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Measuring Political Activity How Online and Offline Political Activities Connect

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Doctoral Dissertation

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1 Introduction

In the last decades, social media has emerged as a powerful platform for political participation, shaping the ways individuals engage with politics, or political actors engage voters. The extensive adoption of social media in politics encompasses various aspects, including organizing protests and election campaigning, making it indispensable for both citizens and political actors alike.

This has drawn scientific attention: early research argues whether the political activities performed online have real, offline outcomes. The impact of internet usage and the role of social media sites in particular on the results of elections and political activity became a widely researched field (Zhuravskaya et al., 2020). Although social media have been used by political campaigns and parties for years now, there are ambivalent opinions about its role in politics and democratic processes (Y. Kim et al., 2013). Studies have investigated that social media might increase exposure to heterogeneous perspectives and thus promote civic engagement in a society (Y. Kim et al., 2013), or, in a pessimistic scenario, discourage it through controlling information spreading (Morozov, 2017).

However, online behavior produces a vast amount of data about political behavior, which is researched in social sciences widely for various reasons. It is suitable for getting information about social groups that are not researchable otherwise (Norris, 1999), or for political prediction. Predicting real-life events, such as the outcome of elections based on social media data lead to accurate forecasts in some cases (e.g.: Barclay et al., 2015; MacWilliams, 2015), but failed in others (e. g.: Chung & Mustafaraj, 2011; Theocharis & Lowe, 2016), depending on the country and the social media site used as dataset. Coping with the problem, former research employed several diverse techniques in attempting to predict political events from social media activities. One commonly used technique to estimate the offline popularity of a political actor (e.g., a political party) is combining traditional polls with social media data (MacWilliams, 2015). Other studies forecast offline popularity through its online popularity (number of 'likes', 'shares' or 'followers' on their pages, etc.) applying weights to balance the dissimilarities between the population and the users of the social media site (Koltai & Stefkovics, 2018; Oser et al., 2013; Xie et al., 2016). This method was successfully used in some cases, but usually, such cases were characterized by specific conditions. Such conditions may mean a focus on select sites, select locations, or a select culture (Valenzuela et al., 2018). This means that the demographic proportions of the members of social media sites do not necessarily reflect accurately the proportions of the general population, and this disproportion may vary across geographies, as social media sites' usage differs across countries and cultures. Thus, even within a methodological framework, the issue of comparability of results arises. To answer this problem, this thesis will present a Bayesian methodological framework that could help compare previous findings, and in doing so, will show how the connection between political activity on social media sites and offline politics is supported by the literature. Additionally, the analysis of Hungarian panel survey will compare the results in a culturally specific context.

This idea of the connection is supported by empirical evidence from various research, however, there are still unknown factors of how exactly online political activities can have real-world implications. The primary objective of this thesis is to address the existing gap in scientific research by providing new insights into the relationship between online and offline political activities and the factors that shape it. To achieve this goal, the thesis adopts a two-fold approach. First, it conducts a comprehensive literature review to understand how online activities can potentially influence offline actions. Second, the thesis narrows its focus to the phenomenon of information sharing and dissemination on social media platforms, analyzing two factors that may affect this process: emotions and network structure.

Sharing is one of the most crucial actions to explore on social media. It is present on most social media platforms, and represents a user activity that enables individuals to repost or forward content originally created by others, often accompanied by additional comments or remarks. This act of sharing serves as a tool for expressing personal opinions and beliefs while also disseminating information to a broader audience. Through sharing, users can actively participate in shaping online discourse, amplifying certain messages, and engaging in discussions with their social networks. Communication models highlight the significance of hearing information from others, and from a political standpoint, sharing content on social media can be viewed as an act of mobilization. Additionally, previous research has shown a correlation between the number of shares a post receives and the offline popularity of politicians (Bene, 2019).

Thus, this research aims to explore the dynamics of political behavior on social media, with a specific focus on the act of sharing political content. As the social media usage differs culturally, the analysis narrows its focus to Hungary. In Hungary, the most popular social media platform is Facebook, thus this research analyzes how emotions affect sharing content on it.

Emotions play a pivotal role in political decision-making, and their effect extends to the online sphere. Understanding the role of emotions in sharing behavior is crucial, and this research focuses on two aspects of emotions: emotional valence and diversity. By examining the impact of emotional valence on sharing behavior, this thesis aims to determine whether negative or positive emotions have a stronger propensity to drive sharing activity. Prior research found significant connections between emotional valence and shares of a post (Hansen et al., 2011). Positive (Berger et al., 2010; Stieglitz & Dang-Xuan, 2013), negative (Heimbach & Hinz, 2016; Stieglitz & Dang-Xuan, 2013) and neutral (Hoang et al., 2013) emotions were linked in the literature to message spread on social media.

Furthermore, investigating the relationship between emotional diversity and the number of shares on posts can shed light on whether a diverse array of emotions leads to increased engagement.

To capture the nuances of social media interactions over time, this study also incorporates the time dimension. Prior research has predominantly relied on cross-sectional data to explore the emotional content of posts and its correlation with user engagement on social media platforms. However, it is important to recognize that while the emotional content of a post may remain constant, the reactions of users, as measured by Facebook Reactions, and the platform's algorithm can significantly influence future interactions and sharing behavior, leading to temporal variations. A longitudinal approach is suited to capture these time-dependent dynamics and unveil how emotional influences evolve over the lifespan of a post.

Network structure also plays a critical role in information spreading. Social media platforms are shaped by the underlying real-life social network structures (Vepsäläinen et al., 2017). Consequently, the dissemination of shared news and information on social media exhibits variation depending on the specific network structure (Moreno et al., 2004; Pegoretti et al., 2012). As a result, sharing behavior can yield diverse effects within the context of different social media applications. For example, earlier studies suggest that homophily and algorithms create echo chambers on social media. However, the network structure of social media platforms, such as Facebook, is often unknown, making it challenging to directly observe and analyze. Consequently, to assess information dissemination on social media, researchers frequently resort to employing various network types to simulate and model the underlying mechanisms of these platforms. In this thesis, an agent-based model is adapted to test the impact of different network structures, such as tie lengths and density, on the occurrence of echo chambers and homophily. By modeling social media and information dissemination, the research aims to explore whether these phenomena are indeed influenced by specific network characteristics. This approach helps to understand how individual choices on social media emerge as a macro-societal phenomenon and what role the supposed social media algorithms play in it.

In summary, the thesis proposes three research questions about political engagement online to give a comprehensive picture about the role of social media in politics. The first question addresses the connection of online and offline political activities. The analysis contains a Bayesian Update method to ground the connection between online and offline political participation, and an analysis of a national Hungarian panel survey to assess the specific context of the thesis.

Literature review suggests the importance of sharing as the key between both platforms. Sharing behavior can be influenced by various factors. The second research question addresses the effect of emotions on sharing political content on social media. For this purpose, data from Hungarian political actors' Facebook pages were analyzed The effects of emotions were analyzed from two perspectives: valence and diversity. The analysis regarding the valence of emotions differentiates between the content-related and other effects that evoke reactions to the posts. Content-related findings suggest that the presence of more negative emotions is associated with more shares in total. This finding aligns with the theory that negative emotions tend to drive higher levels of engagement and sharing on social media platforms (e. g. Heimbach & Hinz, 2016; Stieglitz & Dang-Xuan, 2013). Negative emotions – particularly expressed through Angry reactions – play role in the non-post-specific influence as well: over time, the presence of these reactions means higher number of Shares, while Love reactions decrease it in the first period of a post's lifespan. These other influences might be the consequence of the algorithm behind the social media platform, or the effect of users' reactions influencing future engagement. These factors can vary over time; thus the analysis contained the temporal aspect. These were measured with fixed effect regression to control the unique characteristics of posts and reveal the general factors that affect interactions to posts. Diversity of emotions can also influence sharing on social media (Freeman et al, 2020). The findings of the thesis regarding this issue suggest that over time, the dispersion of reactions decreases and became more concentrated, while the analysis of the different reactions' effect on each other shows that additional "Care" reactions were significantly influenced by preceding reactions, Additionally, the number of New Likes in the previous time step consistently predicted an increase in other New Reactions, except for New Angry reactions, which exhibited a reverse relationship with New Likes.

A novel element in the analysis of the network structure's effect on information diffusion is the importance of small world networks. In most cases, in small world networks, individuals shared the information more than in preferential attachment networks. This might be the results of the model specification of the preferential attachment networks. In preferential attachment networks, the role of a "central person" is crucial: if that central person is very negative towards a politician, it will not share the information, despite many of their friends did. Thus, high centralization in this model may stop the diffusion process, while in less centralized or more dense networks the information easier bypasses easier.

This suggests the importance of small world networks regarding information diffusion that aligns with previous research (e. g. Pegoretti et al, 2012). Homophily's impact varies depending on the network structure; in some cases, it contributes to more shares, while in others, its effect is less pronounced. It exhibits a negative trend, particularly in denser networks, although this isn't the case in larger networks with lower density and larger small-world networks. Filtering mechanisms inherently have a negative impact, but homophily tends to alleviate this effect under certain network conditions.

This research presents novel contributions to the field by applying innovative methods for the analyses, such as Bayesian Updating and agent-based modeling, offering new analytical approaches to studying online and offline political activity and information diffusion. Additionally, including temporal aspect to Facebook data analysis can offer a deeper understanding of the role of reactions on posts to the mostly cross-sectional analysis in the field. Secondly, it focuses on the Hungarian political landscape, providing context-specific insights into the relationship between online and offline political participation and social media usage. Thirdly, by exploring the impact of emotional content on sharing behavior on a popular social media platform, it reinforces the role of negative emotions in information spreading. Lastly, the research identifies the impact of network structures and emotions on information dissemination, offering new insights into how these factors interact in shaping online political engagement.

The thesis is structured as follows:

The Background Chapter commences first by providing scientific definitions and previous research of the essential concepts of online and offline political participation, along with social media. Furthermore, this section introduces the concept and significance of sharing on social media, which forms the central focus of the thesis. Subsequently, it offers a concise historical overview of social media.

Next, it explores the theoretical and empirical aspects of the connection between offline and online political engagement. This subchapter contextualizes the following research by supporting the relevance of using social media data for political analyses and predictions. While the topic of the relationship of online and offline political activities has been extensively studied, the thesis contributes new statistical evidence to the existing scientific literature. Additionally, a national survey analysis from Hungary corroborates the correlation between engaging in online and offline political activities. Understanding this context is crucial as it provides the motivation and importance for the subsequent research.

Following that, chapter “Background” delves into the theoretical background of the two primary aspects that this thesis focuses on, as the main factors influencing sharing behavior on social media. The initial aspect explored in this chapter is the role of emotions, specifically focusing on two dimensions: valence and diversity. Empirical researches related to these aspects are also discussed in this section. Continuing with the topic, the chapter next delves into the dynamics of information spreading on social media platforms. It explores the commonly used methods for analyzing information dissemination and introduces key phenomena such as echo chambers, polarization, and other network characteristics that play a crucial role in shaping the flow of information on these platforms.

Chapter “Research Questions” provides a brief summary of the theoretical and empirical background, setting the stage for the areas where this dissertation contributes to the scientific field. By building upon existing knowledge, this chapter introduces the specific topics and research questions that this study aims to explore and address, namely the effect of emotional valence and diversity on sharing information on social media, and the role of network characteristics on information spreading. This thesis follows an explanatory research approach, where the stated questions are answered through the research process.

Chapter “Data” provides a comprehensive overview of the data used in this study, which is sourced from Hungarian political actors' Facebook accounts. Chapter “Method” delves into the various methods employed throughout the research, including detailed explanations of different regression techniques and the agent-based model. The chapter aims to present a clear and transparent account of the data collection process and the methodologies used to analyze the data, ensuring the rigor and validity of the research findings. By providing in-depth descriptions of the data and methods, this chapter serves as a solid foundation for the subsequent analyses and interpretations presented in the thesis.

The “Results” chapter provides separate discussions for each Research Question, presenting the findings and analyses in a comprehensive manner. In the Conclusion section, this thesis addresses the research questions posed at the beginning of the study and provides comprehensive answers based on the empirical findings and analyses. The main contributions of the research are emphasized, highlighting its novelty and significance in the context of existing literature on political participation and information spreading on social media.

In chapter “Further Research and Limitations”, this thesis acknowledges the constraints and limitations of the research conducted. It highlights the need for a comprehensive understanding of the complex nature of social media dynamics in relation to emotional valence and diversity, and the influence of network characteristics on information dissemination. The chapter also offers an outlook to the possible further researches in the field based on the research of emotional valence and diversity, as well as the exploration of network characteristics.

2 Background

The aim of the chapter is to state the relevance of the investigated topic and introduce the scientific literature of the field. In order to accomplish this, the chapter is structured into four sections. Firstly, it lays the foundation by introducing key concepts such as political participation, social media, and sharing on social media, providing their scientific definitions, historical context, and relevant empirical researches.

The second major part of the chapter explores the crucial aspect of assessing the relationship between online and offline political participation. This section underscores the relevance of this topic in understanding the interconnectedness of digital and traditional political engagement.

The third part delves into the role of emotions in the context of social media. It introduces the concept of emotional valence and diversity, which are subsequently employed in the analysis to investigate their impact on sharing behavior.

Lastly, the fourth section focuses on information spreading on social media platforms. It addresses various methods used for analyses, including the phenomena of echo chambers, polarization, and other network characteristics, which are crucial in understanding the dynamics of information dissemination in the online environment.

2.1 Definitions: political participation, social media

Political participation can be defined according to the widely used definition of Verba et al (1995) as an 'activity that is intended to or has the consequence of affecting, either directly or indirectly, government action'. Early research of political participation defined it mostly as electoral participation, but over time the definition was extended to less conventional political or even non-political activities, such as protests and volunteering for a social cause (Ruess et al., 2021). However, the definition commonly excludes passive forms of political engagement, such as consuming political news and being attentive to politics in general (Gibson & Cantijoch, 2013). Krueger (2008) argues that on the internet, boundaries between active and passive participation are blurred. Gibson and Cantijoch (2013) point out that online expressive political actions are more influential and reach a wider audience than their offline counterpart, e. g. posting an online comment for a news article versus sending a letter to a newspaper editor. New modes of activities complicate conceptualizing online political participation, thus most research treat it as a mode of engagement or define a wide range of different participatory forms online (e. g.: Dimitrova et al., 2014; Oser et al., 2013), that varies between platforms too (Lazer & Radford, 2017).

Political participation is a necessary element of democracies (Verba et al, 1995). Research shows that in Western societies, traditional forms of political participation are in decline due to a general decline in overall civic engagement; (Putnam, 2000) and the new forms of political participation that emerge are less embedded in hierarchical structures or are opposed to the parliamentary realm, even (Vissers & Stolle, 2014). The internet, especially the web 2.0 (Kushin and Yamamoto, 2010) facilitated these new forms of political engagement (Oser et al., 2013; Ruess et al., 2021): online political activity can mirror offline activities, recreating the same actions in an online environment, e. g. signing petitions online (Vissers & Stolle, 2014). In some cases, the online form of participation takes over the offline form of the same action: e. g. contacting political actors via email became as popular in the US in the early 2000's as by post or via telephone (Best & Krueger, 2005). Moreover, online political participation is possible without an offline counterpart: for example, using hashtags or sharing pictures, photos in support of a case (Vissers & Stolle, 2014). The internet can support the ways of traditional participation or offer new ways of political participation by facilitating new forms of political action (Ruess et al., 2021), that can be viewed as an expanded platform of communicating and accessing information, thus a public sphere in itself (Polat, 2005). Especially, social network sites combine these features (Vitak et al., 2011), as they require low effort for political participation (Ruess et al., 2021).

The concept of social media is continuously evolving, thus there are only a few widely accepted formal definitions of it (Ellison & Boyd, 2013). McCay-Peet and Quan-Haase (2016) summarized the definitions of social media in the literature and proposed an overall definition:

> „Social media are web-based services that allow individuals, communities, and organizations to collaborate, connect, interact, and build community by enabling them to create, co-create, modify, share, and engage with user-generated content that is easily accessible." – (McCay-Peet & Quan-Haase, 2016:17).

Another, often used definition by Kaplan and Haenlein is that social media refers to the internet-based applications that have the interactive characteristics of web 2.0 and allow the creation and exchange of user generated content (Kaplan & Haenlein, 2012).

The term 'web 2.0' refers to the second generation of the World Wide Web, which was the first phase of the internet designed in the early 1990's (Toledano, 2013). The first version of the internet was static and as a new technological innovation, it attracted business investors, without accordingly high profits. That business challenge emerged in the early 2000's after the "dot com bubble burst" (Bene, 2019). After the burst, the internet as business or innovation was marked as overhyped and needed a reintroducing (O'Reilly, 2005), so the appearance of web 2.0 is an attempt to redefine a sector after an economic crisis (Bene, 2019). Technically, there is little that is new about web 2.0 as the technology for the tools that are becoming popular was already available (Ellison & Boyd, 2013). The change is more about the role of the internet, function, use and attitudes towards it (Bene, 2019). Web 2.0 is more supporting towards user activities, than the more static web 1.0 (O'Reilly, 2005). Boyd and Ellison (2007) argue that while earlier communication was also present on the internet, it was more personal, and the changes around the switch to the web 2.0 made online communication widely adopted in the form as it is nowadays. Consequently, platforms where the content is the result of user activities emerge, presenting social media and social network sites.

The term 'social media' is related to the term 'social network sites' as social media includes other types of social media (McCay-Peet & Quan-Haase, 2016). In their theoretical framework, authors differentiate between ten types of social media:

- Bookmarking,
- Microblogging: connecting users by short updates (Twitter, Tumblr),
- Blogs and forums: online forums to communicate via messages or comments (e. g. Wordpress),
- Media sharing: platforms for various media sharing, such as Youtube, Flickr, Pinterest,
- Social news: platforms for sharing news and articles with the possibility to other users to vote for them, and by voting form what items get displayed (e.g., Reddit),
- Collaborative authoring: common content creating, reviewing, and editing, e. g. Wikipedia,

- Web conferencing: services that allow users to create and attend web seminars and similar events, e.g., Skype, GoToMeeting,
- Geolocation-based sites: platforms for users to connect regarding the location, such as Foursquare,
- Scheduling and meeting: platforms for group events (Doodle, Google Calendar),
- and finally, social network sites.

Social network sites are a popular but not exclusive form of social media, as social media refers to blogs, microblogs, and video sharing sites, too (Kushin & Yamamoto, 2010). McCay-Peet and Quan-Haase's (2016) investigated the occurrence of both terms in scientific papers and found that from 2003 to 2008, there was twice as many mentions of social network sites than of social media; but between 2009 and 2014 this trend reversed. Social network sites are often used as a synonym to social media, but this typology treats social network sites as a form of social media.

Boyd and Ellison (2007) define three criteria of social network sites: online environments that allow their users to (1) construct a public or semi-public profile within a bounded system; (2) articulate a list of other users with whom they share a connection; and (3) view and traverse their list of connections and those made by others within the system.

The connection can be unilateral or bilateral, depending on the site. Social network sites have rapidly transformed into prominent channels for individuals to access news and information (Chen, 2019). Social network sites can be aptly described as graphs or networks, where nodes represent individuals and edges signify the connections between these individuals. This interconnected structure allows users to establish connections and share content with others, facilitating the dissemination of information across the platform. The first social network site, SixDegrees, was launched in 1997. The project eventually failed, according to later evaluations, because people had few personal contacts online. This failure highlighted that beyond the technical capabilities, the audience is also vital for these sites to get popular. Bene (2019) argues that web 2.0 tools are only can only be successful if mass use and the need for activity are already emerging. The first big success was the Friendster site, launched in 2002, whose subsequent downfall was precisely due to the fact that it was not able to attract a significant number of users in a short period of time because of the technical and operational challenges posed by the large and rapid growth of the From 2003, MySpace was able to reach a wider audience, and later Facebook which was launched in 2004 as a closed university site has been the most used social networking site in the world (Boyd & Ellison, 2007).

Over time, the content of social media sites that fit the social network sites criteria has changed, and continues changing still (Ruess et al., 2021); for example, the various microblog services did not qualify as social network site in the definition by Kushin and Yamamoto (2010), but they did by the criteria of boyd and Ellison (2007). Thus, in the following, this thesis uses the term social media and understands it as the broader concept.

The typical use of social media consists of heterogeneous practices regarding the platform design and technological features (Skoric & Zhu, 2016). As for political participation, researchers usually differentiate between informational and expressive usage of social media (Skoric & Zhu, 2016). Informational use contains news seeking on social media and getting information about politics there, which was linked to offline political participation in several countries (Gil de Zúñiga et al., 2012; Skoric & Zhu, 2016). The expressive use refers to a wide scale of online activities from writing posts to engage in a conversation online: these activities were considered as exchanging political ideas and expressing political opinion on social media, and were linked to offline events, such as elections and protests in studies (Kushin & Yamamoto, 2010; H. G. D. Zúñiga, 2013). Zúñiga (2013) found that only expressive blog use was a positive predictor of online and offline participation, while consumptive blog use did not make a significant difference.

Shah et al (2001) found no or negative relationship between social capital and recreational types of use of the Internet. Different types of Internet usage are present in later research: Skoric and Zhu (2016) differentiate between informational, expressive and discussion- or interest-oriented usage of social media. Skoric et al (2016) use a differentiation between a "sender" and a "receiver" effect of online expression, that means that in interpersonal discussions, the sender's role could have a direct or an indirect effect on citizen engagement. According to this distinction, the uses of social media can be different: informational, consumptive, expressive, relational, identity and entertainment (Zúñiga, 2013).

