Ordered Logistic Model
mlogit	Multinomial Logistic Regression
ologit	Ordered Logistic Regression
omodel	Ordered Logistic Model
RRR	Relative Risk Ratios
SM	Social Media
SIT	Social Identity Theory
VIF	Variance Inflation Factor

List of Figures

List of Tables

1. Introduction

Given the constant growth of digitalization in today's modern world, the ability of social media platforms to shape communication and information sharing habits cannot be ignored nor underestimated. Such platforms not only have a notable impact on individuals' opinions, attitudes, and behaviors but at the same time, social media has revolutionized the way people connect, share information, and interact with each other in the online world.

Within the constant expansion of social media platforms development, LinkedIn excels as a major professional networking platform that is essential for connecting professionals, by enabling information and knowledge sharing, and cultivating professional communities. The varied features tailored to professional development provided by the platform are essential, such as the option of creating and sharing a comprehensive online résumé, joining industry-specific groups, following significant personalities in the desired field, and participating in discussions on relevant themes together with peers, to name just a few. LinkedIn excels as a strong platform for those looking to forge meaningful relationships, share industry insights, and navigate the ever-changing professional landscape due to its sole focus on professional networking and career development.

The American Psychology Association defines group polarization in its dictionary as the propensity of individuals in a group to adopt viewpoints that are more extreme than their initial ones when discussing a topic. As a result, given the past opinions of every individual, the group as a whole tends to respond in more extreme ways than one might have originally expected.

Although most research on group polarization has traditionally been done in offline settings, recent studies emphasize the necessity of investigating the way it manifests in online settings, including social media. In one of the early papers on group polarization, Sunstein (1999) argues that social media platforms can enhance this phenomenon due to the personal choices of like-minded individuals and the reinforcement of pre-existing beliefs through exposure to similar perspectives. Sunstein (1999) researched group polarization and its consequences, discovering that when people engage in group discussions with other people who share their points of view, they tend to accept more extreme viewpoints and beliefs. According to his research, a number of crucial mechanisms contribute to group polarization. Firstly, when interactions with people who share similar views occur, they are exposed to strong arguments that validate and share their pre-existing beliefs. Secondly, individuals participate in social comparison in order to distinguish themselves and align more closely with the prevailing attitudes of their community. Third, group dynamics such as the desire for social acceptability and the fear of diverging from the group contribute to the amplification of extreme perspectives. Sunstein's research underlines the tremendous importance of social interactions within groups, offering light on the mechanisms behind the establishment of group polarization. Postmes, Spears, and Lea (2000) conducted a study on the establishment of group norms in computer-mediated communication and their relationship to group polarization. The results of their study suggest that computer-mediated communication platforms, which include social media, can have significant effects on the establishment of group norms. The authors discovered that when people engage in online discussions with like-minded peers, group norms tend to become more extreme over time. This phenomenon arises as a result of a social comparison and information sharing process in which individuals seek validation and conformity within their group. The study also highlighted the significance of anonymity in online spaces, which can amplify the impacts of group polarization by decreasing inhibitions and encouraging a sense of freedom to express extreme beliefs. These findings give light on the methods through which computer-mediated communication contributes to the polarization of attitudes and opinions inside online groups.

In addition to group polarization research, analyzing information dispersion and social media behavior provides useful insights. Stieglitz and Dang-Xuan (2013) discovered that emotions expressed in microblogs on social media platforms influence individual sharing behavior, thereby contributing to polarization dynamics. Yang and Counts (2015) conducted a study predicting information sharing behaviors on social media and identified a variety of factors, including user traits and network structures, that influence sharing patterns.

Despite its increasing significance among professionals of multiple industries, it is essential to delve into the issue of group polarization within LinkedIn’s professional groups. This phenomenon has implications for the quality of interactions among professionals and the decision-making processes they engage in. Therefore, investigating this aspect is crucial for understanding and enhancing the overall effectiveness of LinkedIn as a professional platform. In their systematic literature review on group polarization, Iandoli, Primario and Zollo (2021) underline that despite differences in their theories and findings, a multitude of scholars emphasize their concerns about the impact that group polarization in the online environment has on the “quality of online discourse and the well-being of democracy” (Iandoli, Primario and Zollo, 2021).

In conclusion, academic research on group polarization and social media behavior indicates the possibility for polarization within online platforms comparable to LinkedIn. Hence, this thesis aims to broaden our understanding of group polarization dynamics in professional contexts by focusing on LinkedIn's professional groups.

By conducting a study specifically focused on LinkedIn, this master thesis aims to contribute to the understanding of group polarization dynamics within professional groups and the unique factors at play on this platform. The thesis aims to have three primary objectives, which will be enumerated below.

Firstly, to assess the prevalence and extent of group polarization within professional communities on LinkedIn. Secondly, to examine the relationship between social identity and group polarization within professional groups on LinkedIn. Lastly, this thesis aims to assess the impact of information sharing practices on group polarization within professional groups on LinkedIn. Research by Stieglitz and Dang-Xuan (2013) on emotions and information diffusion in social media platforms provides insights into the influence of information sharing practices on group dynamics. Their study highlights the potential contribution of emotional expression in microblogs to the sharing behavior and potential polarization dynamics. Thus, the proposed master’s thesis aims to address the following research question:

What is the role and what are the drivers of Group Polarization within professional groups on LinkedIn?

The thesis will expand on previous research to investigate the importance of social identity and information sharing practices, contributing to the current literature while providing practical implications for professionals and organizations wishing to effectively manage online professional communities.

This thesis follows the common structure, starting with a comprehensive theoretical background on the topic, followed by the presentation of the implied methodology. The results chapter will present demographics and descriptive statistics, before addressing the statistical analysis of the data. In the discussion section, the interpretation of results will be explained, limitations will be acknowledged, and further research recommendations will be provided. Finally, a conclusion will be written to highlight and summarize the key findings of this thesis.

2. Theoretical Background

The objective of the following chapter of this thesis is to build a comprehensive theoretical background, which further serves as the foundation for understanding possible key drivers of group polarization within professional groups on LinkedIn. Constructs such as social identity theory, the mechanics of social media interactions and the dynamics of online group behaviors will be investigated, based on the extensive existing literature in the fields of social psychology, media studies and communication theory. Existing theoretical frameworks provide key insights into how professional identities are developed and challenged within LinkedIn, a platform that goes beyond the traditional borders of professional engagement. By connecting such diversified theoretical components, this chapter builds the base for the analysis of group polarization, uncovering the complex relationships between individual behaviors, group dynamics, and the digital structures facilitating professional relationships.

2.1. Group Polarization: Core Concepts and Social Media Implications

Polarization is a phenomenon that has been discussed and observed in many different areas of research. Many scholars have contributed to the literature on group polarization within their discipline over the years, which includes social sciences as well as political and communication studies to name just a few (Iandoli et al., 2021). According to Isenberg (1986), the phenomenon of Group Polarization arises when more extreme viewpoints are being embraced by group members, after taking part in or being a witness to diverse group discussions. Nowadays, the Dictionary of Psychology by Andrew M. Colman defines the term of Group Polarization (GP) as “the tendency for involvement in a group to cause the attitudes and opinions of the group members to become more extreme, in the direction of the predominant attitudes and opinions in the group” (Colman, 2015). The same publication notes that the effect is explained by collective involvement and group participation making group norms visible, strengthening normative individual attitudes and beliefs, and driving them to shift deeper in the direction of group norms (Colman, 2015).

Such phenomena have been studied by scholars as early as 1961, when James Stoner observed the so-called “risky shifts" in group decisions (Myers and Lamm, 1976). Stoner’s concept of risky shifts underlined that decisions which are taken within a group turn out to be riskier than the average of what each individual would have decided to do before being in the said group (Stoner, 1961). After this discovery, research in this direction was intensified and by the late 1960’s, it was obvious that not only the so-called “risky shifts” are phenomena that emphasize extremes in group decisions. Thus, in 1969, the social psychologists S. Moscovici and his colleague came up with the term Group Polarization (GP) for these phenomena of group decision making (Moscovici & Zavalloni, 1969). In their paper on GP, Moscovic and Zavalloni examined a group of 140 male students from a secondary school in group discussions about Charles De Gaulle and America. This resulted in students holding more extreme views and disfavoring America over Charles De Gaulle after their discussions (Moscovic & Zavalloni, 1969).

Seven years later, Myers and Lamm (1976) explained the theoretical foundations of GP and “how attitudes develop in a social context” (Myers and Lamm, 1976). According to the two aforementioned researchers, the following theories prevailed in early studies on GP:

- *Social decision rules* - wherein the ways in which individual decisions might be blended with one another to create a group decision are explained.
- *Informational influence* - where people learn as a result of receiving and offering strong arguments on the subject that is in question.
- *Social comparison effects* - which explains how comparing one’s own attitudes with those of other group members, can create an effect of wishing to perceive and present oneself in a favorable manner, when related to others.

- *Responsibility dynamics* - where having an extensive number of members in a group could make other members feel less accountable for a given decision.

In the 1970s, considerable debate arose on whether persuasive argumentation alone could account for GP. Following this debate, Daniel Isenberg's meta-analysis published in 1986 containing data on both the persuasive arguments as well as social comparison theories, managed to answer the question on which mechanisms were dominant in regard to GP. The author came to the conclusion that there was strong evidence for both effects acting in tandem, with persuasive arguments theory working when social comparison did not, and vice versa (Isenberg, 1986). Festinger's (1954) social comparison and Tajfel et al.'s social identity theory (SIT) gives an explanation of polarization as the result of people consolidating their sense of group membership. The core of the social comparison theory notes that individuals frequently self-evaluate by comparing themselves to other people. Additionally, Festinger's (1954) findings proved that "individuals will adjust their opinions based on how other people value them" (Primario et al., 2017). Hence, if a group discussion occurs and an individual notices that his standpoint does not align with the dominant position, he will tend to shift towards it (Festinger, 1954). The persuasive arguments theory states that before a group discussion, its members will develop arguments in favor of their own position regarding the discussed topic, which tend to be more extreme so that the other members will be convinced of the individual's beliefs (Mercier et al., 2011). The three aforementioned theories explain two different needs of groups. While the need for internal cohesiveness is met by social comparison and SIT, the group's ability to adapt and survive is aided by the persuasive argumentation theory's capacity of neutralizing outside threats.

Despite having been studied successfully and extensively in face-to-face settings till the late 1980's, a fresh interest in GP has resulted from the growing significance of the Internet in interpersonal communication and information consumption in the late 1990's and early 2000's (Iandoli et al., 2021). Cass Sunstein has been a pioneer in the field of GP in social media (SM) and published several well-recognized papers on the topic (Sunstein, 1999; Sunstein, 2001). The researcher identified a key concept behind GP through investigating online information cocoons created by like-minded individuals, and lastly hypothesizing that GP would weaken public discourse on one side and support extremism on the other (Balcells and Padró-Solanet, 2016). Subsequently with Sunstein's pioneering work, other scholars deep dived in the topic of GP in the context of SM and came up with different findings about the effects of using such platforms. With nearly 5 billion users of SM networks in 2023 (Number of Worldwide Social Network Users 2027 | Statista, 2023), there is no wonder that the topic captured the interest of researchers worldwide. According to studies such as Prior (2007) and Bennet & Iyengar (2008), the development of new media technologies over the past 30 years has resulted in the expansion of media channels and thus the creation of a high-choice media environment. Rainie & Wellman (2012) also state that the popularity increase of digital and social media and the development of online social networks further individualized people's information environment. The topic of SM dynamics and people's information sharing practices will be discussed in chapter 2.3 of this thesis.

Initial work such as Garrett (2009), Stroud (2010) or Pariser (2011) hold SM responsible for the emergence of an increasingly fragmented, misinformed, and inclined towards manipulation and social negativity public sphere. The same researchers accused SM of promoting these developments of the public sphere by a combination of design affordances and algorithms that lead to the formation of "ideologically homogeneous information bubbles" (Iandoli et al., 2021) and thus leading to GP effects (Iandoli et al., 2021). Later studies mitigated these initial concerns and provided evidence on important aspects of information sharing habits on SM platforms. Firstly, Barberá (2014) provided crucial evidence that information sharing practices increase the exposure to diversified topics. Secondly, Becker et al. (2019) proved that information sharing also promotes wisdom in partisan crowds. Thirdly, more recent studies prove that initial fears of SM potentially polarizing and manipulating people's decisions and opinions have been exaggerated (Dubois and Blank, 2018). Lastly, studies have proven that there is no concrete evidence that SM and the emergence of the Internet make online discussions more polarized than they actually are in a real-life setting (Gentzkow and Shapiro, 2011; Prior, 2013; Boxell et al., 2017). Other scholars challenge the perspective of diversity and present proof of GP being created due to increased exposure to online interactions and politically charged content on SM. This content is usually created by so-called “disagreeable others”, which polarizes people’s emotions and further causes social division (Yardi and Boyd, 2010; Iyengar et al., 2012; Settle, 2019). When differing fractions clash to further their own agendas through public arguments and contentious discussions, the existence of diversity can easily backfire (Garrett et al., 2014; Kim and Kim, 2019).

According to Iandoli et al. (2021), despite the amount of diverse findings in the literature on GP over the last decades, they still show common conceptual pillars structured in two mechanisms. These mechanisms mentioned by Iandoli et al. (2021) in their literature review are homophily and discursive argumentation, and the authors note that these can operate both independently from each other or in combination. The APA Dictionary of psychology defines homophily as “the tendency for individuals who are socially connected in some way to display certain affinities” (APA Dictionary of Psychology, 2018). Iandoli et al. (2021) also note about the mechanism of homophily that it can “lead to the creation of information bubbles in which certain beliefs become dominant thanks to mutual positive reinforcement among like-minded peers” (Iandoli et al., 2021). As when speaking about discursive argumentation, Mercier and Sperber (2011) note that this phenomenon is defined as the process by which individuals as well as groups use reasoning to rhetorically overcome their opponents in order to achieve their intended objectives. The exposure to information diversity is what produces GP in the case of discursive argumentation mechanism, whereas the lack thereof leads to GP in the case of the homophily mechanism. Interaction over online mediums such as SM is an enabler for both aforementioned mechanisms, as they have both the ability to aggregate similar users as well as exposing them to information that is hostile from an ideological point of view (Iandoli et al., 2021). A third mechanism that favors the appearance of GP in online settings according to Iandoli et al. (2021) is selective exposure/sharing, which similarly to homophily, suppresses the diversity of available information (Iandoli et al., 2021). Scholars proved that selective exposure/sharing and homophily can be enhanced or amplified by design features (Giese et al., 2020) and algorithms (Pariser, 2011) used on SM.

2.2. The Digital Self: Social Identity Theory and Its Implications in Online Networks

As briefly mentioned in the previous chapter of this thesis, SIT arose in the 1970's as a new socio-psychological viewpoint on group actions (Tajfel, 1978; Tajfel & Turner, 1979). According to the theory, people typically desire to and gain from having positive social identities connected to the groups they are a member of. The SIT consists of one fundamental process: categorization. People often define themselves or others based on a variety of attributes, including ethnicity, gender, nationality, or common interests, to name just a few. These differentiations shape one's perception of oneself and contribute to the development of a social identity. In his study, Turner (1982) highlights that classification can play a crucial role in the shaping of behaviors and perceptions within social groups.

But when thinking about the existence of unprivileged or low-status groups, the question of why people would want to identify with such groups that have a negative reflection on them arises. SIT provides an answer to this question through three variables that have an effect on how individuals deal with identity concerns: "the permeability of group boundaries, the legitimacy of intergroup relations, and their stability" (Van Zomeren et al., 2008). Permeability of boundaries refers to the possibility of a disadvantaged group member to leave and find a higher status one, opposed to impermeable groups which offer no such options (Hirschmann, 1970). And if their group offers no possibility of leaving, individuals must make the best out of their circumstances. One of the actions that group members can take in such a situation, according to SIT, is engagement in collective action. With individuals taking such actions, scholars proved that disadvantaged group members could influence the differences in intergroup status (Tajfel, 1978; Turner & Brown, 1978; Ellemers, 1993).

It is important to note that the media also plays an important role in shaping and reflecting social identities. Investigating how different socio-economic groups are portrayed in the media provides insight into both power dynamics and social standards. In his study, Hall (1973) discovered that media depiction aids in the creation of social identities and influences how people perceive both themselves and others. SIT notes that individuals tend to pursue social comparison for the enhancement of their own self-esteem. This is connected to favoring in-groups and marginalizing out-groups, which contributes to a positive social identity. In their findings, Tajfel and Turner (1986) claimed that media messages frequently reinforce such social comparisons, causing people to have a more positive perception of their in-group. Existing social identities are not only represented through media, but its use also encourages the formation of new ones. Stereotypical portrayals of certain groups can have an impact on how in-group members perceive themselves. Dovidio and Gaertner (2000) found that media stereotypes can influence social categorization and contribute to the ongoing existence of biases. SIT also left its mark on the study of intergroup relations and provided insights on communication dynamics among various social groups. The notion of intergroup relations emphasizes the importance of perceived intergroup status and its corresponding communication patterns. Furthermore, different levels of power have an influence on communication strategies, which contribute to either maintaining or challenging social identities (Brown and Levinson, 1987).

In connection to intergroup communication, media serves as a powerful tool in shaping it. On one hand, the media can have a huge contribution in the reduction of intergroup tensions, by highlighting different points of view and encouraging communication between different social groups. On the other, it can also propagate prejudices and sustain power inequalities, which may further worsen existing differences.

With today's digitized society and the emergence of social media platforms and online communities, the SIT has gained additional dimensions. The internet and its different online environments offer individuals a multitude of opportunities to express and explore their social identities. In their research, Ellison et al. (2014) emphasized the role of SM in supporting the development of digital social identities. The same research also highlighted how online interactions have an effect on people's offline social identities. While SM platforms can be used by individuals to connect with similar peers, they also enable the formation of digital in-groups. The ease by which online communities can be formed based on shared interests or identities can lead to both the reinforcement of existing social identities and the creation of new ones.

Lapin (2011) published the following interview statement of LinkedIn's CEO Jeff Weiner, when he was asked back in 2010 to compare his platform to the competition: *"Facebook is largely a social utility platform. LinkedIn is a professional network…. The key distinction is that as a professional you want people to know who you are. People are searching for you or people like you whether you like it or not"* (Lapin, 2011). When comparing the platform to Facebook, LinkedIn's users are mostly professionals employed by different (mostly large) firms. The initial scope of the website was facilitation of professional connections, but it also offers recruitment and advertising services to companies (Van Dijck, 2013). In 2023, LinkedIn registered over 700 million users worldwide, making it the largest professional website in the world (Degenhard, 2023).

Since its launch in 2003, LinkedIn underwent a series of changes, a lot of them being introduced due to Facebook's success on the SM market. The more chronological and uniform display of professional identities was introduced in 2009, emphasizing personal content and profile information. Additionally, resembling a sleek CV and exposing only essential information about one's education and work background, LinkedIn "discourages any forms of self-expression or emotional attachments, as these signals might be detrimental to someone's professional image" (Van Dijck, 2013). In other terms, LinkedIn profiles serve as symbols of expected professional conduct. By showcasing skills to peers and other users, each profile creates an idealized representation of the user's professional identity. When creating a profile on LinkedIn, users are asked to highlight specific skills or include recommendations from past colleagues or peers. The Questions and Answers feature provides users the opportunity to answer questions posted by people in different professions, thus answering them offers a boost in the user's professional identity and public image. Use of this feature can also underline the user's skills, expertise and sociability. By showcasing such skills, the users not only enhance their professional value on the job market, but also enhance the reputation of the company they work for. LinkedIn's CEO Jeff weiner was aware of this bidirectional impact of the platform, and stated in an interview for the Wall Street Journal back in 2011 that "the behavioral changes taking place as a result of that infrastructure, the way in which people represent their identity, the way in which people are connecting with others, and the way in which they're sharing information, knowledge, opinions, ideas" (Raice, 2011) to be more important.

2.3. Social Media and Information Sharing: Dynamics and Relevance for Group Polarization

The Cambridge Dictionary defines social media as those types of media "that allow people to communicate and share information using the internet or mobile phones" (Cambridge Dictionary, 2023). However, existing platforms differentiate themselves by the types of information that users share on them. When searching for the most popular social media platforms, the majority of articles on the internet will enumerate Facebook, Twitter, Instagram and LinkedIn among the top ten. While Twitter allows its users to post short messages with a limited word count and is considered a microblogging platform, Facebook allows one to share photos, text, and video content with friends and family. Instagram focuses on purely visual content and became the workplace of different influencers or the platform where socialites communicate with their followers through posts, stories or short videos called reels.

The literature review by Iandoli et al. (2021) shows there are three categorizations of SM design features, based on users' online actions, that can have an influence on GP: "how users are passively exposed to information (feeding and prioritizing), how they actively express and share contents, and how they value and assess feedback and reactions from other" (Iandoli et al., 2021).

Firstly, according to research done by Dubois and Blank (2018) and Settle (2019), SM is especially good at reaching an extensive audience while exposing them in a passive way to both wanted and unwanted content. In line with these findings, algorithms that establish the user's newsfeed, such as ones used by Facebook, can go in two ways. On one aspect, they can reinforce the user's opinion by emphasizing content posted by like-minded people or show tailored advertisements based on the users liking behaviors (Paravati et. al, 2019). Bessi et al. (2016b) provide evidence that such a content promotion strategy can reduce diversity and restrict the exposure of users to alternative content. On another aspect, the same algorithms can expose the user to diverse content, which does not necessarily align with his beliefs or likings. A study done on Facebook by Settle (2019), shows that exposure to so-called "disagreeable others" on the newsfeed nurtures the appearance of affective polarization. Their findings may apply to other SM platforms, for example Twitter, which provide opportunities for the development of weak ties and exposure to hostile diversity.

Secondly, in the context of SM, GP can also be nurtured by the user's information sharing behavior. Twitter is a good example of SM where "users tend to be less private when sharing content thanks to the broadcasting of content to large and unknown fellowship via the retweet function" (Iandoli et al., 2021).

Evidence is offered by previous literature on GP that use of the retweet function by SM users can signal both endorsement of agreement (Conover et al., 2011; Weber et al., 2013; Lai et al., 2019) as well as the opposite, signaling disagreement with what the original tweet's message was (Guerra et al., 2017). Other SM platforms, such as Facebook, which are primarily designed to foster closer relationships and more private and intimate networks, offer the potential to be better suited for information dissemination among friends and like-minded individuals (Bessi et al., 2016a; Del Vicario et al., 2016). However, according to research, these friends and peers seem to be particularly good at spreading false information that aligns with their ideological orientation and preferences (Bessi et al., 2016a; Del Vicario et al., 2016). Furthermore, according to research by Settle (2019), the ability to create complex and detailed personal profiles supports the development of strong digital identities on both personal and group level.
Lastly, the measurement of social appreciation seems to be the final factor that clearly favors online GP in terms of feedback assessment. According to Kuang and Fabricant (2019), it may not be a coincidence that Facebook's popularity and earnings increased significantly following the launch of the "like" button. Similarly to the number of visualizations or retweets in the case of Twitter, these features of SM platforms "directly translate into metrics of impact and visibility of our digital presence" (Iandoli et al., 2021).

In their literature review on the impact of GP on the quality of online debate in SM, Iandoli et al. (2021) emphasize that while scholars report positive effects of online GP when talking about increased trust in institutions (Johnson et al., 2017) or improvements in accuracy of beliefs (Becker et al., 2019), their analysis "reveals dominance of negative social consequences" (Iandoli et al., 2021). The researchers group these into three categories: fragmentation of the online public sphere, radicalization of opinions and diffusion of online misinformation (Iandoli et al., 2021). When talking about the first category, scholars such as Settle (2019) support the argument of SM fostering the increase of growing polarization in society, further stating that the platforms nurture affective polarization by exposing users to controversial topics. For the second category, even with existing studies providing evidence of SM pushing its users towards more extreme feelings, political beliefs or attitudes (Weber et al., 2013; Brady et al., 2017; Romenskyy et al., 2018), there is no strong evidence in support of the idea that online GP enabled by SM is a causal antecedent for offline mobilization. The last category, diffusion of online misinformation, is supported by several empirical studies and brings evidence of GP favoring the spread of fake news and misinformation (Törnberg, 2018; Zollo, 2019).

Connected to these nuanced findings on GP in SM, the work of Yarchi, Baden, and Klingler-Vilenchik (2020) offers critical insights into the topic. Their research, focused on the use of algorithmic methods, examined the nature of political polarization across diverse SM platforms, including Twitter, WhatsApp, and Facebook. The findings show that polarization manifests differently across platforms. Twitter showed patterns of homophilic interactions that tend to intensify positional polarization, whereas WhatsApp showed a trend towards de-polarization over time. In terms of user interaction, expressed opinions and emotions, Facebook proved to be the least homophilic SM platform, suggesting a less polarized environment. These researcher's findings could be relevant for understanding the dynamics on professional networking platforms such as LinkedIn. Yarchi, Baden, and Klingler-Vilenchik's (2020) study underscores the imperative that the design and algorithmic features of a platform can profoundly influence the nature and degree of GP. This further highlights the potential for LinkedIn's design and user interaction dynamics to shape professional discussions, potentially either mitigating or intensifying polarization among its users.