As both types of use were linked to offline political participation in prior studies, in the following analysis, this thesis does not differentiate between these subtypes of the political related usage of social media but considers online political participation on social media in a unified, general sense.

Recently, social media play a major role worldwide: Facebook, Twitter and in some countries, local social network sites are the most popular (Vitak et al., 2011). As of January 1, 2023, the third most popular website worldwide to access the internet was Facebook (facebook.com), and the fourth was Twitter (twitter.com)[1].

In Hungary, the most popular social network site was WiW.hu, a local social media application, which gained popularity starting from 2002. However, since 2010, Facebook has emerged as the largest and most widely used social networking site in the country (Bene, 2019)

2.1.1 Social media as public sphere

With the rise of social media in the 1990's (McAfee, 2006; Shirky, 2011), more research used the theory Habermas's (Habermas & Burger, 1991) public sphere to understand social media (Loader and Mercea 2011; Fuchs, 2014; Kruse et al., 2018), and investigated social media separately from general internet usage.

According to Habermas, the public sphere is a critical element of deliberative democracies, as it should provide unlimited access to information and a possibility to equal and protected participation without institutional or economical influence (Habermas & Burger, 1991; Kruse et al., 2018). Some characteristics of social media seem to fit these criteria of a public sphere: Boyd and Ellison (2007) define social network sites as tools that allow users to maintain their large network of social ties easily and that way it promotes social capital and interpersonal trust. Bennett and Segerberg (2012) find that it can help individuals to disseminate and create political content. This way, it allows these individuals to express and form their political beliefs. Furthermore, in theory, anyone has access to social media sites, and can distribute information on them, thus making information accessible, and participation possible without outside influence (Jenkins & Deuze, 2008; Loader & Mercea, 2011), just as Habermas' definition required. Arguments against social media as a public sphere criticize the exclusion of information from the part of the user (Jenkins & Deuze, 2008) and the inequalities of accessibility in practice

[1] Data from similarweb.com. Accessed: 31 January, 2023.

(Fuchs, 2012). Kruse et al (2017) provide empirical evidence about users avoiding political discourse on social media due its nature; thus, not using it as a public sphere. Social media is present in both democracies and autocratic regimes and debates about its role in politics are still ongoing. In democratic regimes, social media is often viewed as a tool for the masses to make their voices heard, (Tucker et al., 2017) and in autocracies as tool of propaganda and surveillance (Morozov, 2017). Contrary to this approach, Tucker et al (2017) argue that this approach originates from the idea of the possibility of freedom of information on social media, which is a democratic idea by nature, but in itself, *„social media are neither inherently democratic nor inherently undemocratic"* (Tucker et al, 2017:48), rather it held a space for political interests and conflicts. Tufekci (2018) emphasizes the responsibility of social media in democracies for the rise of populism and fake news. This dichotomy in the way of how the role of social media in politics is perceived, that can be simplified to on the one hand as the optimistic approach, and on the other hand as the pessimistic scenario, is running through the research of the topic. In the following subchapter these opposing approaches are investigated in more detail.

2.1.2 The role of social media in different political activities

As the previous subchapter summarized, there were numerous expectations towards social media to change political communication. With the increasing popularity of social media and the increasing amount of social media data, scientific research focused on empirical research in the field. Such research analyzed mostly offline political events, such as campaigns, elections or protests, or linked the social media usage to political interest in general. The following sections summarize the evidence such empirical research obtained.

2.1.3 Social media and political protests

The idea of social media facilitating or influencing political activities was researched regarding protests in the early 2000's, as social media usage has been linked to political protests worldwide (Jost et al., 2018; Zhuravskaya et al., 2020). Studies find that social media play a key role in coordinating protests and political information spreading (Zhuravskaya et al., 2020). Anecdotal and scientific reports claim the importance of social network sites in the Occupy protests or in the Arab Spring protests (Howard et al., 2011; Vissers & Stolle, 2014). Jost et al (2018) provide evidence about the role of Facebook during the protests in Ukraine in 2014 (Euromaidan), and Twitter in the case of Turkey in

2013 (Gezi Park demonstration), US in 2012 (Occupy Wall Street) and Spain in 2012 (Indignados movement). In all the four cases, they found that social media facilitated news spreading vital to coordinate a protest - such as legal or medical support and presence of police and transmitted emotionally motivating messages to both those supporting and opposing the protest. In contrast, Comunello and Anzera (2012) attempted to evaluate the impact of social media on the Arab Spring protest. They concluded a more complex role of social network sites and rejected the idea of social media simply causing or repressing social movements, as the access was limited to the sites, and the causes behind a protest multifactorial, but supported the idea of social media as a tool of political participation.

2.1.4 Social media in campaigns

Social network sites are not only connected to politics through protests. Not only in the case of protests, but also in general there are controversial results on if, and how online and offline platforms connect, or whether the activities happening on social media have any impact on offline events (Theocharis & Lowe, 2016). Johnson and Perlmutter (2010) consider the 2003-2004 Howard Dean campaign in the US elections as the prototype of campaigns in the internet era, and the 2007-2008 Barack Obama campaign as a successful follow-up. The 2016 US elections continued using social media in campaigns (Enli, 2017) and raising it to a 'second level'. Research since these elections claim to explain the connection between the support generated on social media and offline.

The nature of political campaigns and the tools they use for communication change over time (Strandberg, 2006). Norris (2001) differentiates between the premodern, the modern and the postmodern stages of political campaigns. In political communication, according to Blumler and Kavanagh (1999) the first age was between 1850 and 1960, when parties utilized mainly printed press and face-to face interactions to gain voters, and the main form of communication between citizens and political parties were the partisan media. In the second, modern age, campaigns became increasingly coordinated. At this stage, around the 1960's television became the main platform of politicians, while party identification became weaker in the society. The third age, the postmodern, began in the 1990's when limited television access became multi-channel and the internet gained importance as the new form of communication. The number of non-voters, parties and swing voters increased.

Magin et al (2017) argues that the web 2.0 changed political campaigns, as with the decline of party identification they needed to find new ways to engage voters, thus introducing the fourth phase of political campaigns. The current phase of online campaigns is the updated version of the third attributed by more nonvoters and swing-voters and new communicational channels such as social media network sites. Their research highlights that while the US campaigns are commonly used as a starting point for research, applying the same classification to other countries may yield different results due to structural factors like technological adoption rates and legal constraints. In a broader context, the functions of election campaigns have been extensively studied, with Magin et al (2017) arguing that these functions serve three main goals:

1. Disseminate Information: Campaigns aim to effectively communicate information about candidates, their policies, and positions to the electorate, helping voters make informed choices.
2. Interact: This refers to the dynamic dialogue between political figures and voters, where campaigns seek to persuade potential voters through direct engagement and personalized communication.
3. Mobilize: Campaigns strive to mobilize and engage voters actively, encouraging them to participate in the political process, spread campaign messages, and persuade others through their interactions.

Citizens' activation through mobilization efforts by politicians can occur both online and offline. Larsson (2015) states on Norwegian example, that on the online front, it is not uncommon for party leaders to encourage their supporters to share specific posts on Facebook as a way to engage and mobilize their online audience. Using Facebook as a campaigning tool can help these functions in a hybrid way. Lilleker et al (2015) notes that as the most widespread Web 2.0 service, it is suitable for all three functions of a campaign stated above. Information can spread via tailored messages and ads, via direct and indirect communication. Interaction can happen via Facebook’s feed channel, and mobilization concerned on social media as the action of sharing in campaigns.

In the following, regarding the political participation this thesis focuses on sharing on social media.

2.1.5 Sharing political messages on social media

Katz and Lazarsfeld's (2017) two-step model of communication, established in 1955, describes how messages from the media are mediated by opinion leaders who can influence the masses through interpersonal communication. Initially applied to the general flow of information, the model has been researched in the context of politics both before and after the rise of the internet and social media. Early studies focused on actors of diffusion and factors related to information, such as timing and demographics of the receiving group. With the advent of the internet, the two-step flow model gained significance in politics as it aimed to replace the traditional mass media audience, potentially weakening one-step communication forms. Bene (2019) argues that on social media, the effect of the two-step flow can prevail due to the presence of opinion leaders who communicate about political topics, leading to more authentic and personally relevant messages for users. These factors contribute to the influence of the two-step flow in the realm of online and offline political engagement.

The two-step flow of information on social media refers to the indirect influence that occurs when content is passed on by visitors and followers to their own acquaintances (R. K. Gibson & McAllister, 2015). In this process, direct visitors and followers are not the primary targets of influence; instead, it is their friends and followers who are affected by the content they share. This phenomenon highlights the importance of social connections and networks in the dissemination of information and the potential impact it can have on a wider audience beyond the initial group of direct visitors and followers.

Adding to the importance of shares on social media, Bene’s (2018) research shows that the average number of shares on politicians' Facebook pages is correlated with electoral outcome, while likes and comments are not. His results suggest that the main effect of Facebook posts on political participation lies in sharing contents. His thesis analyzed the Facebook during the campaign running up to the 2014 Hungarian elections and found that the number of shares on a post by a political actor had a weak but significant effect on the votes. His analysis also attempted to understand the mechanism behind the causal link and provided argument that the Facebook campaign was responsible for the two-step effect. Bene's research findings from the Hungarian elections in 2014 revealed a significant positive association between the average number of shares on candidates' Facebook pages and the electoral outcome. However, other Facebook performance indicators, such as the average number of likes and comments, did not show a significant association with electoral outcomes. The results suggest that a social media campaign can lead to additional votes through the two-step flow effect. This effect implies in this case that the extra votes are likely to come from voters who receive candidates' messages through their friends, effectively mediating the content to them. Without this social media mediation, these voters might not have been exposed to the given content.

Regarding political topics, Magin et al (2017) consider sharing political content as a common, low-threshold mass-centered form of mobilization, as it integrates voters into the campaign. In their research, Magin et al (2017) interviewed German and Austrian political parties that named Facebook as the most important campaigning tool and considered the main goal of their campaign is to share their message, however, their analysis of Facebook posts suggests that this was more successful in the case of smaller parties.

Klinger's (2013) analysis of the Swiss campaign aligned with Magin's findings and further emphasized that political parties tend to utilize social media primarily for informative purposes rather than mobilization. In other words, social media platforms were more commonly employed as a means to disseminate information and political messages to the public, rather than actively engaging and mobilizing supporters for specific actions.

Understanding online political activity as a campaigning technique sheds light on the pivotal role of sharing in linking online and offline political participation on social media. Sharing can serve as a micro-level link that connects the virtual realm of social media with real-world political engagement. When parties or politicians engage in online political activity, particularly through social media campaigns, they utilize sharing as a powerful tool to disseminate their messages and content to a broader audience. By encouraging users to share their posts, these political actors leverage the social networks of their supporters, effectively turning them into amplifiers and advocates for their campaigns. As users share political content on social media, they engage in an act of expressing their opinions and political stances while simultaneously informing others. This two-step flow of information, as identified in previous research (Bene, 2018), allows political content to reach individuals who might not have otherwise encountered it, creating an extended reach and influence.

In this way, sharing plays a critical role in bridging the gap between online and offline political participation. Firstly, sharing has significant mobilizational potential, as it allows politicians and parties to activate their supporters and engage them in online political activities. When party leaders urge their followers to share specific content, it can lead to increased participation and involvement in political campaigns both online and offline. Secondly, sharing also correlates with offline popularity, making it an important metric for assessing the overall reach and impact of political content. Posts that receive a high number of shares not only gain visibility within online social networks but may also influence offline discussions and interactions. As content spreads from user to user, it has the potential to reach a broader audience, which can have real-world implications for political events and outcomes.

In essence, sharing acts as a powerful conduit, fostering a two-way flow between online and offline political engagement. By mobilizing citizens through social media and extending the reach of political messages beyond online platforms, sharing plays a critical role in bridging the gap between digital political participation and its real-world effects.

2.2 Assessing the relationship between online and offline political participation

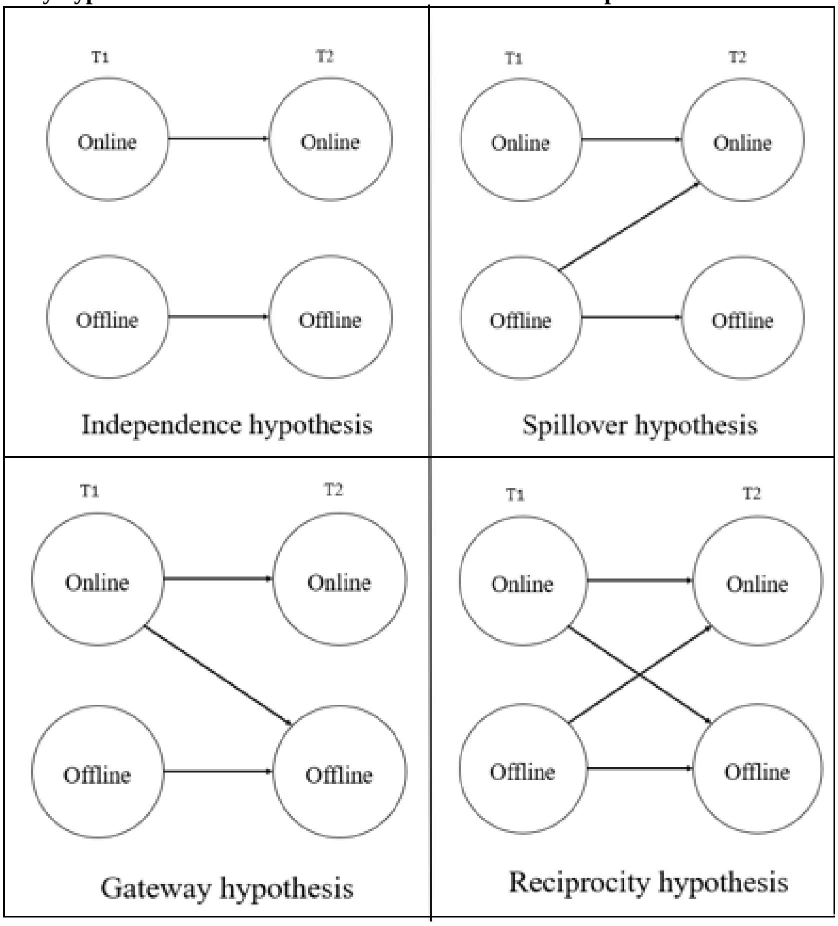
In the subsequent sections, the thesis delves into the theoretical background and existing evidence from studies that have examined the interplay between online and offline political participation. The advantages and disadvantages of utilizing social media data are also discussed to shed light on the potential and limitations of using this type of data in political research. The emphasis is placed on highlighting the significance of this topic by exploring how social media enables the analysis of otherwise hard-to-reach social groups

2.2.1 Theoretical frameworks

In this subchapter, the thesis introduces two distinct theoretical approaches that aim to analyze the longitudinal influence of online and offline platforms. These theoretical frameworks can help understanding how online political activities can have lasting effects on offline behavior.

T. Kim et al. (2016) introduced the first approach, which is summarized in Figure 1. Figure 1 presents the four-way hypothesis discussed in the study, encompassing the independence, spillover, gateway, and reciprocity hypotheses. These hypotheses aim to explore the interactions between online and offline political activities, investigating how their dynamics can mutually influence one another over time..

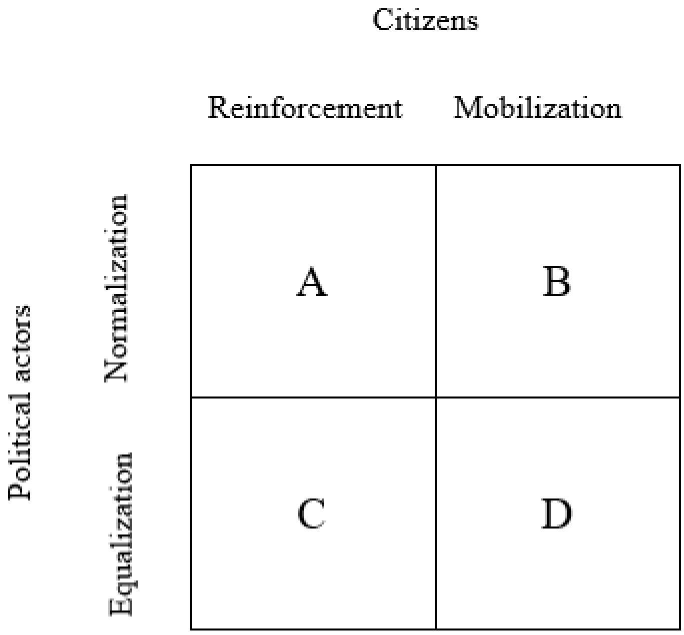
Figure 1. Four-way hypothesis on the relation between online and offline platforms. Source: T. Kim et al, 2016



The independence theory suggests that these behaviors develop separately, with weak or little correlation between them; online activities encourage online participation forms and the same with offline (Vissers et al., 2012). The spillover hypothesis posits that online participation reflects individuals' existing engagement in offline politics. In contrast, the gateway hypothesis proposes that online platforms provide low-effort entry points for individuals who may not have engaged in politics otherwise, potentially leading them to participate in offline activities. Lastly, the reciprocity hypothesis argues that online and offline participation mutually influence each other, creating a feedback loop of engagement.

The second model is from Strandberg (2006). This study introduces another theoretical framework that categorizes the possible offline outcomes of online political activities into four distinct types. The research analyzes the political environment using the following typology: normalization, equalization, mobilization, and reinforcement. Each category represents a different way in which online activities by political actors and citizens may influence and interact with the offline political landscape. This analytical approach is presented in Figure 2.

Figure 2 Strandberg's (2006) typology about the four political environments. Source: Strandberg, 2006.



Norris (1999) highlighted that the internet can engage citizens to political activities, and described the role of the internet in political activities either reinforcing already existing structures amongst the politically active or mobilizing those who could otherwise not act. Citizens can expect from social media to broaden the publicity and get more information (mobilization) or it can reflect their offline activities (reinforcement). From the perspective of the political actors' online campaign can replicate offline activities (normalization) or it can equalize the offline social differences online (equalization).

The equalization theory supports the idea of political campaigns becoming more 'equal' on the internet than they would be solely offline, because it lowers the cost of reaching and informing masses (Margolis et al., 2003). Empirical research about small parties in the EU support this theory (Norris, 2003): a cross-national analysis reveals that the websites of smaller parties gave them more visibility than traditional mass media did.

Contrary to the democratizing effect of the internet, the normalizing theory states that the internet can only reflect the structures in the offline mechanisms (Strandberg, 2006; Margolis et al, 2003).

From the citizens' point of view, the internet can have a reinforcing or mobilizing effect

(Strandberg, 2006). Oser et al (2013) investigated whether online participation mobilizes previously less engaged social groups or reinforces already existing patterns in political participation. Their research confirms the mobilizing theory regarding gender and age, but they also found socioeconomic status inequalities reinforced in online political participation.

The theory about the mobilizational effect of social media is related to the optimistic scenario about the social media as public sphere: Norris (1999) argues that internet provides vast amount of information to citizens, allows them to engage through various low-cost forms into political activities and because of its interactive nature enhances connections between citizens and political organizations.

2.2.2 Empirical research

Several empirical have explored the relationship between social media use and offline political participation, with various aspects of activities in focus. Early research focused on the frequency of Internet usage in general and its relationship with offline civic participation (Miner, 2015; Wellman et al., 2001) and found evidence of the reinforcing effect of the internet (Best & Krueger, 2005). Boulianne (2009) found a significant, albeit small relationship between civic engagement and internet usage. Analyses of data from the early 2000s have yielded varying results regarding the connection between internet penetration and voter turnout. Some studies, such as Falck et al. (2014), found limited evidence of a link, while others, like Gavazza et al. (2019), reported no significant connection. Zhuravskaya et al. (2020) explained this discrepancy, suggesting that the type of internet usage played a crucial role, as in the early days, the internet was not extensively used for political purposes, leading to a lack of interest in politics among those with internet access.

In the 2010's, studies analyzed the connection by theorizing the online activities in various ways. Skoric & Zhu (2016) focused on three types of social media use and measured offline political participation by assessing respondents' engagement in activities such as participating in resident dialogues and helping a political party. They found that the informational use of egocentric social media, specifically reading news about politics on platforms like Facebook, was positively related to offline political participation. However, expressive uses of egocentric social media, such as commenting or writing posts, did not predict offline participation. Holt et al. (2013) investigated the relationship between media use, political interest, and political participation across different age groups. Their measure of offline political participation included activities such as signing petitions, attending demonstrations, and arguing for one's opinion. They found that both attention to political news in traditional media and the use of social media for political purposes had positive effects on both political interest and offline political participation. Towner and Muñoz (2018) focused on older individuals and examined the effect of online media on participation compared to traditional media consumption. They measured offline participation using an index based on activities such as contacting politicians, attending political meetings, and making offline donations. The study suggested that social media use encouraged older people to participate in other online activities, but it had no significant correlation with offline political participation. Valenzuela et al. (2009) investigated the correlation between Facebook usage and offline political participation. Their measure of offline political participation was based on an index of respondents' involvement in various civic and political activities, such as volunteering for community projects, working for political groups, and voting. The study found a positive correlation, but the association was weak, leading to the conclusion that social media might not be sufficient to encourage people to participate in politics offline. T. Kim et al. (2016) identified online activities connected to political participation and measured offline participation through the frequency of political discussions with friends and family. The study suggested that social networks used for political purposes can predict the level of political participation. Strömbäck et al. (2018) analyzed the relationship between media use and political participation, finding that social media news consumers were more likely to participate in politics offline. Their measure of offline political participation included activities such as attending political rallies, signing petitions, and contacting politicians. Lane et al. (2017) examined the effect of social media political information sharing on offline political participation. They measured offline political participation through an index of activities such as attending political meetings, working for candidates, and contacting public officials. Groshek and Krongard (2016) investigated the effect of streaming on behavior and measured offline political participation by the frequency of engaging in activities such as making campaign contributions, volunteering for campaigns, and attending political rallies. Tai et al. (2020) defined online political activities as "e-participation" and constructed an index that measures diverse online political activities. Their measure of offline participation included activities such as attending political rallies, speeches, or organized protests. The study demonstrated that greater e-participation is associated with greater offline citizen participation, especially among less affluent individuals. G. de Zúñiga et al. (2017) aimed to test the relationship between online social capital and offline political capital. They used an index to measure offline participation, involving activities such as involvement with political groups or campaigns, participating in social movement groups, and attending protests and political rallies. Dimitrova et al. (2014) examined the relationship between online news consumption, social media use, and offline political participation. Their measure of offline political participation included activities like attending demonstrations, contacting politicians, and visiting campaign rallies. The study found that consuming online news had no effect on offline political participation, while social media use had a stronger impact.