Despite the diversity of theories and findings, there are shared concerns among authors and IT specialists regarding the impact of GP on the quality of online interactions. With SM being an enabler for online discussions, it nevertheless proved to have an enhanced negative impact on the quality of such interactions. Shearer (2018) underlined in their paper that SM is more and more being used as a primary news source by younger generations, as they enable fast access to information. Additionally, the author argues that such platforms can't be compared to any traditional news media when talking about the speed at which news travels and its outreach, as well as the ability of content manipulation (Shearer, 2018). Lastly, independent of the information quality or the extent of its dispersion, conversational diffusion is a major driver of SM's business model. Settle (2019) argues that the impact of being exposed to and actively engaging in online discussions on the emergence of GP have not received enough attention, despite its pervasiveness.

The detailed exploration of GP across varying SM platforms, highlighted by the vast body of literature, underline the need to understand how such dynamics play out in more specialized and professional contexts, such as LinkedIn. The diverse range of mechanisms and effects revealed by prior literature, such as echo chambers on Facebook (Bessi et al., 2016b) or the political debates on Twitter (Balcells and Padró-Solanet, 2016), contribute to the understanding of social media's influence on public opinion and discourse. Above all, studies similarly to those by Barbera (2014) and Brady et al. (2017) indicate the dual role that SM plays in both mitigating and amplifying polarization, a difference that calls for further exploration of the phenomenon of GP in the realm of professional networking.

As a platform predominantly focused on professional development and networking, LinkedIn distinguishes itself from other SM platforms due to its target audience along with the nature of fostered interactions. Furthermore, LinkedIn's user base is primarily composed of professionals from different industries, making it an invaluable resource for job seekers, recruiters, and professionals looking to broaden their networks and seize new opportunities. As opposed to other platforms where personal life and political opinions are frequently discussed, LinkedIn centers around professional identities, career growth, and industry-specific discussions. These characteristics raise questions about the nature and extent of GP within such a network. Understanding if and how GP occurs on LinkedIn not only contributes to the broader discourse on SM and polarization but also provides insights into the dynamics of professional networking in an increasingly digitized world. Such understanding is essential, given the platform's significant role in supporting professional interactions, career development, and industry-specific trends. Therefore, examining GP on LinkedIn is a necessary analysis into the structure of professional identity and communication in the age of digitalization.

3. Methodology

The following chapter will first describe the developed research model. Then, it will proceed with presenting details on the implied research method, participants selection and adopted research method. Lastly, it will explain the used survey design in detail.

3.1. Research Model

Figure 1 below illustrates the proposed research model of this thesis. The figure shows the relationship between the key variables, namely Group Polarization as the dependent variable (DV) and Social Identity and Sharing Behavior as independent variables (IV).

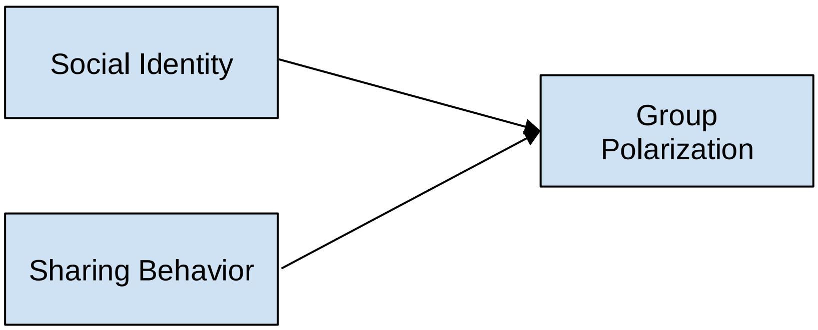

Figure 1 - Research Model

For the development of the proposed research model, both the DV and the IV's are operationalized through the combination of multiple survey questions. The used approach allows for a more nuanced measurement of the considered constructs, which improves the robustness and reliability of the proposed analysis. The IV's, which indicate the drivers of GP within professional groups on LinkedIn, are derived from respondents' answers to a series of questions designed to capture their multifaceted character. Similarly, the DV which represents the manifestation of GP within the said groups, is built using responses to questions that collectively assess the level and qualities of polarization experienced by respondents on LinkedIn.

In order to combine responses to various survey questions, the calculation of aggregate scores is used, which reflect the strength or existence of the variables of interest. For example, where relevant, responses are averaged to produce a single metric that represents a respondent's perspective or behavior in relation to the constructs that are being studied in this thesis. The choice of this methodological approach is explained by the complexities of group interactions on SM platforms, where a single question may not effectively capture the variety of experiences and perspectives among LinkedIn professional group members.

Section 3.4 Survey Design of this thesis offers a detailed view about the exact survey questions used, as well as the rationale for the specific selections. The exact methodology of response aggregation in variables will also be discussed in section 4.2 Variable Operationalization.

3.2. Research Method, Participants Selection and Data Collection Process

Following the in-depth review of the relevant literature and development of the research question and research model, a description of the chosen research method will be provided. In order to test the relationships between the IV's and the DV, the collected survey data will be interpreted within a statistical analysis. Several reasons support the choice of a quantitative research method. Quantitative approaches are well-suited for survey-based research as they allow a systematic measurement and analysis of variables. By converting subjective experiences and opinions in quantitative data, statistical techniques to test theories and hypotheses can be used, identify relationships between variables, and generalize findings to a larger population (Bryman, 2012). The use of quantitative methods in surveys is supported by their ability to provide objective data that can be subjected to rigorous statistical testing, resulting in clear, evidence-based insights into complex phenomena (Creswell & Creswell, 2017). Moreover, the structure and scalability of quantitative surveys allow for data collection from various respondents, strengthening the representativeness and external validity of results (Fowler Jr, 2013). In the context of SM platforms such as LinkedIn, this aspect is particularly important as the vast user base is amenable to such approaches (Smith, 2015). Given the increasing number of computer-aided statistical tools available today, the survey approach became more popular as the processing and analysis of collected data became less complicated. Lastly, the use of surveys allows for the collection of large amounts of data by allowing one to ask the same questions, making this method energy-efficient, providing more precise data, and increasing the external validity and sample representation (Gürbüz, 2017).

Thus, this thesis employed a survey-based research approach, using a structured survey consisting of 17 questions categorized into four blocks: demographics, social identity, social media use and information sharing behaviors, and GP measurement. Qualtrics Experience Management was used for the survey development, with a license provided by the Department of Marketing at the University of Vienna. Before publication, the survey was constructed and tested to prove compatible for both a desktop as well as a mobile version. In order to reach its final audience, the survey was distributed through multiple online channels, such as LinkedIn, WhatsApp, and Facebook groups. This was done by using an anonymous link. As the thesis aims to address the topic of GP within LinkedIn networks, the short description at the beginning of the survey stated that the survey is directed towards LinkedIn users. To ensure this, an additional question at the beginning of the survey asking participants whether or not they are LinkedIn users was used. This allowed LinkedIn users to continue the survey, while directing non-users towards the thank you message at the end of the survey. Thus, participant recruitment was conducted using convenience sampling, targeting active LinkedIn users. In order to achieve high response rates, no geographic restrictions were implied for respondents. The designed survey had a completion time of approximately five minutes, making it short and simple. Data collection spanned over two weeks, between December 20th, 2023, and January 4th 2024

3.3. Survey Design

In order to fulfill the aim of this thesis, more explicitly to determine the type of relationship between the presented variables, choosing an analytical survey that will be distributed via the Internet seemed to be the most fitting approach of data collection methods. Using an online survey proves to be a fast and low-cost method of collecting relevant research data. Additionally, this method proves to not be influenced by misleading public opinions as it is not administered by a person (Gübüz, 2017). The survey was split into four blocks of questions and also included an introductory description. These can be found in Appendix A of this thesis.

The first block focused on demographic information about the participant such as age, gender, country of residence, highest level of education, field of employment and level of professional experience in the aforementioned field. All questions of block one were formulated as a single possible answer multiple choice type question, except for the one regarding the current country of residence, which was designed with a drop-down menu where participants could choose the corresponding country from the given list. By collecting data on the aforementioned demographics, this survey aims to identify trends and correlations that might have an influence on individuals' propensity towards GP. Understanding individual demographic profiles could shed light on how various factors, such as educational background or professional experience influence the creation or reinforcement of polarized online groups. Hughes, Camden, and Yangchen's (2022) study emphasizes the need for precise demographic information to improve the quality and usefulness of research findings in social sciences, particularly in studies that examine complex social phenomena such as GP. These factors are significant in investigating the manners in which GP occurs across different segments of the population on SM. Age, for example, can influence an individual's presence on digital platforms as well as predisposition to echo chambers, with variable levels of participation and critical thinking skills. Gender influences the types of discussion and polarized content that users may encounter or engage with, reflecting broader societal norms and biases that affect SM platforms. Education level and field of employment add additional dimensions to the research, providing insights into how professional networks and educational backgrounds influence opinion development and the likelihood of engaging in contentious conversations. Finally, professional experience can reveal to what extent an individual's professional identity and networks impact their opinions and online behaviors. By taking advantage of these demographic factors, the survey intends to contribute to a better understanding of the mechanisms that drive group polarization in social media, providing useful insights for both academic research and practical actions to minimize the negative effects of polarization.

The second block of questions was precisely developed to delve into the nuances of social identity among respondents, using a thorough set of six questions to capture the varied characteristics of this concept. By using a seven-point Likert scale for nuanced measurement, these questions were designed to assess the depth of respondents' feelings and thoughts regarding their social identity within their LinkedIn network. The used scale provided a more granular analysis, with four of the six questions ranging from 1 = "not at all" to 7 = "very much", allowing respondents to describe the extent to which they identify with their LinkedIn network. The remaining two questions, ranging from 1 = "strongly disagree" to 7 = "strongly agree", were meant to assess the extent to which respondents agreed or disagreed with statements regarding their social identity. The structuring of the questions in block two were split into three categories of Social Identity, namely “cognitive”-, “affective”-, and “evaluative”- Social Identity, similarly to the ones developed by Dholaika et al. (2004). This classification is essential for understanding the many levels of social identity as experienced on LinkedIn. By adapting Dholaika et al. ‘s (2004) framework to the setting of LinkedIn networks, the study aimed to adjust the assessment to the specific digital environment of professional networking.

For the “cognitive” component of social identity, participants were asked to consider the degree of overlap between their self-image and the collective identity of their LinkedIn network. The second question of this block sought to determine the extent to which people regard their personal identities as connected with the professional personalities that build their LinkedIn network, particularly when they consider themselves to be members of the network.

The questions used for the “affective” dimension of social identity aimed to elicit responses that reveal respondents’ emotional relationship with their LinkedIn network. The two questions aimed to assess the respondents’ emotional attachment to their network on one side, and the sense of belonging within this digital community on the other.

Lastly, the “evaluative” component of social identity was looked into by using questions that prompted respondents to self-assess their perceived value and significance within their LinkedIn networks. This line of inquiry was designed to assess respondents’ self-perceptions of their contributions to and standing in their LinkedIn network. By assessing their own value and importance, respondents provide insights into how their LinkedIn network contributes to their overall social identity.

This detailed layering of questions, which progress from cognitive alignment to emotional connection and evaluative self-perception, provides a comprehensive perspective for understanding the processes of social identity construction on LinkedIn. It employs a nuanced approach to exploring how professional networks on social media platforms, such as LinkedIn, influence people’s perceptions of their own social identity, thereby contributing to the debate around digital identity and community belonging in the age of digitalization and social media.

The third block of the survey was designed to delve into the frequencies of social media usage and participants sharing behavior in online social networks and expands on the research of Lee et al. (2014), focusing on the frequency and characteristics of LinkedIn usage among respondents while also integrating insights from Nordbrandt (2021) to investigate the use of other social media platforms. Lee et al.'s (2014) study on social media behaviors provides an indispensable context for the first two questions in this block, which aim to assess the level of involvement respondents have within their LinkedIn network. The first question of block three aims to measure the temporal aspect of LinkedIn use by asking participants to estimate both their weekly hours spent on the platform as well as the frequency of access. This allows for a more detailed understanding of LinkedIn's role in respondents' professional lives, reflecting Lee et al.'s (2014) focus on the importance of assessing both the duration and frequency of social media interactions for an in-depth picture of digital engagement.

Expanding further on Lee et al. 's (2014) methodology, the second question explores the qualitative dimension of LinkedIn use across six different activities: getting news, posting news, talking about industry-specific topics, talking about politics, sharing industry-specific news and lastly sharing news about politics. This wide-ranging inquiry is designed as a multiple-choice question, as king participants to rate the frequency of each activity on a six-point Likert scale ranging from 1 = "Never" to 6 = "Daily", thus offering a nuanced perspective on LinkedIn's multifunctionality as highlighted in Lee et al.'s paper. The final question of block three is inspired by Nordbrandt (2021), and it focuses on the participants' engagement with social media networks other than LinkedIn. The inquired social media networks were Facebook, Instagram, Twitter, Snapchat, Reddit and YouTube. Nordbrandts (2021) paper on the different landscapes of social media usage emphasizes the need of understanding how professional networking sites such as LinkedIn fit into the broader spectrum of digital platforms used by individuals. This broader viewpoint is critical for understanding LinkedIn's unique position within the professional networking sector compared to other social media, which might rather be used for personal interactions. These three questions combine the insights from Lee et al. (2014) and Nordbrandt (2021) to give an in-depth look into social media use trends among professionals.

This survey block attempts to provide a comprehensive understanding of the evolving importance of professional networking sites in a digitized world by quantifying time spent on LinkedIn, assessing the platform's various uses, and positioning LinkedIn within the larger social media ecosystem. This approach not only enriches the survey by delving deeper into LinkedIn's utility and integration into daily routines of professionals, but it also frames LinkedIn's usage within the larger field of social media platforms, emphasizing the unique ways in which professionals navigate the digital networking landscape. By investigating how professionals use LinkedIn for a variety of interactions and comparing these patterns to their involvement on other social media platforms, key drivers of group polarization might be identified. These drivers could include the selective dissemination of industry specific news, which could lead to echo chamber effects, as well as participation in polarized political discussions, which can reinforce group identities and divisions. The broad scope of these questions, grounded in the frameworks of Lee el al. (2014) and Nordbrandt (2021), offers a robust dataset from which insights regarding LinkedIn's role in supporting or mitigating group polarization within professional networks can be extracted. This in-depth exploration has significance for developing strategies that promote healthy, inclusive, and diverse professional exchanges on LinkedIn, directly addressing the thesis's focus on the dynamics of group polarization.

The fourth and final block of questions dives into the dynamics of GP within professional networks on LinkedIn, building on the work of Druckman and Levendusky (2019). The researchers' findings provide an important framework for developing questions that explore the complexities of political alignment and information diversity within social networks. The scope of Druckman and Levendusky's original survey questions was broadened and adapted to account for LinkedIn's global nature and diversity of users. For the first question, instead of categorizing respondents by party, a more universally applicable Likert scale was used. The seven-point scale ranged from 1= "very progressive/liberal" to 7= "very conservative", with a midpoint labeled as 4= "neutral". This adjustment provides relevancy and inclusivity to the question, ensuring that respondents across various nations could respond to it, and thus not limiting the respondents to a single region.

For respondents who chose “neutral”, a follow-up question was asked. By doing so, a more nuanced self-assessment of political beliefs was implied. The answer possibilities for the follow-up question were “closer to liberalism”, “closer to conservatism” and “neither”. This methodological selection increases the granularity of the collected data, allowing for a more in-depth investigation of political identities within professional networks on LinkedIn. The following question in the final block seeks to assess the diversity of information within respondents’ networks, which is crucial for understanding the mechanics of GP and echo chamber effects in digital professional environments.

The final question of the survey was self-developed and marks a significant expansion of the survey’s scope, attempting to reveal respondents' behavioral reactions to content that challenges and contradicts their beliefs. The developed question is essential for understanding how different engagement styles affect GP on LinkedIn, whether they mitigate or intensify it. Academic literature supports the use of self-developed questions in quantitative research, particularly in master’s theses, as a means of addressing specific research gaps and adapting the inquiry to specific study objectives (King, Keohane, & Verba, 1994). Designing original questions allows researchers to explore previously untapped areas within their field of study, generating new insights and expanding academic discourse (Bryman, 2012).

The survey’s final question, underpinned by the variety of possible reactions to opposing viewpoints, from engaging in constructive dialogue to reporting content, presents a complex lens through which to evaluate user behavior in the face of disagreement. Thus, the question asked respondents to rate five individual actions they can undertake when facing disagreeable content on a five-point Likert scale. The provided response scale, ranging from 1= “never” to 5 = “always”, allows for a more in-depth assessment of these activities, shedding light on the social dynamics that impact GP on LinkedIn.

The study of user behavior in response to opposing opinions on LinkedIn, as detailed in the survey’s final question, is based on a strong theoretical framework that examines the relationship between digital communication patterns and GP. The approach draws upon seminal work such as Suler’s (2004) exploration of the Online Disinhibition Effect, which elucidates the impact of online anonymity on polarized interactions. Furthermore, Sunstein’s (2001) insights into the formation of echo chambers due to personalized information filters provided an important perspective on the mechanisms of polarization. The empirical evidence provided by Bail et al. 's (2018) work on the role of SM in increasing political polarization provides additional evidence towards the importance of looking into LinkedIn user reactions. Lastly, Garrett's (2009) study on politically motivated selective exposure among internet news users underlines individual's tendency towards engaging with information that supports their existing beliefs, a behavior that is pivotal to understanding the dynamics of GP within professional networks on LinkedIn. The mentioned studies all support the inclusion of a self-developed research question targeted towards determining how professionals navigate content that challenges their viewpoints on LinkedIn. This question not only adds to the broader discourse on digital communication and polarization, but it also aligns with the objectives of this thesis by providing nuanced insights into the specific behaviors that may mitigate or intensify GP on SM.

The mixture of literature-backed and self-developed questions in this survey helps to address the research question about the role and drivers of GP within professional groups on LinkedIn. By combining already established frameworks with tailored questions, this survey block has the potential of significantly contributing to the understanding of online professional interactions, as well as the broader implications for social cohesion and discourse within online professional networks.

4. Results

This chapter of the presented thesis will delve into a detailed overview of descriptive statistics, based on the survey's outline. Then it will proceed with an overview on the operationalization of the variables that will be used in the statistical analysis. Finally, the pursued statistical analysis will be described in detail.

4.1. Descriptive Statistics

4.1.1. Demographics

4.1.1.1. What is your age?

In the total sample of 177 observations, more than 80 respondents (47%) were in the 25-35 years old category. The second largest category were 18-25 year old's, with 33 respondents (19%). The third largest category was the one of 36 to 45 year old's which contained 29 responses. Lastly, 23 respondents found themselves in the category of 46 to 55 year old's (13%) and the age category of 55 and older had only 9 responses in our sample (5%).

4.1.1.2. Which of the following best describes your gender identity?

In our final sample, out of 177 registered responses, 105 were female which account for 59% of the data. 72 respondents were male (41%). None of the respondents in the final sample were in the category *Other* or *Prefer not to say*.

4.1.1.3. In which country do you currently live in?

When asked about the country they currently live in, three countries defined the majority of our sample. 67 respondents (37,9%) lived in Austria at the time when the survey was completed. The second country represented in the sample was Romania with 64 respondents, accounting for 36,2% of the sample distribution. The third noticeable country in the sample was Germany, with 19 respondents (10,7%). The remaining 27 respondents were distributed across the globe, as depicted in Table 3 of Appendix B.

4.1.1.4. What is the highest degree or level of education that you have completed?

Out of the 177 responses selected for the final sample, 83 respondents (46,9%) completed a Master's degree or an equivalent, 65 (36,7%) completed a Bachelor's degree or an equivalent, 15 (8,5%) respondents indicated they have completed High school or an equivalent. From all the respondents, only 14 (7,9%) have indicated the completion of a PhD or equivalent diploma.

4.1.1.5. In which field/industry are you currently employed?

As depicted in Table 5, the respondents' frequencies were distributed across industries as follows. Information Technology & Communication was the leading industry of our sample, with 48 (27,1%)

individuals stating they are currently employed in this field. 41 (23,2%) respondents stated they are currently employed within another industry as the ones listed above. 27 (15,3%) individuals stated they currently work in Public Administration, Defence, Education, Human Health, and Social Work, closely followed by the 26 (14,7%) respondents currently employed in Financial & Insurance activities. Both the Industry as well as the Construction & Real Estate sectors consisted of 14 (7,9%) responses each. The remaining 7 (4%) respondents work in the Wholesale & Retail Trade, Transportation, Accommodation & Food sector.

4.1.1.6. What is your level of professional experience in the field?

A total of 84 (47,5%) respondents indicated they have an experience level of over 5 years in their current field. 69 (39%) of respondents stated having an intermediate level, between 1 and 5 years of experience and the last 24 (13,6%) of the respondents indicated that they are a beginner in their corresponding field.

4.1.2. Social Identity Dimensions

4.1.2.1. Connection to LinkedIn

When asked about the degree of overlap between their self-image and the identity of their LinkedIn network as perceived, 48 (27,12%) of the survey participants stated that the degree of overlap is considerable. 39 (22,03%) stated that they perceive the mentioned overlap to be moderate, while 32 (18,08%) perceive a somewhat overlap with their LinkedIn network. When looking at the neutral statement, 22 (12,43%) of the respondents perceived their overlap as such, and 20 (11,3%) stated a slight overlap between their self-image and the identity of their LinkedIn network. Lastly, looking at the two extremes of our range, only 9 (5,08%) participants perceive a strong overlap of their self-identity with their LinkedIn network, while 7 (3,96%) participants perceive no overlap at all.

	Please indicate to what degree your self-image overlaps with the identity of your LinkedIn network as you perceive it	How would you express the degree of overlap between your personal identity and the identity of the group mentioned above when you are actually part of the group and engaging in group activities
Not at all (1)	7	7
Slightly (2)	20	24
Somewhat (3)	32	22
Moderately (4)	39	51
Neutral (5)	22	36
Considerably (6)	48	34
Very much (7)	9	3
Total	177	177
Mean	4,29	4,12
Std. Deviation	1,61	1,46

Table 1 - Frequency distribution of Connection to LinkedIn

As for the degree of overlap between the participants personal identity and the identity of their LinkedIn network when they themselves are to be part of the group and engage in group activities, 51 (28,81%) of the respondents stated they perceive a moderate overlap, 36 (20,34%) participants view it as neutral, 34 (19,21%) see a considerable overlap between the two items, 24 (13,56%) see a slight overlap and 22 (12,43%) think the two items somewhat overlap. In this case, the two extremes also show the least participants, with 7 (3,95%) perceiving no overlap at all and 3 (1,7%) stating that the overlap is very much existent.

4.1.2.2. Relationship to LinkedIn Network

The response distribution of the relationship to their LinkedIn network in the presented sample was as follows: 48 (27,1%) said they are not at all attached to their network, 42 (23,7%) stated being slightly attached and 27 (15,3%) somewhat attached to their corresponding LinkedIn network. 25 (14,1%) participants stated they have a moderate attachment to their LinkedIn network, while 21 (11,9%) stated they have a neutral position towards their attachment. Lastly, only 12 (6,8%) stated being considerably attached to their network and only 2 (1,1%) of the participants find themselves being very attached to their LinkedIn network.

	How attached are you to your LinkedIn Network?	How strong would you say your feelings of belongingness are towards your LinkedIn Network?
Not at all (1)	48	41
Slightly (2)	42	31
Somewhat (3)	27	28
Moderately (4)	25	42
Neutral(5)	21	18
Considerably (6)	12	17
Very much (7)	2	0
Total	177	177
Mean	3,09	2,85
Std. Deviation	1,62	1,65

Table 2 - Frequency distribution of Relationship to LinkedIn network

The second part of this question asked participants to rate the strength of the feeling of belongingness towards their LinkedIn network, and participants responded as follows: 42 (23,7%) declared it as being moderate, while 41 (23,2%) declared no attachment at all. 31 (17,5%) stated a slight attachment towards their LinkedIn network, 28 (15,8%) respondents said they were somewhat attached and 18 (10,2%) had a neutral position towards their attachment to their LinkedIn network. Lastly, only 17 (9,6%) survey participants out of 177 said they are considerably attached to their LinkedIn network, while none of them chose the very much category.

4.1.2.3. Position within LinkedIn Network

Respondents had to state whether or not they consider themselves a valued member of their LinkedIn network. The sample distribution was presented as follows: 50 (28,2%) of the respondents had a neutral view and chose neither agree nor disagree, 37 (20,9%) disagreed and did not see themselves as a valuable member within their network, 29 (16,4%) individuals somewhat agreed with the statement while 25 (14,1%) of the participants strongly disagreed. 23 (13%) participants somewhat disagreed with being a valuable member of their LinkedIn network. Lastly, only 12 (6,8%) considered themselves as valuable members of their network and agreed with the given statement, while only 1 (0,6%) participant strongly agreed.