Overall, the listed studies above all investigated the understanding of the relationship between social media use and offline political participation with employing various measures to capture the complexity of individuals' engagement in political activities. While some studies suggest a positive relationship between social media use and offline political participation, others present mixed or nuanced findings. To assess this diversity in the results of research in this field, comparisons of studies also analyzed the phenomenon, by discussing the outcomes from different backgrounds.

A meta-analysis, conducted by Boulianne (2016), investigated the relationship between Internet use and offline political participation using various approaches to data collection in cross-sectional observational studies. The study revealed that there are weak to modestly positive relationships between Internet use and offline political participation. This means that individuals who engage with the Internet for political purposes are more likely to participate in offline political activities as well. The positive correlation suggests that the studies in the field overall support the idea of the internet as a platform that encourages and facilitates individuals to become more politically active in the offline realm.

2.2.3 Political predictions

Besides the general correlation between the occurrence of political participation in online and offline platforms, research in the field of political science and social media has delved into how user engagement on online platforms can be used to predict offline political events. Online political behavior produces a vast amount of data about political behavior, which can be utilized in forecasting political outcomes. Research explored how the extent of user interactions, content sharing, and sentiments expressed on social media platforms can offer insights into real-world political outcomes, such as election results and the popularity of politicians. For instance, Williams and Gulati (2009) found a weak correlation between the support candidates received on Facebook during the 2008 US elections and their actual election results. In a similar vein, MacWilliams (2015) utilized a combination of Facebook metrics, including likes and user interactions with candidates' pages, to predict the 2012 US election outcomes. In other countries, social media played a significant role in election campaigns as well. Barclay et al. (2015) examined the 2014 Indian elections on Facebook and discovered a strong positive correlation between the number of 'likes' on a party or candidate's official fan page and their share of the popular vote. Xie et al. (2016) employed a prediction model to analyze the 2016 Taiwan election. They integrated demographic statistics to weight the sample based on age distribution in the population and utilized filtered social media data to effectively represent public opinion. Their findings revealed that the number of 'likes' on Facebook posts emerged as a robust predictor for election outcomes, showcasing the significance of social media engagement in shaping electoral results. In a separate perspective, Enli (2017) presents a historical development of social media usage in politics. According to Enli, the Obama campaign in 2008 marked the initial phase of engaging with voters through social media. The subsequent stage, evident in the 2016 elections, saw a deeper and more sophisticated interaction with voters using these platforms. Finally, the third step witnessed the professionalization of social media in political campaigns, signifying its increasing importance as a strategic tool for political communication and mobilization. This evolution highlights the transformative role of social media in modern political landscapes and underscores its growing significance in electoral processes.

These successful international studies have sought to estimate election outcomes. For instance, Koltai and Stefkovics (2018) employed similar approaches to estimate party popularity in Hungary. They compared the number of likes on various political parties' and politicians' pages with the results of monthly representative polls. Initially, they found no evidence of a correlation between poll results and like numbers, potentially due to demographic differences between the general population and Facebook users in Hungary. To address this issue, the authors applied weighting to their Facebook data, considering that 56 percent of the Hungarian population used Facebook based on the representative survey. This weighting aimed to align the Facebook data with the sociodemographic proportions of the overall voter population. While this adjustment modified the results, the differences between the number of likes and monthly polls increased after weighting.

These studies collectively illustrate the potential of using social media engagement as a tool to forecast offline political events. Predicting real-life events, such as the outcome of elections based on social media data lead to accurate forecasts in some cases (e.g.: Barclay et al., 2015; MacWilliams, 2015), but failed in others (e. g.: Chung & Mustafaraj, 2011; Theocharis & Lowe, 2016), depending on the country and the social media site used as dataset. Coping with the problem, former research employed several diverse techniques in attempting to predict political events from social media activities. One commonly used technique to estimate the offline popularity of a political actor (e.g., a political party) is combining traditional polls with social media data (MacWilliams, 2015). Other studies forecast offline popularity through its online popularity (number of 'likes', 'shares' or 'followers' on their pages, etc.) applying weights to balance the dissimilarities between the population and the users of the social media site (Koltai & Stefkovics, 2018; Oser et al., 2013; Xie et al., 2016). This method was successfully used in some cases, but usually, such cases were characterized by specific conditions.

2.2.4 Social media and political mobilization of underrepresented social groups

Furthermore, as social media platforms gained popularity, expectations arose that they could lead to stronger engagement among traditionally underrepresented social groups, such as women, youth, and low-income individuals. Studies conducted by Loader & Mercea (2011) and Vitak et al. (2011) pointed towards the potential democratizing effect of social media, offering opportunities for broader participation in the political process. Despite the optimistic outlook, criticism has also emerged regarding the supposed democratizing effect of social media sites. Scholars like Morozov (2017) have raised concerns about the impact of social media on politics, questioning whether it genuinely fosters greater political engagement or if it perpetuates echo chambers and misinformation.

Young people are the most frequent social media users (Loader & Mercea, 2011; Vissers & Stolle, 2012), so in their research Holt et al (2013) tests whether social media mobilizes younger citizens while traditional media mobilizes older citizens. Results show that using social media for political purposes does have a positive influence on political interest and offline political participation in an analogous way that paying attention to political news in traditional news media has. Vissers and Stolle (2014) researched undergraduate students and the results underline the mobilization and reinforcement effect of online political participation: In their 2011 Canada survey, they found that Facebook usage mobilized a group that otherwise would not be active offline; while in the most cases students who were politically active offline were the ones active online, too. They found that regarding the socio-demographic variables, politically active people were different from politically not active students; distinguishing activists from non-activists, which can be explained by the evidence that resourceful people take on a broader variety of actions. Oser et al (2013) argue that the campaign of Barack Obama successfully mobilized traditionally less engaged populations such as young people and women. Kushin and Yamamoto (2010) found that online expression, e. g. sharing political news predicted situational political involvement especially among young users, but there was no correlation with attention to social media itself.

Examining the Hungarian youth's political participation based on previous research (Angyal E. et al., 2017), it is evident that while their interest in politics is higher than the European average, their participation in various political activities, such as protests or signing petitions, remains relatively low. Trust in political parties is also low among Hungarian young people compared to the European average. Repeated surveys, such as the Hungarian Youth Research conducted every four years since 2000, show fluctuations in political interest among the youth. In 2016, nearly half of young people displayed no interest in politics. Education levels also influence interest, with higher education correlating with greater interest in public matters. Membership in political or civic organizations can serve as an important marker of higher political interest and overall willingness to engage in public affairs. Sports and church organizations were found to be the most common among young people, according to the Hungarian Youth Survey. Taking the Momentum Movement as an example, social media played a vital role in mobilizing Hungarian youngsters with traditionally low political activity. Research by Angyal et al. (2018) investigated the political socialization paths of the core members of this movement. The study highlighted the significance of family, the limited impact of formal education, and the necessity of informal peer group effects. Additionally, online-based communities and social network sites were identified as influential factors in their political engagement.

Feezell et al (2016) analyzed longitudinal data from 2006-2010, finding that online activities might predict offline political activities, especially amongst the 18-30 years old. Their article used a multi-method survey of 425 undergraduate students to investigate the correlation between political activity and political knowledge and being a member of a Facebook group. The independent variables included a self-reported answer about how many political groups the respondent was a member of, the intensity of Facebook usage, and an index based on several questions about how often respondents read and post messages. The dependent variable was a composite scale of ten forms of offline political participation. Results showed that participation in online political groups is strongly correlated with offline political participation.

2.2.5. Researching underrepresented social groups with social media data

Previous research has shown that young people are more likely to be politically active online than older adults (Kim, 2016), while participating less in traditional surveys (Loader & Mercea, 2011). Measuring their political activity through national representative surveys has been difficult anyway, due to their relatively low proportion in the population. This emphasizes the significance of social media data for understanding their political behavior. Analyzing social media data, then, could present a way to approach them. However, analyzing data that is available on social media requires a different approach than analyzing a probability sample, which is traditionally used more in social sciences.

In Hungary, the issue of collecting data about young people and their political engagement has been a challenge for traditional survey methods due to declining response rates and other problems (Stefkovics, 2021). The transition from in-person questionnaires in the 1970s to online surveys in the early 2020s reflects the changing landscape of data collection methods (Stefkovics, 2021). Social media data, characterized by its large volume, velocity, and variety, offers an alternative to traditional self-reporting surveys (McCay-Peet & Quan-Haase, 2016). Analyzing social media data provides actual information about users' behavior and can be obtained faster and more affordably than conventional surveys (Tufekci, 2014).

Non-probability sampling methods, common in social media data collection, can help reach social groups that are traditionally less politically active, such as young people (Loader & Mercea, 2011). Social media usage is particularly high among the youth, making it a valuable source for studying their political preferences and behavior (Holt et al., 2013; Vissers & Stolle, 2012). However, analyzing social media data for predicting offline political outcomes requires considering the selection probabilities, which are not always available in social media data (Cukier & Mayer-Schoenberger, 2013).

The use of big data and digitalized life in research offers opportunities for prediction and pattern exploration in economics and social sciences (Mol et al., 2017). However, there are challenges, including issues related to data privacy, data management, and digital inequalities (Shaw & Hargittai, 2018). Despite these challenges, non-probability sampling and big data methods play a crucial role in investigating hardly approachable social groups and fields that cannot be fully explored by traditional survey methods (Vincze, 2017). These methods - which are more precise than conventional surveys and can deal with the decreasing response rate problem - can mainly support the research of fields that are unable to be explored by probability sampling methods (Mol et al., 2017).

In summary, research shows that young people, while traditionally less politically active, are highly active users of social media. Social media data provides a means to access information about this hard-to-reach social group, which may be challenging to collect through conventional national surveys. The impact of internet usage and the role of social media sites in particular on the results of elections and political activity is a widely researched field (Zhuravskaya et al., 2020). Although social media have been used by political campaigns and parties for years now, there are ambivalent opinions about its role in politics and democratic processes (Y. Kim et al., 2013). Studies have investigated that social media might increase exposure to heterogeneous perspectives and thus promote civic engagement in a society (Kim et al., 2013), or a pessimistic scenario, discourage it through controlling information spreading (Morozov, 2017).

2.3 Sharing political messages and emotions

In this thesis, the focus is on the political participation aspect of sharing information on social media, as it can serve as an indicator of offline mobilization, as noted by M. Bene (2018). Sharing information on social media can also be seen as a form of mobilizing potential voters and exemplifies the growing impact of social media on political participation, as suggested by Larsson (2015). Moving forward, the chapter will delve into the impact of emotions on sharing behavior online, as theories suggest that sharing plays a crucial role in political activities in both online and offline contexts.

2.3.1 Emotions in politics

Emotions are central to politics, as research indicates their significant role in decision making and political behavior (Sturm-Wilkerson, 2021; Muraoka et al, 2021; Jonas&Hoffmann, 2013). Eberl et al (2021) argues that political attitudes are composed of both cognitive and emotional components, with the emotional aspect often having a strong influence on the perception and evaluation of issues and events. Emotions can impact the level of engagement with political messages and campaigns, as well as the processing and recalling of information. They can shape individuals' responses to political communication and play a crucial role in shaping their overall attitudes and behavior, and thus the process of decision making. In 1956, Downs introduced the theory of the rational voter. This theory suggests that rational individuals, motivated by utility maximization, would assess the potential benefits of voting compared to the associated costs. According to this viewpoint, individuals would only choose to vote if the expected benefits outweigh the costs. This hypothesis is derived from economic principles of rational behavior. However, it is counterintuitive because the likelihood of an individual's vote being pivotal or tie-breaking in a large-scale political system is extremely small. As a result, the expected benefits of voting may be lower than the time cost involved, leading to the conclusion that rational individuals would choose not to vote. The theory since has gained a lot of extension, e. g. in Cebula et al (2005). Traditionally there has also been a perception of conflict between the role of emotions and rational models of voter behavior, debating whether the information or the emotional part of political communication is more important in convincing voters, but in recent research emotions are viewed as complementary to rationality, playing an important role in decision-making processes (Jones&Hoffmann, 2013).

Studies explaining the role of emotions in politics widely use the Affective Intelligence Theory (AIT) of Marcus (2000), e.g., Sturm-Wilkinson et al, 2021 and Jones&Hoffman, 2012. AIT draws on neuroscience to explain how emotions influence political behavior and demonstrates how different emotional states influence citizens' engagement with politics. According to the theory, emotions have a preconscious impact by activating two different subsystems when people react to different settings. Positive emotions like enthusiasm, pride, or hope signal the activation of the dispositional system, leading individuals to rely on heuristics and make routine decisions in familiar settings, while feelings of anxiety indicate the activation of the surveillance system, making individuals more aware of unfamiliar environments and reducing reliance on habitual behavior. This distinction may explain how the rational models of voter behavior may depend on emotions – in different emotional setting different decision might be rational (Sturm Wilkinson et al, 2021).

2.3.2 Transferring emotions online

The role of emotions in politics might be supported by the AIT theory. However, the topic of the thesis is the social media, so the first question is whether the emotions can be transferred, having similar effect online.

The role of emotions in politics is a complex and multi-faceted topic. The earlier introduced Affective Intelligence Theory suggests that emotions play a crucial role in political decision-making and behavior. Emotions can influence individuals' attitudes, perceptions, and actions in the political sphere. However, when it comes to the context of social media, it raises the question of whether emotions can be effectively transferred and have similar effects online as they do in offline interactions.

Research in the field of digital communication and social media suggests that emotions can indeed be transferred and have an impact on online platforms. Stieglitz and Dang-Xuan (2013) have shown that emotional content can be transferred and thus evoke emotional responses in receivers online, through computer-mediated communication (CMC). CMC utilizes various markers of emotions, including verbal cues (such as emotion words and linguistic markers) and nonverbal cues (like emoticons). Emoticons and emojis help express emotions, emphasize points, share humor, appear empathetic, and regulate tones when communicating online without seeing each other's facial expressions (Sturm Wilkerson et al, 2021). They suggested that the addition of emoticons to textual messages online makes it easier for readers to understand the intended tone, attitudes, and emotions of the messages. However, the digital environment introduces unique dynamics, such as the limited number of nonverbal cues and the ability to curate and selectively present oneself. These factors can shape the way emotions are expressed, perceived, and interpreted online. There is a scientific debate whether these constraints shape communication on the online platforms, or the platforms are shaped by user behavior. One perspective suggests that platforms primarily shape user behavior through their design and functionality. The affordances provided by the platform, such as the ability to like, share, or comment on posts, structure and guide user interactions. In this view, the platform sets the boundaries and constraints within which users navigate and communicate, influencing the patterns and dynamics of online interactions. On the other hand, another perspective emphasizes the role of user behavior in shaping the platforms themselves. Users engage with and appropriate the platform in ways that may not have been originally intended by its designers. User-generated content, user interactions, and emerging social norms can influence the evolution and development of the platform. This perspective highlights the active role of users in shaping the dynamics of online communication platforms.

The theory of affordances might explain this phenomenon in the context of social media. The concept of affordance, originally rooted in ecological psychology, was first used to explain how both human beings and animals perceive and interact with their surroundings (Nagy and Neff, 2015). It focuses on the relationship between the properties of an object and the possible actions or uses that people perceive it to have. There are numerous ways to conceptualize affordance, as it became popular in various fields.

Affordance is a common term used in communication, referring to the virtual platforms located in the online space. Regarding social media, affordance might be an approach to understand how technology and society relate: Bucher and Helmond (2017) introduce the term as a main tool to analyze social media interfaces and the relationship between technology and users. Social media offers a space for social activities, interactions, communication, content creation, and information consumption, which is structurally defined in a specific way. Social media platforms consist of specific codes, algorithms, protocols, interfaces, and default settings, which operate invisibly to the user in a seemingly natural manner, while influencing the form and content of social activities conducted on the platform. The social activities cannot be transformed to technological forms directly; thus, the platform actively shapes and reshapes the social realm (Bene M, 2019). However, these technological and automation solutions are outcomes of human activities, and as such, they cannot be separated from the characteristics of their creators.

Hutchby (2001) argues that between social constructivism and technological determinism, communicative affordance could be the third, middle term that takes both approaches in account, as technologies are socially constructed and materially constructing simultaneously. Nagy and Neff (2015) also underline this role of affordances, stating that in previous research affordances have served as a middle ground between technological determinism and social construction, allowing researchers to acknowledge the materiality and functions of technology while emphasizing that users' actions shape and utilize these functions. They conclude that in communication theory, affordances mostly refer to the things users get from technology; meanwhile technology studies highlight the options users can do with these technology, thus focusing on the role of affordances from another perspective: the broader influence of technology on social dynamics, highlighting the interplay between technology and human agency.

> *"Specifically, Hutchby develops the concept of 'communicative affordances' referring to the 'possibilities for action that emerge from […] given technological forms' (2001a: 30). This definition emphasizes how affordances are both functional and relational; 'functional in the sense that they are enabling, as well as constraining' and relational in terms of drawing 'attention to the way that the affordances of an object may be different for one species than for another' (Hutchby and Barnett, 2005: 151 emphasis in the original). Moreover, 'affordances can also shape the conditions of possibility associated with an action: it may be possible to do it one way, but not another' (Hutchby and Barnett, 2005: 151)." (Bucher-Helmond, 2017, 10)*

Affordance is used regarding social media because it focuses not only on the technology but the types of communication and social interaction that social media features suggest. However, as Nagy and Neff (2015) argue, this approach has focused on what technology enables users to do, often overlooking the underlying black boxes, algorithms, and automatic processes. This limited perspective fails to account for the broader dynamics of how technology shapes experiences beyond what tools explicitly offer to individuals.

To emphasize the complexity, and to exceed the dichotomy between the socially and technologically determined, Nagy and Neff (2015) introduce the term 'imagined affordances'. They argue that affordances are not solely limited to determining the possibilities and constraints for human users in their conscious and rational actions, but it encompasses the processes of mediation, as well as the role of affect and emotion. This approach emphasize that affordances are not only determined by objective properties of artifacts or technologies but are also influenced by individual perceptions, subjective experiences, and the emotional and affective dimensions of human interaction with them. Imagined affordances emerge between the users' perceptions, attitudes, and expectations, as well as the materiality and functionality of technologies, and the intentions and perceptions of designers.

In other approach, the dynamics and features of technology can be conceptualized with high-level affordances, while low-level affordances refer to the “materiality of the medium” (Bucher-Helmond, 2017, 12).

Affordances are a main term in analyzing Facebook. Nagy and Neff (2015) claim that Facebook offers social affordances. While users of Facebook have the capability to make certain choices that can influence the content they see in their News Feed, thereby shaping their overall experience within the platform, the Facebook designers determine which affordances they want to incorporate into the News Feed. In the realm of design, the creators of tools, such as Facebook, incorporate specific affordances into their products. Consequently, users often have limited visibility into the intricate workings and complexities behind these affordances, which can affect their understanding of how their News Feed is curated.

Sturm Wilkerson et al (2021) understand Facebook reactions as affective affordances. In 2016, Facebook expanded its Like button to include reactions such as Love, Haha, Wow, Sad, Angry, and later added a Care reaction in 2020. According to Sturm Wilkerson et al (2021), these reactions, along with emoticons and emojis, are ubiquitous on social media platforms and serve as > *“one-click feedback cues” (Carr, Hayes, and Sumner 2018, 142) or “paralinguistic digital affordances” (Hayes, Carr, and Wohn 2016, 172)*< (cited by Sturm Wilkerson et al, 2021, 4) . They are distinct from deeper forms of engagement like commenting, but they allow users to provide emotive feedback and enable the collection of more detailed user data. Facebook reactions in their study are considered as affective affordances because they enable users to both affect and be affected by others. While individual Facebook reactions represent specific emotions, they become affective affordances when users interact with them, producing cascading effects.

However, Facebook Reactions have limitations as affective affordances since they only allow users to symbolically communicate one emotion at a time from a predetermined set, limiting emotional expression to discrete choices, rather than allowing for the simultaneous expression of multiple – not previously configured – emotions. In this context, affective affordances are defined as the relational expression of emotions through the technological functions that represent discrete emotions. They can also serve as cues for others to be influenced, potentially inspiring further emotional responses. Affects arise from how individuals navigate their feelings within the constraints of preconfigured choices, using strategic ways to appropriate the available functions even if they may not perfectly align with their actual emotions.