	I am a valuable member of my LinkedIn Network	I am an important member of my LinkedIn Network
Strongly disagree (1)	25	21
Disagree (2)	37	34
Somewhat disagree (3)	23	19
Neither agree nor disagree (4)	50	53
Somewhat agree (5)	29	25
Agree (6)	12	24
Strongly agree (7)	1	1
Total	177	177
Mean	3,58	3,34
Std. Deviation	1,59	1,52

Table 3 - Frequency distribution of Position within LinkedIn network

Additionally, they were also asked about how much of an important member they believe they are within their LinkedIn network. 53 (29,9%) participants neither agree nor disagree with the statement, 34 (19,2%) disagreed and considered not being an important member of their LinkedIn network, 25 (14,1%) somewhat agreed with the statement and 24 (13,6%) agreed. Additionally, 21 (11,9%) of the participants strongly disagreed with the presented statement. Lastly, 19 (10,7%) respondents somewhat disagreed with being an important member within their LinkedIn network while only 1 (0,6%) of the participants strongly agreed with the given statement.

4.1.3. Usage Behavior

4.1.3.1. Average use of LinkedIn

Figure 2 displays a side-by-side depiction of a boxplot and a histogram, representing the distribution of the variable *hweek*, which measures the respondents LinkedIn usage in hours per week. The boxplot reveals that the median usage time is within the lower quartile of the boxplot, which, along with the interquartile range, is positioned between 0 and 5 hours of LinkedIn use per week. This further suggests that most respondents reported a moderate use of LinkedIn. Noticeably, there are also several outliers scattered above the upper whisker of the boxplot. Some respondents reported to be using LinkedIn for up to almost 40 hours a week.

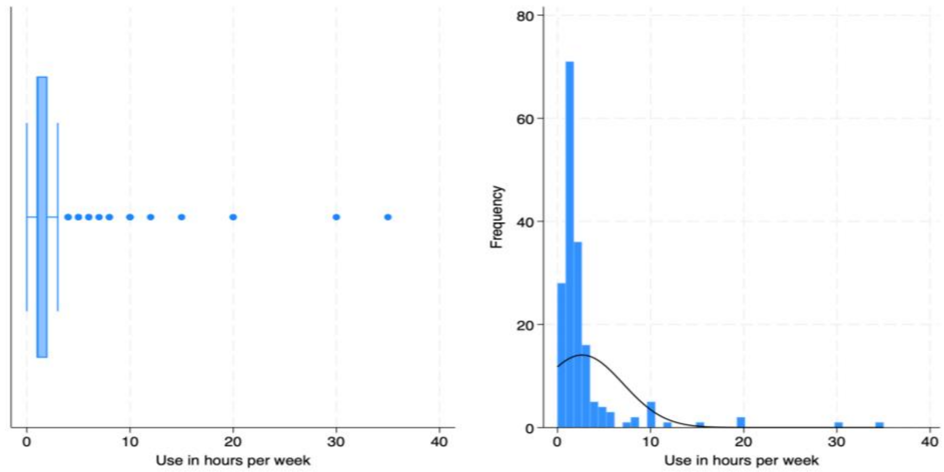

Figure 2 - Comparison of histogram and boxplot for the usage of LinkedIn in hours per week

The histogram on the right side of Figure 2 supports the findings of the boxplot with its highest frequency around the 0 hours mark, indicating that a large number of respondents reported low use of LinkedIn. The frequency decreases sharply for the higher number of hours, with very few respondents indicating a use of more than 10 hours per week. The right-skewed distribution suggests that while the majority of the sample are light users of LinkedIn, there is a minority of heavy users. The given pattern implies that while the majority of the surveyed user base belongs rather to casual browsers, there are also potentially professional users who utilize LinkedIn extensively for networking and business purposes.

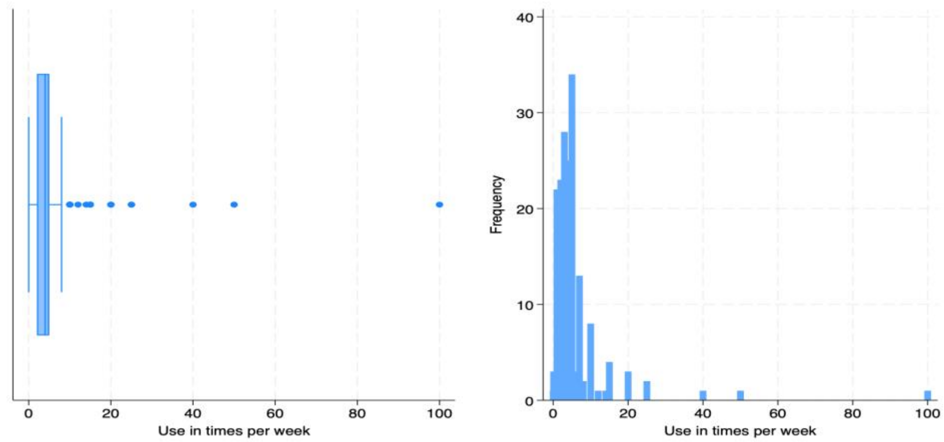

Figure 3 - Comparison of histogram and boxplot for the usage of LinkedIn in times per week

Figure 3 displays the side-by-side depiction of the variable *timesweek* in the form of a boxplot and a histogram, similarly to *hweek* above. However, this variable measures the respondents' usage of LinkedIn in times per week, i.e the amount of times they open and actively use the SM network in a week and is discrete. The boxplot on the left side reveals that the interquartile range spans between 0 and 10, indicating that about 50% of respondents use LinkedIn up to 10 times per week. The median of the distribution is closer to the upper end of the boxplot, suggesting that the majority of respondents are moderate LinkedIn users, similarly to the interpretation of Figure 1. The variable timesweek also shows several outliers scattered above the upper whiskers of the boxplot, with the most extreme one indicating a use of 100 times per week. The frequency decreases for the higher amount of times per week, with few respondents indicating a use of more than 10 times per week.

Also in the case of *timesweek*, the histogram reinforces the interpretation of the boxplot with its highest concentration between the 0 to 10 times per week range. Similarly to the findings in Figure 2, the histogram is right skewed, suggesting a minority of heavy users.

4.1.3.2. Activities pursued on Linkedin

Participants were asked to rate the frequency with which they use LinkedIn for six activities. The distribution of our sample for each of the six activities resulted as follows:

I use LinkedIn…						
	… to get news	… to post news	… to talk about industry specific topics	…to talk about politics	… to share news about industry specific topics	…to share news about politics
Never (1)	18	75	63	147	65	154
Rarely (2)	58	77	73	22	73	15
Once per month (3)	11	15	21	3	23	3
Once per week (4)	43	5	14	4	15	3
Multiple times a week (5)	38	5	5	1	1	2
Daily (6)	9	0	1	0	0	0
Total	177	177	177	177	177	177
Mean	3,29	1,80	2,03	1,25	1,95	1,21
Std. Deviation	1,49	,92	1,07	,65	,94	,67

Table 4 - Frequency distribution of Activities pursued on LinkedIn

When stating the frequency of getting news over LinkedIn, 58 (32,8%) stated they rarely use the platform for such an activity, 43 (24,3%) said they use it once per week for getting news, 38 (21,5%) stated using it multiple times per week while 18 (10,2%) respondents stated they never use LinkedIn for such purposes. Lastly, 11 (6,2%) participants use LinkedIn about once per month to get news and only 9 (5,1%) participants use their LinkedIn feed as a daily news source.

Looking at the habits of posting themselves news on LinkedIn, 77 (43,5%) participants stated they rarely do so, followed closely by 75 (42,4%) individuals who never use their LinkedIn platform to post news. 15 (8,5%) individuals use LinkedIn for posting news about once per month, while the categories multiple times per week and once per week each contained 5 (2,8%) responses. None of the 177 respondents use LinkedIn to post news on a daily basis.

The distribution of the third category in Table 10, talk about industry specific topics, looked as follows: 73 (41,2%) individuals stated they rarely use LinkedIn for such activities, while 63 (35,6%) stated they never use the platform for talking about their industry specific topics. 21 (11,9%) participants use it about once per month, 14 (7,9%) stated using it once per week and 5 (2,8%) participants use Linkedin multiple times per week to talk about industry specific topics with their peers. Lastly, only one (0,6%) individual stated they use LinkedIn daily to pursue such activities.

In the fourth category, talk about politics, 147 (83,1%) out of 177 participants stated they never use LinkedIn for such activities, clearly building the majority. Only 22 (11,9%) individuals rarely use the platform to talk about politics, while the remaining 8 participants were dispersed over using it once per week, once per month or multiple times per week. No participant uses LinkedIn on a daily basis to talk about politics.

When asked about how often they use LinkedIn to share news about industry specific topics, 73 (41,2%) participants stated they rarely do so, while 65 (36,7%) stated they never use LinkedIn for such activities. On the other spectrum, 23 (13%) individuals use LinkedIn about once per month to post such news, 15 (8,5%) post about once per week while only one (0,6%) individual uses LinkedIn multiple times per week to share industry specific news with his network. Similarly to the previous category, none of the respondents uses LinkedIn on a daily basis for such activities.

The last activity of this question, sharing news about politics, clearly showed that LinkedIn is not the platform for such activities, as 154 (87%) out of 177 participants chose never. Only 15 (8,5%) participants stated to rarely do so, while the last 8 participants were distributed across once per month, once per week and multiple times per week. Also in this case, the daily option showed no registered responses in this category.

4.1.3.3. Use of other Social Media

In the last part of the Usage Behavior questions, participants were asked to state the frequency with which they use other popular SM platforms. The frequencies of use for each platform were dispersed as follows.

When asked about the usage of Facebook, 66 (37,3%) participants stated a daily use, 31 (17,5%) multiple times per week, 29 (16,4%) chose rarely, 28 (15,8%) stated they never use Facebook, 21 (11,9%) use it about once per week and lastly only 2 (1,1%) use it about once per month.

	Facebook	Instagram	Twitter	Snapchat	Reddit	YouTube
Never (1)	28	24	115	130	115	4
Rarely (2)	29	7	25	15	33	17
Once per month (3)	2	3	5	1	8	8
Once per week (4)	21	4	12	6	7	21
Multiple times a week (5)	31	17	10	11	7	56
Daily (6)	66	122	10	14	7	71
Total	177	177	177	177	177	177
Mean	4,11	4,97	1,91	1,84	1,75	4,81
Std. Deviation	1,94	1,82	1,54	1,64	1,34	1,38

Table 5 - Frequency distribution of Use of other Social Media

Looking at the use of Instagram, it is definitely a more popular SM platform as compared to Facebook. 122 (68,9%) use Instagram on a daily basis while only 24 (13,6%) of participants stated they never use this platform. Lastly, 17 (9,6%) use it multiple times per week, 7 (4%) rarely open Instagram, 4 (2,3%) use it about once per week and the least individuals, 3 (1,7%), use Instagram about once per month. The third SM platform inquired in the survey was Twitter, where the majority of our sample, 155 (65%) respondents, stated they never use it. 25 (14,1%) of respondents stated they rarely use Twitter, only 12 (6,8%) use it about once per week, while there were 10 (5,6%) participants in each of the categories multiple times a week as well as daily. Lastly, the category once per month received 5 (2,8%) responses from our total sample.

The fourth SM platform, Snapchat, also shows a rather low popularity among our sample with 130 (73,4%) responses situated in the never category. 15 (8,5%) individuals stated they rarely use this SM, while on the other end of the spectrum 14 (7,9%) stated to use it on a daily basis. 11 (6,2%) individuals within our sample stated to use Snapchat multiple times per week, 6 (3,4%) use it about once per week and lastly only one (0,6%) stated to use it about once per month.

When having to state the usage of the Reddit platform, similarly to Snapchat or Twitter, the majority of participants, 115 (65%), implied they never use this SM platform. 33 (18,6%) stated to rarely use Reddit and 8 (4,5%) use it about once per month. The remaining 21 respondents were equally distributed among the last three categories: once per week, multiple times per week and daily. Each of the three categories contained 7 (4%) responses.

Lastly, the sixth SM platform that participants were asked to rate was YouTube. The majority of respondents, 71 (40,1%), declared to use the platform on a daily basis, followed by 56 (31,6%) using it multiple times a week, 21 (11,9%) with once per week, and 17 (9,6%) who stated to use it rarely. 8 (4,5%) use YouTube about once per month and only 4 (2,3%) respondents stated that they never use YouTube.

4.1.4. Group Polarization

4.1.4.1. Political Views

When analyzing the political views of respondents, they were initially asked to position themselves on a spectrum ranging from very progressive/liberal to very conservative, with seven total categories available for selection, as depicted in Table 6. The respondent's frequency distribution of this variable is summarized in the same table.

The frequency distribution and corresponding percentages indicate a tendency towards more progressive/liberal views among our sample, with moderately progressive/liberal viewpoints being the most frequent, with 66 (37,29%) responses. The mean of 3,05 suggests a slight overall tendency towards progressive/liberal views among survey respondents. The standard deviation of 1,37 indicates variability in political views across our sample.

When respondents selected neutral in the initial question about political views, a follow-up question asked them to specify if their inclinations are rather towards liberalism, conservatism, or neither. To capture a better understanding of the respondents' political views, the responses to both questions were combined to create the variable *pol_view* displayed in Table 6.

Political Views	Frequency	Percent	Cumulative Percent
Very progressive/ liberal (1)	12	6,78	6,78
Moderately progressive/ liberal (2)	66	37,29	44,07
Slightly progressive/ liberal (3)	48	27,12	71,19
Neutral (4)	15	8,47	79,66
Slightly conservative (5)	26	14,69	94,35
Moderately conservative (6)	9	5,08	99,44
Very conservative (7)	1	0,56	100
Total	177	100	
Mean	3,05		
Std. Deviation	1,37		

Table 6 - Frequency distribution of Political Views

This variable adjusts the *Neutral* category based on the responses given in the follow-up question, and thus refines the classification of political views as follows. The respondents who initially chose *Neutral* and *closer to liberalism* in the follow-up question were recoded to *Slightly progressive/liberal*. Similarly, the combination of *Neutral* and *closer to conservatism* was recoded to *Slightly conservative*. Lastly, participants who answered *Neutral* and *neither* were kept as *Neutral* in the new variable. The recording process ensured that the political views are captured accurately, reflecting each respondent's self-identified political orientation, enhancing the precision of the political spectrum analysis.

4.1.4.2. LinkedIn feed content diversity

To explore the diversity of individual LinkedIn feeds and the potential for group polarization, participants were asked whether their feed primarily consists of content that aligns with their own viewpoints or includes a diversity of perspectives and opinions. The aim of this question was to assess the exposure to diverse content, which could indicate a lower likelihood of polarization, as opposed to a feed that mostly aligns and reinforces existing beliefs and opinions, which could indicate a higher propensity for polarization.

Type of content	Frequency	Percent	Cumulative percent
Mostly diverse (1)	28	15,82	15,82
Unsure (2)	29	16,38	32,20
Balanced mix (3)	80	45,20	77,40
Mostly aligns (4)	40	22,60	100
Total	177	100	
Mean	2,74		
Std. Deviation	,98		

Table 7 - Frequency distribution of Type of content

The results, summarized in Table 7, show that a *Balanced mix* of content is the dominant answer within our sample, with 45,2% of respondents indicating that their feed consists of a relatively equal mix of both aligning and diverse content. Respondents indicating *Unsure* or *Mostly diverse* content taken together account for 32,2% of the sample, indicating that a significant amount of users encounter a variety of viewpoints within their LinkedIn feed. In contrast, *Mostly aligns*, which indicates a more homogenous LinkedIn feed, accounts for 22,6% of responses.

On the employed scale, where *Mostly diverse* is equal to one and *Mostly aligns* is equal to four, the mean value equals 2,74, suggesting that on average, LinkedIn feeds are perceived to lean slightly towards a mixed content. The standard deviation of 0,98 implies a noticeable variation among respondents. Overall, the captured data from our sample illustrates a moderate level of diversity within respondents' LinkedIn feeds, which could imply a decreased likelihood of perceiving group polarization on the platform.

Encounter of challenging content on LinkedIn

The aim of this section is to evaluate the frequency with which respondents encounter content that challenges their viewpoints in their LinkedIn feed, a factor that can influence the degree of group polarization they might experience. The survey question asked participants how frequently they encounter content on LinkedIn that triggers them to reconsider or rethink their opinions, with response options ranging from *Very often* to *Never*.

Table 8 illustrates these responses, showing that a majority of respondents, accounting for 40,11%, indicated to *Occasionally* encounter and notice challenging contents. The second largest group, accounting for 36,16%, stated to rarely encounter such contents in their LinkedIn feed. Only a small proportion of 1,69% of respondents indicated to come across challenging content *Very often*. On the other hand, 12,43% of survey respondents *Never* encounter content that prompts them to reconsider or rethink their existing opinions, which could indicate a higher probability for GP, due to a homogenous feed. The mean of 3,48 which is closer to *Rarely* and a standard deviation of 0,89 support the conclusion that respondents infrequently encounter challenging content on LinkedIn. The tendency towards less frequent exposure to diverse perspectives could contribute to a higher risk of GP within their LinkedIn network.

Encounter of challenging content	Frequency	Percent	Cumulative Percent
Very often (1)	3	1,69	1,69
Often (2)	17	9,60	11,30
Occasionally (3)	71	40,11	51,41
Rarely (4)	64	36,16	87,57
Never (5)	22	12,43	100
Total	177	100	
Mean	3,48		
Std. Deviation	,89		

Table 8 - Frequency distribution of encounter of challenging content on LinkedIn

4.1.4.3. Reaction to challenging content on LinkedIn

Table 9 displays survey responses on how participants react when facing topics or opinions on LinkedIn that they strongly disagree with. The responses are categorized into five actions: *Engage in Constructive Dialogue, Scroll Past or Ignore, Express Dissent or Disagreement, Unfollow or Hide Content,* and *Report or Flag Content.* Each action could be rated separately, on a five-point scale which ranges from *Never (1)* to *Always (5)*. The numbers displayed in Table 15 are the frequencies with which respondents engage in each of the five actions, as well as the corresponding mean and standard deviation.

	Engage in Constructive Dialogue: Attempt to engage in a respectful conversation to understand differing viewpoints	Scroll Past or Ignore: Choose not to interact or engage with the content and continue browsing	Express Dissent or Disagreement: Share your viewpoint or disagreement in a polite manner	Unfollow or Hide Content: Take actions to hide or unfollow sources of content that consistently share opposing views	Report or Flag Content: Report or flag content that appears offensive, inappropriate, or violates community guidelines
Never (1)	109	17	108	59	80
Sometimes (2)	51	30	51	75	58
About half the time (3)	10	13	3	17	13
Most of the time (4)	6	61	10	21	15
Always (5)	1	56	5	5	11
Total	177	177	177	177	177
Mean	1.53	3.62	1.60	2.08	1.97
Std. Deviation	.80	1.34	.98	1.07	1.19

Table 9 - Frequency distribution of reaction to challenging content on LinkedIn

For *Engage in Constructive Dialogue*, the majority of respondents (109) indicated to never engage in such actions when facing disagreeable content. The mean response of 1.53 suggests that engaging in constructive dialogue is the least frequent action taken.

Scroll Past or Ignore had a more varied response, with 61 respondents stating they take this action *Most of the time*, followed by 56 respondents who *Always* scroll past or ignore disagreeable content. This action also holds the highest mean score, 3.62, which suggests that ignoring disagreeable content is a common behavior among our sample. Similarly to the previous action, *Express Dissent or Disagreement* shows a low mean score of 1.60, with 108 respondents choosing *Never*. This suggests that openly disagreeing with content is not a commonly taken action among LinkedIn users.

The responses for *Unfollow or Hide Content* are more dispersed across the frequency scale, with a mean of 2.08. The majority of respondents, 75, stated they *Sometimes* undertake this action within their LinkedIn feed, indicating a moderate tendency for unfollowing or hiding disagreeable content. The mean score of 1.97 for *Report or Flag Content* suggests this being a slightly less frequent action among respondents, with 80 of them choosing *Never*. This also indicates a general indifference towards reporting or flagging content unless the topic is clearly challenging or inappropriate.

Overall, survey findings indicate there is a preference towards passive actions, such as scrolling past or ignoring, over active participation, such as conversation or disagreement, when respondents encounter disagreeable content in their LinkedIn feed. This tendency may contribute to a more homogenous feed, limiting exposure to varied topics or opinions and potentially increasing polarization. The standard deviations reveal heterogeneity in responses, with *Scroll Past or Ignore* having the highest variance, suggesting different levels of tolerance for addressing disagreeable content.

4.2. Operationalization of Key Variables

4.2.1. Social Identity

During the investigation into the phenomenon of GP within professional groups on LinkedIn, Social Identity was operationalized as a key IV, reflecting an individual's degree of identification with a specific social group. To construct the *social_identity* variable, the values of the survey questions in block two, that delved into the three dimensions of Social Identity, were aggregated. This composite variable encapsulates six fundamental aspects, as captured by questions eight, nine and ten of the survey, self-image overlap with the LinkedIn network, LinkedIn network image overlap with the self, emotional attachment to the network, feeling of belongingness, feeling of being a valued member of one's own network and the importance of group membership to one's self-concept.

The six factors were chosen based on their theoretical significance to the SIT, as defined by Tajfel and Turner (1979), which posits that individuals derive a sense of self from their group memberships. Given the Cronbach's alpha (α) value of 0.87 for the aggregation of responses into a single variable called *social_identity*, it was confidently assumed that such a composite variable is fitting and demonstrates a high level of internal consistency between the six questions it captures. Cronbach's alpha is a measure of reliability and internal consistency of a group of scale or test items; a value greater than 0.7 is generally deemed as acceptable in social science research, indicating that the items assess the same construct (Cronbach, 1951). Given the resulting alpha value of 0.87 that exceeds the mentioned threshold, we can assume that the six factors successfully capture various facets of Social Identity. The strong reliability supports the aggregation of these six factors into a single variable, allowing for a more cohesive investigation of how Social Identity influences behaviors and perceptions among LinkedIn users. This methodological choice strengthens the robustness of findings by ensuring that a construct that is both reliable and valid for measuring the intended construct is being analyzed.

Thus, the factors were aggregated into a single variable, *social_identity*, by summing the numerical values of the responses to the six corresponding questions (α = .87) in the survey. As each item was measured on a Likert scale ranging from "not at all"/"strongly disagree", which was coded as 1, to "very much"/"strongly agree", coded as 7, the minimum aggregated score was equal to six if a respondent chose the lowest intensity of all items, and a maximum of 42 for a respondent who chose the highest intensity for all items. The employed scoring system quantifies the strength of respondents' Social Identity within their LinkedIn network, providing the basis for the statistical analysis of its role in GP.

Given the Likert scale measurements of *social_identity* and its yielded scores which represent aggregated responses that varied in intensity of agreement or disagreement, standardization of this continuous variable was an important step that has been taken before proceeding with the statistical analysis. The wide range of scores needed a method to enable a more meaningful comparison across respondents. By standardizing *social_identity*, the scores were transformed into a uniform scale with a mean of zero and standard deviation of one. The standardization process allows for a neutralization of scale difference effects, enabling a more accurate comparison of Social Identity's strengths on individuals. By standardizing the variable, the interpretability of the statistical analysis is enhanced making it possible to determine the relative level of each respondent's Social Identity strength within their LinkedIn interactions and its impact on GP perceptions more precisely.

4.2.2. Sharing Behavior

Similarly to Social Identity, Sharing Behavior has been identified as a critical variable for understanding the dynamics of information dissemination within professional groups on LinkedIn. The *sharing_behavior* variable is a summative index calculated from the numerical values of all the subpoints in question 11 of the survey, which delves into the frequency of six actions performed on LinkedIn, as described in chapters 3.3 and 4.1 of this thesis.

The motivation for combining these actions into a single variable comes from the literature of online social behavior, which argues the frequency of content sharing is indicative of user engagement and active participation in digital communities (Lee, 2016). Similarly to the case of Social Identity, Cronbach's alpha was calculated for Sharing Behavior, yielding a value of 0.76, demonstrating a commendable level of internal consistency among the survey items that comprise this composite variable. The alpha value confirms the reliability of the Sharing Behavior measure in capturing the nuanced facets of respondents' engagement and participation on LinkedIn. The internal consistency plays an important role for ensuring that the variable appropriately reflects the frequency and extent of sharing behaviors on LinkedIn, and thereby providing a solid foundation for examining its impact on GP and the dynamics of information flow within the network. Accordingly, the composite variable *sharing_behavior was* calculated similarly to *social_identity*, by summing the numerical values of corresponding responses.

Each item in this question was assessed on a scale ranging from "Never" (equal to 1) to "Daily" (equal to 6). This scaling allowed us to quantify sharing behavior with a minimum possible score of six, representing a complete absence of sharing activities, and a maximum of 36, denoting daily engagement in all six types of sharing behaviors identified. The creation of this variable allows for quantitative analysis of the degree and frequency of information sharing activities among professionals on LinkedIn, which is expected to provide valuable insights into the drivers of GP on LinkedIn.