2.3.3 The effect of emotions in sharing information on social media

Emotions can play a facilitating role in the act of sharing content with others for several reasons. In their study, Berger and Milkman (2010) explored the role of emotions in the context of sharing information: firstly, emotional stimuli often elicit ambiguous sensations, and by discussing and sharing emotional content, individuals can gain a deeper understanding of their own feelings. This process allows them to explore and make sense of their emotions (Rime, Mesquita, Philippot, and Boca, 1991). Secondly, when emotional material challenges individuals' beliefs or their worldview, they may be inclined to share it with others as a way to cope or reduce feelings of cognitive dissonance. Sharing such content can help individuals reconcile conflicting thoughts and create a sense of coherence (Festinger, Riecken, and Schachter, 1956). Thirdly, sharing emotional content can serve to strengthen social bonds. By sharing their emotions with others, individuals can deepen their social connections and foster a sense of closeness and understanding (Peters and Kashima, 2007).

Eberl et al (2021) argues that emotional reactions to a political message depend on content characteristics, such as valence framing and issue salience. According to appraisal theory (Scherer, 2005), individuals evaluate issues, situations, and events based on their personal relevance, pleasantness, certainty, or coping potential. These evaluations then determine the specific emotional responses of individuals. This transactional appraisal process assesses events and their consequences in relation to the appraiser's salient needs, desires, or goals. Consequently, if an issue is not personally relevant to an individual, it is unlikely to elicit an emotional response. The concept of issue salience, which refers to the importance of an issue to an individual, has long been recognized to vary among citizens. Some issues may be a focal point for certain individuals while being disregarded by others. Individuals are expected to be more cognitively, behaviorally, and emotionally engaged with issues that are personally salient to them (Eberl, et al, 2021).

To analyze the impact of the sentiment of a message on emotions, Eberl, et al, 2021 introduces the concept of valence framing. Media effects studies have shown that messages conveying a negative sentiment, such as news stories about war, terrorism, or crime, are more likely to elicit negative emotions in audiences. Similarly, negative news stories about the cost of migration can trigger negative affective responses, and positive framing in messages can evoke positive effects, such as hope or enthusiasm. On the other hand, balanced messages that highlight both the risks and benefits of an issue are less likely to elicit clear emotional responses. In terms of strategic political communication, studies have found that negative political advertisements generate negative emotions, while positive ads evoke positive emotions. This suggests that the emotional responses triggered by political messages can vary depending on the valence (positivity or negativity) of the content.

In Freeman et al.'s (2020) study, the diversity of emotions evoked by posts is used additionally as a measure to assess the emotions' effect on user engagement. The diversity of response in their research refers to the extent to which users' responses to a post simultaneously point in different emotional directions. This diversity can indicate various scenarios, such as controversial content or the absence of consensus on how a subject should be perceived or interpreted by a group of responders. A higher diversity of emotional responses about a post or article suggests that there is significant variation in how individuals react to the content. This lack of consensus indicates that the topic or issue is eliciting diverse emotional reactions among users.

Diversity of Reactions might be important to perceive the public opinion climate online, as Leong and Ho (2021) argues. In their study they refer to the Spiral of Silence theory by Noelle-Neumann (1974). According to the SOS theory, individuals are driven by an innate fear of isolation, influencing their actions. Those who believe their views align with the majority tend to express themselves confidently, while those who perceive their views as opposing the majority often choose to remain silent (Noelle-Neumann, 1974). In their study, Leong and Ho (2021) proves that Reactions are used to assess the public opinion regarding a topic on Facebook, and that, in line with the SOS theory, individuals were more inclined to express their views when they accurately perceived the prevailing opinion climate to align with their own position on the issue.

2.3.4 Empirical research on emotional valence and diversity

Based on these theories, numerous empirical research focused on the valence of posts in analyzing the factors behind sharing them on social media. B. Zhang & Vos (2015) argue that spreading is important part of the research from different angles. In their structural literature review they found that most research attention analyzed how a message can be spread ‘rapidly and widely’ on the internet, as it is the goal in political campaign (Magin, 2017). Reducing the diffusion might be also interesting in the case of “fake news” (Cheng et al., 2021). Targeting might be also the goal in message spreading (B. Zhang, 2015). Zhang (B. Zhang, 2015) emphasize the importance of monitoring the social media environment in all cases. Their research suggests that in “going viral”, the positive emotional background can facilitate being shared on social media.

Berger et al (Berger et al., 2010) found similarly that content virality is positively associated with its positivity and emotionality (particularly with the emotions anger, awe, and anxiety) and negatively related to sadness. Berger et al analyzed emailing New York Times articles shared on email lists and found that users prefer to share positive rather than negative content.

Their research was repeated in a German context by Heimbach und Hinz (2016), with an extension to not only examining the sharing on email lists but also on social media. They found that the number of shares on an article depends on the medium where it can be shared: on Facebook, the posts most shared were linked to angry and awe emotions. They found nonlinear effect of positive emotions of a post on the number of shares: highly positive posts were shared less but moderate positive emotions gained more shares.

The difference in the logic of shares regarding the media platform appears in other research: On Twitter, Stieglitz and Dang-Xuan (2013) found that political tweets were significantly correlated with more emotions: both positive and negative emotions increased retweets. Hoang et al (2013) found that emotionally neutral tweets were more likely to be retweeted in general on their Twitter sample. In the case of political contents, their analysis found that users were more likely to retweet an emotional post by a user from different political affiliation, than they would retweet a neutral post by someone from similar political background. Authors concluded that emotions have a stronger effect on sharing information on Twitter than similar political views.

In Larsson's (2015) study, the relationship between the content of posts on the Facebook pages of Norwegian party leaders and the number of reactions they received was examined. The findings indicated that critical posts tended to receive a higher average number of shares. Hansen et al. (2011) explored the connection between the sentimental content of a post on Twitter and its likelihood of being shared. The results supported the theory of strong emotions affecting virality, as they found that negative news was retweeted more frequently than positive news. Moreover, they analyzed news and social tweets separately and found that in the case of news segments, the overall finding was reinforced, while for social tweets, positive content was more likely to be shared. Both studies contribute to our understanding of how emotional content can impact the virality of posts on social media platforms, highlighting the role of strong emotions in driving user engagement and sharing behavior.

These researches are using some kind of content analysis regarding content of the post. Content analysis is a research method that involves systematically analyzing and categorizing the content of text, images, or other forms of communication to identify patterns, themes, or trends. In these studies, content analysis was used to analyze the textual content of the posts on social media platforms like Facebook and Twitter to determine the presence of emotional content, such as positive or negative sentiments, and its association with user engagement metrics like shares or retweets. By using content analysis, these studies were able to quantify and measure the emotional content of the posts, allowing them to draw conclusions about the relationship between emotions and user engagement on social media platforms. In most cases, emotions detected with language analysis determine the emotions in the research (Eberl et al, 2021, Hansen et al, 2011).

Contrary to this approach, Muraoka et al (2021) propose focusing on the reactions Facebook affords its users to interact with the posts. They claim the reactions might be understood as some kind of metadata, that is associated with social media posts rather than the textual content itself. This association with the posts is based on the result of other studies, such as Eberl et al. (2020) that proved that Facebook reactions are correlated as expected with the sentiment expressed in post texts – negative language evokes negative emotions and positive language positive emotions – except for the Like button, which is the oldest reaction button in use and thus has a more diverse meaning. Similarly, de León et al in their 2021 study summarize how previous research categorized Facebook Reactions based on their emotional valence, and suggest that Love is a clear positive, while Sad and Angry are negative emotions, with Likes and Hahas being vaguer reactions.

Muraoka et al (2021) thus suggest that Facebook reactions can be used to study mass emotions, as they provide valid information about emotional responses to the content.

In summary, based on the previous chapters, it can be stated that emotions play a significant role in politics and social media. Emotions are commonly employed for political purposes and can be effectively transferred through online platforms. Empirical research supports the idea that Facebook Reactions serve as a form of emotional feedback, with negative sentiment posts tending to elicit negative emotional Reactions, and positive sentiment posts evoke positive Reactions. Furthermore, the two-step flow effect suggests that sharing political posts online is influenced by the endorsement and sharing behaviors of trusted sources in one's social network.

2.4 Spreading information on social media

Sharing is a fundamental aspect of information dissemination on social media platforms. When users share content such as posts, articles, or videos, they contribute to its wider visibility and potential reach. This process allows information to spread rapidly across networks, reaching not only direct followers but also their extended connections. Sharing plays a vital role in amplifying messages, facilitating discussions, and engaging audiences in various topics, including politics. As a result, it can significantly impact the spread of political information, influence public opinion, and even mobilize individuals to participate in offline political activities. Understanding the dynamics and factors influencing sharing behavior is crucial for comprehending the role of social media in shaping public discourse and political engagement.

The previous subchapter assessed the emotions' effect on sharing behavior on social media. In this section, the focus shifts to examining how social network characteristics influence the spread of information on social media. Social network characteristics play a pivotal role in determining how information flows within a network and reaches a wider audience. The structure of social networks, including the pattern of connections, interactions, and ties among users, can have a profound impact on the speed and extent of information dissemination.

Research has explored different models of information diffusion, examining how messages propagate through social networks and who the key actors are in driving this process. Early studies, such as Katz and Lazarsfeld's two-step model, highlighted the role of opinion leaders in mediating information flow. These opinion leaders, who are influential and politically engaged, can shape public opinion by disseminating information to their social circles.

With the rise of social media, the dynamics of information diffusion have evolved. Online platforms offer unique opportunities for content to go viral, reaching vast audiences within a short time. The phenomenon of viral spreading is influenced not only by influential individuals but also by the nature of the message, its authenticity, and the user's exposure to political content unintentionally.

Moreover, the structure of social media platforms themselves, with their algorithms and user behavior, plays a crucial role in determining which content gains traction and achieves wider visibility. Social media companies design their platforms to promote engagement, and certain types of content, such as emotionally charged or highly shareable posts, tend to perform better.

Understanding the interplay between social network characteristics, user behavior, and platform algorithms is essential for comprehending how information spreads on social media. This knowledge can shed light on the mechanisms that shape public discourse, influence political opinions, and mobilize individuals to engage in various forms of political participation, both online and offline. By delving into the effect of social network characteristics on information spreading, this chapter aims to deepen our understanding of the complex dynamics of social media as a political communication tool.

Information diffusion on online social networks involves two main components: the information being disseminated and the social network itself, through which the information spreads (Wani & Ahmad, 2015). Spreading information on social media is highly efficient, and Viksnin et al (2017) even argue that it is more effective than traditional mass media channels. Various theories attempt to explain how information spreads online. One such theory by Kempe et al (2003) suggests that targeting influential members of the network initially can trigger a cascade of influence, leading to widespread dissemination. Social scientists have explored the mechanisms of disseminating ideas and opinions through two main approaches: the first approach focuses on using mathematical models to study the evolving state of social networks over time, while the second approach centers on investigating the stability of networks. Understanding these diffusion models is essential for comprehending how information propagates on online platforms, shaping public opinion and influencing social behavior.

2.4.1 Role of network characteristics

The concept of social networks refers to the social connections of people (Valenzuela et al., 2018). Individuals can benefit from social connections, as through them can they have access to and use the resources of other individuals. Regarding politics, this benefit can be the opportunity to reach otherwise unrecognized people and thus lowering the campaigning costs (Valenzuela et al., 2018).

On social media, the connections emerge from distinct real life social network structures (Vepsäläinen et al., 2017). Boyd and Ellison (2007) argued that the main attribute of a social media platform is to create and display connections with others on the platform, via a semi-public or public profile. The social network behind the social media platform is a core attribute of a social media platform. In their article, Valenzuela et al (2018) claim that in the literature of network science, most authors use two types of connections in a social network: weak and strong ties.

Shared news on social media spread differently regarding the network structure (Moreno et al., 2004; Pegoretti et al., 2012), thus sharing can cause different effects regarding the social media applications. Centola (2010) summarizes two main theories regarding the issues of strong or weak ties. The first hypothesis known as the 'strength of weak ties' posits that networks characterized by numerous "long ties," exemplified by small world structures, are more effective in disseminating a social behavior over greater distances and at a faster pace compared to networks where ties are tightly clustered. In this view, the spread of behavior is likened to a simple contagion, such as the transmission of a disease or information, where a single interaction with an "infected" individual is usually adequate to convey the behavior. The advantage of long ties lies in their ability to minimize redundancy in the diffusion process by linking individuals whose social circles do not overlap. Weak ties connect acquaintances rather than closer friends or family members, thus linking farther clusters together. Granovetter (1973) suggests that weak ties imply more resources as they provide access to novel information and more diverse perspectives. Valenzuela (2018) states that according to Granovetter’s theory, in large networks with weak ties, information and new opportunities might spread rapidly and through them people, who otherwise do not necessarily know each other, can connect. This means that political mobilization might be successful in such networks that way.

Other hypotheses challenges this notion, suggesting that, the adoption of social behavior is a complex contagion, necessitating contact with multiple sources of influence before individuals are persuaded to embrace the behavior. According to this hypothesis, clustered networks, which feature more redundant ties providing social reinforcement for behavior adoption, might be better suited to facilitate the diffusion of behaviors across large populations. Strong ties refer to the relationship between people close to each other, such as friends and family. These connections might offer less new opportunities but might provide other resources, such as support (Kenny, 1994). Networks with more strong ties tend to be more homogenous, which attribute might facilitate reinforcing the ideas and adapt behaviors. Valenzuela et al (2014) claim that political activities require reinforcement, and political mobilization might be the result of adapting behavior from others. They assume, that in contrary to weak ties, through which information might rapidly diffuse, the "strength of strong ties" lies in attaining influence.

Regarding the social media applications, Valenzuela et al (2018) claim that different network structures are typical of the two most popular site, Facebook and Twitter. Their article claims that connections on Facebook mean real interpersonal relationships, while the structure of Twitter supports following people who are not in personal contact with the user. Thus, they understand networks on Facebook containing mostly strong ties and Twitter weak ties. Bucher (2012) investigated the algorithm structuring the flow of information on Facebook. Facebook applies an automated process to select the most relevant content for the users' News Feed. The research analyzed the main page of Facebook in 2011, and since then, it has been updated, but the goal is similar: to create more personal content for the users. Some parts of the algorithm are known, for example it labels content as more relevant if a friend reacts to it or shares it, but the whole mechanism is hidden (Bucher, 2012). Users typically share content with close connections, which underlines the strong-tied character of Facebook. Strong ties on Facebook cause a greater influence on connections, because of the emotional closeness. Vepsäläinen et al (2017) concludes from the literature that on Facebook, emotional closeness makes users to read longer and more elaborate messages from their friends, which may strengthen its persuasive power. Opinions from more distant acquaintances might be read by the users only for their informational value, thus they might be less important for political mobilizational goals. Results of the research of Vepsäläinen (2017) suggests that this phenomenon prevails in the investigated Chilean context: on Facebook, strong-tie connections are conductive to further protest behavior, while exposure to weak ties conveys a much weaker influence on this type of political activity.

Simulating real social media networks is a difficult task, as the social network structure and the algorithm responsible for content showing of the different social network sites are unknown for research purposes. Thus, research use simulations of social networks to estimate the algorithm's 'black box nature' (Bucher, 2012). Different simulation approaches emphasize different attributes of social networks. There are several modeling approaches that are widely used to achieve this end. Chan (2019) presents three widely applied types of networks to model social network sites: preferential attachment (PA) networks; random (variant of Erdős-Rényi model) network; and small-world networks.

Flache and Macy (2014) suggest that the possibilities for contacting people regardless the different geographical and social environments increased rapidly with the internet. This assumption led to questions about how cultural differences will carry on in a globalized setting. However, Watts and Strogatz (1998) have established that clustering as a strong phenomenon may co-exist with greater connectedness, as it is enough to have long ties for a small proportion of people to decrease the distance in a network.

Macy and Centola (2007) define the distance in a network with the length of the shortest path between neighbors after removing their shared tie. Short ties are the attributes of clusters and long ties connect local clusters that otherwise would not connect. The distance of the tie, what can be considered as short or long depends on the other network characteristics.

Impact of the network structure was analyzed in different models of opinion dynamics and diffusion. Flache and Macy (2014) specify the effects of network attributes to information spreading based on previous research. Based on Granovetter's theory of the 'strength of weak ties,' research on 'small-world' networks suggests that connections between different clusters within a social network, known as long-range ties, can foster cultural diffusion, cohesion, and integration. Their research validates that the impact of increased connectivity on social integration and polarization relies on the underlying micro-mechanisms of cultural interaction. When considering solely positive influence and selection, long-range ties lead to more cultural integration and assimilation. However, when both positive and negative influences are taken into account, the outcome is reversed, with long-range ties serving as pathways for the transmission of locally developed polarization to otherwise nonpolarized areas of the network.

The small world model (in contrast to random networks) was shown to be more efficient in a simulation model of diffusion of new products with network externalities (Pegoretti et al., 2012). Its feature of containing ties that bridge long distances was also shown to propagate faster diffusion of information in an experimental setting in contrast to a lattice-structured network (Centola, 2010).

Beyond the pure structure, a critical feature of networks with respect to political opinions is homophily due to its direct consequence on the echo chamber mechanism. Lazarsfeld and Merton defines homophily as the inclination in a society for people to interact more with others with similar characteristics rather than with people with different ones (Lazarsfeld & Merton, 1954). This emerges along two key social dimensions: status and values (Lazarsfeld & Merton, 1954; McPherson et al., 2001). Value homophily, however, might contribute to the development of the phenomenon called “echo chambers” on social media.

2.4.2 Polarization and echo chambers

Homophily regarding political topics can on one hand support the social media as a public sphere, but on the other hand, can reinforce established opinions as echo chambers (Colleoni et al., 2014). Political polarization refers to the distinction of like-minded people regarding political topics (Gillani et al., 2018). Hargittai et al (2008) showed that people with the same political interest and opinion tend to behave similar on the internet, as they read and visit similar webpages. Higher level of political polarization can help predicting political participation and can cause harm to democracies via concentrating the power (Kubin & von Sikorski, 2021). Gillani et al (2018) argues, that political polarization is also available offline and was there before the internet, the social media platforms offer a new way to express and thus exacerbate political polarization. The effect of social media on political polarization is a popular topic because of the homophilic nature of social media: people usually see content from other with similar opinion (Tsfati et al., 2020), and that is especially researched regarding the spread of disinformation. Tsfati et al (2020) argue that in the dissemination of disinformation echo chambers play a major role.

Echo chambers are defined as clusters formed by users with a homogeneous content production and diffusion, in which one’s beliefs are reinforced due to repeated interactions with individuals sharing the same points of view (Cota et al., 2019). Selective exposure (value homophily) and confirmation bias are key mechanisms contributing to formation of echo chambers (Quattrociocchi et al., 2021). Bauman et al (2020) defines echo chambers as a phenomenon emerging from polarization: the segregation of opinion space might cause a reflection in the interaction among social media users. Simulation models have shown that social influence in opinion dynamics and echo chambers in case of controversial issues leads to polarization of opinions instead of developing a consensus, and the segregation of the network into several separated communities (Baumann et al., 2020; Z. Li & Tang, 2015). Such dynamics of polarization was also observed empirically on social networks (Del Vicario et al., 2016). From the point of view of news sharing, a polarized outcome may correspond to a limited diffusion of the news, where the news reach only that cluster of users, which had initially favorable attitudes.

Echo chambers might also be the consequence of the algorithms used by social media. Personalized recommender algorithms are routinely used by e-commerce and social media to filter content that fits the preferences of the user (Ge et al., 2020). Recommending friends on social media itself contributes to echo chambers in case homophily is present (Cinus et al., 2022). In addition, presence of content filtering according to the preferences of the user also contributes to the positive feedback loop of echo chambers (B. Jiang et al., 2021). Quattrociocchi et al (2021) found higher segregation in news consumption on Facebook than in Reddit, and they also found higher biases in the information diffusion due to the clusters on social media based on content curating algorithms that are not tweakable by users (Facebook, Twitter) in contrast to other platforms, e.g., Reddit. In the case of Facebook, they found that the user's attitude ('leaning') affects who the final recipients of the information are, thus increasing the polarization in information diffusion.

Echo chambers were also linked to the spread of misinformation: in their 2015 study, del Vicario et al investigated the spread of contents were not verifiable. They found two separate, highly segregated communities in opinions regarding conspiracy and scientific topics and users tend to share a content in a specific narrative, to friends with similar interests – to the other member of a same echo chamber. While the consumption patterns are similar, the cascade of diffusion of scientific news and conspiracy news differ: science news reach higher level of diffusion quickly with a lower level of interest; and conspiracy news diffuse more slowly.

Baumann et al (2020) proposed a model to explain how moderate initial conditions can evolve to radicalism, through the reinforcement of extreme opinions. The research proposes a simulation model that combines network and opinion dynamics to reproduce features of empirical social networks characterized by polarization and echo chambers. The model is based on three main assumptions inspired by empirical evidence: aggregated social influence, heterogenous activity, and homophily in interactions. The role of opinion reinforcement and controversy in opinion polarization is defined in the model as one of the key features driving the transition between global consensus and radicalization.

2.4.3 Models of information diffusion

In the realm of information spreading on social media, researchers have employed various models to study user behavior, algorithms, and network characteristics. One prominent approach is examining online social influence, which delves into the dynamics of information and opinion dissemination across online networks (van Maanen & van der Vecht, 2013). To understand how information spreads, two popular models, the linear threshold model and the independent cascade model, have been utilized and are the focus of this chapter, drawing insights from the works of Viksnin et al (2017) and Kempe et al (2003).

A social network can be modeled as a directed or undirected graph. In these models directed graphs $G = (V, E)$ are used, with a set of nodes $V = \{v_1, v_2 \dots v_m\}$ and edges $E = \{e_{1,}e_2 \dots e_m\}$. Nodes can have an active or inactive state from the perspective of the information diffusion.

The two most popular information diffusion models to simulate information spread on social networks are the Linear Threshold Model (LT) and the Independent Cascade Model (IC) (B. Jiang et al., 2021).

The linear threshold model is a mathematical representation of how a user's decision to adopt a new behavior, such as sharing a particular post, is influenced by their connections within the network. In this model, each user has a threshold, and if the number of their connected friends who have adopted the behavior exceeds this threshold, they are likely to adopt it as well. This model simulates the cascading effect of information spreading through a network, as a user's decision to share content can trigger a chain reaction of adoption by their connected peers.

In the linear threshold model nodes can turn from inactive state to active state. Nodes are influenced by their neighbor and each one has a threshold at which number of adjacent nodes do they become active.

$$\sum_{j=1}^{n} w_{ij} > f_i$$

In this condition, i – the analyzing node, j – the adjacent node, $w_{i,j}$ – the influence of the active neighboring node on analyzing node, f_i – the threshold number for the analyzing node. If this condition is true, the nodes become active.

On the other hand, the independent cascade model focuses on the probabilities of information spreading from one user to another. In this model, each edge between users in the network has a certain probability of transmitting information. When a user shares content, their connected peers receive the information with a given probability. This model captures the stochastic nature of information diffusion, where each transmission has an independent chance of occurring.

In this model, after a node becomes active, it gets a chance to activate adjacent nodes with a certain probability. A node becomes active in time *t,* when it can activate neighbor *w,* with a probability $p_{v,w}$, based on the parameter of the network. This probability can be structured as a parameter of the model (Chan, 2019). If *v* succeeds, then *w* will become active in step t + 1; but whether *v* succeeds, it cannot make any further attempts to activate w in subsequent rounds. The process runs until no more activations are possible.

By employing these types of models, researchers can gain insights into how user decisions, network connections, and algorithmic factors collectively contribute to the spread of information on social media. Analyzing user behavior through these models helps to uncover patterns of information diffusion, understand the influence of influential individuals, and examine the impact of platform algorithms in shaping the flow of information within online networks. Ultimately, these investigations contribute to a more comprehensive understanding of the mechanisms that govern information spreading on social media platforms.

Considering the basic diffusion models, researchers apply similar methods to investigate information spreading on social media sites. Viksnin et al (2017) analyzed the Vkontakte social media platform, where members can 'like' and 'repost' news which are shared by their 'friends'. This social media site can be treated as a usual network, so the basic distribution model is the same: vertex *i* which connected with vertex *j* active neighbors at time *t* activates if their impact is stronger than the threshold of i. They calculate the impact based on the influence, activity of nodes and the relevance of the news.

$$\sum_{j=1}^{n} D_{ij}\, A_i L_t > f_i$$

Here D_{ij} is the influence of the neighbor *j* to the node i; A_i is the activity of i, L_t is the relevance of the information at time *t.* D_{ij} is calculated based on the proportion of likes and reposts and shares.

$$D_{ij} = \frac{Like_{ij} Repost_{ij} Friends_{ij}}{Like_i Repost_i Friends_i}$$

The $Like_{ij}$ refers to the number of likes on node i from node *j*; $Repost_{ij}$ means the number of reposts on *i* from j, and $Friends_{ij}$ means the number of common friends.

The relevance is calculated according to the proportion of real and possible number of likes for news at time *t*.

$$L_t = LP_{t-1} - LP_t$$

$$LP_t = \frac{Like_{t-1+} Repost_{t-1}}{PosLike_{t-1} + PosRepost_{t-1}}$$

These information diffusion models can be implemented into models to simulate spreading on social media. Research use agent-based models (ABM) to simulate that. ABM is a method that enables the simulation of macro-level phenomena by modeling the micro-level decisions and interactions of individual agents. It adheres to a 'generative paradigm,' wherein micro-level attributes are defined to generate macro-level structures based on empirical observations or theoretical expectations. ABMs have proven effective in analyzing complex phenomena in various network architectures, including information diffusion and the interplay between online and offline political activity. Hedström and Ylikoski (2010) propose a mechanistic approach that emphasizes the underlying elements and mechanisms responsible for macro-level changes, categorizing them as situational mechanisms, action-formation mechanisms, and transformational mechanisms. While situational and action-formation mechanisms have been extensively studied, linking individual actions to social outcomes (transformational mechanisms) presents challenges. ABM serves as an analytical tool to explore and explain large-scale phenomena, bridging the gap between individual-level actions and macro societal changes.

The roots of ABM can be traced back to Thomas Schelling's work on segregation in the 1960s, and the advancement of computational power in the 1990s facilitated the modeling of large-scale phenomena (Bianchi & Squazzoni, 2015). Next to Schelling's (1971) segregation model, another widely cited ABM is by Axelrod, 1997 (Axelrod, 1997). His model demonstrated that social influence and homophily locally can lead to global polarization. The simulation involved agents with randomly assigned cultural traits placed on fixed sites. Agents could only interact with adjacent agents, and interaction occurred based on their cultural similarity. Polarization occurred even with changes happening to just one neighbor. Centola et al (2007) built on Axelrod's work and argued that despite growing global interactions, strong self-organization tendencies can help preserve cultural diversity. Their ABM showed that preferential interactions lead to stable "cultural pockets" that do not dissolve into a global monoculture.

ABM has aslo been extensively used to study information diffusion on social networks (Y. Jiang & Jiang, 2014). Chen (2019) simulated information diffusion on different network settings and found a geographic pattern in the process. Li et al (Z. Li & Tang, 2015) developed two ABMs to explore how social influence contributes to group polarization. The models integrated individual preferences and network attributes to study the link between local influence and global polarization patterns. Their simulation suggested that negative and neutral influences promote polarization of political opinions on social media, which was confirmed by a Twitter data analysis.

Van Maanen and Van der Vecht (2013) studied online social network influence in a multi-disciplinary approach, using a behavior model based on psychological arguments for Twitter usage. Their simulation aimed to better understand social influence on social media and was validated using empirical Twitter behavior data around a talent show. Li et al (W. Li et al., 2019) also focused on social influence, developing a simulation that analyzed trends of information diffusion by training agents to approximate real-life influence.

3 Research Questions

The general purpose of this thesis is to explore the ways, if any, of how social media usage affects offline politics.

As it was pointed out, scientific results provided by earlier research about the connection between online and offline political activities are controversial. There are results that support the theory of online political participation affecting offline political participation, while there are results that do not support such views. The nature of social media does not facilitate the conclusion of general scientific statements: it is a culturally specific and a rapidly changing phenomenon. Despite this, social media have played an important role in political campaigns for years now. Theories explaining the effects have been introduced: concerning the political actors, the previous chapter introduced the reasons political campaigns use social media, and it pointed out that the mobilization is a very important role of social media. Mobilization was associated theoretically and through empirical analyses with sharing political content on social media, thus this thesis conceptualizes the mobilizational effect of online politics through the number of shares on a post from a political actor. Sharing a post is influenced by multiple factors: prior research suggests that among others, emotional involvement might affect the number of users who share a post. Also, different types and different cultural backgrounds of social media results in different types of usages, thus this thesis seeks empirical evidence of factors affecting the number of sharing of a post by a political actor in a specified environment: the Hungarian Facebook.

Chapter Background has provided substantial evidence supporting the significance of sharing political information on social media for both voters and political parties. The act of sharing can serve as a mobilization tool and aligns with the two-step flow theory, wherein it plays a crucial role in the dissemination of information. Moreover, sharing on social media has been found to have a connection with offline popularity, as demonstrated by Bene's (2018) research. Within the realm of social media, several factors can influence user sharing behavior.

The previous chapter has highlighted the role of emotions in political decision-making, and it is apparent that emotions can also play a significant role in shaping sharing behavior. The emotions evoked by posts can trigger reactions from users, leading to the spread of information across networks. Additionally, the network characteristics, echo chambers and polarization of social media platforms can also exert an impact on sharing behavior. The structure of social networks, the strength of connections between users, can all contribute to the dynamics of information spreading on social media.

The thesis places significant emphasis on two crucial factors that impact sharing behavior on social media: emotions and network characteristics. As a result, the empirical analysis seeks to address two distinct research questions, each pertaining to these critical factors. The first research question investigates the effect of emotions on sharing behavior, aiming to understand how different emotional reactions influence the likelihood of posts being shared. On the other hand, the second research question delves into the influence of network characteristics on information spreading. By examining various network structures and their impact on the dissemination of political information, the study seeks to shed light on the interplay between social networks and sharing behavior. Overall, the thesis seeks to provide insights into the dynamics of online political engagement and the factors that shape information dissemination on social media platforms.

The overall purpose of this thesis can now be specified as three research questions:

1. Does political activity on social media platforms affect offline political activity?
2. How different emotions contribute to success of the social diffusion of a message shared on Facebook?
3. How do echo chambers, homophily and other network characteristics affect the spreading of a post on a social network?

The following subchapters explain these research questions.

3.1 Online and offline political activities

The first research question addresses the relation of online political activity with offline participation. The first chapter presented articles from different backgrounds that discussed this topic, from the early 2000s. Regarding the popularity of this research topic, Vepsäläinen (Vepsäläinen et al., 2017) even argues that this question is already answered, and instead if asking 'whether' there is an effect, the focus should be on the 'how'.

Nevertheless, the thesis investigates this problem. Regarding the correlation of online and offline political participation, most of the related literature shows a positive relationship, with only a few statistically insignificant positive or negative results having been reported. This in itself suggests a positive correlation, but the emphasis on the theoretical importance of the question in the ongoing debates cannot be ignored.

The chapter Background has introduced diverse theoretical perspectives on the connection between offline and online political activities. As a result of the extensive interest in this topic, numerous empirical research efforts have been conducted in the field, including meta-analyses that systematically compare and synthesize previous studies. One such meta-analysis conducted by Boulianne (2016) examined fourteen studies, utilizing the Ordinary Least Squares (OLS) regression coefficients to assess empirical evidence. Similarly, Skoric (2015) performed a Hunter-Schmidt meta-analysis on 22 studies. Both of these comprehensive analyses converge in supporting the notion of a weak yet positive correlation between online and offline political participation.

Despite the widespread interest, the thesis recognizes the significance of further exploring the connection between online and offline political activity, as it aligns with the two-step flow communication theory, emphasizing the impact of sharing political information on information dissemination. Given the vital role of sharing in social media interactions, the thesis delves into understanding the factors influencing sharing behavior on these platforms. However, before interpreting the specific effects, it is important to thoroughly analyze the general relationship between online and offline political activities.

This thesis adds to the previous literature by comparing scientific articles *with different methodologies,* to add new statistical evidence to the already existing literature between the two types of political activity, grounding the theory of empirical research.

3.2 Emotional effect on sharing

Based on the literature overview, there are different aspects of emotions that can affect sharing behavior. Empirical researches conceptualized variously to capture this effect, but mostly utilized the sentiment of the posts to analyze it. the primary research question concerning emotions is as follows:

RQ2: How do the valence and diversity of emotions evoked by a post influence the number of shares received by that post over time on social media?

This question explores the impact of emotions on sharing posts in three dimensions: valence, diversity, and time. Valence framing is important in sharing behavior (Eberl et al, 20201). Empirical research on the valence dimension, as previously summarized, has yielded ambivalent results. Berger (2010) found that positive news received more shares, while Stieglitz and Dang-Xuan (2013) observed an increase in retweets for both positive and negative emotions. On the other hand, Hansen et al. (2011) found that negative news was shared the most. To gain further insights into the impact of the valence of emotions on sharing content online, this study will use Facebook Reactions as a proxy for the emotions evoked by the post, similar to the approach used in the study of Muraoka et al. (2021). Analyzing the Reactions allows for an examination of the effects of different emotions conveyed by the posts. Based on the existing literature, certain Reactions indicate positive emotional content, while others convey negative emotional content. Additionally, there are some Reactions that may be perceived as vague in terms of emotional valence. By analyzing the Reactions, this research aims to understand how different emotional responses influence the act of sharing posts on social media platforms.

The diversity of emotional response indicates the extent to which user responses to a post point in different emotional directions. Freeman et al (2020) argues that a higher diversity of emotional response about a post or article suggests that there is considerable variation in individuals' reactions, and that there is no consensus about how a particular subject or issue should be received or interpreted by a group of responders. This diversity of emotional response may indicate that the content is controversial or that there is a lack of agreement on how the post should be perceived. Sturm Wilkerson et al (2021) consider Facebook Reactions as affective affordances, thus when analyzing Reactions, the influence of Reactions on each other can be also measured, since they can also serve as cues for others to be affected.

Time is a crucial factor when analyzing the effects of emotions on both diversity and valence. The diversity of Reactions may vary over time, and considering this variation is important for a comprehensive understanding of its impact. Additionally, the valence of reactions may have different effects at different stages of a post's lifespan. Many existing studies in the field rely on cross-sectional data, which provides insights into the relationship between posts, reactions, and shares at a specific point in time. However, the dynamics of sharing posts can vary over time. This thesis contributes to the existing literature by adopting a time-variant approach, which allows for a more in-depth examination of the influence of emotions on sharing behavior over the course of a post's lifespan. This approach provides a more nuanced understanding of how emotions evolve and impact the sharing of content on social media platforms.

3.3 Effect of network structure on sharing

The third research question delves into the influence of network structure on information sharing and dissemination on social media. Understanding how the structure of social networks affects the spread of information is crucial in comprehending the dynamics of online information flow.

RQ3: How does the presence of echo chambers, homophily, and other network characteristics impact the spread of a post within a social network?

Social media platforms are characterized by intricate networks of connections between users. These connections can vary in their strength and frequency of interaction, giving rise to different network structures. The research question seeks to explore how factors such as echo chambers, homophily, and other network characteristics influence the sharing behavior of users and the spread of information.

Echo chambers refer to the phenomenon where individuals are exposed to information that reinforces their existing beliefs and perspectives, leading to a reinforcement of existing opinions and limiting exposure to diverse viewpoints. Homophily, on the other hand, refers to the tendency of individuals to connect and interact with others who share similar characteristics, such as political beliefs or interests.

Previous studies have suggested that echo chambers and homophily can have significant impacts on information dissemination on social media. Echo chambers can lead to the reinforcement of misinformation and the polarization of online communities, while homophily can result in the formation of tightly-knit clusters of like-minded individuals.

Additionally, other network characteristics, such as the structure of small-world networks and preferential attachment networks, play a role in information spreading. Small-world networks are characterized by short paths between nodes, facilitating the rapid spread of information, while preferential attachment networks tend to reinforce the popularity of already popular content.

There is limited knowledge available about the network structure of Facebook, however effects of different network specific characteristics are common, such as the effect of echo chambers. In order to assess the impact of network characteristics on information spreading, a simulated social network site specific to the usage of Hungarian political actors' Facebook pages will be developed, building upon the findings from the first research question. The Literature Review has already provided relevant studies that examine the effects of network structures on information diffusion. Different network characteristics, such as tie lengths and node degree, have been shown to either promote or limit the spread of information.

With a focus on news sharing, it is anticipated that a content filtering algorithm based on user preferences could potentially restrict the diffusion of news sharing. Additionally, the negative influence of homophily, where individuals tend to connect with like-minded people, and preference-based filtering algorithms may amplify each other, leading to further limitations in the dissemination of political news.

The research question aims to investigate how these network characteristics interact and influence the diffusion of information on social media. By using agent-based models and simulations, researchers can analyze the impact of different network structures on information dissemination and the extent to which certain network characteristics may enhance or restrict the spread of information.

Understanding the influence of network structure on information sharing is crucial for comprehending the dynamics of information dissemination on social media. By exploring how echo chambers, homophily, and other network factors shape the flow of information, researchers can gain valuable insights into the mechanisms that underlie the viral spread of content and the formation of online communities. Ultimately, this research question contributes to a more comprehensive understanding of the role of social networks in shaping the information landscape on social media platforms.

4 Data

This chapter introduces the datasets utilized in addressing the first and second research questions. In response to the first research question, two distinct methodologies are employed for analysis: the Bayesian update method, which facilitates a comparative examination of studies, and the inclusion of a Hungarian national survey, both of which are expounded upon in this chapter. Regarding the second research question, the chapter also presents data sourced from Facebook.

4.1 Synthesis of empirical studies

Prior research presented in chapter “Background” proposed different methods to study the relationship between online and offline political participation. Various research designs were applied to different samples, and studies detected both positive and negative connections. To resolve the contradiction there were attempts to conduct meta-analyses based on these articles in order to find a generalizable result on the relationship of the offline and online political participation (e.g. Skoric, 2015; Boulianne, 2016). Meta-analyses, however, are able to compare methodologically similar studies (Kuiper et al., 2012), and the papers presented in the previous chapter came from various backgrounds, from different years, countries, and research designs. Comparing studies from different research designs requires other statistical analysis, which is able to compare the results coming from various backgrounds. Thus, articles that reported the detailed results of a regression analysis (i.e., that at least estimated regression coefficients and their standard errors) were collected from the studies presented in the chapter Background, as the availability of the parameter estimation and its standard error is necessary for conducting Bayesian updating.

The selected articles for the scientific comparison cover a wide range of publication dates, spanning from 2009 to 2021. However, the majority of the chosen articles were published around 2016. This consideration of similar publication dates is crucial because it helps capture the impact of social media changes that might have occurred during that specific period. Although the research studies were conducted in various countries and utilized different samples, they shared a common conceptualization of offline political participation as the dependent variable. The Background section of the thesis provides a comprehensive list of the variables presented in each research article, contributing to a thorough understanding of the factors considered in the analysis and their relevance to the relationship between online and offline political engagement. The most important characteristics of the articles regarding the comparison are summarized in Table 1.

Table 1.Summary of the studies used in Bayesian Updating

	Article	Type	N	Model
1	Holt et al (2013)	survey	1.387	OLS regression
2	Dimitrova et al (2014)	panel survey	1.358	OLS regression
3	Skoric–Zhu (2015)	survey	2	ML logistic regression
4	Teocharis (2015)	experiment	200	linear regression
5	Visser-Stolle (2014)	panel survey	526	ML regression
6	Feezell et al (2016)	survey	8.861	logistic regression
7	Valenzula et al (2009)	web survey	1.925	OLS regression
8	Kim et al (2016)	survey	571	logistic regression
9	Strömbäck et al (2017)	panel survey	2.398	linear regression
10	Lane et al (2017)	panel survey	594	linear regression
11	Groshek-Krongard (2016)	web survey	1.105	linear regression
12	Tai et al (2019)	survey	1.496	Poisson regression
13	Towner - Munoz (2016)	survey	325	linear regression
14	Zuniga et al (2016)	panel survey	1.024	OLS regression

With Bayesian Updating it is possible to compare studies with different research designs based on their estimated regression parameters and their standard errors. Table 2 shows the regression coefficients and standard errors of the discussed articles. Bayesian Update used 17 regression models from the 14 studies mentioned before. Detailed descriptions of articles are in Literature Review.

Table 2. Regression coefficients and standard errors of the articles in the Bayesian Update analysis

t	Model t	Parameter estimation	Standard error
01	Visser-Stolle (2012)	0.17	0.049
02	Skoric- Zhu (2015)	0.05	0.21
03	Skoric- Zhu (2015)	0.06	0.28
04	Skoric- Zhu (2015)	-0.04	0.12
05	Teocharis-Lowe (2015)	-0.192	0.198
06	Teocharis-Lowe (2015)	-0.208	0.17
07	Holt et al (2013)	0.20	0.03
08	Dimitrova et al (2014)	0.20	0.02
09	Feezell et al (2016)	2.742	1.334
10	Valenzula et al (2009)	0.01	0.03
11	Kim et al (2016)	0.56	0.14
12	Strömbäck et al (2017)	0.6	0.1
13	Lane et al (2017)	0.03	0.04
14	Groshek - Krongard (2016)	0.331	0.034
15	Tai et al (2019)	0.212	0.027
16	Towner - Munoz (2016)	0.029	0.071
17	Zuniga et al (2016)	-0.03	0.024

4.2 Hungarian Panel survey

The data analyzed regarding the Hungarian context is from the project titled "Participation, Representation, and Bias. Election Study 2018" (Részvétel, képviselet, pártosság. Választáskutatás 2018[2] [NKFI K-119603]) of Centre of Social Sciences, PTI. Farkas and Susánszky (2019) introduce the dataset in their article. The objective of the data collection of the project was to gain a more accurate understanding of Hungarian citizens' political participation habits, their relationship with parliamentary representatives, and their political biases and affiliations concerning the 2018 parliamentary elections. The dataset is a comprehensive panel study that consists of three waves within six months related to elections had never been conducted in Hungary before. The first benchmark survey took place between December 2017 and January 2018, before the start of the election campaign. The second wave, known as the pre-election survey,

[2] Details of the project are available at: http://nyilvanos.otka-palyazat.hu/index.php?menuid=930&num=119603&keyword=119603 (Last downloaded: 2023. 08. 29.)

was conducted in March just before the 2018 parliamentary elections, and the third wave, post-election survey, took place approximately one month after the elections.

Panel surveys offer the advantage of observing respondents' opinions over multiple occasions, allowing for tracking changes in their views throughout the research. They are well-suited for testing causal relationships. One crucial requirement for causality is that the cause must precede the effect in time. Therefore, panel surveys can provide more insight into potential causal relationships compared to cross-sectional studies. However, it is important to note that panel surveys alone do not meet all the requirements for establishing causal relationships.