Similarly to the approach used for Social Identity, the variable *sharing_behavior* has also been standardized for the purpose of regression analysis, strengthening its significance in decoding the complexities of information sharing within professional groups on LinkedIn. The decision to standardize *sharing_behavior* originates from the same methodological necessity to position diverse respondent activities on a comparable scale, allowing for a nuanced assessment of how sharing behavior might influence perceptions of GP on LinkedIn. Standardization, which adjusts the mean of *sharing_behavior* variable to zero and its standard deviation to one, improves the statistical analysis's ability to examine the relative influence of sharing behaviors on GP. This transformation ensures that the variable's values reflect deviations from the mean sharing behavior, allowing for a more detailed and comparative view of individual engagement levels within professional groups on LinkedIn.

4.2.3. Group Polarization

The assessment of GP within professional groups on LinkedIn was carefully considered when developing the research model. While it was initially planned to integrate the responses of the three questions related to GP in the fourth survey block into a single composite variable, the approach was ultimately reconsidered. The decision to treat the responses to the three questions as separate dependent variables was motivated by the resulting values of Cronbach's alpha, which indicated low internal consistency when aggregating these items. Cronbach's alpha values are displayed in Table 10.

Aggregated Variable Names	Cronbach's alpha
type_of_content & challenging_content	0.21
Constructive_Dialogue, Scroll_Past, Disagreement, Unfollow & Report	0.47
type_of_content, challenging_content, Constructive_Dialogue, Scroll_Past, Disagreement, Unfollow & Report	0.46

Table 10 - Results of Variable Aggregation

Additionally, the variables *type_of_content* and *challenging_content* were measured on different scales, thus for creation of a composite variable the scales would have required normalization. However, such a transformation might have potentially diluted the unique effects captured by each scale and hidden the multifaceted nature of responses. By excluding normalization and instead assessing *type_of_content* and *challenging_content* separately, this analysis preserves the original scale's integrity and the richness of the data they provide.

Given the Chronbach's alpha value of 0.46 for the variables Constructive Dialogue, Scroll Past, Disagreement, Unfollow, and Report, which is close to the threshold of 0.5 indicating a weak internal consistency, an additional Exploratory Factor Analysis (EFA) was performed on the five variables, in order to see if simplification can be pursued for the statistical analysis of the variables. EFA is a statistical technique used for analyzing underlying structures of a larger set of variables. It contributes to determining the number of latent constructs that can explain the pattern of correlations among observed variables, hence reducing data complexity and improving interpretability (Fabrigar et al., 1999). By using EFA, discovering clusters among the five variables was possible, suggesting that they could be represented more coherently through fewer, more robust composite variables. Using this method was beneficial, as it allowed for a more structured and simplified data analysis, focusing on underlying dimensions that captured the key characteristics of the original variables while dealing with the difficulties of their initial low internal consistency. The pursued EFA highlighted the data's underlying structure, allowing for a more effective and meaningful statistical analysis.

The EFA was performed in Stata 18 and resulted in a distinction between two underlying factors among the original five variables. The Stata output of the EFA command can be found in Appendix C of this thesis. The analysis included the complete dataset of 177 observations and retained two factors which explained a cumulative proportion of 1.47 of the variances, with Factor 1 accounting for 79.16% and Factor 2 for 68.09% of the variance respectively. The rotated factor loadings, which indicate a clear pattern of variable groupings, influenced the decision of building two composite variables out of the five original ones. Constructive Dialogue and Disagreement show significant loadings on Factor 1, while Unfollow and Report have higher loadings on Factor 2. Scroll Past shows loadings on both factors, which indicate its shared variance with both factors. The decision of creating two composite variables is further supported by the varimax rotation's orthogonal (uncorrelated) structure, which suggest distinct data dimension representations of the two factors. Thus, the distinctiveness of these factors post-rotation provides a strong theoretical rationale for treating them as separate dimensions of user behavior, rather than combining all items into a single composite score. The first composite variable will represent active engagement behaviors, while the second composite variable will embody avoidance. Scroll Past will be kept as a stand-alone dependent variable in the analysis.

The segmentation into two composite variables and a stand-alone variable enables a more complex examination of respondents' behavior towards disagreeable content on LinkedIn, highlighting the duality between engagement and avoidance in the digital space. The factor rotation matrix, which depicts the relationship between the original and rotated factors, emphasizes the distinction between the two conceptual domains, supporting the analytical decision to investigate them separately using composite variables in the following analysis.

This conclusion is consistent with having a nuanced approach that recognizes the complexity of GP as it naturally occurs in SM (Bryman, 2012). Consequently, the three GP-related questions will stand as five independent DV's in the analysis, providing a clear lens through which the different dimensions of GP can be viewed, without compromising the measurement granularity or potency of findings.

4.2.4. Social Media Use

To further investigate the possible impact of broader SM activity on GP within professional groups on LinkedIn, *SM_use* was added as a novel variable in our analysis. This variable will serve as a control variable (CV) in the implied models. Based on Lee et al. 's (2014) methodology and Nordbrandt's (2021) expansion, *SM_use* aggregates the frequency of use across other SM platforms, capturing the extent of each respondent's digital interconnectedness beyond LinkedIn. The variable was constructed by summing the frequency of use for Facebook, Instagram, Twitter, Snapchat, Reddit, and YouTube, as indicated by the responses to the last question of block three in the administered survey (α = .41).

Each component of *SM_use* has been assessed on a scale from "never" (equal to 1) to "daily" (equal to 6), with a resulting range from six, which indicates complete absence of use across the given platforms, to a maximum of 36, which indicates daily engagement with each. The motivation for including *SM_use* arises from its ability to reveal cross-platform digital behaviors that may contribute to or reduce GP. Accounting for SM usage patterns allows for better isolation of LinkedIn's specific role in professional group dynamics and identifies whether broader SM activity correlates with the polarization observed on this platform. The variable *SM_use* acts as a CV in the implied regression analyses, allowing to examine the impact of external SM usage on GP, hence improving the understanding of the interaction between multiple digital environments and professional discussions.

Despite the fact that the SM_use variable has a Cronbach's alpha value of 0.41, indicating low internal consistency among the components that measure the use of various SM platforms, we decided to keep it as a composite variable in our analysis for several reasons. First, the lower alpha value might be linked to the inherent diversity of SM platforms and the differing ways in which respondents interact with them. Diversity is critical to understanding SM's overall impact on professional networking behavior and GP on LinkedIn. Usage patterns vary between platforms, reflecting a wide range of digital activities and preferences, that a single, more consistent measure may hide.

Additionally, the variable has an exploratory role in this thesis, aiming to investigate the possible impact that cross-platform SM engagement has on GP within LinkedIn's professional groups. Despite its low reliability coefficient, including this variable allows capturing a wide range of SM interactions that, when taken together, may have a significant impact on the investigated phenomena. It allows investigation of whether a general tendency towards SM engagement correlates with polarization tendencies, rather than assuming that all platforms contribute equally or in the same way to such dynamics.

Given these constraints, the composite variable *SM_use* does not serve as a conclusive measure of the effect of SM engagement on GP, but rather as an indicator tool for looking into the multidimensional landscape of digital behavior. Capturing the complexity of SM use, even with less-than-ideal internal consistency, provides useful insights into the interplay between other platforms and professional discussions on LinkedIn.

4.2.5. Political Views

In this thesis, the operationalization of the *pol_view* variable was designed to capture the complex range of political orientations among respondents, without the usage of specific party names, to allow for a more diverse respondent range. This was achieved by the design of the first question in the last block of the survey, as described in section 3.3 of this thesis. The implied scale of the question was designed based on the seminal work of Druckman and Levendusky (2019), who emphasized the importance of assessing political alignment and information diversity within SM networks. In recognition of the possibility for additional specificity among respondents who characterized their political view as being "neutral", the follow-up question was designed and included in the survey. Literature, such as Huddy (2013) emphasizes the complexity of political identity as a multidimensional construct, thus influencing the decision of merging the responses from the two mentioned questions into a single variable, namely *pol_view*. More specifically, literature points out that a single left-right divide cannot adequately reflect political identity and that complexities provided by using intermediate categories such as “neutral” must be considered.

The coding for the new variable *pol_view* was done as follows: respondents who initially identified themselves as “neutral” in the first question were reassigned to a more precise category based on their responses to the follow-up question. The reassignment process proceeded as follows: for respondents who answered “closer to liberalism” in the follow-up question, *pol_view* was replaced to be equal to three. For respondents who stated being “closer to conservatism”, *pol_view* was replaced to be equal to five. Lastly, for respondents who answered “neither” in the follow-up question, *pol_view* was replaced with the value four, affirming a true neutral stance.

This coding approach allows for more in-depth research into how precisely specified political views correlate with GP within professional groups on LinkedIn. By operationalizing political views in this way, this thesis can contribute to a better understanding of the relationship between political identity, as part of one’s Social Identity, and the dynamics of GP, following literature suggestions for a more nuanced measure of political orientation in social media research (Baldassari & Geleman, 2008; Druckman et al., 2018).

4.2.6. Other Control Variables

In this thesis’s investigation of GP within professional groups on LinkedIn, several control variables were included to ensure the robustness of findings. These include Age, Gender, Education Level, Industry, and Professional Experience Level, as described in chapter 4.1 of this thesis. The use of such control variables is essential for several reasons:

Age. According to literature, age has a significant influence on SM use and political views. Older and younger users may differ in terms of involvement and content consumption or sharing, influencing GP dynamics.

Gender. Gender has been proven to influence both SM interaction patterns as well as political engagement. Controlling for gender allows this thesis to account for such disparities, resulting in a more accurate picture of GP across varied groups of professionals on LinkedIn.

Education Level. Respondents' individual information processing abilities and political attitudes can be influenced by their educational background. By controlling for education level, this thesis aims to separate the effects of LinkedIn's professional interactions from the broader cognitive and informational biases imposed by different levels of education.

Industry. Different industries may have distinct cultures and norms that have an influence on the extent and nature of facing GP. Controlling for industry ensures that this thesis's findings are not distorted by industry-specific dynamics.

Professional Experience**.** One's experience level within their specific industry can influence professional networking habits and exposure to GP. More experienced professionals may have differing interaction patterns and tolerance for opposing views compared to less experienced professionals.

While data on respondents' countries were also collected through the survey, this variable was not included among the CV's of this thesis due to the data's broad dispersion and insufficient representation for each country. The decision to omit "Country" as a CV was made to ensure that this analysis remains focused on parameters with enough data to provide relevant insights into the dynamics of GP on LinkedIn, thereby enhancing the validity and reliability of analysis results.

By carefully selecting and justifying given CV's, the present thesis tries to provide a detailed understanding of GP on LinkedIn, taking into account a variety of factors that could influence the observed phenomena. The chosen approach underscores the commitment to methodological rigor and the pursuit of significant conclusions drawn from the investigation of GP in professional networks on SM.

4.3. Statistical Analysis Methodology

The administered survey reached a total number of 285 registered responses; however, after proceeding with data cleansing, the final sample consisted of 177 observations. For results descriptives as well as for the data analysis, Stata 18 was used. For better understanding the relationships between the independent and dependent variables and given that the DV's are categorical, an ordinal logistic regression analysis was conducted. The decision to use ordinal logistic regression analysis for this thesis is based on the complex nature of the DV, Group Polarization, which was captured through three distinct survey questions.

Alternatively, to combine these into a single composite variable, the decision of treating them as independent variables with ordered categories was made. The methodological decision is not arbitrary but is supported by multiple rationales that not only justify, but also highlight the usefulness of ordinal logistic regression analysis for the presented dataset.

First, each corresponding survey question was designed to tap into distinct aspects of GP. An ordinal logistic regression is well-suited for this type of scenario as it preserves the original nature of the responses, allowing for an analysis which preserves the data's ordered structure. The approach ensures the preservation and effective representation of the various gradations and relationships inherent in the survey responses, resulting in a more realistic depiction of GP on LinkedIn.

Furthermore, ordinal logistic regression is well-known for its analytical precision when dealing with ordered categorical data. It allows for the investigation of relationships between the IV's and the ordered categories of the DV, providing insights into how each dimension increased the likelihood of higher levels of GP. The granularity of this analysis allows for a better understanding on how each dimension, as represented by the survey questions, contributes towards the explanation of the DV's occurrence.

The decision to preserve survey questions as independent variables for the presented DV improves the model's fit and accuracy. The approach ensures a closer alignment between the proposed model and the empirical reality by accounting for the complex nature of the construct being examined, resulting in precise and dependable findings.

From a theoretical standpoint, this methodological choice is well-founded. Agresti (2010), provides a comprehensive foundation on the statistical techniques for ordinal data analysis, including ordinal logistic regression. Additionally, McCullagh's (1980) seminal work on regression models for ordinal data provides the statistical foundation for this approach, validating its use in this thesis.

Finally, practical considerations play a significant role in this decision. By representing the DV, Group Polarization, through five different and separate variables, results can be interpreted more easily. This clarity allows for the capture of actionable insights and suggestions based on particular survey items, increasing the utility and impact of the proposed study.

In conclusion, the use of an ordered logistic regression analysis in this thesis is a deliberate and careful decision. It builds on the extensive information offered by the survey questions, fits with both theoretical and empirical concerns, and provides a thorough framework for analyzing the complex relationship of the given data. The used approach not only broadens the study, but also ensures that the findings are robust, nuanced and ultimately more meaningful for both academic research as well as practical value.

4.4. Analysis Results

Before diving into the actual regression analysis of this thesis, the descriptive results will be presented. These will set the stage for the following regression analysis. The initial descriptive examination will focus on the basic relationships within the presented data set, establishing an essential understanding of the variables at play. Following the descriptive analysis, a thorough investigation into the drivers of GP within professional groups on LinkedIn will be pursued, guided by the central research question of this thesis. Given the ordered nature of survey responses, and the objective to identify the nuanced impact of different predictors, an ordinal logistic regression (ologit) is fitting for this approach. This chapter will proceed through the statistical landscape, starting with descriptive statistics and on to the construction of the used regression models. All additional test results will be included in Appendix B of this thesis.

4.4.1. Results of Descriptive Analysis

Given the descriptive statistics from chapter 4.1 and variable operationalization methods used and described in chapter 4.2 of this thesis, Table 11 below presents the final list of variables that will be used for the statistical analysis in this thesis. The table provides a comprehensive overview of the variables that will be included in the statistical analysis of this thesis. It presents the key characteristics of each variable: label, number of observations (N), mean value, standard deviation (sd), minimum (min), and maximum (max) scores observed in the analyzed sample containing 177 observations. The variables include a wide range of measurements, ranging from the type of content that respondents encounter on their LinkedIn feeds to standardized constructs such as Social Identity or Sharing behavior, as well as demographic information such as Age, Gender, and Level of Education. Notably, the continuous variables Social Identity, Sharing Behavior and Social Media Use have been standardized to ensure comparability and appropriateness for regression analysis. The presented summary table serves as an anchor for the subsequent analysis, providing a clear overview of the data that will be studied to explore the nuanced nature of GP on LinkedIn. The extensive list of variables emphasizes the research design's thoroughness, providing foundational information that will be critical for the following correlation analysis, and ensuring a rich understanding of the study's empirical base.

Following the examination of the correlation table for the considered variables, several notable relationships emerge. These provide preliminary insights into the dynamics of the analyzed phenomena. It is important to note that while the presented correlations are indicators of relationships between variables, they do not prove causality. Table 12 shows the pairwise correlation coefficients between each pair of variables, as well as their related p-values, allowing for determination of the statistical significance.

		(1)	(2)	(3)	(4)	(5)
VARIABLES	LABELS	N	mean	sd	min	max
type_of_content	Type of Content	177	2.746	0.982	1	4
challenging_content	Challenging Content	177	3.480	0.892	1	5
Active_Engagement	Active Engagement	177	1.672	0.815	1	5
Passive_Avoidance	Passive Avoidance	177	2.192	1.004	1	5
Scroll_Past	Scroll Past	177	3.616	1.340	1	5
SocialIdentity_std	Social Identity Standardized	177	-3.47e-09	1.000	-1.927	2.121
SharingBehavior_std	Sharing Behaviour Standardized	177	3.62e-09	1.000	-1.375	4.587
Age	Age	177	2.390	1.087	1	5
Gender	Gender	177	1.593	0.493	1	2
Education	Education	177	2.542	0.761	1	4
Industry	Industry	177	4.316	1.922	1	7
prof_exp	Professional Experience	177	2.339	0.706	1	3
pol_view	Political View	177	3.045	1.369	1	7
SMUse_std	Social Media Use Standardized	177	0	1.000	-2.723	3.172
Constructive_Dialogue	Constructive Dialogue	177	1.525	0.798	1	5
Disagreement	Disagreement	177	1.605	0.978	1	5
Unfollow	Unfollow	177	2.085	1.076	1	5
Report	Report	177	1.977	1.196	1	5
social_identity	Social Identity	177	21.28	7.410	7	37
sharing_behavior	Sharing Behaviour	177	11.54	4.025	6	30
SM_use	Social Media Use	177	19.40	4.919	6	35

Table 11 - Final list of variables used for analysis

Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) type_of_content	1.000												
(2) challenging_content	-0.119	1.000											
	(0.114)												
(3) Active_Engagement	-0.076	-0.267	1.000										
	(0.313)	(0.000)											
(4) Passive_Avoidance	-0.019	-0.116	0.272	1.000									
	(0.798)	(0.124)	(0.000)										
(5) Scroll_Past	0.025	0.079	-0.272	0.207	1.000								
	(0.744)	(0.295)	(0.000)	(0.006)									
(6) SocialIdentity_std	0.136	-0.231	0.325	0.076	-0.306	1.000							
	(0.072)	(0.002)	(0.000)	(0.315)	(0.000)								
(7) SharingBehavio_std	0.042	-0.282	0.440	0.161	-0.217	0.535	1.000						
	(0.580)	(0.000)	(0.000)	(0.032)	(0.004)	(0.000)							
(8) Age	-0.018	0.181	0.145	-0.079	-0.224	0.206	0.070	1.000					
	(0.808)	(0.016)	(0.054)	(0.294)	(0.003)	(0.006)	(0.354)						
(9) Gender	0.055	-0.122	-0.178	0.090	0.210	-0.087	-0.030	-0.339	1.000				
	(0.466)	(0.106)	(0.018)	(0.234)	(0.005)	(0.252)	(0.695)	(0.000)					
(10) Education	0.140	0.074	0.013	-0.018	-0.079	-0.018	0.018	0.306	-0.120	1.000			
	(0.063)	(0.325)	(0.860)	(0.811)	(0.298)	(0.809)	(0.816)	(0.000)	(0.110)				
(11) Industry	0.070	0.027	-0.082	-0.073	0.074	-0.100	-0.013	-0.108	0.113	-0.141	1.000		
	(0.355)	(0.723)	(0.277)	(0.335)	(0.328)	(0.187)	(0.869)	(0.151)	(0.135)	(0.061)			
(12) prof_exp	0.018	0.209	-0.013	-0.044	-0.078	0.118	0.042	0.626	-0.255	0.322	-0.038	1.000	
	(0.807)	(0.005)	(0.861)	(0.558)	(0.303)	(0.116)	(0.583)	(0.000)	(0.001)	(0.000)	(0.619)		
(13) SMUse_std	0.141	-0.170	0.071	0.118	0.038	0.008	0.106	-0.307	-0.001	-0.085	0.023	-0.204	1.000
	(0.061)	(0.023)	(0.349)	(0.118)	(0.617)	(0.916)	(0.160)	(0.000)	(0.987)	(0.261)	(0.764)	(0.006)	

Table 12 - Pairwise correlations

Active Engagement and Sharing Behavior show a positive, significant correlation ($r = 0.440$, $p < 0.001$). This indicates that individuals with greater active engagement on LinkedIn are also more likely to share content, which further aligns with the expectations that more engagement would correlate with higher sharing frequencies. Similarly, Social Identity also shows a moderate positive correlation with both Active Engagement ($r = 0.325$, $p < 0.001$) and Sharing Behavior ($r = 0.535$, $p < 0.001$). This finding supports the belief that a stronger Social Identity is associated with higher active engagement on LinkedIn.

On the contrary, Challenging Content shows a negative correlation with both Active Engagement ($r = -0.267$, $p < 0.001$) and Sharing Behavior ($r = -0.282$, $p < 0.001$). This correlation suggests that content which is perceived as challenging is less frequently associated with engagement or sharing activities.

The significant positive correlation between Age and Education ($r = 0.306$, $p < 0.001$) suggests a potential tendency of achieving higher levels of education with increasing Age within the sample. On the other hand, Gender and Age show a strong negative correlation ($r = -0.339$, $p < 0.001$). This may suggest demographic tendencies or potential differences in LinkedIn use across gender lines and related to age.

Demographic variables, such as Gender, Education, Industry, and Professional Experience demonstrate varying correlations with content interaction behaviors, indicating the complex interaction between demographic factors and how respondents interact with content on LinkedIn. Particularly, Professional Experience and Age show a strong, positive correlation ($r = 0.626$, $p < 0.001$), which is to be expected given that experience is usually accumulated over time.

Scroll Past exhibits a negative correlation with Social Identity ($r = -0.306$, $p < 0.001$) which could imply that respondents who have a strong social identity are less likely to scroll past content on LinkedIn without interacting.

The findings of this correlation analysis lay the groundwork for the statistical analysis that will be pursued in this thesis and serve as an integral step in answering the proposed research question. Notably, the relationship between engagement, sharing behavior, and social identity provide preliminary insights into potential drivers of GP, indicating that individual identity and interaction with content may have a significant impact on collective behavior within professional networks on LinkedIn. The correlation of demographics and content interaction patterns provide an additional layer of complexity, pointing to the multifaceted nature of GP. As this thesis progresses, the identified relationships will be investigated through statistical models to better understand their contribution to the phenomena of GP on LinkedIn. The primary objective of this thesis is not only to identify the drivers, but also to understand how they influence the dynamics of professional interactions and collective attitudes within LinkedIn. This exploration seeks to provide a comprehensive understanding of GP based on empirical data, set to contribute to theoretical perspectives in academic research while also providing practical implications for professionals involved in managing and nurturing LinkedIn's professional groups. By shedding light on the dynamics of the mentioned social processes, the findings of this thesis aim to be useful for further development of strategies for polarization mitigation in professional networks such as LinkedIn.

4.4.2. Regression Results

Based on the foundational relationships set by the correlation analysis, this thesis acknowledges the multi-faceted nature of GP, as captured by the five distinct DV's: Type of content, Challenging Content, Active Engagement, Passive Avoidance, and Scroll Past. To fully investigate the intricate dynamics at play, five separate regression models will be analyzed, each corresponding to one of the five DV's. The approach is based on the assumption that each component of GP can be influenced by differing aspects, resulting in individual analysis. By building and examining separate models, a comprehensive understanding of the phenomena can be gained, uncovering both similarities and differences across different dimensions of polarization. The creation of separate models is not only methodologically robust but also aligns with the aimed research objectives, presenting a comprehensive, multi-faceted portrayal of GP within professional groups on LinkedIn. By implementing this analytical strategy, this thesis aims to elicit the nuanced variable interplay, and address both the academic study of GP as well as the practical concerns of managing and mitigating existing effects in professional social networking contexts.

4.4.2.1. Type of Content

Based on the results of the correlation analysis, the first model of the regression analysis has Type of content as its DV, indicating its significance for engagement and information dissemination within LinkedIn networks. Social Identity and Sharing Behavior will be used as IVs in the model, as they are assumed to be key drivers influencing how content is perceived and interacted with by users. Lastly, Political Views will be included as a control variable in the model, recognizing its possible influence on content interaction and ensuring that the IV's effects on the DV are not affected by underlying political biases. The model aims to identify the impacts of social identification and sharing propensities on the encounter of various types of content while controlling for political view, resulting in a focused examination of the factors that might influence the perceptions of GP on the platform.

The ordinal logistic regression model was computed as follows. In the first model, only the influence of Social Identity and Sharing Behavior was estimated. In the second model, the control variable Political view was added to determine if any additional variance was explained by this inclusion. Lastly, before interpreting the results, all necessary conditions for an ordinal logistic regression were reviewed and tested. The first assumption implies that the DV is ordered, which is the case for *type of content*, given the data descriptives in the previous chapters. Second, one or more IVs should be either continuous, categorical or ordinal. In this model's case the assumption is fulfilled, given that both Social Identity as well as Sharing Behavior are continuous variables which have been standardized, and Political View is categorical with seven ordered categories. Third, the assumption of no multicollinearity was tested by first running the model as a multiple linear regression and then running the Variance Inflation Factors (VIF) command in Stata 18. The conducted VIF analysis proved that the condition for no multicollinearity was met. With Social Identity and Sharing Behavior displaying VIFs of 1.43 and 1.57 respectively, and even the highest category of Political View presenting a VIF of 4.14, none of the included variables approached the concerning and commonly set thresholds at a VIF of 5 or 10. The overall mean VIF of 2.33 further supports the assumption of no multicollinearity, confirming the reliability of the regression coefficients of the presented analysis. Lastly, the proportional odds assumption will be tested. This assumption implies that the effect of the IV's on the DV is constant across all categories of the DV, thus resulting in only one coefficient per predictor. The assumption was tested by using the ordered logistic model (*omodel)* command in Stata, which provides the same result as the *ologit* command, with an additional likelihood-ratio test to see whether the coefficients are equal across categories. The likelihood-ratio test yielded a significant p-value ($p = 0.0012$), which indicates that the null hypothesis of having proportional odds is to be rejected. This means the effect of the IVs on the DV does not stay constant across all categories. This assumption violation suggests that the chosen model might not accurately represent the data. To address this issue, a multinomial logistic regression (mlogit) was used, as this type of regression does not require the proportional odds assumption and can model the DV without ordering constraints.