The questionnaire-based panel study contains questions about political participation among others. The variables regarding online and offline political participation are constructed similar to the examined literature. This is due to the intention to get a dataset that is comprehensive with European research.

In the national survey, participants were asked about their engagement in various forms of offline political activities. The questions covered a wide range of participational behaviors, allowing respondents to indicate their involvement in different aspects of the political process. These activities included:

- Contacting a member of Parliament or a local government representative to voice concerns or opinions.
- Participating in a political party's event, showing support for the party and its initiatives.
- Taking part in a political party's campaign or campaign event, actively engaging in promotional efforts.
- Participating in the work of any other political organization or movement, indicating involvement in broader political causes.
- Wearing or displaying political badges, symbols, or emblems to express political affiliations or beliefs.
- Signing petitions or protest letters to advocate for specific causes or policy changes.
- Collecting signatures to support or initiate political initiatives or actions.
- Participating in lawful, public protests such as demonstrations or marches to express dissent or support for specific issues.

- Boycotting certain products for ideological reasons.
- Donating money to political organizations or groups to support their activities or causes.
- Participating in unauthorized protest events, demonstrating willingness to engage in activism despite potential legal consequences.
- Writing newspaper articles or comments on political issues to contribute to public discourse.
- Subscribing to or canceling a daily or weekly newspaper for political reasons, reflecting media consumption choices based on political preferences.
- Calling in to a radio show on political matters to share opinions or participate in discussions.
- Commenting on a television program or voting via SMS on political questions, engaging with political content in media platforms.

The survey responses revealed a wide array of offline political participational forms, highlighting citizens' active engagement and diverse means of expressing their political views and beliefs both online and offline. In the analysis, the focus is on the relationship between these two types of participation.

3. Table Frequencies of variables in the Választáskutatás dataset

	Political activity	Wave 1 (N=2017) It did not occur (%)	Wave 1 (N=2017) It occurred (%)	Wave 2 (N=1509) It did not occur (%)	Wave 2 (N=1509) It occurred (%)	Wave 3 (N=1096) It did not occur (%)	Wave 3 (N=1096) It occurred (%)
Offline	Contacted a member of Parlament	97	3	98	2	97	3
Offline	Contacted a local government representative	94	6	95	5	95	5
Offline	Participated in a political party's event	98	2	97	3	98	2
Offline	Participated in a political party's campaign, or campaign event	97	3	97	3	96	4
Offline	Participated in the work of any other political organization or political movement	99	1	98	2	98	2
Offline	Has worn or displayed political badges, symbols, or emblems	98	2	98	2	98	2
Offline	Signed a petition, or protest letter	94	6	97	3	96	4
Offline	Participated in signature gathering	92	8	95	5	95	5
Offline	Participated in a lawful, public protest (demonstration, march)	97	3	98	2	97	3
Offline	Boycotted certain products for ideological reasons	96	4	98	2	96	4
Offline	Donated money to political organization or group	99	1	99	1	98	2
Offline	Participated in an unauthorized protest event (protest, demonstration)	99	1	98	2	98	2
Offline	Wrote newspaper articles or comments on political issues	99	1	98	2	98	2
Offline	Subscribed to or canceled a daily or weekly newspaper for political reasons	98	2	98	2	98	2
Offline	Called in to a radio show on political matter	99	1	98	2	99	1
Offline	Commented on a television program or voted via SMS on political questions	99	1	98	2	98	2
Online	Commented on an internet forum on political or public affairs topics	94	6	95	5	93	7
Online	Liked posts, events, or videos related to public affairs or politics online	90	10	91	9	91	9
Online	Shared posts, events, or videos related to public affairs or politics online	93	7	94	6	93	7

The variables in the Választáskutatás dataset regarding the different political activities were binary, as Table 3 shows. Respondents answered with yes (1) if the condition applied to them (i. e. they conducted the given political activity) or 2, if it has not been the situation. Sixteen variables measured offline political participation, and three the online. Variables and their absolute frequency in the dataset are presented in Table 4.

4. Table Summary of the frequencies of variables in the Választáskutatás dataset in all waves

	Political activity	It did not occur (n)	It occurred (n)
Offline	Contacted a member of Parlament	4496	123
	Contacted a local government representative	4357	262
	Participated in a political party's event	4508	114
	Participated in a political party's campaign, or campaign event	4471	150
	Participated in the work of any other political organization or political movement	4547	72
	Has worn or displayed political badges, symbols, or emblems	4538	80
	Signed a petition, or protest letter	4414	205
	Participated in signature gathering	4330	289
	Participated in a lawful, public protest (demonstration, march)	4496	124
	Boycotted certain products for ideological reasons	4466	154
	Donated money to political organization or group	4550	70
	Participated in an unauthorized protest event (protest, demonstration)	4552	67
	Wrote newspaper articles or comments on political issues	4543	77
	Subscribed to or canceled a daily or weekly newspaper for political reasons	4534	85
	Called in to a radio show on political matter	4552	67
	Commented on a television program or voted via SMS on political questions	4551	70
Online	Commented on an internet forum on political or public affairs topics	4351	270
	Liked posts, events, or videos related to public affairs or politics online	4183	434
	Shared posts, events, or videos related to public affairs or politics online	4313	307

4.3 Facebook data

To answer the second research question, this thesis uses Facebook data. To narrow the target of the analysis was necessary in order to accept the different affordances that different platforms have, even though they might be hidden (Nagy and Neff, 2015). To deal with the culturally specific attributes of diverse types of social media usage, this thesis focuses on the Hungarian context. Bene (2018) argues that Facebook is the most popular social network site in Hungary used for political purposes and it was used in political campaigns since the 2014 Hungarian elections widely by political actors. Bene and Somodi (2018) has also shown that most Hungarian politicians are available on Facebook. In international research, Twitter data is widely used to research political participation on social media sites (e.g.: (Ceron et al., 2014; Jain & Kumar, 2017). While Facebook data is less accessible in usual, in my research I analyze Facebook data to investigate the political activity of Hungarian social media users. Lilleker et al (2015) compared Twitter and Facebook usage in political campaigns and found Facebook to be more important among strategists. Additionally, as noted earlier, Valenzuela et al (2018) argue that Facebook connections on Facebook resembles more the real social networks, as it is based on interpersonal relationships. Twitter on the other hand, contains mostly connections between users who are not in personal contact with each other.

Although data is more readily available to analyze Twitter usage, through a specific software tool, Crowdtangle, Facebook data was also made available for most research purposes.

Crowdtangle[3] is a Facebook-owned tool that tracks interactions on public content from Facebook pages, groups, verified profiles, Instagram accounts, and subreddits. It does not include paid ads unless those ads began to appear in organic non-paid posts that were subsequently "boosted" using Facebook's advertising tools. It does not include activity by private accounts or posts made visible only to specific groups of followers, either. Crowdtangle does not collect any information about the private accounts that interact with certain posts, however, basic information is available about the Facebook page that created the post – number of likes, number of followers, and country of posting. Accessed data contains every post created over the given time period by the political parties and party leaders introduced in the next chapter.

4.3.1 Hungarian political parties and their leaders

In the following analysis, seven Hungarian parties and their leaders are taken into consideration, all having their own page on the Hungarian Facebook.

Running up to the 2022 general elections, the incumbent party coalition in Hungary was made up of the "Fiatal Demokraták Szövetsége – Fidesz" (Hungarian Civic Alliance – Fidesz) and the "Kereszténydemokrata Néppárt – KDNP" (Christian Democratic People's Party – DNP). The popularity of KDNP has not been measured on its own since 2010, and it has not participated independently in elections since the election of 1998, when it did not get into parliament. Thus, this analysis disregards KDNP as a party, and its titular leader, too, and collects data only about the larger incumbent party (Fidesz).

In the period considered, several parties of the opposition had formed an electoral alliance and were campaigning together since the end of 2020.[4] The electoral alliance was made up of six political parties: "Demokratikus Koalíció – DK (Democratic Coalition – DK)"; "LMP – Magyarország Zöld Pártja (LMP – Hungary's Green Party); "Jobbik Magyarországért Mozgalom (Jobbik – Movement for a Better Hungary); "Momentum Mozgalom (Momentum Movement)"; "Magyar Szocialista Párt – MSZP (Hungarian Socialist Party – MSZP)"; and "Párbeszéd Magyarországért (Párbeszéd – Dialogue for

[3] More details: https://help.crowdtangle.com/en/articles/1140930-what-data-is-crowdtangle-tracking (Accessed on: 29th August 2023)
[4] https://parbeszedmagyarorszagert.hu/hir/megszuletett-teljes-ellenzeki-osszefogas (Accessed on: 29th August 2023)

Hungary)". Polls measured the popularity of this alliance as increasing, closing in on the incumbents' popularity.[5] However, this electoral alliance was a loose formation, and the participating parties decided to hold a primary in late 2021 to select their final candidate running for the office of the Hungarian Prime Minister in 2022. Thus, parties in the opposition were also campaigning against each other throughout most of 2021, and only showed a united front after the primaries in the autumn of 2021[6].

The collected data showcases the competition among seven Hungarian political parties and their leaders, even though six of the parties had already formed an electoral alliance. Table 5 presents an overview of the parties and their respective leaders. In some instances, certain parties had joint leadership, such as LMP and MSZP, which led to the inclusion of both leaders' pages in the dataset, as indicated in the table.

Table 5. Political parties and their leaders in the analysis

Political Party	Party Leader(s)
Demokratikus Koalíció	Ferenc Gyurcsány
Fidesz	Viktor Orbán
Jobbik Magyarországért Mozgalom	Péter Jakab
LMP - Magyarország Zöld Pártja	Máté Kanász-Nagy Erzséber Schmuck
Magyar Szocialista Párt	Ágnes Kunhalmi Bertalan Dr. Tóth
Momentum Mozgalom	András Fekete-Győr
Párbeszéd Magyarországért	Gergely Karácsony Tímea Szabó

The data concerning the activities of these political actors were collected through Crowdtangle. Crowdtangle data can be utilized in two ways: firstly, as a summary of posts from specific users within a certain period, and secondly, as a detailed summary encompassing all posts. This allowed for a comprehensive analysis of the social media activities of the political parties and leaders, enabling researchers to explore their posting patterns, content, and engagement with the public. Data also contains the number of

[5] https://kozvelemenykutatok.hu/2020-januari-kutatasi-eredmenyek-idea/ Last accessed: 31 January 2023.
[6] Report of the Office for Democratic Institutions and Human Rights. https://www.osce.org/files/f/documents/8/0/523892.pdf Last accessed 31 January 2023.

reactions and shares given to each post, in consecutive Timesteps. The first Timestep is numbered as 0, and refers to the first 15 minutes after a content was posted. The last timestep is the 74th timestep, which marks that at least 20 days have passed since the original post. The size of Timesteps is not equal, but follows a pattern that resembles a logarithmic curve, although it is not precisely logarithmic. Initially, the timesteps are set at 15 minutes each and then gradually increase to 30 minutes. Finally, the timesteps expand to encompass a full 24-hour period. Specified end times of Timesteps are exclusive, meaning that the final moment mentioned is not included. For instance, the Timestep 0 has the interval between 0-15 minutes, and refers to any duration between 0 and just under 15 minutes. Once it reaches exactly 15 minutes, it becomes part of the subsequent 15-30 minutes Timestep 1. The detailed list of Timesteps is also available in the Crowdtangle Codebook[7]. Posts in the dataset may have different numbers of observations as the availability of Timesteps may vary due to the level of processing.

The examined period of Facebook posts was 21st and 22nd of January (Friday-Saturday) 2021,[8]. In determining the time range for data collection, certain considerations were taken into account. Firstly, it was decided that the dataset should include two consecutive days to identify users who consistently exhibit high or low performance over time. This allows for a more comprehensive analysis of user behavior and patterns. Additionally, it was important to include both a weekday and a weekend day in the dataset to capture the variations in Facebook usage patterns. This accounts for potential differences in user engagement and interaction based on the day of the week. Considering that the dataset focuses on data from real political parties, it was necessary to balance the inclusion of sufficient data while managing computational capacity. Including more days in the dataset would significantly increase the computational requirements without substantially altering the validity of the results. Therefore, it was determined that including two days provides a suitable balance between data comprehensiveness and computational feasibility. By selecting the two days for data collection, the analysis can still yield insights into user behavior and engagement patterns on Facebook in the context of political parties.

[7] Codebook for Crowdtangle, https://help.crowdtangle.com/en/articles/3213537-crowdtangle-codebook ; (Accessed on: 29th August 2023).

[8] The date of the posts: 2021. 01. 21. 00:00 – 2021. 01. 22. 23:59

In the examined period, 16 Facebook pages posted in a total of 146 times. The collected data contains the total number of different types of reactions on the posts. In Table 6, there is the summary of the posts made by the political actors presented: how many posts did they publish during these two days and how many shares, comments and reactions did they receive. There is one politician, Tímea Szabó, who did not post at all during this period. The further analysis does not contain her Facebook page – in the regression only those are included who posted at least once.

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Table 6. Summary of the 146 posts in the analysis

	Number of posts	Followers at Posting	Number of Likes at Posting	Total Likes	Total Comments	Total Shares	Total Love	Total Wow	Total Haha	Total Sad	Total Angry	Total Care	Total Interactions
Fidesz	28	316,704	318,708	38,805	1,465	5,200	273	46	225	168	341	377	46,900
Magyar Szocialista Párt	17	208,340	215,788	9,937	694	3,342	125	28	50	179	400	153	14,908
Jobbik Magyarországért Mozgalom	15	515,345	519,891	12,335	3,913	7,807	75	389	4,250	950	5,431	49	35,199
Momentum Mozgalom	14	108,055	115,800	3,894	437	301	143	28	163	30	147	66	5,209
Párbeszéd Magyarországért	14	126,894	131,142	7,224	1,363	1,761	22	74	446	1,768	2,030	63	14,751
LMP - Magyarország Zöld Pártja	10	76,343	74,020	209	38	69	4	5	10	5	24	1	365
Demokratikus Koalíció	8	147,142	164,734	9,210	581	1,645	132	52	57	250	166	108	12,201
Gergely Karácsony	7	260,364	270,315	39,745	4,112	4,357	2,078	584	995	105	287	1,227	53,490
Erzsébet Schmuck	7	34,625	31,964	311	27	35	1	3	2	3	13	2	397
Máté Kanász-Nagy	6	5,106	5,226	227	35	65	1	5	7	7	4	3	354
András Fekete-Győr	5	37,268	40,183	4,413	2,219	628	85	43	544	100	299	29	8,360
Péter Jakab	5	189,011	236,578	13,526	1,692	1,862	164	35	129	510	1,033	145	19,096
Viktor Orbán	4	905,161	1,108,986	32,417	5,178	741	632	57	1,324	20	295	439	41,103
Bertalan Dr. Tóth	2	33,722	35,404	8,222	599	4,428	50	116	213	697	990	53	15,368
Ferenc Gyurcsány	2	267,311	289,082	3,130	1,191	839	343	6	111	15	42	148	5,825
Ágnes Kunhalmi	2	41,165	42,208	1,164	252	30	77	0	4	0	0	169	1,696
Tímea Szabó	0	-	-	0	0	0	0	0	0	0	0	0	0
Total	146	-	-	184,769	23,796	33,110	4,205	1,471	8,530	4,807	11,502	3,032	275,222

Source: Crowdtangle

Table 6 contains the information relevant to this thesis from the summarized dataset. According to this dataset, in the examined period, political actors collected in total more than 275,000 interactions to their Facebook posts. 'Like' reactions constituted more than two-thirds of the interactions, while sharing the posts accounted for 12 percent of the cumulative interactions. Predominantly, political parties outpaced individual politicians in terms of posting frequency. Fidesz emerged as the most prolific contributor, sharing 28 posts. Among the political figures, Gergely Karácsony and Erzsébet Schmuck stood out as the most active, each posting 7 times.

The average number of reactions to posts made by politicians differs from the average number of reactions to posts made by political parties. For instance, in the case of Fidesz and Jobbik, the popularity of the party leaders aligns with the popularity of their respective parties. However, there are instances where the popularity of an individual politician differs from that of their party. One example is Gergely Karácsony, whose party, Párbeszéd, received significantly fewer reactions in total compared to him as an individual.

The Facebook pages with the most followers at the time of posting belonged to the Fidesz, Jobbik and MSZP, and among the politicians, to Viktor Orbán, Gergely Karácsony and Péter Jakab. Similar to the pages' popularity, the most interactions in the examined time period happened to these political actors. Most comments were gained by the same actors, with one exception: instead Péter Jakab, the posts by András Fekete-Győr were the third most commented among the politicians.

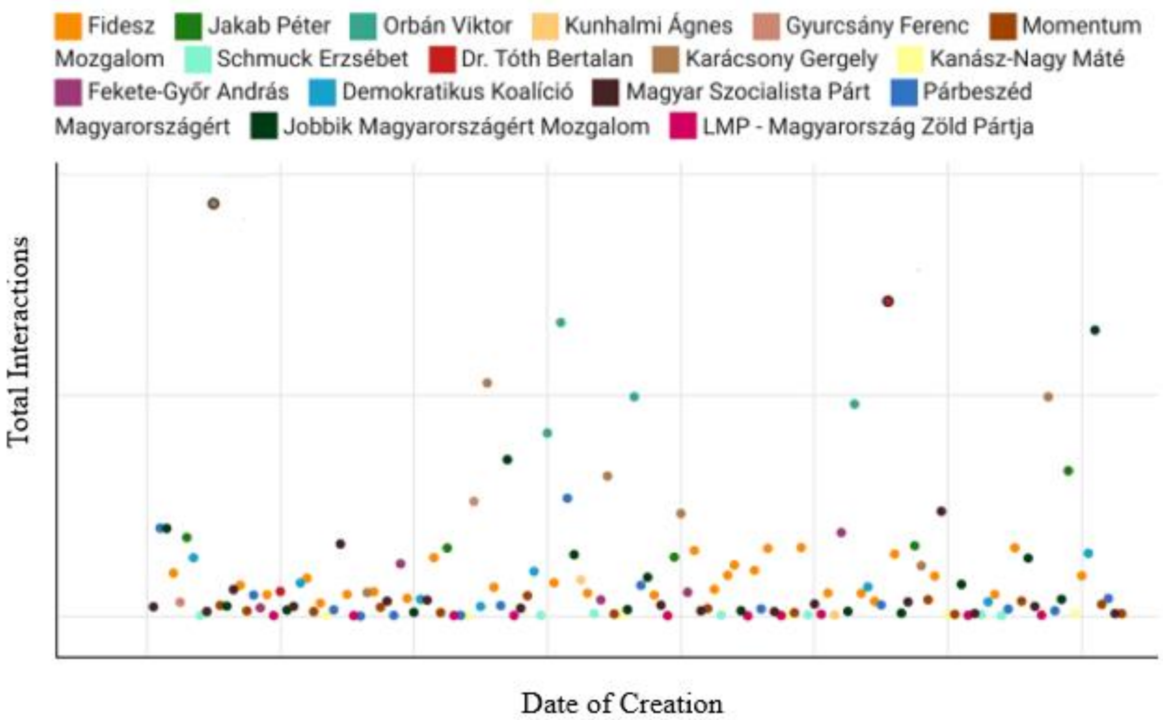
The posts by Jobbik, Fidesz and MSZP were shared the most. Among the politicians, Bertalan Dr Tóth posts were shared in total the most, alongside with Péter Jakab and Gergely Karácsony.

Angry reactions were the highest in the case of the post of the Bertalan Dr Tóth and Péter Jakab, leader of Jobbik. Among the parties, Jobbik reached the highest number of angry reactions, and the otherwise not outstanding Párbeszéd the second. Love reactions differ from Likes: the politician Karácsony and the party DK achieved the more of it. The differences in the number of this type of reaction are bigger than it was on the likes. Fidesz and Jobbik and their party leaders received less Love reactions than Likes.

Karácsony's posts were Liked, Loved and Wowed the most in the examined time period. The most Haha and Angry reactions were reached by the posts of Jobbik. The most Sad reactions went to the posts by Párbeszéd.

Figure 3 shows each posts and the number of total interactions with them. Each dot represents a post by a political party or its leader – different colors mark different actors. It shows that the high average number of interactions to Gergely Karácsony's post was because of one extremely attractive post by him. Figure 3 also shows that other exceptionally highly interacted posts came from also politicians, and not from parties: Bertalan Dr Tóth, Viktor Orbán and Péter Jakab also published very popular post during the examined time period, that might have contributed to their average high number of interactions, without other consistent high performing posts.

Figure 3. Posts and total interactions by political actors during the examined time period.



Source: Crowdtangle. Created with Datawrapper

Figure 3 shows that while other posts by Gergely Karácsony were also popular, there is one outlier amongst them.

Figure 4 shows the content of this post. It was about Gergely Karácsony congratulating the President of the United States, Joe Biden for his inauguration. The politician assessed the speech of the President, which was considered – according to the language of the post and the Reactions given to it – an emotionally positive post.

Figure 4 The most popular post in the examined timeframe

Source: Facebook

This post reached in total 18,668 interactions, out of them 14,287 reactions were likes, 1060 comments, 1349 shares. The overall emotional attitude of this post reflected by reactions were positive, as the emotional reactions consisted of 1222 Love, 568 Care, 134 Haha, 28 Angry, 13 Wow, and 7 Sad reactions.

Details about this post contain the temporal development of reactions.