.	Model 1.1	Model 1.2
Mostly_diverse		
Social Identity Standardized	0.641	0.638
Sharing Behavior Standardized	1.478	1.462
Political View=Moderately progressive/ liberal		0.697
Political View=Slightly progressive/ liberal		0.738
Political View=Neutral		0.724
Political View=Slightly conservative		2.827
Political View=Moderately conservative		0.861
Political View=Very conservative		0.000
Intercept	0.336	0.347
Unsure		
Social Identity Standardized	0.649	0.630
Sharing Behavior Standardized	0.219	0.217
Political View=Moderately progressive/ liberal		2.235
Political View=Slightly progressive/ liberal		0.980
Political View=Neutral		1.692
Political View=Slightly conservative		1.477
Political View=Moderately conservative		1.199
Political View=Very conservative		0.000
Intercept	0.179	0.114
Balanced_mix		
Social Identity Standardized	1.000	1.000
Sharing Behavior Standardized	1.000	1.000
Political View=Moderately progressive/ liberal		1.000
Political View=Slightly progressive/ liberal		1.000
Political View=Neutral		1.000
Political View=Slightly conservative		1.000
Political View=Moderately conservative		1.000
Political View=Very conservative		1.000
Intercept	1.000	1.000
Mostly_aligns		
Social Identity Standardized	0.887	0.858
Sharing Behavior Standardized	1.042	1.240
Political View=Moderately progressive/ liberal		1.407
Political View=Slightly progressive/ liberal		0.513
Political View=Neutral		0.419
Political View=Slightly conservative		0.932
Political View=Moderately conservative		0.265
Political View=Very conservative		0.000
Intercept	0.507	0.594

Table 13 - Multinomial Logistic Regression results for Type of Content

Due to the violation of the proportional odds assumption which is of central importance for the *ologit* model's validity, it has been decided to not use it for further interpretation. As a result, the primary focus will be shifted towards the *mlogit* model. This choice ensures that the analysis is methodologically sound and appropriate for the data's characteristics.

The analysis of the base and extended model of *type_of_content* highlights the effects of Social Identity and Sharing Behavior. In the base model with no control variables (Model 1), an increase in Social Identity is marginally associated with a decrease in the relative risk of content being "Mostly diverse" as compared to the base category "Balanced mix". An increase in Sharing Behavior on the other hand suggests an increase in relative risk for the same outcome, but it does not show statistical significance. The introduction of the CV *pol_view* in the second model slightly alters the relative risk ratios, but without a significant change in outcomes. The pseudo R-squared for Model 2 indicates that approximately 11.14% of the variation in the DV is explained by this model, as compared to 7,56% in Model 1. Although the explanatory power of the model increases with the introduction of the CV *pol_view*, the non-significant impact of this additional variable supports a further examination of the practical relevance to the model's overall explanatory power.

4.4.2.2. Challenging Content

The second model uses Challenging Content as its DV, to shed light on how this aspect of content engagement is influenced by the constructs of Social Identity and Sharing Behavior, serving as IVs, similarly to the previous model. Additionally, based on the correlation analysis, Professional Experience, Age, and Social Media Use will be integrated as CVs in this model. The variables were selected based on the demonstrated relationship with the DV and IVs, aiming to provide more understanding for the drivers of encountering challenging content in one's LinkedIn feed.

Similarly, to the first model, an ordinal logistic regression will be pursued, and the corresponding assumptions will be checked. Also in this case, the first two assumptions of the ordinal logistic regression are fulfilled. The VIF command is used following a linear regression of the variables to check for multicollinearity. None of the seven variables approached the concerning and commonly set thresholds at a VIF of 5 or 10, all of them presenting values lower than two. The overall mean VIF of 1.42 reassures the correctness of the no multicollinearity assumption of this model. As before, the proportional odds assumption was tested by running the omodel command on the same set of variables, to retrieve the likelihood-ratio test. The results of the test suggest that the model fulfills the proportional odds assumption, thus the relationship between each pair of outcome groups is consistent across the levels of the predictor variables.

The analysis of this model revealed that an increase in Social Identity significantly correlates with a higher likelihood of encountering challenging content on one’s LinkedIn feed. This underscores the role of professional identity in content interaction dynamics. On the other hand, Sharing Behavior did not demonstrate a significant effect on Challenging Content. This suggests that the tendency to share might not have a direct influence on how individuals engage with content perceived as challenging. The introduction of the three CV’s added depth to the proposed model, and professional experience proved to be a notable factor in this regression. This suggests that respondents' career level may have an influence on their willingness to engage with challenging content, potentially due to the different career stages they find themselves at or professional confidence. While included for a more comprehensive analysis, SM use and Age did not show statistically significant impacts on the DV. This could further indicate that the use of other SM or participants Age do not prove to be decisive factors in the assessment of engagement with challenging content.

As a whole, the proposed model’s significance underlines the complex relationship between Social Identity and challenging content engagement on LinkedIn. The relationship, controlled by professional experience, sheds light on how one’s professional identity and career experiences influence content interaction patterns in professional online networks.

	Model 2.1	Model 2.2
Challenging Content		
Social Identity Standardized	0.804	0.681
Sharing Behavior Standardized	0.623	0.601
Social Media Use Standardized		0.813
Professional Experience=Beginner		1.000
Professional Experience=Intermediate		1.464
Professional Experience=Advanced		1.864
Age=18-25		1.000
Age=26-35		0.735
Age=36-45		2.706
Age=46-55		0.926
Age=55+		4.019
/		
cut1	-4.239	-4.009
cut2	-2.190	-1.862
cut3	0.050	0.552
cut4	2.064	2.774

Table 14 - Ordinal Logistic Regression Results for Challenging Content

4.4.2.3. Active Engagement

In the third regression model proposed by this thesis, Active Engagement acts as the DV, while similarly to the previous two models, Social Identity and Sharing Behavior remain the IV's. Additionally, the model will include four control variables, namely Age, Gender, Level of Education and Professional Experience. Similarly to the previous two models, the inclusion of the variables has been decided based on the correlation analysis provided in subchapter 4.4.1 of this thesis.

Given the 177 observations in the sample, which is rather on the small side, and the predominantly categorical nature of the proposed CV's, conducting separate regressions for each CV is a justifiable approach in this case. By doing so, the risk of overfitting will be avoided. Additionally, separate regressions allow for a more attentive investigation of the variable relationship. While acknowledging the limitations of this method of analysis, such as its inability to capture interactions between CV's, it provides a clear direction for future research, where more complex models could be employed. Thus, four ordinal logistic regression models will be created and analyzed in Stata. As for the previous models, the four conditions of the ordinal logistic regression will be verified for each of the models, before continuing with the regression interpretation.

Given the five categories of Active Engagement, which range from Never to Always, the DV of this model fulfills the assumption of being ordered. Second, the same IV's will be used as in the previous models and thus fulfilling the second assumption of an ordered logistic regression model. Third, multicollinearity is checked by running a linear regression with the same variables to check the VIF values. For the model with Age as a CV, the overall mean VIF value of 1.52 suggests no multicollinearity in this model, thus fulfilling the model assumption. Lastly, the proportional odds assumption will be verified. The likelihood-ratio test shows a significant p-value ($p = 0.000$) for this model, suggesting a strong evidence against the proportional odds assumption. Thus, the fourth assumption is violated, suggesting that the effect of the predictors is not consistent across all categories of the DV. Due to the violation of the proportional odds assumption, a mlogit regression will be pursued instead. This approach does not require the proportional odds assumption but is still suitable for analyzing the given DV. By shifting to a mlogit model, the proposed analysis aims to model the proposed relationship in an accurate way, ensuring the robustness and methodological accuracy of findings.

The mlogit displayed the relative risk ratios (RRR), showing how a one unit increase in the predictors affect the likelihood of being into a specific category of the DV, compared to the baseline "Never". The model highlights Sharing Behavior to be a significant predictor across the different categories of Active Engagement. It significantly increased the likelihood of being in "Sometimes" or "About half the time" with RRR's of 2.189 and 3.890, respectively, showing a considerable influence on Active Engagement. On the contrary, Social Identity shows no significant associations. Notably, the model shows stability issues for "Most of the time" and "Always", as the two categories contained very few observations. Additional tests were also performed, by using the *fitstat* command after running the regression in Stata. The improvement of the log likelihood from the intercept only model (-190.447) to the full model (-142.213) underscores the model fit enhancement provided by the chosen predictors. This is further supported by the likelihood ratio chi2(24) of 96.269, with a p-value of 0.000, indicating a considerable improvement over the model with no predictors. Model fit statistics such as McFadden's R2 (0.253) and adjusted count R2 (0.330) indicate that the model explains roughly 25.3% of the variance in Active Engagement. Collectively, these measures underline the model's efficacy in capturing the dynamics of Active Engagement. For the second regression, Gender will be used as a CV. As before, the first two assumptions of ologit are fulfilled in this case. The mean VIF value of 1.27 shows that the no multicollinearity assumption also holds. The violation of the proportional odds assumption is shown by the significant p-value ($p = 0.0005$) of the likelihood ratio test. Thus, a mlogit regression will be performed on this model.

The mlogit regression between the proposed DV, IVs and CVs uses “Never” as the baseline category. The model's statistical significance and fit are robust, with a noticeable improvement in log likelihood compared to the intercept-only model. The highly significant LR chi2 statistic underlines the predictors collective contribution to the model. The importance of Sharing Behavior as a key driver of Active engagement is being highlighted by the RRR's. Even with some predictors failing to reach statistical significance in certain categories and encountering wide confidence intervals in others, implying data sparsity, the overall model has significant explanatory power, explaining approximately 19% of the variance in Active Engagement as indicated by McFadden's R2. The proven predictive accuracy as suggested by Count R2, and the improvement in model fit metrics such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), emphasize the model's effectiveness in capturing Active Engagement dynamics, nevertheless leaving room for improvement.

Social Identity's impact varies across categories, showing significance only for “Most of the time”. On the contrary, Sharing Behavior consistently increased the likelihood of more active engagement across several categories. Gender differences emerge particularly showing that females are significantly less likely to be in the “Sometimes” category, indicating gender disparities in engagement patterns. Overall, while Sharing Behavior consistently predicts a higher engagement, the effects of Social Identity and Gender highlight the complex interaction of factors that determine the different engagement levels. The varied significance across outcomes underlines the need for further investigation or a larger dataset to properly understand these interactions.

Keeping the same IVs and DV as for the previous regressions, the third regression includes Education as its CV. As in the previous two models, the first two assumptions of the ologit regression are fulfilled. Multicollinearity proved to not be an issue in this case, as the mean VIF value is 2.34. On the other hand, the proportional odds assumption was again violated, as shown by the significant p-value ($p = 0.0000$) of the likelihood ratio test. Due to this violation, an mlogit regression will be performed.

The proposed model demonstrates significant predictive capability. The significant LR chi2 of 75.32 ($p < 0.0000$) confirms the model's efficiency in predicting Active engagement compared to the null. The pseudo R2 of 0.1987 suggests that the proposed model accounts for 19.87% of the variance in the DV, while additional measures like ML (Cox-Snell) R2 and Cragg-Uhler (Nagelkerke) R2 indicate a higher explanatory power. The regression shows differential impacts of Sharing Behavior and Social Identity on various categories of Active Engagement, while Education Level proves no consistent significant effects. A one unit increase in Social Identity has a variable effect across Active engagement categories, with "Sometimes" having a 31.5% higher relative risk than "Never", however not achieving statistical significance. Sharing Behavior has a considerable impact across all categories of Active Engagement, increasing its likelihood by 121.79%, as seen in the "Sometimes" category. The results highlight the importance of Sharing Behavior in fostering Active Engagement on LinkedIn. On the contrary, Education does not demonstrate a statistically significant impact on Active Engagement. This finding suggests that for the collected data, Education does not prove to be a distinguishing factor for different levels of Active Engagement. The lacking effect could be determined by the sample size, potential variable intercorrelations, or the nuanced aspects of Education that can't be captured by education levels alone. While Social Identity seems to have a nuanced and varied influence on Active Engagement, Sharing Behavior emerges as a consistently significant predictor in the presented case. The analysis indicates that initiatives aiming at improving Sharing Behavior may be beneficial in increasing active participation. In contrast, Education appears to have a minimal effect on the DV, emphasizing the need for further exploration into how different aspects of the educational background may interact with SM engagement patterns in professional groups on LinkedIn.

The fourth CV chosen for modeling with the same DV and IV's as before is Professional Experience. The same ologit model is being persuaded, with verification of the four assumptions before model interpretation. The first two assumptions continue to be fulfilled by the model. The mean VIF value of 1.9 suggests no multicollinearity, thus fulfilling the third assumption of ologit regressions. The violation of the proportional odds assumption is shown by the significant p-value ($p = 0.0000$) of the likelihood ratio test. Thus, an mlogit regression will be used alternatively.

As for the previous models with Active Engagement as a DV, Sharing Behavior significantly increases the likelihood of higher engagement across multiple categories, emphasizing its pivotal role in fostering engagement on LinkedIn. Social Identity's impact varies, being notably significant for "Most of the time", suggesting a nuanced relationship with the categories of Active Engagement. The included CV, Professional Experience, shows mixed effects, with no significant impact on the lower categories of Active Engagement. The variable shows a negative effect on the higher levels of Active Engagement. As for the model fit, the improved log likelihood and a pseudo R2 of 0.2072 emphasize a decent explanatory power, accounting for 20.72% of the variability in the DV. The significant LR chi-square emphasizes the model's enhanced fit over the basic model with no predictors. Overall, the proposed model highlights Sharing Behavior as a consistent driver of Active Engagement, with Social Identity and Professional Experience contributing to the complex landscape of Active Engagement determinants within professional groups on LinkedIn.

	Model 3.1	Model 3.2	Model 3.3	Model 3.4
Never				
Social Identity Standardized	1.000	1.000	1.000	1.000
Sharing Behavior Standardized	1.000	1.000	1.000	1.000
Age=26-35	1.000			
Age=36-45	1.000			
Age=46-55	1.000			
Age=55+	1.000			
Gender=Female		1.000		
Education=Bachelor's degree or equivalent			1.000	
Education=Master's degree or equivalent			1.000	
Education=PhD or equivalent			1.000	
Professional Experience=Intermediate				1.000
Professional Experience=Advanced				1.000
Intercept	1.000	1.000	1.000	1.000
Sometimes				
Age=26-35	1.401			
Age=36-45	3.578			
Age=46-55	5.365			
Age=55+	3.930			
Social Identity Standardized	1.201	1.292	1.316	1.265
Sharing Behavior Standardized	2.189	2.345	2.218	2.214
Gender=Female		0.360		
Education=Bachelor's degree or equivalent			0.819	
Education=Master's degree or equivalent			1.046	
Education=PhD or equivalent			2.141	
Professional Experience=Intermediate				0.942
Professional Experience=Advanced				2.167
Intercept	0.397	1.465	0.778	0.540
About_half_the_time				
Age=26-35	0.552			
Age=36-45	0.426			
Age=46-55	0.507			
Age=55+	0.000			
Social Identity Standardized	0.798	0.714	0.689	0.793
Sharing Behavior Standardized	3.890	4.299	4.100	4.006
Gender=Female		0.593		
Education=Bachelor's degree or equivalent			0.638	
Education=Master's degree or equivalent			0.523	
Education=PhD or equivalent			0.000	
Professional Experience=Intermediate				0.447
Professional Experience=Advanced				0.213
Intercept	0.322	0.271	0.336	0.471
Most_of_the_time				
Age=26-35	0.001			
Age=36-45	0.004			
Age=46-55	0.518			
Age=55+	0.000			
Social Identity Standardized	4367.703	364.531	353.760	698.167
Sharing Behavior Standardized	30.608	6.513	7.254	9.511
Gender=Female		0.419		
Education=Bachelor's degree or equivalent			0.446	
Education=Master's degree or equivalent			0.312	
Education=PhD or equivalent			0.000	
Professional Experience=Intermediate				0.056
Professional Experience=Advanced				0.053
Intercept	0.000	0.000	0.000	0.000
Always				
Age=26-35	1.2e+128			
Age=36-45	9.69e+46			
Age=46-55	1.2e+100			
Age=55+	1.1e+204			
Social Identity Standardized	4.50e+78	6.631	11.187	6.559
Sharing Behavior Standardized	0.000	0.418	0.034	0.315
Gender=Female		0.000		
Education=Bachelor's degree or equivalent			10.937	
Education=Master's degree or equivalent			6.956	
Education=PhD or equivalent			1.18e+09	
Professional Experience=Intermediate				1.027
Professional Experience=Advanced				1.31e+08
Intercept	0.000	0.014	0.000	0.000

Table 15 - Multinomial Logistic Regression results for Active Engagement

4.4.2.4. Passive Avoidance

The fourth regression model analyzed in this thesis uses Passive Avoidance as its DV, Social Identity and Sharing Behavior as the IV's and Political View as the CV. The IV's as well as the CV included in this model have been selected based on the correlation analysis presented earlier in this thesis. Given the five categories of the DV and the continuous nature of the IV's, the first two assumptions of the ordered logistic regression are fulfilled. The mean VIF value of 2.33 suggests no multicollinearity is present in the proposed model, thus fulfilling the third assumption of an ologit regression. Nevertheless, the proportionality of odds assumption is being violated, as suggested by the significant p-value ($p = 0.0000$) of the likelihood ratio test. Due to this assumption violation, a generalized ordered logistic model (gologit2) will be employed in this case. Compared to an ologit model, the gologit2 relaxes the proportional odds constraint, allowing for differing estimates of odd ratios between outcome categories. The flexibility makes this model appropriate for the presented data set, where the assumption of proportional odds ratio has been violated. By choosing gologit2, the nuanced relationships between the predictors can be modeled more accurately, ensuring a more robust analysis of the proposed factors.

	Model 4
Passive Avoidance	
Social Identity Standardized	0.959
Sharing Behavior Standardized	1.394
Political View=Very progressive/ liberal	1.000
Political View=Moderately progressive/ liberal	1.077
Political View=Slightly progressive/ liberal	0.771
Political View=Neutral	0.250
Political View=Slightly conservative	0.522
Political View=Moderately conservative	1.978
Political View=Very conservative	0.455
/	
cut1	-1.389
cut2	0.641
cut3	1.960
cut4	3.484

Table 16 - Regression Model results for Passive Avoidance

In the presented regression analysis, Sharing Behavior keeps standing out as a significant predictor. It notably decreases the likelihood of "Never" engaging in Passive Avoidance behavior (Odds Ratio: 2.0704,

$p = 0.01$), highlighting its influential role in the model. Social Identity shows a varying impact, nevertheless without statistical significance. Political View shows mixed effects in the model, mostly not statistically significant, suggesting limited influence on such behavior.

The overall model significance is supported by the LR chi2 of 65.18 ($p < 0.0001$), indicating a better fit compared to a model without predictors, yet it only explains about 13.78% of the variance in the DV, as shown by the Pseudo R2 value. The model's modest explanatory power shows that there are other influential factors that the model does not account for. The chosen gologit2 model provides a more accurate reflection of the complex relationship pictured, offering insights into the nuanced ways in which Passive Avoidance can be influenced by the proposed IV's and CV.

4.4.2.5. Scroll Past

The last regression model analyzed in this thesis uses Scroll Past as its DV, Social Identity and Sharing Behavior as the IVs and two CVs, namely Age and Gender. As an ologit regression is aimed, the four assumptions will be tested. The first two conditions are being met. The mean VIF of 1.52 suggests no multicollinearity. The p-value of 0.0059 of the likelihood ratio test indicates a violation of the proportionality of odds assumption. Thus, a gologit2 regression will be performed.

The model shows that a stronger Social Identity score significantly influences the likelihood of never scrolling past content that is perceived as challenging, indicating a nuanced relationship between Social Identity and engagement behaviors. Similarly, Sharing Behavior has an impact on engagement, increasing the likelihood of never scrolling past content perceived as challenging. Additionally, Age and Gender also seem to play an influence, with older individuals (55+) being significantly likely to never scroll past challenging content, suggesting age-related differences. Gender differences are also notable, with females tending to scroll past challenging content about half the time compared to males. The model fit statistics show a significant fit improvement compared to the intercept only model. The pseudo R2 value of 0.1978 suggests that almost 20% of the variance in the DV is explained by the proposed model. The likelihood ratio test confirms the model's ability to capture the dynamics of Scroll Past beyond what would be expected by chance.

	Model 5
Never	
Social Identity Standardized	5.186
Sharing Behavior Standardized	1.378
Age=18-25	1.000
Age=26-35	1.277
Age=36-45	0.053
Age=46-55	7.75e+06
Age=55+	0.009
Gender=Male	1.000
Gender=Female	1.306
Intercept	9.646
Sometimes	
Social Identity Standardized	1.215
Sharing Behavior Standardized	0.905
Age=18-25	1.000
Age=26-35	3.135
Age=36-45	0.000
Age=46-55	0.421
Age=55+	0.000
Gender=Male	1.000
Gender=Female	1.399
Intercept	1.671
About_half_the_time	
Social Identity Standardized	0.597
Sharing Behavior Standardized	0.543
Age=18-25	1.000
Age=26-35	0.964
Age=36-45	6.45e+07
Age=46-55	3.249
Age=55+	1.89e+07
Gender=Male	1.000
Gender=Female	2.823
Intercept	1.140
Most_of_the_time	
Social Identity Standardized	0.627
Sharing Behavior Standardized	0.586
Age=18-25	1.000
Age=26-35	0.705
Age=36-45	1.545
Age=46-55	1.229
Age=55+	1.868
Gender=Male	1.000
Gender=Female	1.980
Intercept	0.335

Table 17 - Regression model results for Scroll Past

In summary, the proposed gologit2 model sheds light on the interplay of Social Identity, Sharing Behavior Age, and Gender in affecting user interaction with challenging content, particularly their tendency to scroll past. The model's complex approach, which accounts for varying impacts across engagement levels, provides a more accurate depiction of the factors that drive scrolling past behaviors within professional groups on LinkedIn.

5. Discussion

In this final section of the thesis, the results obtained in the previous chapters will be discussed. Connections to existing findings and patterns will also be discussed and included in this chapter. Moreover, the implications of the presented results will be described, as well as the acknowledgement of the research's limitations. The chapter will be concluded with future research recommendations.
The proposed thesis aimed to uncover the role and drivers of Group Polarization within professional groups on LinkedIn. Based on prior findings, the presented research question aimed to unravel the effects of Social Identity and Sharing Behaviors on the presence of Group Polarization in respondents' LinkedIn networks. As elaborated in the Theoretical Background chapter of this thesis, the influence of Social Identity on GP was already elaborately examined through the lens of SIT. The categorization process is central to SIT, through which individuals define themselves and others based on criteria such as gender or professional affiliations. Self-perception is not the only factor shaped by the categorization process, but also how one behaves in social groups (Tajfel, 1978; Tajfel & Turner, 1979). Furthermore, the media has an important role in reflecting and shaping social identities. Its portrayal of socioeconomic groups has an influence on both societal standards and individual self-perceptions. Media not only fosters social comparison that favors in-groups, but it can also reduce or worsen intergroup tensions and biases, influencing GP. With the ongoing digitization of societies and the increasing popularity of SM platforms such as LinkedIn, the SIT takes on new dimensions. Such online settings allow people to explore and express their social identities, reinforcing existing identities and beliefs, and creating new digital in-groups. In the particular case of LinkedIn, the platform makes it easier to display and develop professional identities by emphasizing skills and achievements in order to foster professional relationships and strengthen one's market value. This digital representation contributes to the broader discussion on how social identities influence and are influenced by group behaviors, such as polarization, in both online and offline settings.

By the nuanced examination employed in both the descriptive as well as the regression analysis part of this thesis, the significant influence on Social Identity on GP within professional groups on LinkedIn was emphasized. Social Identity, which was measured by standardized scores, showed a positive correlation with both Active Engagement and Sharing Behavior, suggesting that individuals who have a stronger sense of belonging or identification with their network are more likely to express active participation behaviors and share content on the platform. This indicates that Social Identity is not only a concept shaping self-perception, but it also influences their interaction patterns, from choosing content with which to engage with, to deciding whether to share or ignore certain information.

However, the impact of Social Identity did not have a uniformly positive impact on all variables connected to content engagement. The dynamics of Challenging Content differed, implying that encountering content that was seen as challenging may not coincide with the mechanisms by which Social Identity normally increases engagement. This aligns with van Zomeren et al.'s (2008) investigation into the relevance of Social Identity in collective action within disadvantaged groups. The nuanced findings, in which challenging content is addressed less frequently, may reflect the theory's discussion on the permeability of group boundaries and the methods individuals use to shape their social identities within these types of environments.

Furthermore, the observed inclination of individuals with stronger social identities to less frequently scroll past content without engagement is consistent with the research on social comparison for self-esteem increase through in-group favoritism (Tajfel & Turner, 1986). This kind of behavior can be interpreted as a desire to preserve a positive Social Identity by active engagement with content that reinforces group norms and values. The significant relationship between Social Identity and engagement behaviors observed in this study provides empirical evidence to the theory's relevance in digital professional networks such as LinkedIn.

The conducted analysis further highlights sharing behavior's pivotal role in predicting engagement, implying that the act of sharing is a manifestation of active participation and, as a result, a marker of GP. The relationship underlines the importance of participatory activities in creating a feeling of community and shared identity within professional networks. An important finding across the models underlines the role of sharing behavior in determining various forms of engagement, which could further indicate a polarized or less polarized LinkedIn network. For Active Engagement, sharing behavior proved to be a key determinant. The variable significantly increased the likelihood of "Sometimes" or "About half the time" categories of Active Engagement, indicating a robust correlation between Sharing Behavior and engagement levels. This suggests that people who often share content are more engaged within the platform, which adds to the vibrancy and dynamism of professional discussions. This is consistent with the findings of Iandoli et al. (2021), which state that SM design features, such as how users actively express and exchange content, have a significant impact on GP. The literature emphasizes the dual role of SM platforms in creating both unity and division, with sharing behavior serving as a catalyst for both information sharing and the reinforcement or challenge of pre-existing views and beliefs. The regression results for Passive Avoidance also highlighted the importance of Sharing Behavior. Notably, Sharing Behavior was found to reduce the likelihood of "Never" participating in passive avoidance behaviors, indicating that active sharers are more willing to engage with content, even if this is a challenging one or contradicts their beliefs and opinions. Such behavior further indicates a proactive approach to content engagement, which could either reduce or increase polarization, highly depending on the nature of the shared content and the conversational context. This finding is consistent with prior literature. Furthermore, the expressed sharing behavior on platforms such as Twitter and Facebook indicates how user interactions have a significant impact on the polarization process. For example, retweeting can either support and enhance agreement within groups of like-minded people or indicate disagreement and prompt division. Such behaviors, which reflect the broader dynamics at play across SM platforms, highlight the importance of sharing in defining the appearance of GP. It showcases the potential for LinkedIn sharing behaviors to affect professional discussions, either fostering polarization by promoting specific opinions or countering it by exposing a diverse variety of perspectives.

Moreover, similar constructs to the "like" button on Facebook which are also present on LinkedIn, highlight the significance of sharing behavior in assessing and strengthening group norms and identities. This type of features, by quantifying engagement and approval, help to increase the visibility and influence of shared content, playing an important part in the formation and amplification of GP. The last model in the analysis emphasized that Sharing Behavior even has an influence on Scroll Past. Based on the model's findings, having a higher Social Identity score increases the likelihood of not scrolling past challenging content. This finding further highlights the multifaceted connection between Social Identity, Sharing Behavior, and content engagement habits, implying that those who actively share content are more engaged and less likely to just scroll past content without interacting with it.

The results of the proposed regression models highlight the subtle impact of Sharing Behavior in shaping the dynamics of professional networks on LinkedIn. Individuals that are also active sharers contribute to the information flow within the network, which may influence polarization dynamics by disseminating diverse perspectives or reinforcing existing viewpoints. Already existing literature on the exploration of GP across SM platforms emphasize the complex interplay between platform design, user behaviors, and content distribution. Yarchi, Baden and Klinger-Vilenchik (2020) indicate that platform-specific dynamics, such as algorithms or the nature of user interactions, have a significant influence on the degree and nature of polarization, making it crucial for understanding GP within LinkedIn, where professional identity and career-oriented discussions prevail.

The dual role of SM is further highlighted by the discussion on the impact of GP on online discourse quality: while rapid information sharing is facilitated on the one side, the quality of interactions through the spread of misinformation and creation of echo chambers is lowered on the other. This duality emphasizes the need to investigate the particular processes by which sharing behavior on LinkedIn influences professional discussions, and, by extension, GP within this professional setting. Additionally, the correlation between Sharing Behavior and Active Engagement suggests the existence of a feedback loop. Active participation through sharing leads to higher engagement levels, which further have an influence on the discussions happening within the platform. Despite that, the impact of Sharing Behavior on Passive Avoidance suggests a proactive engagement with content. This could double as a mechanism for exposure to diverse opinions or, on the contrary, strengthen existing biases, depending on the content's nature. The addition of CV's such as age, political view, and gender in the different models enables a more nuanced understanding of the dynamics at play. While the introduction of political views only shows mixed effects, the impact of gender and age on engagement patterns indicates demographic tendencies and disparities in LinkedIn usage, bringing a new layer of complexity to the study of GP.

5.1. Theoretical Implications

The theoretical implications of the presented thesis contribute to the understanding of GP within professional networks such as LinkedIn. The analysis, which is based on the interplay between Social Identity and Sharing Behavior, adds to the existing theoretical frameworks in areas such as SIT, online behavior, and professional network dynamics.

The contribution to SIT (Tajfel & Turner, 1979; Turner, 1982) is done by illustrating how professional identities are constructed and manifested on LinkedIn, a platform that differentiates itself from other SM platforms. The findings reveal that social identity, besides influencing individual behaviors and perceptions, plays an important role in shaping engagement patterns within LinkedIn, aligning with Van Zomeren et al.'s findings on the importance of group identity in collective actions. The thesis further contextualizes the author's findings within the digital era's professional network landscape.

In addition, the thesis builds on the work of Ellison et al. (2014), who highlighted the impact of SM on social identity formation, by providing empirical evidence on how content sharing and interaction patterns on LinkedIn contribute to the reinforcement or mitigation of GP. This insight enriches the theoretical knowledge on how digital platforms can be used to develop and express professional identities, challenging and expanding on Hall's (1973) work on media representation and identity formation.

When it comes to online behavior, this thesis provides an in-depth look at how sharing behavior on LinkedIn influences the formation of GP. The presented positive correlation between active engagement and content sharing (Iandoli et al., 2021; Dubois & Blank, 2018) emphasizes the dual role of sharing behavior in enabling both the diffusion of information and the possibility of polarization through selective information dissemination. The duality contributes to the theoretical debate on the mechanisms of GP in SM (Bessi et al., 2016a; Del Vicario et al., 2016), implying that the professional contest of LinkedIn introduces distinct dynamics compared to less specific SM platforms.

Furthermore, the thesis emphasizes the complex relationship between social identity and engagement with challenging content, providing theoretical insights into the dynamics of content interaction within professional settings. This expands on Settle's (2019) results, which examined the impact of disagreeable content exposure on affective polarization, by bringing them to a professional environment where the implications and effects of such interactions are framed differently.

Finally, this thesis adds to the existing understanding of how GP influences the quality of online debate and discussions among professionals (Shearer, 2018; Settle, 2019). By exploring the relationship between Social Identity, Sharing Behavior, and GP, the study highlights the complex relationship of factors that enable or prevent constructive professional interactions. It proposes theoretical possibilities for future research into how digital platforms might be structured and managed to promote constructive professional development and community building, while limiting the potential risks of polarization.

5.2. Practical Implications

The practical implications arising from this thesis are valuable for professionals, organizational leaders, and platform developers who want to improve interaction quality and engagement within professional networks similar to LinkedIn. Based on the examination of Social Identity and Sharing Behavior, the presented study provides practical recommendations for fostering constructive professional interactions and minimizing the effects of GP.

To begin, the need for fostering strong professional identities within online networks is emphasized by the significant impact of Social Identity in influencing engagement patterns and content interactions. Individuals and organizations should be encouraged to actively build an online presence that reflects their professional beliefs and goals, not only by highlighting skills and accomplishments but also by engaging in content sharing and fostering discussions that reinforce a positive professional identity. By doing so, professionals can take advantage of the platform's potential for career development while simultaneously contributing to a more harmonized professional community.

Second, the findings on sharing behavior highlight the dual nature of content distribution on LinkedIn. Both professionals and organizations should be cautious of the shared content, acknowledging that their actions contribute to a larger public. AS the correlation between Active Engagement and sharing behavior suggests, supporting the sharing of more diverse and high-quality content can help build a more educated and engaged professional network. Such actions can be supported by platform developers through creation of features that facilitate the discovery and promotion of broader perspectives instead of reinforcing echo chambers. Furthermore, the relationship between social identity, sharing behavior, and engagement with challenging content suggests a potential for fostering professional development and learning. Platforms such as LinkedIn can develop features that promote exposure to a more diversified range of perspectives and support constructive debate on professional topics. For example, by implementing features that provide context for challenging content could help reduce polarization and support a more nuanced understanding of intricate problems.

The findings suggest that methods for managing GP within professional networks should address the underlying dynamics of social identity and sharing behavior. This could range from creation of community norms that encourage constructive interactions to providing users with resources and training on how to effectively engage in professional settings. Furthermore, platform developers and organizational leaders should be aware of algorithms potential influence on content exposure patterns and user behavior.

Lastly, given the continuous growth of SM platforms in terms of usage, popularity, and importance, there is an obvious need for research continuation. The presented thesis lays the groundwork for such discussions, providing insights that can enhance both the creation of platform features and organizational strategies targeted towards increasing professional involvement in online settings.

5.3. Limitations and future research suggestions

The findings of the proposed thesis can be concluded for the presented sample. As with other studies, the current research has several limitations, which will be addressed as follows:

First, the sample size is small compared to similar studies. While 177 observations are sufficient for a preliminary analysis, it poses constraints on the generalizability of the presented study. Additionally, the chosen cross-sectional design, which captures behaviors and views at a single point in time, limits the ability to determine causality or monitor how the presented dynamics change over time. Longitudinal research could provide more detailed insights into how social identity and sharing behavior changes over time, allowing for a better understanding on how they interact and affect GP.

Furthermore, as the study relies on self-reported metrics, it increases the probability of bias, as respondents' opinion of their activity may differ from their actual online behavior. Incorporating data provided by LinkedIn profiles, if available, could help address these issues and provide a better understanding of user engagement in future research.

When talking about the variables included in this study, while guided by theoretical and empirical foundations, they might not capture all the factors that influence engagement and polarization on LinkedIn. Future research should investigate a broader range of variables, including specific LinkedIn features like endorsements and groups, to gain a better understanding of the dynamics at play. Methodological challenges, such as the violation of the proportional odds assumption, highlight the complexity of modeling social behaviors. The forced deviation to multinomial logistic regression and generalized logistic regression, though methodologically sound, further highlight the given complexities and call for further investigation of alternative statistical methodologies that account for the nuanced character of the presented data.

Given the LinkedIn centric approach of this thesis, its findings may not be immediately applicable to other SM or professional networking platforms, which have differing user demographics and interaction patterns. A comparative study across platforms could reveal platform-specific vs universal determinants of professional polarization.

Finally, while the thesis indirectly acknowledges the impact of platform algorithms on content exposure and user behavior, the ambiguity of these algorithms restricts a deeper investigation. Future research collaborations between academia and industry may reveal mechanisms by which algorithmic selection impacts user experiences and contributes to group polarization.

6. Conclusion

To address the proposed research question "What is the role and what are the drivers of Group Polarization within professional groups on LinkedIn?", this thesis explores the intricacies of social identity and sharing behavior as key factors influencing the emergence and perception of group polarization within the professional networking platform LinkedIn. The findings provide detailed insights into how professional identity and engagement behaviors, based on SIT, contribute to the dynamics of group polarization within professional online networks. The significance of social identity for fostering engagement and shaping content interactions on LinkedIn is emphasized through the presented analysis. It provides support to the assumption that a strong sense of professional identity not only motivates active engagement but may also result in the creation of homogenous clusters dominated by shared professional values and perspectives. This, in turn, may result in a polarized environment in which opposing viewpoints are less noticeable or engaged with, emphasizing the importance of social identity in the facilitation or mitigation of group polarization.

Similarly, the study highlights sharing behavior as a significant driver of group polarization, given its ability to amplify content and perspectives that match the group's prevailing viewpoints. Such behavior highlights LinkedIn's interactive nature, in which users actively select and spread content that promotes their professional identity and group affiliations. Such dynamics can worsen group polarization by limiting exposure to diverse ideas and reinforcing existing beliefs.

The practical implications associated with the presented findings are significant for LinkedIn and its users. In order to mitigate the inherent tendency towards homogeneity and polarization, they propose measures that foster exposure to and engagement with various points of view. LinkedIn may need to fine-tune its algorithms and features in order to promote a broader range of content and interactions. Users, particularly professionals looking to use LinkedIn for career advancement purposes and networking, are encouraged to engage more thoughtfully with varied information and opinions, fostering a professional atmosphere that embraces diversity and open dialogue.

Given the presented limitations of this thesis, such as its sample size and scope, future research is essential in expanding existing understandings of group polarization within professional networks. Longitudinal studies or comparative analyses of various social media platforms may provide additional insights into the mechanics of group polarization and the role of digital platforms in shaping professional discourses.

In conclusion, the presented thesis enhances the understanding of the drivers of group polarization within professional groups on LinkedIn. It addresses the presented research question by emphasizing the importance of social identity and sharing behavior. This study adds to the existing research on managing and navigating professional interactions in digital spaces by providing theoretical and practical insights, with the goal of fostering a more inclusive and varied professional environment on LinkedIn.

References

Adebayo, J., Tiziana, M., Virdee, K., Friedman, C., & Yaneer, B.-Y. (2014). An exploration of social identity: The structure of the BBC news-sharing community on Twitter. *Complexity*, *19*(5), 55–63. https://doi.org/10.1002/cplx.21490

Agresti, A. (2010). *Analysis of Ordinal Categorical Data*. John Wiley & Sons.

Alexandra. (2022, August 25). *The Difference Between Social Media Platforms*. SocialBee. https://socialbee.com/blog/difference-between-social-media-platforms/

Alrubaian, M., & AL-Qurishi, M. (2019). Credibility in Online Social Networks: A Survey. *IEEE Access*, *7*, 2828.

APA Dictionary of Psychology. (n.d.). Retrieved July 8, 2023, from https://dictionary.apa.org/

APA Dictionary of Psychology. (2018). https://dictionary.apa.org/

Bail, C. A., Argyle, L. P., Brown, T. W., Bumpus, J. P., Chen, H., Hunzaker, M. B. F., Lee, J., Mann, M., Merhout, F., & Volfovsky, A. (2018). Exposure to opposing views on social media can increase political polarization. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(37), 9216–9221. https://doi.org/10.1073/pnas.1804840115

Balcells, J., & Padró-Solanet, A. (2016). Tweeting on Catalonia's Independence: The Dynamics of Political Discussion and Group Polarisation. *Medijske Studije*, *7*, 124–141. https://doi.org/10.20901/ms.7.14.9

Baldassarri, D., & Gelman, A. (2008). Partisans without constraint: Political polarization and trends in American public opinion. *American Journal of Sociology*, *114*(2), 408–446. https://doi.org/10.1086/590649

Barberá, P. (2014). *How Social Media Reduces Mass Political Polarization. Evidence from Germany, Spain, and the U.S.* https://www.semanticscholar.org/paper/How-Social-Media-Reduces-Mass-Political-Evidence-Barber%C3%A1/1b779a49db6b0a220e9a6195f7a278540fe101f6

Becker, J., Porter, E., & Centola, D. (2019). The wisdom of partisan crowds. *Proceedings of the National Academy of Sciences*, *116*(22), 10717–10722. https://doi.org/10.1073/pnas.1817195116

Bennett, W. L., & Iyengar, S. (2008). A New Era of Minimal Effects? The Changing Foundations of Political Communication. *Journal of Communication*, *58*(4), 707–731. https://doi.org/10.1111/j.1460-2466.2008.00410.x

Bessi, A., Petroni, F., Vicario, M. D., Zollo, F., Anagnostopoulos, A., Scala, A., Caldarelli, G., & Quattrociocchi, W. (2016a-10-01). Homophily and polarization in the age of misinformation. *The European Physical Journal Special Topics*, *225*(10), 2047–2059. https://doi.org/10.1140/epjst/e2015-50319-0

Bessi, A., Zollo, F., Vicario, M. D., Puliga, M., Scala, A., Caldarelli, G., Uzzi, B., & Quattrociocchi, W. (23 Aug 2016b). Users Polarization on Facebook and Youtube. *PLOS ONE*, *11*(8), e0159641. https://doi.org/10.1371/journal.pone.0159641

Boxell, L., Gentzkow, M., & Shapiro, J. M. (2017). Greater Internet use is not associated with faster growth in political polarization among US demographic groups. *Proceedings of the National Academy of Sciences*, *114*(40), 10612–10617. https://doi.org/10.1073/pnas.1706588114

Brady, W. J., Wills, J. A., Jost, J. T., Tucker, J. A., & Van Bavel, J. J. (2017). Emotion shapes the diffusion of moralized content in social networks. *Proceedings of the National Academy of Sciences*, *114*(28), 7313–7318. https://doi.org/10.1073/pnas.1618923114

Brown, P., & Levinson, S. C. (1987). *Politeness: Some universals in language usage* (pp. xiv, 345). Cambridge University Press.

Chi, Y.-Y. (2012). Multivariate methods. *WIREs Computational Statistics*, *4*(1), 35–47. https://doi.org/10.1002/wics.185

Colman, A. M. (2015). Group polarization. In *A Dictionary of Psychology*. Oxford University Press. https://www.oxfordreference.com/display/10.1093/acref/9780199657681.001.0001/acref-9780199657681-e-3624

Conover, M. D., Ratkiewicz, J., Francisco, M., Gonçalves, B., Flammini, A., & Menczer, F. (2011). *Political Polarization on Twitter*. 89–96. Scopus.

Creswell_Research_Design_ Qualitative, Quantitative, and Mixed Methods Approaches (2018) 5th Ed.pdf. (n.d.). Retrieved February 22, 2024, from https://www.docdroid.net/XAQ0IXz/creswell-research-design-qualitative-quantitative-and-mixed-methods-approaches-2018-5th-ed-pdf

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, *16*(3), 297–334. https://doi.org/10.1007/BF02310555

Degenhard, J. (n.d.). *Global: Number of LinkedIn users 2018-2027*. Statista. Retrieved January 23, 2024, from https://www.statista.com/forecasts/1147197/linkedin-users-in-the-world

Del Vicario, M., Bessi, A., Zollo, F., Petroni, F., Scala, A., Caldarelli, G., Stanley, H. E., & Quattrociocchi, W. (2016). The spreading of misinformation online. *Proceedings of the National Academy of Sciences*, *113*(3), 554–559. https://doi.org/10.1073/pnas.1517441113

Dholakia, U. M., Bagozzi, R. P., & Pearo, L. K. (2004). A social influence model of consumer participation in network- and small-group-based virtual communities. *International Journal of Research in Marketing*, *21*(3), 241–263. https://doi.org/10.1016/j.ijresmar.2003.12.004

Druckman, J. N., & Levendusky, M. S. (2019). What Do We Measure When We Measure Affective Polarization? *Public Opinion Quarterly*, *83*(1), 114–122. https://doi.org/10.1093/poq/nfz003

Druckman, J. N., Levendusky, M. S., & McLain, A. (2018). No Need to Watch: How the Effects of Partisan Media Can Spread via Interpersonal Discussions. *American Journal of Political Science*, *62*(1), 99–112. https://doi.org/10.1111/ajps.12325

Dubois, E., & Blank, G. (2018). The echo chamber is overstated: The moderating effect of political interest and diverse media. *Information, Communication & Society*, *21*(5), 729–745. https://doi.org/10.1080/1369118X.2018.1428656

Ellemers, N. (1993). The Influence of Socio-structural Variables on Identity Management Strategies. *European Review of Social Psychology*, *4*(1), 27–57. https://doi.org/10.1080/14792779343000013

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods*, *4*(3), 272–299. https://doi.org/10.1037/1082-989X.4.3.272

Festinger, L. (1954). A Theory of Social Comparison Processes. *Human Relations*, *7*(2), 117–140. https://doi.org/10.1177/001872675400700202

Gaertner, S. L., & Dovidio, J. F. (2000). *Reducing intergroup bias: The common ingroup identity model* (pp. xiii, 212). Psychology Press.

Garrett, R. K. (2009). Echo chambers online?: Politically motivated selective exposure among Internet news users1. *Journal of Computer-Mediated Communication*, *14*(2), 265–285. https://doi.org/10.1111/j.1083-6101.2009.01440.x

Garrett, R. K., Gvirsman, S. D., Johnson, B. K., Tsfati, Y., Neo, R., & Dal, A. (2014). Implications of pro- and Counterattitudinal Information Exposure for Affective Polarization. *Human Communication Research*, *40*(3), 309–332. https://doi.org/10.1111/hcre.12028

Gentzkow, M., & Shapiro, J. M. (2011). Ideological Segregation Online and Offline *. *The Quarterly Journal of Economics*, *126*(4), 1799–1839. https://doi.org/10.1093/qje/qjr044

Ghaisani, A. P., Handayani, P. W., & Munajat, Q. (2017). Users' Motivation in Sharing Information on Social Media. *Procedia Computer Science*, *124*, 530–535. https://doi.org/10.1016/j.procs.2017.12.186

Giese, H., Neth, H., Moussaïd, M., Betsch, C., & Gaissmaier, W. (2020). The echo in flu-vaccination echo chambers: Selective attention trumps social influence. *Vaccine*, *38*(8), 2070–2076. https://doi.org/10.1016/j.vaccine.2019.11.038

Guerra, P., Nalon, R., Assunção, R., & Jr, W. M. (2017). Antagonism Also Flows Through Retweets: The Impact of Out-of-Context Quotes in Opinion Polarization Analysis. *Proceedings of the International AAAI Conference on Web and Social Media*, *11*(1), Article 1. https://doi.org/10.1609/icwsm.v11i1.14971

Gürbüz, S. (2017). *Survey as a Quantitative Research Method*.

Hall, S. (1973). *Encoding and decoding in the television discourse | 35 | CCCS Selected*. https://www.taylorfrancis.com/chapters/edit/10.4324/9780203357071-35/encoding-decoding-television-discourse-stuart-hall

Hirschman, A. O. (1970). *Exit, voice, and loyalty: Responses to decline in firms, organizations and states*.

Huddy, L. (2013). From group identity to political cohesion and commitment. In *The Oxford handbook of political psychology, 2nd ed* (pp. 737–773). Oxford University Press.

Hughes, J. L., Camden, A. A., Yangchen, T., Smith, G. P. A., Domenech Rodríguez, M. M., Rouse, S. V., McDonald, C. P., & Lopez, S. (2022). INVITED EDITORIAL: Guidance for Researchers When Using Inclusive Demographic Questions for Surveys: Improved and Updated Questions. *Psi Chi Journal of Psychological Research*, *27*(4), 232–255. https://doi.org/10.24839/2325-7342.JN27.4.232

Iandoli, L., Primario, S., & Zollo, G. (2021). The impact of group polarization on the quality of online debate in social media: A systematic literature review. *Technological Forecasting and Social Change*, *170*, 120924. https://doi.org/10.1016/j.techfore.2021.120924

Isenberg, D. J. (1986). *Group Polarization: A Critical Review and Meta-Analysis*.

Iyengar, S., & Hahn, K. S. (2009). Red Media, Blue Media: Evidence of Ideological Selectivity in Media Use. *Journal of Communication*, *59*(1), 19–39. https://doi.org/10.1111/j.1460-2466.2008.01402.x

Jayles, B., Escobedo, R., Pasqua, R., Zanon, C., Blanchet, A., Roy, M., Tredan, G., Theraulaz, G., & Sire, C. (2020). Collective information processing in human phase separation. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *375*(1807), 20190801. https://doi.org/10.1098/rstb.2019.0801

Johnson, T. J., Kaye, B. K., & Lee, A. M. (2017). Blinded by the Spite? Path Model of Political Attitudes, Selectivity, and Social Media. *Atlantic Journal of Communication*, *25*(3), 181–196. https://doi.org/10.1080/15456870.2017.1324454

Kim, M., Jun, M., & Han, J. (2022). The relationship between needs, motivations and information sharing behaviors on social media: Focus on the self-connection and social connection. *Asia Pacific Journal of Marketing and Logistics*, *35*(1), 1–16. https://doi.org/10.1108/APJML-01-2021-0066

Kim, Y., & Kim, Y. (2019). Incivility on Facebook and political polarization: The mediating role of seeking further comments and negative emotion. *Computers in Human Behavior*, *99*, 219–227. https://doi.org/10.1016/j.chb.2019.05.022

King, G., Keohane, R. O., & Verba, S. (1994). *Designing Social Inquiry: Scientific Inference in Qualitative Research* (STU-Student edition). Princeton University Press. https://www.jstor.org/stable/j.ctt7sfxj

Kligler-Vilenchik, N., Baden, C., & Yarchi, M. (2020). Interpretative Polarization across Platforms: How Political Disagreement Develops Over Time on Facebook, Twitter, and WhatsApp. *Social Media + Society*, *6*(3), 2056305120944393. https://doi.org/10.1177/2056305120944393

Kuang, C., & Fabricant, R. (2019). *User Friendly: How the Hidden Rules of Design are Changing the Way We Live, Work & Play*. Random House.