Figure 5 Number of total shares on the most popular post by Karácsony Gergely

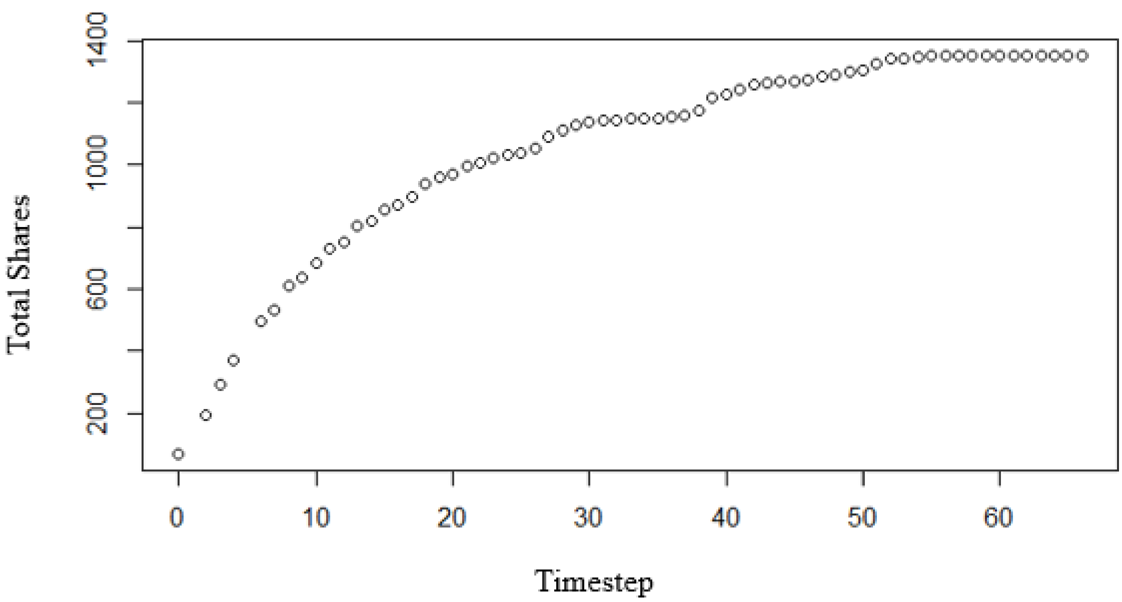


Figure 6 illustrates the pattern of New Shares accumulated from one Timestep to the next. The data reveals that the most substantial increase in new shares occurs within the first twelve timesteps, approximately 4.5 to 5 hours after the post was created. During this period, the post gains more than half of its total shares, accounting for 55.8 percent of the overall shares. The final timestep in the analysis is timestep 66, which corresponds to 12 days after the post was published. In this timestep, there is a slight decrease in the number of shares, dropping from 1350 to 1349. Over the last 12 timesteps, the post receives a total of 3.6 percent of the overall shares.

Figure 6 Number of new shares by timesteps on the most popular post in the dataset

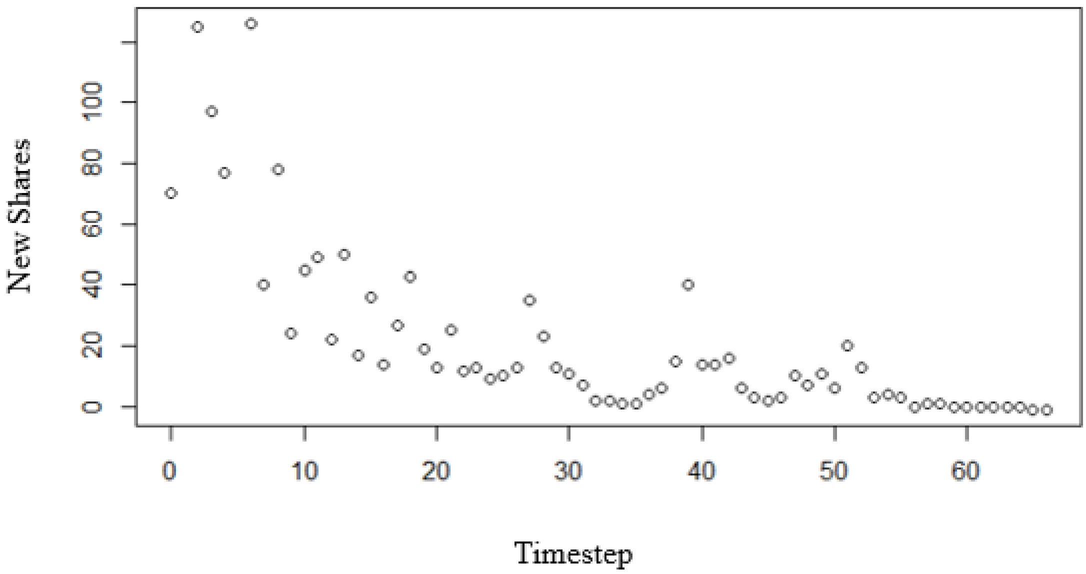


Figure 6 shows the number of new shares received by the post across different timesteps. It reveals a decreasing trend in the number of New Shares over time. As the post progresses through its lifespan, there is a decline in the influx of new shares. This indicates that the initial stages of the post's existence tend to attract a higher volume of shares, while the rate of new shares gradually diminishes with time.

4.3.2 Independent variables

The summarized dataset contains:

- page name of the political actors' Facebook page,
- user ID of the political actors' Facebook page,
- the post's Facebook ID,
- number of 'likes' on the page at the time of posting,
- number of followers of the page at the time of posting,

- date of creating the post,
- the type (photo, link, native video, status, live video),
- number of total ‘likes’, ‘comments’, ‘shares’, ‘love’, ‘wow’, ‘haha’, ‘sad’, ‘angry’, ‘care’,
- in case of video (native video or live video): video share status (original or crossposted), post views, total views, video URL,
- URL,
- message – the text of the post
- link and final link,
- sponsorship – ID and name (if any),
- number of total interactions, and
- Overperforming Score: Crowdtangle’s own calculation of a performance of a post, based on the interactions made to the post. Similar statistics have been available on different names through the changes of Facebook (e.g.: the ‘PTAT’ number in the analysis of MacWilliams, 2015).

In the subsequent analyses presented in this thesis, the following information was utilized: the date of the posts, the number of followers and likes on the page at the time of posting, the unique IDs of the posts, and the total number of reactions, comments, and shares received. However, the type, message, and sponsored status of the posts were excluded from the analysis.

Reactions are the focus of the analysis. Users on Facebook have the ability to express a range of emotional responses to posts through the "react" feature. By clicking the "Like" button, users can indicate their approval or positive sentiment towards a post, which is the default reaction. Additionally, users can access other reaction types such as "Wow," "Sad," "Angry," "Love," and "Haha" by hovering or long-pressing the Like button. Users can choose only one reaction type and can give it only once for each post; however, they can change or retrack it.

Detailed information for each post is available through Crowdtangle:

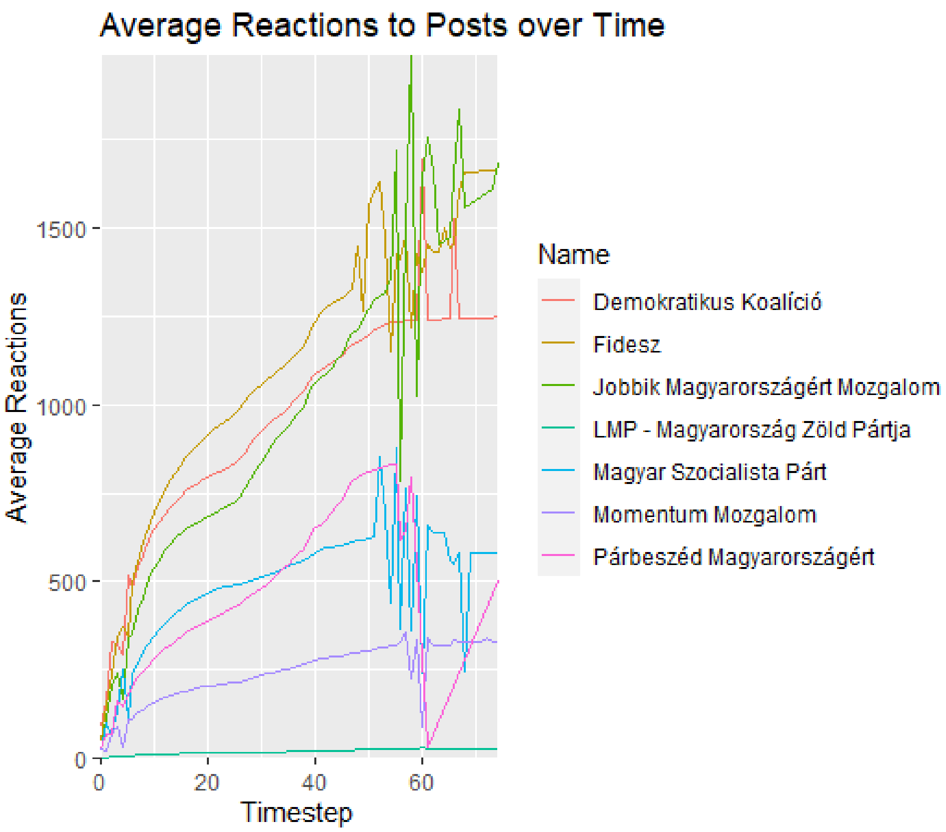
- post ID,
- date of data collection
- Timesteps

- Likes and average Likes in a timestep,
- Comments and average Comments in a timestep,
- Shares and average Shares in a timestep,
- total and average number of 'Love, Wow, Haha, Sad, Angry, Care reactions
- post views, total views, average views (for videos and live videos).

Since the types of posts are not included in the analysis, in the following the average and total views are excluded from the analysis. This data structure allows analyzing the lifespan of a post, as it offers information about the numbers of reactions in each Timestep, and it can help to get more accurate results than only cross-sectional analyzes, as it can be used to determine the dynamics of spreading.

The average reactions politicians and parties got to their posts in each timestep are on the next figures (Figure 7 and Figure 8). In contrast to the summary of posts, the following figure shows the average lifespan of the posts regarding the different reactions.

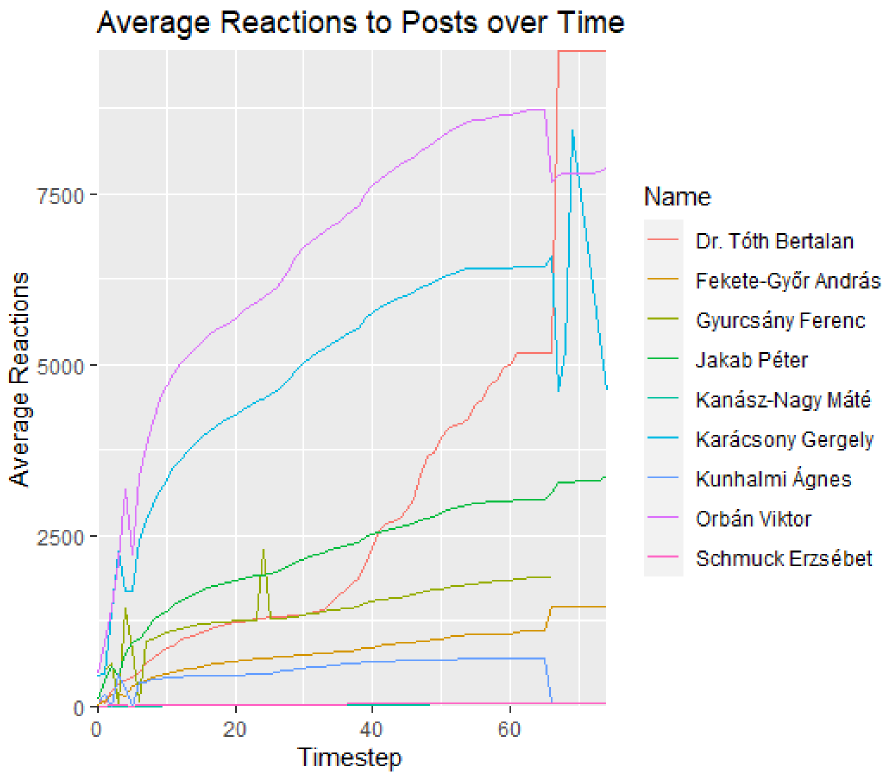
Figure 7 Reactions to Posts of Political Parties. Data from Crowdtangle



As it was shown by Table 3, Figure 7 shows that in all timesteps the most reactions were gained by three parties: Jobbik Magyarországért Mozgalom, Fidesz and Demokratikus

Koalició. The proportion of reactions in time is similar in their cases, as it is in the case of the next three actor: LMP, MSZP and Momentum gained.

Figure 8 : Reactions to Posts of Political Politicians. Data from Crowdtangle



The most Likes on post by politicians and parties reflects the total number of Reactions. Overall, the reaction most often used is Like as Table 2 showed. The different Reactions separately and in total were used in the analysis as independent variables.

Additionally, to assess the time-related dimensions of reactions to a Facebook post, one variable was created based on the Timestep variable and was incorporated in the analysis as an independent variable. Specifically, as the time-related aspect of the posts is in the focus of the research question, the interactions between time periods and Reactions are included to examine whether certain types of Reactions are more likely to occur in the early phase of a post, while others are more likely to emerge later. To investigate this phenomenon, the model incorporates interactions with a binary Time-Period variable, distinguishing between the first part of the lifespan and the latter part. The boundary for this division is set at the Timestep when the post reaches half of its total shares. By incorporating these interactions into the analysis, it becomes possible to analyze the patterns of reaction occurrence over time and gain insights into how the timing of different types of reactions may influence the post's engagement dynamics. Reactions might have separate different effects in the first than in the second time period in the lifespan of a post.

To calculate the Time Period variable, the maximum shares of each post are determined and divided by two. If the number of shares in a specific Timestep is less than or equal to half of the post's Total Shares, that Timestep is categorized as belonging to the first Time Period. Conversely, timesteps with shares exceeding the half mark are assigned to the second Time Period. Among the 146 posts analyzed, three posts had a Total Share count of zero, they were excluded from the calculation.

7. Table Description of Timesteps for Time Period variable

	Minimum	Maximum	Median	Mean
Timestep where posts reach half of their Total Shares (N=143)	0	57	10	15.1

According to Table 7, the 143 posts that remained reached half of their Total Shares, on average, by the 15th Timestep. The majority of posts achieved this milestone by the 10th Timestep, with the highest Timestep at which a post reached half of its total shares being 57.

5 Method

In this chapter, the methods utilized for the analysis are presented separately by topics. First, the analysis of emotions is followed, which includes various regressions to explore their influence on sharing behavior. The type of dataset and the research questions necessitate different methodological approaches, and the pros and cons of each method are presented alongside their application.

The presentation of the agent-based model, used for the analysis of the effect of network characteristics, showcases its ability to provide a comprehensive view of information diffusion in different networks, considering various conditions and contexts. This dynamic approach offers deeper insights into the complexities of information spread within social networks.

Throughout the chapter, a comprehensive and rigorous methodological approach is demonstrated, considering the specific needs of each analysis. By exploring various techniques and presenting their respective strengths and weaknesses, the research aims to ensure the validity and integrity of the findings. The agent-based model contributes to a deeper understanding of the factors influencing information diffusion, enriching the overall study.

5.1 Online and offline political activities

5.1 1 Bayesian update

For the first research question this thesis compares the existing research results. For this aim, a Bayesian Update method is utilized. I introduce this research, both method and results, as in my previous research (Angyal & Fellner, 2020).

Bayesian Updating combines evidence for positive, negative and null effect of the predictor of interest – in this case the online participation – on the dependent variable, which is the offline participation in this case. The method can be employed to evaluate the hypotheses:

H_0: null effect

$H_>$: positive effect

$H_<$: negative effect

The method uses Bayes Factors (BF) to test evidence of each hypothesis. The result is a likelihood ratio (LR) test and shows how more likely are the hypotheses according to the others.

Investigating the hypotheses, the parameter estimates of the T studies ($\hat{\beta}_1^t$) and the standard errors ($\hat{\sigma}_{\beta_1}^t, t = 1, \ldots, T$) are necessary. This method does not combine the estimates but summarizes the evidences of the hypotheses.

Steps of Bayesian updating:

1. Assume that the three hypotheses (H_0, $H_>$, $H_<$) are equally likely, so the prior probabilities (denoted with $\pi_0^0, \pi_>^0, \pi_<^0$ respectively) are 1/3.

2. Calculate the likelihood by using the first study's parameter estimate and standard error.

3. Based on the likelihood, the Bayes Factors can be determined ($BF_{>u}^1, BF_{<u}^1$), which shows that how much more support a hypothesis have versus an unconstrained hypothesis on the parameter of interest.[9]

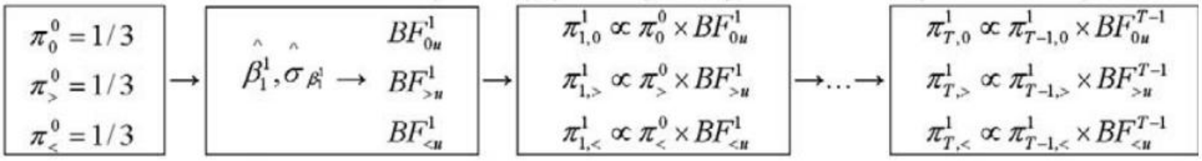
4. Based on prior probabilities and Bayes Factors, posterior model probabilities can be determined (denoted with $\pi_{1,0}^1, \pi_{1,>}^1, \pi_{1,<}^1$ respectively), that shows the probabilities of each hypotheses based on the first regression.

5. These posterior model probabilities are treated as prior probabilities of the hypotheses when we move on to the second study. Based on them, posterior model probabilities can be calculated for the second regression.

6. This process is repeated for each study shown in Figure 8. At the last step, one earns the posterior model probabilities where all the information of the T studies is considered (these are $\pi_{T,0}^1, \pi_{T,>}^1, \pi_{T,<}^1$ respectively).

[9] The hypothesis without constraints on the parameter of interest functions only as a technical tool.

9. Figure Process of Bayesian Updating



Source: Kuiper et al (2012).

Formally, the method is described in Kuiper et al. (Kuiper et al., 2012). The main principles are as follows.

In case of regression modelling, the dependent variable is a function of the explanatory variables. From all the independent variables used in the models under review, our main concern is the one that denotes the marginal effect of the theoretical concept that is to be tested. In our example, this underlined variable is the one that captures the effect of online political participation.

It is not necessary to use homogeneous models in terms of design (cross-sectional or panel surveys, experiments can be analyzed together), data collection or either regression specification. All that is needed are the estimated effect and its uncertainty, namely the regression coefficient and its standard error, on which the partial significance tests (t-tests) are based on inferential statistics.

With these two inputs, we can estimate the likelihood functions on the parameter of interest, that is following a normal distribution with a mean of the parameter estimation and a variance of the square of the standard error of the parameter estimation. For the hypothesis testing of H0, H>, H< the analysis use conjugate priors, and thus ensures that the parameter's distribution is a normal distribution.

The prior distributions of the parameter are determined in case of each of the three hypotheses, which are proportional to the normal distribution mentioned above, if the parameter does not contradict the concrete hypothesis.

A priori it is assumed that all the three hypotheses are equally likely, thus the parameter equals to zero. Consequently, the prior confirms H> in 50 per cent of the cases and H< in 50 per cent of the cases as well. The variance of the prior must be determined as it has to become a noninformative prior. For this purpose, we produce the 99 per cent confidence intervals for all the models under review, and based on them, we create the 99 per cent credibility interval for the regression parameter.

The posterior probability is proportional to the product of the prior and the likelihood. To define the posterior distribution for each hypothesis, we create the unrestricted posterior distribution function of the parameter.

After that, Bayes Factors are computed. Bayes Factors show the support of a certain hypothesis compared to another, in the form of the ratio of the marginal likelihoods of each hypothesis. By the Bayes Factors, posterior model probabilities can be defined, which means the relative support of a certain hypothesis opposite to a finite set of hypotheses (which is now three).

The main principle of Bayesian Updating is that in the first step, uninformative priors can be used for the purpose of computing posterior model probabilities. But after that, for all other model *t*, we can use the posterior model probabilities of model *t-1* as prior probabilities. It can also be shown that the order of the models does not have any effect on the final results, which will denote the posterior model probabilities for the last model (model *T*), i.e., it means the probability of each hypothesis regarding all the information of the models under review.

In this research I test whether online political participation

H_0: does not have an impact on offline political participation,

$H_>$: affects positively offline political participation,

$H_<$: affects negatively offline political participation.

For the analysis I used the R code of Kuiper (2012).

5.1.2 Hungarian Panel survey analysis

After analyzing the overall effect of online political activities on offline activities, this Chapter aims to evaluate whether the results obtained from Hungarian data align with the broader empirical evidence. The investigation of the Hungarian context is crucial as it acknowledges the potential cultural differences in social media and online platform usage between countries. Focusing on a specific unit of analysis can enhance the validity of the results obtained from the study. A national panel survey was utilized to investigate the connection between online and offline political activities using national-specific data. By analyzing this data, the study aimed to uncover specific patterns and behaviors within the Hungarian population regarding their engagement in political activities. Understanding these unique characteristics could provide insights into how social media and online platforms are influencing offline political participation in the Hungarian context.

The analysis involved creating two summary variables to capture the overall level of political activity: an offline and a general online activity variable. The offline variable was derived from the variables related to offline political activities, while the general online activity variable was based on the summation of variables related to online political activities.