Lai, M., Tambuscio, M., Patti, V., Ruffo, G., & Rosso, P. (2019). Stance polarity in political debates: A diachronic perspective of network homophily and conversations on Twitter. *Data & Knowledge Engineering*, *124*, 101738. https://doi.org/10.1016/j.datak.2019.101738

Lapin, N. (2011, May 23). *LinkedIn CEO: The Forgotten Interview*. CNBC. https://www.cnbc.com/2011/05/23/linkedin-ceo-the-forgotten-interview.html

Lee, J. K., Choi, J., Kim, C., & Kim, Y. (2014). Social Media, Network Heterogeneity, and Opinion Polarization. *Journal of Communication*, *64*(4), 702–722. https://doi.org/10.1111/jcom.12077

Lin, X., Sarker, S., & Featherman, M. (2019). Users' Psychological Perceptions of Information Sharing in the Context of Social Media: A Comprehensive Model.

International Journal of Electronic Commerce, *23*(4), 453–491. https://doi.org/10.1080/10864415.2019.1655210

McCullagh, P. (1980). Regression Models for Ordinal Data. *Journal of the Royal Statistical Society. Series B (Methodological)*, *42*(2), 109–142.

Measuring Affective Polarization of Online Topic-Based Communities: A Computational Study of Collective Anxiety on Weibo. (n.d.). JMIR Preprints. Retrieved January 25, 2024, from https://preprints.jmir.org/preprint/25702

Mercier, H., & Sperber, D. (2011). Why do humans reason? Arguments for an argumentative theory. *Behavioral and Brain Sciences*, *34*(2), 57–74. Scopus. https://doi.org/10.1017/S0140525X10000968

Montano, D. (2017). *Multivariate hierarchical Bayesian models and choice of priors in the analysis of survey data*. https://www.tandfonline.com/doi/epdf/10.1080/02664763.2016.1267120?needAccess=true

Moscovici, S., & Zavalloni, M. (1969). The group as a polarizer of attitudes. *Journal of Personality and Social Psychology*, *12*(2), 125–135. https://doi.org/10.1037/h0027568

Myers, D. G., & Lamm, H. (n.d.). *The Group Polarization Phenomenon*.

Paravati, E., Naidu, E., Gabriel, S., & Wiedemann, C. (2020). More than just a tweet: The unconscious impact of forming parasocial relationships through social media. *Psychology of Consciousness: Theory, Research, and Practice*, *7*(4), 388–403. https://doi.org/10.1037/cns0000214

Pariser, E. (2011). The Filter Bubble: What the Internet is Hiding from You. *Penguin UK*. https://www.academia.edu/34426834/The_Filter_Bubble_Eli_Pariser

Peralta, A. F., Neri, M., Kertész, J., & Iñiguez, G. (2021). Effect of algorithmic bias and network structure on coexistence, consensus, and polarization of opinions. *Physical Review E*, *104*(4), 044312. https://doi.org/10.1103/PhysRevE.104.044312

Powers, E., Koliska, M., & Guha, P. (2019). “Shouting Matches and Echo Chambers”: Perceived Identity Threats and Political Self-Censorship on Social Media. *International Journal of Communication*. https://www.semanticscholar.org/paper/%E2%80%9CShouting-Matches-and-Echo-Chambers%E2%80%9D%3A-Perceived-and-Powers-Koliska/3e3c878fd938028e37fae5a394f24c5c8a343756

Primario, S., Borrelli, D., Iandoli, L., Zollo, G., & Lipizzi, C. (2017). Measuring Polarization in Twitter Enabled in Online Political Conversation: The Case of 2016 US Presidential

Election. *2017 IEEE International Conference on Information Reuse and Integration (IRI)*, 607–613. https://doi.org/10.1109/IRI.2017.73

Prior, M. (2007). *Post-Broadcast Democracy: How Media Choice Increases Inequality in Political Involvement and Polarizes Elections*. Cambridge University Press.

Prior, M. (2013). Media and Political Polarization. *Annual Review of Political Science*, *16*(1), 101–127. https://doi.org/10.1146/annurev-polisci-100711-135242

Raice, S. (2011, September 19). LinkedIn CEO Tries to Look Past Valuation. *Wall Street Journal*. http://online.wsj.com/article/SB10001424053111903895904576546700522834810.html

Rainie, H., Rainie, L., & Wellman, B. (2012). *Networked: The New Social Operating System*.

Romenskyy, M., Spaiser, V., Ihle, T., & Lobaskin, V. (2018). Polarized Ukraine 2014: Opinion and territorial split demonstrated with the bounded confidence XY model, parametrized by Twitter data. *Royal Society Open Science*, *5*(8), 171935. https://doi.org/10.1098/rsos.171935

Schmidt, A. L., Peruzzi, A., Scala, A., Cinelli, M., Pomerantsev, P., Applebaum, A., Gaston, S., Fusi, N., Peterson, Z., Severgnini, G., De Cesco, A. F., Casati, D., Novak, P. K., Stanley, H. E., Zollo, F., & Quattrociocchi, W. (2020). Measuring social response to different journalistic techniques on Facebook. *Humanities and Social Sciences Communications*, *7*(1), Article 1. https://doi.org/10.1057/s41599-020-0507-3

Settle, J. E. (2019). *Frenemies: How Social Media Polarizes America*. Cambridge University Press.

Shearer, E. (2018). *Social media outpaces print newspapers in the U.S. as a news source*. https://policycommons.net/artifacts/617003/social-media-outpaces-print-newspapers-in-the-us/1597739/

Social media. (n.d.). Retrieved July 8, 2023, from https://dictionary.cambridge.org/dictionary/english/social-media

Statista. (2023). *Number of worldwide social network users 2027*. Statista. https://www.statista.com/statistics/278414/number-of-worldwide-social-network-users/

Stieglitz, S., & Dang-Xuan, L. (2013). Emotions and Information Diffusion in Social Media—Sentiment of Microblogs and Sharing Behavior. *Journal of Management Information Systems*, *29*, 217–248. https://doi.org/10.2753/MIS0742-1222290408

Stoner, J. A. F. (1961). *A comparison of individual and group decisions involving risk* [Master's Thesis, Massachusetts Institute of Technology]. https://dspace.mit.edu/bitstream/handle/1721.1/11330/33120544-MIT.pdf

Stroud, N. J. (2010). Polarization and Partisan Selective Exposure. *Journal of Communication*, *60*(3), 556–576. https://doi.org/10.1111/j.1460-2466.2010.01497.x

Suler, J. (2004). The Online Disinhibition Effect. *Cyberpsychology & Behavior : The Impact of the Internet, Multimedia and Virtual Reality on Behavior and Society*, *7*, 321–326. https://doi.org/10.1089/1094931041291295

Sunstein, C. R. (1999). *The Law of Group Polarization*. https://chicagounbound.uchicago.edu/law_and_economics/542/

Sunstein, C. R. (2002). On a Danger of Deliberative Democracy. *Daedalus*, *131*(4), 120–124.

Tajfel, H. (1978). The achievement of inter-group differentiation. In *Differentiation between social groups* (pp. 77–100). London: Academic Press.

Tajfel, H., & Turner, J. C. (1979). An integrative theory of intergroup conflict. In *The social psychology of intergroup relations* (p. (pp. 33-37).). Brooks/Cole.

Tajfel, H., & Turner, J. C. (1986). *The Social Identity Theory of Intergroup Behavior* (p. 293). https://doi.org/10.4324/9780203505984-16

Thompson, N., Wang, X., & Daya, P. (2020). Determinants of News Sharing Behavior on Social Media. *Journal of Computer Information Systems*, *60*(6), 593–601. https://doi.org/10.1080/08874417.2019.1566803

Törnberg, P. (2018). Echo chambers and viral misinformation: Modeling fake news as complex contagion. *PLOS ONE*, *13*(9), e0203958. https://doi.org/10.1371/journal.pone.0203958

Turner, J., & Brown, R. J. (1976). *Social status, cognitive alternatives, and intergroup relations: (668292012-213)*. https://www.semanticscholar.org/paper/Social-status%2C-cognitive-alternatives%2C-and-Turner-Brown/e7a3b5a39d637ed8d1531fc40db0762811ffb274

Turner, J. C. (1981). Towards a cognitive redefinition of the social group. *Cahiers de Psychologie Cognitive/Current Psychology of Cognition*, *1*(2), 93–118.

Valensise, C. M., Cinelli, M., Nadini, M., Galeazzi, A., Peruzzi, A., Etta, G., Zollo, F., Baronchelli, A., & Quattrociocchi, W. (2024). *Reply to "Comment on The COVID-19 infodemic does not affect vaccine acceptance"*. https://doi.org/10.31219/osf.io/sxd5t

Van Zomeren, M., Postmes, T., & Spears, R. (2008). Toward an integrative social identity model of collective action: A quantitative research synthesis of three socio-psychological perspectives. *Psychological Bulletin*, *134*(4), 504–535. https://doi.org/10.1037/0033-2909.134.4.504

Wang, Z., Chen, C., & Li, W. (2022). Joint Learning of User Representation With Diffusion Sequence and Network Structure. *IEEE Transactions on Knowledge and Data Engineering*, *34*(3), 1275–1287. https://doi.org/10.1109/TKDE.2020.2995075

Weber, I., Garimella, V. R. K., & Batayneh, A. (2013). Secular vs. Islamist polarization in Egypt on Twitter. *Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, 290–297. https://doi.org/10.1145/2492517.2492557

Yardi, S., & Boyd, D. (2010). Dynamic Debates: An Analysis of Group Polarization Over Time on Twitter. *Bulletin of Science, Technology & Society*, *30*(5), 316–327. https://doi.org/10.1177/0270467610380011

Zollo, F. (2019). Dealing with digital misinformation: A polarised context of narratives and tribes. *EFSA Journal*, *17*(S1), e170720. https://doi.org/10.2903/j.efsa.2019.e170720

Appendix A: Survey Questions

Dear participant,

my name is Andreea Simina Fernea and I am currently enrolled as a Business Administration Master's degree student at the University of Vienna. As part of my Master Thesis on the topic of group polarization in Social Media, I have developed the following online survey, which aims to provide new insights into the phenomenon of group polarization within LinkedIn networks. Please note that this survey is intended for individuals who actively use LinkedIn for professional networking purposes. Your insights as a LinkedIn user are valuable in this study.

The survey will only take 5 minutes to complete. All your answers are provided anonymously and no personal data will be saved.

Thank you very much for taking the time to complete this survey and for helping me complete my research!

*Do you use LinkedIn?

○ No ○ Yes

Next page >

*What is your age?

○ 18-25

○ 26-35

○ 36-45

○ 46-55

○ 55+

Next page >

* Which of the following best describes your gender identity?

- ◯ Male
- ◯ Female
- ◯ Other
- ◯ Prefer not to say

Next page >

* In which country do you currently live in?

Select one

Next page >

* What is the highest degree or level of education that you have completed?

- ◯ High school degree or equivalent
- ◯ Bachelor's degree or equivalent
- ◯ Master's degree or equivalent
- ◯ PhD or equivalent

Next page >

* In which field/industry are you currently employed?

- ◯ Construction & Real Estate
- ◯ Financial & Insurance activities
- ◯ Industry
- ◯ Information Technology & Communication
- ◯ Public Administration, Defence, Education, Human Health and Social Work
- ◯ Wholesale & Retail Trade, Transportation, Accommodation & Food
- ◯ Other

Next page >

* What is your level of professional experience in the field?

◯ Beginner (< 1 year)

◯ Intermediate (1-5 years)

◯ Advanced/Expert (> 5 years)

Next page >

* Please answer the following questions regarding your connection to LinkedIn:

	Not at all	Slightly	Somewhat	Moderately	Neutral	Considerably	Very much
Please indicate to what degree your self-image overlaps with the identity of your LinkedIn network as you perceive it:	◯	◯	◯	◯	◯	◯	◯
How would you express the degree of overlap between your personal identity and the identity of the group mentioned above when you are actually part of the group and engaging in group activities?	◯	◯	◯	◯	◯	◯	◯

Next page >

* Please answer the following questions regarding your relationship to your LinkedIn network:

	Not at all	Slightly	Somewhat	Moderately	Neutral	Considerably	Very much
How attached are you to your LinkedIn Network?	◯	◯	◯	◯	◯	◯	◯
How strong would you say your feelings of belongingness are towards your LinkedIn network?	◯	◯	◯	◯	◯	◯	◯

Next page >

* On average, I use LinkedIn...

hours per week (please estimate)

times per week (please estimate)

Next page

* Please rate the frequency with which you use LinkedIn for the following activities:

	Never	Rarely	Once per month	Once per week	Multiple times a week	Daily
I use LinkedIn to get news	○	○	○	○	○	○
I use LinkedIn to post news	○	○	○	○	○	○
I use LinkedIn to talk about industry specific topics	○	○	○	○	○	○
I use LinkedIn to talk about politics	○	○	○	○	○	○
I use LinkedIn to share news about industry specific topics	○	○	○	○	○	○
I use LinkedIn to share news about politics	○	○	○	○	○	○

Next page

* Please indicate how often you use the following social media platforms

	Never	Rarely	Once per month	Once per week	Multiple times a week	Daily
Facebook	○	○	○	○	○	○
Instagram	○	○	○	○	○	○
Twitter	○	○	○	○	○	○
Snapchat	○	○	○	○	○	○
Reddit	○	○	○	○	○	○
YouTube	○	○	○	○	○	○

Next page

* Generally speaking, when it comes to political views, where do you position yourself on a spectrum from more progressive/liberal to more conservative?

- ◯ Very progressive/ Liberal
- ◯ Moderately progressive/ Liberal
- ◯ Slightly progressive/ Liberal
- ◯ Neutral
- ◯ Slightly conservative
- ◯ Moderately conservative
- ◯ Very conservative

Next page >

* Would you say your LinkedIn feed primarily consists of content that aligns with your own viewpoints or includes diverse perspectives and contrasting opinions?

- ◯ Mostly aligns
- ◯ Balanced mix
- ◯ Mostly diverse perspectives
- ◯ Unsure

Next page >

* How often do you come across content on LinkedIn that challenges your viewpoints and prompts you to reconsider or rethink your opinions?

- ◯ Very often
- ◯ Often
- ◯ Occasionally
- ◯ Rarely
- ◯ Never

Next page >

* When you come across topics or opinions on LinkedIn that you strongly disagree with, how do you typically respond or act? Please rate the frequency of your actions:

	Never	Sometimes	About half the time	Most of the time	Always
Engage in Constructive Dialogue: Attempt to engage in a respectful conversation to understand differing viewpoints.	○	○	○	○	○
Scroll Past or Ignore: Choose not to interact or engage with the content and continue browsing.	○	○	○	○	○
Express Dissent or Disagreement: Share your viewpoint or disagreement in a polite manner.	○	○	○	○	○
Unfollow or Hide Content: Take actions to hide or unfollow sources of content that consistently share opposing views.	○	○	○	○	○
Report or Flag Content: Report or flag content that appears offensive, inappropriate, or violates community guidelines.	○	○	○	○	○

Next page >

Thank you for your time and valuable insights in completing this survey for my Masters thesis.
Your contribution is immensely appreciated!

Your response has been registered.

For SurveyCircle users (www.surveycircle.com): The Survey Code is: QZ5C-DUMK-FPSP-MCCH

Appendix B: Descriptive Statistics

Age Group	Frequency	Percent	Cumulative Percent
18-25	33	19	19
26-35	83	47	66
36-45	29	16	82
46-55	23	13	95
55+	9	5	100
Total	177	100	

Table B 1 - Frequency distribution of Age

Gender	Frequency	Percent	Cumulative Percent
Male	72	41	41
Female	105	59	100
Other	0	0	-
Prefer not to say	0	0	-
Total	177	100	

Table B 2 - Frequency distribution of Gender

Country	Frequency	Percent	Cumulative Percent
Austria	67	37,9	37,9
Romania	64	36,2	74
Germany	19	10,7	84,7
Croatia	4	2,3	87
Netherlands	4	2,3	89,3
Canada	3	1,7	91
Hungary	3	1,7	92,7
United Kingdom	3	1,7	94,4
Italy	2	1,1	95,5
Bosnia Herzegovina	1	0,6	96
India	1	0,6	96,6
Latvia	1	0,6	97,2
Philippines	1	0,6	97,7
Poland	1	0,6	98,3
Portugal	1	0,6	98,9
Switzerland	1	0,6	99,4
United States	1	0,6	100
Total	177	100	

Table B 3 - Participants distribution by Country

Degree/Education level	Frequency	Percent	Cumulative Percent
High school degree or equivalent	15	8,5	8,5
Bachelor’s degree or equivalent	65	36,7	45,2
Master’s degree or equivalent	83	46,9	92,1
PhD or equivalent	14	7,9	100
Total	177	100	

Table B 4 - Participants distribution by education level

Industry	Frequency	Percent	Cumulative Percent
Construction & Real Estate	14	7,9	7,9
Financial & Insurance activities	26	14,7	22,6
Industry	14	7,9	30,5
Information Technology & Communication	48	27,1	57,6
Public Administration, Defence, Education, Human Health and Social Work	27	15,3	72,9
Wholesale & Retail Trade, Transportation, Accommodation & Food	7	4,0	76,8
Other	41	23,2	100
Total	177	100	

Table B 5 - Participants distribution by Industry

Experience Level	Frequency	Percent	Cumulative Percent
Beginner (<1 year)	24	13,6	13,6
Intermediate (1-5 years)	69	39	52,5
Advanced/Expert (> 5 years)	84	47,5	100
Total	177	100	

Table B 6 - Participants distribution by experience level

Appendix C: Regression Results

Factor analysis/correlation Number of obs = 177
Method: principal factors Retained factors = 2
Rotation: orthogonal varimax (Kaiser off) Number of params = 9

Factor	Variance	Difference	Proportion	Cumulative
Factor1	0.968	0.136	0.792	0.792
Factor2	0.833	.	0.681	1.472

LR test: independent vs. saturated: chi2(10) = 132.35 Prob>chi2 = 0.0000
Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
Constructive_Dialogue	0.648	0.053	0.577
Scroll_Past	-0.394	0.315	0.745
Disagreement	0.579	0.277	0.588
Unfollow	0.033	0.574	0.669
Report	0.238	0.569	0.619

Factor rotation matrix

	Factor1	Factor2
Factor1	0.802	0.597
Factor2	-0.597	0.802

Table C 1 - Factor Analysis for Constructive Dialogue, Scroll Past, Disagreement, Unfollow, and Report

type_of_content	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
SocialIdentity_std	.156	.087	1.79	.076	-.016	.328	*
SharingBehavior_std	-.042	.087	-0.48	.629	-.214	.13	
Constant	2.746	.073	37.38	0	2.601	2.891	***

Mean dependent var	2.746	SD dependent var	0.982
R-squared	0.020	Number of obs	177
F-test	1.751	Prob > F	0.177
Akaike crit. (AIC)	497.175	Bayesian crit. (BIC)	506.703

**** $p<.01$, ** $p<.05$, * $p<.1$*

Table C 2 - Linear Regression for Model 1.1

Variable	VIF	1/VIF
Sharing Behavior	1.400	0.714
Social Identity	1.400	0.714
Mean VIF	1.400	

Table C 3 - VIF results for Model 1.1

```
note: pol_view6 omitted because of collinearity.
Iteration 0:  Log likelihood = -227.10789
Iteration 1:  Log likelihood = -221.44166
Iteration 2:  Log likelihood =  -221.4005
Iteration 3:  Log likelihood = -221.40049

Ordered logit estimates                         Number of obs   =       177
                                        LR chi2(8)      =      11.41
                                        Prob > chi2     =     0.1793
Log likelihood = -221.40049                     Pseudo R2       =     0.0251

------------------------------------------------------------------------------
type_of_co~t | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
SocialIden~d |   .2977392   .1710878     1.74   0.082    -.0375867    .6330651
SharingBeh~d |   .0842063   .1895878     0.44   0.657     -.287379    .4557915
   pol_view1 |   .8251644   .8343597     0.99   0.323    -.8101505    2.460479
   pol_view2 |   .9906436   .6721678     1.47   0.141    -.3267811    2.308068
   pol_view3 |    .608009   .6801605     0.89   0.371    -.7250811    1.941099
   pol_view4 |   .3967031   .7713113     0.51   0.607    -1.115039    1.908445
   pol_view5 |  -.0821426   .7270705    -0.11   0.910    -1.507175    1.342889
   pol_view7 |   .4883116   1.720984     0.28   0.777    -2.884755    3.861378
-------------+----------------------------------------------------------------
       _cut1 |  -1.141144   .6355566          (Ancillary parameters)
       _cut2 |  -.1674433   .6238664
       _cut3 |   1.912459   .6425001
------------------------------------------------------------------------------

Approximate likelihood-ratio test of proportionality of odds
across response categories:
         chi2(13) =     34.02
       Prob > chi2 =    0.0012
```

Figure C 1 - Omodel result (Stata Output)

type_of_content	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
SocialIdentity_std	.641	.174	-1.63	.102	.376	1.092	
SharingBehavior_std	1.478	.358	1.61	.107	.919	2.377	
Constant	.336	.077	-4.76	0	.214	.526	***
SocialIdentity_std	.649	.187	-1.50	.133	.369	1.14	
SharingBehavior_std	.219	.102	-3.26	.001	.088	.546	***
Constant	.179	.063	-4.87	0	.09	.358	***
o	1	.	.	.	.	.	
o	1	.	.	.	.	.	
o	1	.	.	.	.	.	
SocialIdentity_std	.887	.206	-0.51	.608	.563	1.4	
SharingBehavior_std	1.042	.246	0.17	.862	.656	1.655	
Constant	.507	.099	-3.48	.001	.345	.743	***
Mean dependent var		2.746	SD dependent var			0.982	
Pseudo r-squared		0.076	Number of obs			177	
Chi-square		34.316	Prob > chi2			0.000	
Akaike crit. (AIC)		437.899	Bayesian crit. (BIC)			466.485	

*** *p<.01*, ** *p<.05*, * *p<.1*

Table C 4 - Multinomial Logistic regression for Model 1.1

type_of_content	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
SocialIdentity_std	.638	.182	-1.57	.116	.365	1.117	
SharingBehavior_std	1.462	.401	1.38	.166	.854	2.503	
Political View : b~r	1	.	.	.	.	.	
Moderately progres~l	.697	.677	-0.37	.71	.104	4.677	
Slightly progressi~l	.738	.704	-0.32	.75	.114	4.792	
Neutral	.724	.852	-0.27	.783	.072	7.265	
Slightly conservat~e	2.827	2.793	1.05	.293	.407	19.609	
Moderately conserv~e	.861	1.146	-0.11	.91	.063	11.702	
Very conservative	0	.003	-0.01	.988	0	.	
Constant	.347	.298	-1.23	.218	.064	1.867	
SocialIdentity_std	.63	.186	-1.57	.117	.353	1.122	
SharingBehavior_std	.217	.107	-3.10	.002	.083	.57	***
Political View : b~r	1	.	.	.	.	.	
Moderately progres~l	2.235	2.168	0.83	.407	.334	14.966	
Slightly progressi~l	.98	.982	-0.02	.984	.137	6.985	
Neutral	1.692	1.971	0.45	.652	.172	16.595	
Slightly conservat~e	1.477	1.714	0.34	.737	.152	14.355	
Moderately conserv~e	1.199	1.957	0.11	.912	.049	29.392	
Very conservative	0	.127	-0.01	.992	0	.	
Constant	.114	.109	-2.26	.024	.017	.747	**
o	1	.	.	.	.	.	
o	1	.	.	.	.	.	
Political View : b~r	1	.	.	.	.	.	
2o	1	.	.	.	.	.	
3o	1	.	.	.	.	.	
4o	1	.	.	.	.	.	
5o	1	.	.	.	.	.	
6o	1	.	.	.	.	.	
7o	1	.	.	.	.	.	
o	1	.	.	.	.	.	
SocialIdentity_std	.858	.206	-0.64	.522	.536	1.373	
SharingBehavior_std	1.24	.334	0.80	.425	.731	2.101	
Political View : b~r	1	.	.	.	.	.	
Moderately progres~l	1.407	1.122	0.43	.669	.295	6.717	
Slightly progressi~l	.513	.432	-0.79	.428	.099	2.671	
Neutral	.419	.457	-0.80	.425	.05	3.55	
Slightly conservat~e	.932	.867	-0.08	.939	.15	5.776	
Moderately conserv~e	.265	.377	-0.93	.351	.016	4.323	
Very conservative	0	.002	-0.02	.986	0	.	
Constant	.594	.438	-0.71	.48	.14	2.521	

Mean dependent var	2.746	SD dependent var		0.982
Pseudo r-squared	0.111	Number of obs		177
Chi-square	50.581	Prob > chi2		0.001
Akaike crit. (AIC)	457.635	Bayesian crit. (BIC)		543.391

*** *p<.01, *** *p<.05, ** *p<.1*

Table C 5 - Multinomial Logistic regression for Model 1.2

Linear regression

challenging_content	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
SocialIdentity_std	-.145	.075	-1.95	.053	-.292	.002	*
SharingBehavior_std	-.206	.074	-2.76	.006	-.353	-.059	***
SMUse_std	-.075	.066	-1.14	.257	-.205	.055	
Professional Exper~B	0	.	.	.	.	.	
Intermediate	.223	.213	1.05	.295	-.197	.643	
Advanced	.322	.246	1.31	.192	-.164	.808	
Age : base 18-25	0	.	.	.	.	.	
26-35	-.144	.188	-0.77	.445	-.514	.227	
36-45	.402	.269	1.50	.136	-.128	.932	
46-55	-.063	.276	-0.23	.819	-.608	.482	
55+	.596	.36	1.65	.1	-.115	1.307	
Constant	3.22	.18	17.84	0	2.864	3.576	***

Mean dependent var	3.480	SD dependent var	0.892
R-squared	0.205	Number of obs	177
F-test	4.790	Prob > F	0.000
Akaike crit. (AIC)	440.382	Bayesian crit. (BIC)	472.143

**** $p<.01$, ** $p<.05$, * $p<.1$*

Table C 6 - Linear regression for Model 2.1

Variable	VIF	1/VIF
Social Identity	1.460	0.683
Sharing Behavior	1.460	0.685
SM Use	1.150	0.870
~~Professional Experience~~		
2	2.850	0.350
3	4.000	0.250
~~Age~~		
2	2.330	0.430
3	2.620	0.382
4	2.290	0.437
5	1.660	0.602
Mean VIF	2.200	

Table C 7 - VIF results for Model 2.1

Ordered logistic regression

challenging_content	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
SocialIdentity_std	.804	.135	-1.30	.194	.579	1.117	
SharingBehavior_std	.623	.111	-2.66	.008	.44	.883	***
cut1	-4.239	.59	.b	.b	-5.395	-3.083	
cut2	-2.19	.247	.b	.b	-2.674	-1.707	
cut3	.05	.155	.b	.b	-.254	.354	
cut4	2.064	.234	.b	.b	1.605	2.523	

Mean dependent var	3.480	SD dependent var	0.892
Pseudo r-squared	0.036	Number of obs	177
Chi-square	16.525	Prob > chi2	0.000
Akaike crit. (AIC)	451.267	Bayesian crit. (BIC)	470.324

*** *p<.01*, ** *p<.05*, * *p<.1*

Table C 8 - Ordered Logistic Regression results for Model 2.1

Goodness of fit for Model 2		
Log-likelihood		
Model	-219.634	
Intercept-only	-227.896	
Chi-square		
Deviance(df=171)	439.267	
LR(df=2)	16.525	
p-value		0.000
R2		
McFadden		0.036
McFadden(adjusted)		0.010
McKelvey & Zavoina		0.104
Cox-Snell/ML		0.089
Cragg-Uhler/Nagelkerke		0.096
Count		0.418
Count(adjusted)		0.028
IC		
AIC	451.267	
AIC divided by N		2.550
BIC(df=6)	470.324	
Variance of		
e		3.290
y-star		3.672

Table C 9 - Goodness of fit measures for Model 2.1

Ordered logistic regression

challenging_content	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
SocialIdentity_std	.681	.122	-2.14	.032	.479	.968	**
SharingBehavior_std	.601	.11	-2.78	.006	.42	.861	***
SMUse_std	.813	.125	-1.34	.179	.602	1.099	
Professional Exper~B	1	.	.	.	.	.	
Intermediate	1.464	.731	0.76	.445	.55	3.896	
Advanced	1.864	1.072	1.08	.279	.604	5.752	
Age : base 18-25	1	.	.	.	.	.	
26-35	.735	.321	-0.70	.481	.312	1.731	
36-45	2.706	1.688	1.60	.11	.797	9.187	
46-55	.926	.59	-0.12	.904	.266	3.227	
55+	4.019	3.302	1.69	.09	.803	20.114	*
cut1	-4.009	.71	.b	.b	-5.401	-2.618	
cut2	-1.862	.452	.b	.b	-2.748	-.976	
cut3	.552	.419	.b	.b	-.269	1.373	
cut4	2.774	.473	.b	.b	1.847	3.702	

Mean dependent var	3.480	SD dependent var	0.892
Pseudo r-squared	0.089	Number of obs	177
Chi-square	40.655	Prob > chi2	0.000
Akaike crit. (AIC)	441.138	Bayesian crit. (BIC)	482.428

*** *p<.01*, ** *p<.05*, * *p<.1*

Table C 10 - Ordered Logistic regression results for Model 2.2

Goodness of fit for Model 2.2		
Log-likelihood		
Model	-207.569	
Intercept-only	-227.896	
Chi-square		
Deviance(df=164)	415.138	
LR(df=9)	40.655	
p-value		0.000
R2		
McFadden		0.089
McFadden(adjusted)		0.032
McKelvey & Zavoina		0.230
Cox-Snell/ML		0.205
Cragg-Uhler/Nagelkerke		0.222
Count		0.486
Count(adjusted)		0.142
IC		
AIC	441.138	
AIC divided by N		2.492
BIC(df=13)	482.428	
Variance of		
e		3.290
y-star		4.270

Table C 11 - Goodness of fit measures for Model 2.2

Active_Engagement	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
o	1	.	.	.	.	.	
o	1	.	.	.	.	.	
Age : base 18-25	1	.	.	.	.	.	
2o	1	.	.	.	.	.	
3o	1	.	.	.	.	.	
4o	1	.	.	.	.	.	
5o	1	.	.	.	.	.	
o	1	.	.	.	.	.	
SocialIdentity_std	1.201	.271	0.81	.417	.772	1.868	
SharingBehavior_std	2.189	.624	2.75	.006	1.251	3.828	***
Age : base 18-25	1	.	.	.	.	.	
26-35	1.401	.781	0.60	.545	.47	4.179	
36-45	3.578	2.345	1.94	.052	.99	12.926	*
46-55	5.365	3.759	2.40	.016	1.359	21.18	**
55+	3.93	3.669	1.47	.143	.631	24.493	
Constant	.397	.197	-1.86	.063	.15	1.052	*
SocialIdentity_std	.798	.287	-0.63	.531	.394	1.616	
SharingBehavior_std	3.89	1.486	3.56	0	1.84	8.226	***
Age : base 18-25	1	.	.	.	.	.	
26-35	.552	.366	-0.90	.37	.151	2.026	
36-45	.426	.416	-0.87	.382	.063	2.881	
46-55	.507	.616	-0.56	.576	.047	5.483	
55+	0	0	-0.00	1	0	.	
Constant	.322	.176	-2.07	.039	.11	.942	**
SocialIdentity_std	4367.703	17516.057	2.09	.037	1.685	11320797	**
SharingBehavior_std	30.608	44.362	2.36	.018	1.787	524.219	**
Age : base 18-25	1	.	.	.	.	.	
26-35	.001	.005	-1.49	.136	0	8.339	
36-45	.004	.016	-1.39	.164	0	9.537	
46-55	.518	1.208	-0.28	.778	.005	50.181	
55+	0	0	-0.00	1	0	.	
Constant	0	0	-2.03	.043	0	.604	**
SocialIdentity_std	4.502e+78	5.200e+82	0.02	.987	0	.	
SharingBehavior_std	0	0	-0.02	.988	0	.	
Age : base 18-25	1	.	.	.	.	.	
26-35	1.24e+128	4.13e+132	0.01	.993	0	.	
36-45	9.687e+46	3.330e+51	0.00	.997	0	.	
46-55	1.16e+100	4.35e+104	0.01	.995	0	.	
55+	1.11e+204	4.24e+208	0.01	.99	0	.	
Constant	0	0	-0.01	.989	0	.	

Mean dependent var	1.672	SD dependent var	0.815
Pseudo r-squared	0.253	Number of obs	177
Chi-square	96.269	Prob > chi2	0.000
Akaike crit. (AIC)	340.626	Bayesian crit. (BIC)	429.558

**** p<.01, ** p<.05, * p<.1*

Table C 12 - Multinomial Logistic Regression results for Model 3.1

	mlogit
Log-likelihood	
Model	-142.313
Intercept-only	-190.447
Chi-square	
Deviance(df=149)	284.626
LR(df=24)	96.269
p-value	0.000
R2	
McFadden	0.253
McFadden(adjusted)	0.106
Cox-Snell/ML	0.420
Cragg-Uhler/Nagelkerke	0.475
Count	0.667
Count(adjusted)	0.330
IC	
AIC	340.626
AIC divided by N	1.924
BIC(df=28)	429.558

Table C 13 - Goodness of fit measures for Model 3.1

Multinomial logistic regression

Active_Engagement	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
o	1	.	.	.	.	.	
o	1	.	.	.	.	.	
Gender : base Male	1	.	.	.	.	.	
2o	1	.	.	.	.	.	
o	1	.	.	.	.	.	
SocialIdentity_std	1.292	.283	1.17	.242	.841	1.986	
SharingBehavior_std	2.345	.664	3.01	.003	1.346	4.084	***
Gender : base Male	1	.	.	.	.	.	
Female	.36	.131	-2.80	.005	.176	.736	***
Constant	1.465	.416	1.35	.178	.84	2.556	
SocialIdentity_std	.714	.25	-0.96	.336	.36	1.418	
SharingBehavior_std	4.299	1.579	3.97	0	2.093	8.831	***
Gender : base Male	1	.	.	.	.	.	
Female	.593	.338	-0.92	.359	.194	1.811	
Constant	.271	.125	-2.84	.005	.11	.668	***
SocialIdentity_std	364.531	980.083	2.19	.028	1.876	70841.455	**
SharingBehavior_std	6.513	3.855	3.17	.002	2.042	20.779	***
Gender : base Male	1	.	.	.	.	.	
Female	.419	.548	-0.67	.506	.032	5.436	
Constant	0	0	-2.17	.03	0	.328	**
SocialIdentity_std	6.631	9.929	1.26	.206	.352	124.758	
SharingBehavior_std	.418	.738	-0.49	.621	.013	13.333	
Gender : base Male	1	.	.	.	.	.	
Female	0	.001	-0.02	.984	0	.	
Constant	.014	.027	-2.14	.032	0	.692	**

Mean dependent var	1.672	SD dependent var	0.815
Pseudo r-squared	0.190	Number of obs	177
Chi-square	72.497	Prob > chi2	0.000
Akaike crit. (AIC)	340.398	Bayesian crit. (BIC)	391.216

**** p<.01, ** p<.05, * p<.1*

Table C 14 - Multinomial Logistic Regression results for Model 3.2

	mlogit
Log-likelihood	
Model	-154.199
Intercept-only	-190.447
Chi-square	
Deviance(df=161)	308.398
LR(df=12)	72.497
p-value	0.000
R2	
McFadden	0.190
McFadden(adjusted)	0.106
Cox-Snell/ML	0.336
Cragg-Uhler/Nagelkerke	0.380
Count	0.627
Count(adjusted)	0.250
IC	
AIC	340.398
AIC divided by N	1.923
BIC(df=16)	391.216

Table C 15 - Goodness of fit measures for Model 3.2

Multinomial logistic regression

Active_Engagement	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
o	1	.	.	.	.	.	
o	1	.	.	.	.	.	
Education : base H~g	1	.	.	.	.	.	
2o	1	.	.	.	.	.	
3o	1	.	.	.	.	.	
4o	1	.	.	.	.	.	
o	1	.	.	.	.	.	
SocialIdentity_std	1.316	.29	1.25	.213	.855	2.025	
SharingBehavior_std	2.218	.618	2.86	.004	1.284	3.83	***
Education : base H~g	1	.	.	.	.	.	
Bachelor's degree ~t	.819	.576	-0.28	.776	.206	3.25	
Master's degree or~t	1.046	.709	0.07	.948	.277	3.949	
PhD or equivalent	2.141	1.889	0.86	.388	.38	12.068	
Constant	.778	.496	-0.39	.694	.223	2.716	
SocialIdentity_std	.689	.249	-1.03	.303	.339	1.4	
SharingBehavior_std	4.1	1.517	3.81	0	1.986	8.465	***
Education : base H~g	1	.	.	.	.	.	
Bachelor's degree ~t	.638	.623	-0.46	.645	.094	4.321	
Master's degree or~t	.523	.505	-0.67	.502	.079	3.473	
PhD or equivalent	0	0	-0.00	.998	0	.	
Constant	.336	.293	-1.25	.211	.061	1.858	
SocialIdentity_std	353.76	982.01	2.11	.035	1.534	81578.321	**
SharingBehavior_std	7.254	5.228	2.75	.006	1.767	29.79	***
Education : base H~g	1	.	.	.	.	.	
Bachelor's degree ~t	.446	.849	-0.42	.672	.011	18.656	
Master's degree or~t	.312	.594	-0.61	.541	.008	13.007	
PhD or equivalent	0	.001	-0.00	.999	0	.	
Constant	0	0	-2.11	.035	0	.445	**
SocialIdentity_std	11.187	21.509	1.26	.209	.258	484.523	
SharingBehavior_std	.034	.169	-0.68	.499	0	632.669	
Education : base H~g	1	.	.	.	.	.	
Bachelor's degree ~t	10.937	50603.017	0.00	1	0	.	
Master's degree or~t	6.956	30661.458	0.00	1	0	.	
PhD or equivalent	1.184e+09	4.423e+12	0.01	.996	0	.	
Constant	0	0	-0.01	.995	0	.	

Mean dependent var	1.672	SD dependent var	0.815
Pseudo r-squared	0.198	Number of obs	177
Chi-square	75.323	Prob > chi2	0.000
Akaike crit. (AIC)	353.572	Bayesian crit. (BIC)	429.799

**** p<.01, ** p<.05, * p<.1*

Table C 16 - Multinomial Logistic Regression results for Model 3.3

	mlogit
Log-likelihood	
Model	-152.786
Intercept-only	-190.447
Chi-square	
Deviance(df=153)	305.572
LR(df=20)	75.323
p-value	0.000
R2	
McFadden	0.198
McFadden(adjusted)	0.072
Cox-Snell/ML	0.347
Cragg-Uhler/Nagelkerke	0.392
Count	0.571
Count(adjusted)	0.136
IC	
AIC	353.572
AIC divided by N	1.998
BIC(df=24)	429.799

Table C 17 - Goodness of fit results for Model 3.3

Multinomial logistic regression

Active_Engagement	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
o	1	.	.	.	.	.	
o	1	.	.	.	.	.	
Professional Exper~B	1	.	.	.	.	.	
2o	1	.	.	.	.	.	
3o	1	.	.	.	.	.	
o	1	.	.	.	.	.	
SocialIdentity_std	1.265	.278	1.07	.285	.822	1.946	
SharingBehavior_std	2.214	.618	2.85	.004	1.281	3.827	***
Professional Exper~B	1	.	.	.	.	.	
Intermediate	.942	.592	-0.10	.924	.275	3.229	
Advanced	2.167	1.314	1.27	.202	.66	7.112	
Constant	.54	.301	-1.11	.269	.181	1.611	
SocialIdentity_std	.793	.279	-0.66	.509	.398	1.58	
SharingBehavior_std	4.006	1.527	3.64	0	1.898	8.457	***
Professional Exper~B	1	.	.	.	.	.	
Intermediate	.447	.319	-1.13	.26	.11	1.814	
Advanced	.213	.171	-1.92	.054	.044	1.029	*
Constant	.471	.28	-1.27	.205	.147	1.51	
SocialIdentity_std	698.167	2069.115	2.21	.027	2.096	232602.27	**
SharingBehavior_std	9.511	7.291	2.94	.003	2.117	42.733	***
Professional Exper~B	1	.	.	.	.	.	
Intermediate	.056	.132	-1.22	.224	.001	5.827	
Advanced	.053	.131	-1.19	.234	0	6.626	
Constant	0	0	-2.14	.033	0	.395	**
SocialIdentity_std	6.559	10.403	1.19	.236	.293	146.861	
SharingBehavior_std	.315	.571	-0.64	.524	.009	11.029	
Professional Exper~B	1	.	.	.	.	.	
Intermediate	1.027	18222.134	0.00	1	0	.	
Advanced	1.314e+08	1.621e+12	0.00	.999	0	.	
Constant	0	0	-0.00	.998	0	.	
Mean dependent var		1.672	SD dependent var			0.815	
Pseudo r-squared		0.207	Number of obs			177	
Chi-square		78.912	Prob > chi2			0.000	
Akaike crit. (AIC)		341.983	Bayesian crit. (BIC)			405.506	

**** p<.01, ** p<.05, * p<.1*

Table C 18 - Multinomial Logistic Regression results for Model 3.4

	mlogit
Log-likelihood	
Model	-150.991
Intercept-only	-190.447
Chi-square	
Deviance(df=157)	301.983
LR(df=16)	78.912
p-value	0.000
R2	
McFadden	0.207
McFadden(adjusted)	0.102
Cox-Snell/ML	0.360
Cragg-Uhler/Nagelkerke	0.407
Count	0.616
Count(adjusted)	0.227
IC	
AIC	341.983
AIC divided by N	1.932
BIC(df=20)	405.506

Table C 19 - Goodness of fit results for Model 3.4

Generalized Ordered Logit Estimates Number of obs = 177
LR chi2(29) = 65.18
Prob > chi2 = 0.0001
Log likelihood = -203.90186 Pseudo R2 = 0.1378

Passive_Avoidance	Coefficient	Std.	err.	z	P>z	[95%	conf.	interval]
Never								
SocialIdentity_std	-0.247	0.212	-1.160	0.245	-0.662	0.169		
SharingBehavior_std	0.728	0.285	2.550	0.011	0.168	1.287		
pol_view								
Moderately progressive/ liberal	-0.582	0.847	-0.690	0.492	-2.241	1.078		
Slightly progressive/ liberal	-0.568	0.871	-0.650	0.514	-2.275	1.139		
Neutral	-1.801	0.979	-1.840	0.066	-3.720	0.119		
Slightly conservative	-0.539	0.928	-0.580	0.561	-2.358	1.280		
Moderately conservative	-0.898	1.213	-0.740	0.459	-3.275	1.478		
Very conservative	13.816	3596.984	0.000	0.997	-7036.142	7063.775		
_cons	1.796	0.804	2.240	0.025	0.222	3.371		
Sometimes								
SocialIdentity_std	0.163	0.214	0.760	0.445	-0.256	0.583		
SharingBehavior_std	0.252	0.226	1.120	0.265	-0.190	0.694		
pol_view								
Moderately progressive/ liberal	0.563	0.732	0.770	0.442	-0.872	1.998		
Slightly progressive/ liberal	-0.105	0.760	-0.140	0.891	-1.595	1.386		
Neutral	-16.373	1403.925	-0.010	0.991	-2768.015	2735.268		
Slightly conservative	-0.905	0.885	-1.020	0.307	-2.640	0.830		
Moderately conservative	0.983	1.056	0.930	0.352	-1.088	3.053		
Very conservative	-15.928	3527.830	0.000	0.996	-6930.347	6898.491		
_cons	-0.902	0.683	-1.320	0.187	-2.240	0.436		
About_half_the_time								
SocialIdentity_std	-0.287	0.395	-0.730	0.467	-1.061	0.487		
SharingBehavior_std	0.701	0.449	1.560	0.118	-0.179	1.582		
pol_view								
Moderately progressive/ liberal	-0.307	0.867	-0.350	0.723	-2.007	1.393		
Slightly progressive/ liberal	-0.968	0.964	-1.000	0.316	-2.858	0.922		
Neutral	17.640	2944.412	0.010	0.995	-5753.302	5788.582		
Slightly conservative	-17.459	1372.559	-0.010	0.990	-2707.625	2672.707		
Moderately conservative	-0.908	1.548	-0.590	0.558	-3.942	2.126		
Very conservative		0			(omitted)			
_cons	-1.389	0.794	-1.750	0.080	-2.945	0.168		
Mot_of_the_time								
SocialIdentity_std	1.300	1.360	0.960	0.339	-1.365	3.965		
SharingBehavior_std	-2.111	2.041	-1.030	0.301	-6.111	1.890		
pol_view								
Moderately progressive/ liberal	-16.985	884.083	-0.020	0.985	-1749.756	1715.785		
Slightly progressive/ liberal	-1.663	2.308	-0.720	0.471	-6.187	2.860		
Neutral	-14.819	2871.403	-0.010	0.996	-5642.665	5613.027		
Slightly conservative		0			(omitted)			
Moderately conservative	4.761	6.797	0.700	0.484	-8.561	18.083		
Very conservative		0			(omitted)			
_cons	-1.685	1.709	-0.990	0.324	-5.034	1.664		

Table C 20 - gologit2 results for Model 4

	gologit2
Log-likelihood	
Model	-203.902
Intercept-only	-236.491
Chi-square	
Deviance(df=144)	407.804
LR(df=29)	65.179
p-value	0.000
R2	
McFadden	0.138
McFadden(adjusted)	-0.002
Cox-Snell/ML	0.308
Cragg-Uhler/Nagelkerke	0.331
Count	0.424
Count(adjusted)	-0.030
IC	
AIC	473.804
AIC divided by N	2.677
BIC(df=33)	578.617

Table C 21 - Goodness of fit results for Model 4

Generalized Ordered Logit Estimates Number of obs = 177
LR chi2(28) = 140.20
Prob > chi2 = 0.0000
Log likelihood = -186.34936 Pseudo R2 = 0.2734

Scroll_Past	Coefficient	Std. err.	z	P>z	[95% conf.	interval]
Never						
SocialIdentity_std	1.646	0.728	2.260	0.024	0.220	3.072
SharingBehavior_std	0.321	0.385	0.830	0.404	-0.433	1.074
Age						
26-35	0.244	0.903	0.270	0.787	-1.526	2.014
36-45	-2.940	1.317	-2.230	0.026	-5.521	-0.359
46-55	15.863	1353.216	0.010	0.991	-2636.391	2668.118
55+	-4.675	1.466	-3.190	0.001	-7.547	-1.802
Gender						
Female	0.267	0.639	0.420	0.675	-0.984	1.519
_cons	2.267	0.927	2.440	0.015	0.449	4.084
Sometimes						
SocialIdentity_std	0.194	0.321	0.610	0.545	-0.435	0.824
SharingBehavior_std	-0.099	0.256	-0.390	0.698	-0.602	0.403
Age						
26-35	1.143	0.634	1.800	0.072	-0.101	2.386
36-45	-17.643	1591.612	-0.010	0.991	-3137.145	3101.858
46-55	-0.865	0.799	-1.080	0.279	-2.431	0.702
55+	-19.073	2642.387	-0.010	0.994	-5198.056	5159.910
Gender						
Female	0.336	0.511	0.660	0.511	-0.666	1.338
_cons	0.513	0.564	0.910	0.363	-0.593	1.620
About_half_the_time						
SocialIdentity_std	-0.515	0.255	-2.020	0.043	-1.015	-0.016
SharingBehavior_std	-0.611	0.263	-2.320	0.020	-1.127	-0.095
Age						
26-35	-0.037	0.494	-0.070	0.940	-1.006	0.932
36-45	17.983	1431.448	0.010	0.990	-2787.604	2823.570
46-55	1.178	0.740	1.590	0.112	-0.273	2.629
55+	16.754	5140.306	0.000	0.997	-1.01e+04	10091.570
Gender						
Female	1.038	0.458	2.260	0.024	0.140	1.936
_cons	0.131	0.505	0.260	0.795	-0.859	1.121
Most_of_the_time						
SocialIdentity_std	-0.467	0.225	-2.080	0.038	-0.908	-0.027
SharingBehavior_std	-0.534	0.318	-1.680	0.093	-1.159	0.090
Age						
26-35	-0.350	0.464	-0.750	0.451	-1.259	0.560
36-45	0.435	0.661	0.660	0.511	-0.862	1.731
46-55	0.206	0.695	0.300	0.767	-1.156	1.569
55+	0.625	1.544	0.400	0.686	-2.402	3.652
Gender						
Female	0.683	0.416	1.640	0.101	-0.133	1.499
_cons	-1.094	0.498	-2.200	0.028	-2.070	-0.118

Table C 22 - gologi2 results for Model 5

	gologit2
Log-likelihood	
Model	-186.349
Intercept-only	-256.451
Chi-square	
Deviance(df=145)	372.699
LR(df=28)	140.203
p-value	0.000
R2	
McFadden	0.273
McFadden(adjusted)	0.149
Cox-Snell/ML	0.547
Cragg-Uhler/Nagelkerke	0.579
Count	0.379
Count(adjusted)	0.052
IC	
AIC	436.699
AIC divided by N	2.467
BIC(df=32)	538.336

Table C 23 - Goodness of fit for Model 5