Given the relatively low and unbalanced frequency of the original variables representing online and offline political participation, with only a small percentage (one to ten percent) of the sample engaging in these activities, the variables were standardized before creating the composite variables to ensure comparability by giving equal weights to the relatively infrequent activities and the more frequent ones in the composite variable.

Standardization is a statistical technique used to transform variables to have a mean of 0 and a standard deviation of 1. This process allows variables with different scales and ranges to be placed on the same scale, making it easier to compare and interpret their effects in the analysis. By standardizing the variables, the impact of each variable on the outcome can be assessed more accurately and meaningfully, regardless of their original measurement units or magnitudes. Standardization also helps to mitigate potential bias or issues arising from the unbalanced distribution of the variables, allowing for a more reliable analysis and interpretation of the results.

Table 8 provides the descriptive statistics for the online and offline variables, which will be further examined in the analysis. Means indicate that online activities were equally frequent in the three waves, while offline ones occurred somewhat less frequently in Wave 2 compared to the first and the third periods.

8. Table Description of the variables in the regression analysis

Variable	Wave	Mean	Sd.
Online	1	0.00	2.49
	2	-0.01	2.48
	3	0.00	2.65
	All	0.00	2.52
Offline	1	-0.03	8.54
	2	-0.16	9.74
	3	0.00	10.94
	All	-0.06	9.55

To examine the relationship between offline and online political activities, linear regression models were applied. First, by using a pooled OLS approach, the analysis considers data from multiple individuals and time points, treating them as a single dataset. Second, a regression model with fixed effects tested the not unit-specific impact of offline activities on online ones, that is whether individuals tend to be more active offline when they are more active online. In this case the fixed-effects absorb the correlation originating from individual-level differences, such as if e.g., younger people tend to be more active both online and offline.

The analyses used the 'plm' function of the software R.

5.2 Emotions

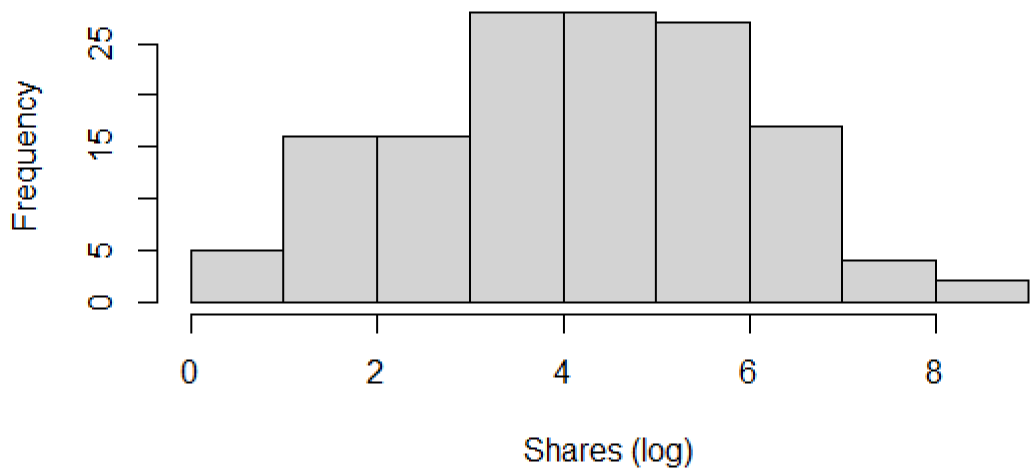
5.2.1 Dependent variables

The analyses focus on utilizing two dependent variables: the count of Shares and the count of additional New Shares for each post within specific time steps. New Shares pertain to the additional shares obtained within each timestep. The analysis also incorporates the Total Shares variable, which represents the cumulative count of shares a post has accumulated within a specific timestep. These variables were central to examining the sharing behavior and its evolution over time in relation to the posts.

Selecting the suitable statistical model required assessing the histograms of the dependent variables to ensure accurate representation and analysis. A histogram is a graphical representation of the distribution of a dataset. Variables were plotted logarithmically because plotting the logarithm of a variable on a histogram can be useful for several reasons:

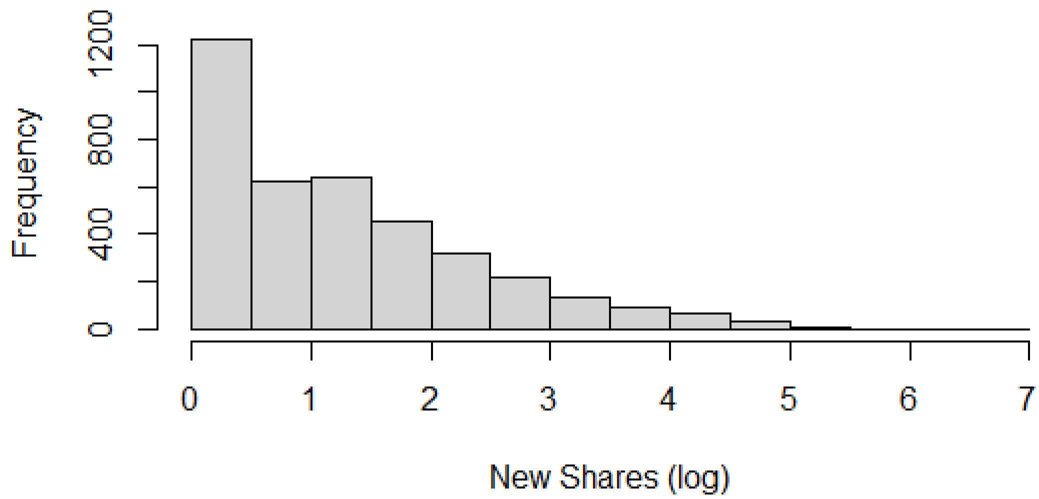
1. The variables have a highly skewed distribution with a long tail, plotting it on a logarithmic scale can help spread out the values and reveal the distribution's shape more clearly.
2. They represent a large range of values, a logarithmic scale can compress the range, making it easier to visualize both the very small and very large values on the same plot.
3. Logarithmic scaling can help focus on patterns in the data that might not be as evident on a linear scale.

9. Table Histogram of Shares



The histogram of the logarithmic Shares variables (Figure 9) displays a relatively symmetrical distribution on a logarithmic scale, with data points evenly spread around the central point. This distribution pattern suggests that linear regression could be applicable.

10. Table Histogram of New Shares



The histogram of New Shares (Figure 10) shows a positively skewed distribution on a logarithmic scale spanning from a minimum of 0 to a maximum of 5, with the highest frequency observed at 1200. This means that the majority of data points are clustered on the left side and the tail extends to the right, thus a suitable model should be utilized in the analysis.

New Shares variable is a discrete count variable, for which research usually apply count regressions, most frequently Poisson or negative binomial regression. Negative binomial regression is a statistical method that is suitable for analyzing over-dispersed count data, where the conditional variance exceeds the conditional mean. This condition is true to the New Shares variable, as Table 9 shows.

9.. Table Description of New Shares variable

	Mean	SD
New Shares (N=9514)	3.3	13.7

Other evidence suggesting the application of negative binomial model regression on this data is the Poisson model's residual deviance divided by the degrees of freedom. Applying Poisson regression on the number of New Shares explained by the lagged version of New Reactions, and New Comments, and Time Period variables, the quotient was 11.8 (112985/9509), thus for these data, the negative binomial model is more appropriate.

The New Shares variable represents the additional number of Shares received by a post in each timestep, with a total of over 9514 entries available. Although there are 74 timesteps for 146 posts, not every timestep has data for every post. The New Shares variable is discrete; however, it may paradoxically have negative values in certain cases due to the nature of Facebook usage. Out of the 9514 New Shares values, there are 120 instances where the value is negative. For the purpose of the analysis, these negative values are treated as 0 to align with the requirements of the negative binomial regression analysis, which assumes a positive discrete count variable as the dependent variable. To analyze the distribution of Reactions in terms of their dispersion, negative binomial regression models are employed. Negative binomial models are suitable for count data analysis when there is overdispersion present.

The data obtained from Crowdtangle was transformed into a panel data frame format where necessary, with post IDs serving as the unique identifiers for each unit. The Timestep variable was used to indicate the progression of time in the dataset. By structuring the data in this panel format, it allowed for the examination of the relationships and patterns over time, enabling the analysis of the effects of Reactions on the number of Shares.

5.2.2 Valence

The research question addressed the impact of emotional valence and diversity over time on the number of shares received. The consideration of emotional valence in this analysis is based on the emotions reflected by the different Reactions. As argued by Muraoka et al. (2021), Reactions such as Love are associated with positive emotions, while Angry Reactions are linked to negative emotions. The Like button, on the other hand, has a more diverse meaning, along with other Reactions that have various usages.

Based on the literature, this research considers the number of Shares on a post can be influenced by three main factors: the emotional content of the post (1), the social influence of how posts get Reactions (2), and the algorithm (3). Firstly, the emotional content of the post plays a significant role in predicting user engagement, as it was shown by Eberl et al (2021). The emotions evoked by the post, such as happiness, anger, or sadness, can elicit diverse reactions and drive users to share the content with their network. Secondly, social influence is another crucial factor. Users can be influenced by their peers to react and share a post, as the affective affordance theory suggests. The act of sharing can be driven by the desire to align with social norms, gain social approval, or engage in discussions with others. Lastly, the algorithm employed by the platform also plays a part, although its precise mechanisms are often undisclosed. The algorithm determines the visibility and reach of a post, potentially amplifying its impact through targeted recommendations or prioritizing popular content. By applying cross-sectional and panel regression analyses on the database, the study aims to uncover how different factors contribute to the changing number of Reactions on posts over time, providing insights into the dynamics and temporal aspects of engagement on the platform.

The analysis was conducted using the R software. R is a widely used statistical software, providing packages that cover the necessary tools and functions to perform the necessary analyses. Packages used in the analysis are marked.

The emotional content of a post

The analysis of valence framing involves conducting a cross-sectional analysis of posts, where the total number of Shares they gained is explained by the total number of Reactions. This approach allows to identify and highlight which emotions are associated with obtaining more or fewer Shares on a post and helps to understand the impact of emotions on sharing behavior on social media platforms, while explaining the effectiveness of valence framing in eliciting user responses and interactions. The emotional content of a post was inferred from the Facebook Reactions the posts' received.

To check this, a linear regression model was applied on the cross-sectional data, as Chapter Data introduced the dependent variable, Total Shares.

$$Share = \beta_0 + \beta_1 Comment + \beta_2 Like + \beta_3 Love + \beta_4 Wow + \beta_5 Haha + \beta_6 Sad + \beta_7 Angry + \beta_8 Care + \varepsilon$$

Where:

- $Share$ is the dependent variable.
- β_0 is the intercept term, representing the expected value of y when all predictor variables are zero.
- $\beta_1, \beta_2, \dots, \beta_8$ are the coefficients for the predictor variables, representing the change in the expected value of y for a one-unit change in each respective

predictor variable while holding other variables constant.

- $Like$, $Comment, Love, Wow, Haha$, $Sad, Angry$, $Care$ are the predictor variables.
- ε represents the error term, capturing the difference between the actual values and the predicted values by the model.

Model used the 'plm' function of R

Not post-specific effects (Social influence and the algorithm)

Revealing other factors, such as social influence and the algorithm, that play role in sharing posts on Facebook regarding the emotions, a fixed effect regression was applied to the data. The assumption in fixed effects models is that there are individual-specific factors that may influence or bias the predictor or outcome variables. To address this concern, fixed effects that control for these time-invariant characteristics thus they can isolate and examine the effect of the predictors on the outcome variable, removing the influence of the individual-specific factors. In the case of analyzing Facebook posts, the effect of time-invariant factors, including the emotional content of the posts, is removed by applying fixed effects. This allows for the separate analysis of the effects of reactions over time, independent of the inherent emotional content of the posts. This is responsible for uncovering the factors that play a role in sharing a post in general, not those that are affected by the content of each post, or the properties of the poster (politician). Thus, coefficients of the fixed-effect regressions correspond to factors related to social influence and the social media algorithm, however, it cannot separate them form each other.

As Chapter Data noted, New Shares can be considered as count data, which is a discrete variable. In such cases, a nonlinear model would be more suitable and provide a better fit for the data. Most research use Poisson or negative binomial regression to analyze count data from Facebook (e.g. Eberl et al, 2020). Poisson regression is suggested in cases where mean and the variance of the explained variable is similar, and negative binomial regressions could be a better fit when the variance is bigger than the mean, as it is in the case of New Shares variable.

Fixed effects in regression analyses are used when the interest is the impact of variables that vary over time. Fixed effects (FE) explore the relationship between predictor and outcome variables within the Facebook page, since each page has its own individual characteristics that may or may not influence the predictor variables. With the application of fixed effects, it is assumed that something within the individual may impact or bias the predictor or outcome variables and it is necessary to control for this. FE removes the effect of those time-invariant characteristics so we can assess the net effect of the predictors on the outcome variable. Another important assumption of the FE modeling is that those time-invariant characteristics are unique to the individual and should not be correlated with other individual characteristics. The fixed effects regression model is a commonly used method to address selection bias and estimate causal effects in observational data. In this case, the fixed effect panel regression model can estimate the effect of new reactions and new comments on new shares, while controlling for the unit-specific differences that are not observed in the data. The coefficients on the independent variables indicate how much the dependent variable is expected to change for a one-unit increase in each independent variable, holding constant the other independent variable and the fixed effects, thus addressing concerns related to unobserved heterogeneity. (Mummolo & Peterson, 2018).

Fixed effects can be implemented into negative binomial regressions. Negative binomial fixed effect regressions (NB FE) were performed with the 'glm.nb' function of MASS package in R. As alternative models, linear fixed effects models were also conducted. The fixed effect panel regressions used the 'plm' function of the package of the same name, with model specification "within".

The analysis contains three different regression models. The regression is based on the following equation.

$$log\big(E(Y)\big) = \beta_0 + \beta_1 X + \beta_2 X \ldots + \beta_p X_p + \xi i$$

Where:

- *log()* is the natural logarithm function.
- *E(Y)* is the expected value of the response variable *Y*.
- $\beta_0, \beta_1, \beta_2, \ldots, \beta_p$ are the coefficients (parameters) to be estimated.
- $X_1, X_2, \ldots, X_p$ are the predictor variables.
- *p* is the number of predictor variables.
- ξ_i represents the unit-specific fixed effects.

First, the different reactions were assessed separately. For this, the dependent variable

New Shares is explained with the *t-1* lagged version on New Like, New Comments, New Love, New Wow, New Haha, New Angry, New Sad, and New Care reactions. The equation is the following.

$$log\ (NewShare_{i,t}) = \beta_0 + \beta_1 NewLikes_{i,t-1} + \beta_2 NewComment_{i,t-1} + \beta_3 NewLove_{i,t-1} + \beta_4 NewWow_{i,t-1} + \beta_5 NewHaha_{i,t-1} + \beta_6 NewAngry_{i,t-1} + \beta_7 NewSad_{i,t-1} + \beta_8 NewCare_{i,t-1} + \xi_i$$

Where:

Second, the analysis added the Time Period variable and its interactions with the different Reactions to the regression. This approach aimed to achieve a more intricate comprehension of how Reactions evolve throughout the lifespan of a post.

$$log\ (NewShare_{i,t}) = \beta_0 + \beta_1 NewLikes_{i,t-1} + \beta_2 NewComment_{i,t-1} + \beta_3 NewLove_{i,t-1} + \beta_4 NewWow_{i,t-1} + \beta_5 NewHaha_{i,t-1} + \beta_6 NewAngry_{i,t-1} + \beta_7 NewSad_{i,t-1} + \beta_8 NewCare_{i,t-1} + \beta_8 TimePeriod_i + \beta_8 TimePeriod\ x\ NewLikes_{i,t-1} + \beta_8 TimePeriod\ x\ NewComments_{i,t-1} + \beta_8 TimePeriod\ x\ NewLoves_{i,t-1} + \beta_8 TimePeriod\ x\ NewWow_{i,t-1} + \beta_8 TimePeriod\ x\ NewHahas_{i,t-1} + \beta_8 TimePeriod\ x\ NewSad_{i,t-1} + \beta_8 TimePeriod\ x\ NewAngry_{i,t-1} + \beta_8 TimePeriod\ x\ NewCares_{i,t-1} + \xi_i$$

Third, the general effect of Comments and Reactions over time on the number of Shares of a Facebook post was analyzed, to differentiate between overall user engagement and emotional reactions in two versions. Thus, the regression was applied with the number of New Shares as a dependent variable, and the quantity of New Reactions and New Comments in the previous Timestep as independent variable. Additionally, the Time Period variable was added as independent variable to the model.

$$log\ (NewShare_{i,t}) = \beta_0 + \beta_1 NewReactions_{i,t-1} + \beta_2 NewComments_{i,t-1} + \xi_i$$

$$log\ (NewShare_{it}) = \beta_0 + \beta_1 NewReactions_{i,t-1} + \beta_2 NewComment_{i,t-1} + \beta_3 TimePeriod_i + \xi_i$$

5.2.3 Diversity

Second, the analysis focuses on the diversity of emotions evoked by posts. According to Freeman (2020), diversity measures both the number of different special reaction types (Like, Love, Haha, Sad, Angry, Wow in the case of Facebook) present for a given post, as well as how evenly distributed those reactions are. A higher diversity score indicates that there is a wide variety of emotional responses to the post, with users expressing different emotions in their reactions. On the other hand, a lower diversity score suggests that the emotional responses are more concentrated or limited to a specific emotion. Diversity of Reactions might be the result of social influence: Reactions might function as emotional cues to the users. This analysis aims to understand how the diversity of emotional responses changes over the lifespan of the posts, because the concentration of Reactions might vary over time, especially if influenced by each other.

Regarding diversity, the analysis first focuses on examining the social influence presented in the Reactions over time by analyzing the variance of Reactions. The variance of Reactions can serve as a cue to understand how the different Reactions concentrate and change over time. Second, a regression analysis measures the effect of Reactions on each other: how different Reactions affect the number of other Reactions on a post. Additionally, the proportion of different Reactions is measured: it can provide insights into user engagement over time. To quantify this, the Herfindahl-Hirschman Index (HHI) is utilized, which measures the concentration of Reactions and reflects the level of diversity or homogeneity in emotional responses. By calculating the HHI, the study can gauge the extent to which certain emotional Reactions dominate or whether there is a more balanced distribution of Reactions over time.

Influence

The aspect of Reactions influencing each other in time is based on the idea of the affective-affordance-attribute of Facebook Reactions. This reflects to their characteristic which allows other users to affect by the Reaction itself. To assess the influence of Reactions on each other, a fixed effect model is used. In this case, the different reactions are the independent variables of the regression. The equations used in the analysis are as follows.

$$
\begin{aligned}
NewLikes_{it} = \beta_0 &+ \beta_1 NewShares_{i,t-1} + \beta_2 NewComment_{i,t-1} + \beta_3 NewLove_{i,t-1} \\
&+ \beta_4 NewWow_{i,t-1} + \beta_5 NewHaha_{i,t-1} + \beta_6 NewAngry_{i,t-1} \\
&+ \beta_7 NewSad_{i,t-1} + \beta_8 NewCare_{i,t-1} + \xi_i + \varepsilon_{it}
\end{aligned}
$$

$$
\begin{aligned}
&NewComments_{it} \\
&\quad = \beta_0 + \beta_1 NewShares_{i,t-1} + \beta_2 NewLikes_{i,t-1} + \beta_3 NewLove_{i,t-1} \\
&\quad + \beta_4 NewWow_{i,t-1} + \beta_5 NewHaha_{i,t-1} + \beta_6 NewAngry_{i,t-1} \\
&\quad + \beta_7 NewSad_{i,t-1} + \beta_8 NewCare_{i,t-1} + \xi_i + \varepsilon_{it}
\end{aligned}
$$

$$
\begin{aligned}
NewLoves_{it} = \beta_0 &+ \beta_1 NewShares_{i,t-1} + \beta_2 NewComment_{i,t-1} + \beta_3 NewLikes_{i,t-1} \\
&+ \beta_4 NewWow_{i,t-1} + \beta_5 NewHaha_{i,t-1} + \beta_6 NewAngry_{i,t-1} \\
&+ \beta_7 NewSad_{i,t-1} + \beta_8 NewCare_{i,t-1} + \xi_i + \varepsilon_{it}
\end{aligned}
$$

$$
\begin{aligned}
NewWows_{it} = \beta_0 &+ \beta_1 NewShares_{i,t-1} + \beta_2 NewComment_{i,t-1} + \beta_3 NewLove_{i,t-1} \\
&+ \beta_4 NewLikes_{i,t-1} + \beta_5 NewHaha_{i,t-1} + \beta_6 NewAngry_{i,t-1} \\
&+ \beta_7 NewSad_{i,t-1} + \beta_8 NewCare_{i,t-1} + \xi_i + \varepsilon_{it}
\end{aligned}
$$

$$
\begin{aligned}
NewHahas_{it} = \beta_0 &+ \beta_1 NewShares_{i,t-1} + \beta_2 NewComment_{i,t-1} + \beta_3 NewLove_{i,t-1} \\
&+ \beta_4 NewWow_{i,t-1} + \beta_5 NewLikes_{i,t-1} + \beta_6 NewAngry_{i,t-1} \\
&+ \beta_7 NewSad_{i,t-1} + \beta_8 NewCare_{i,t-1} + \xi_i + \varepsilon_{it}
\end{aligned}
$$

$$
\begin{aligned}
NewSads_{it} = \beta_0 &+ \beta_1 NewShares_{i,t-1} + \beta_2 NewComment_{i,t-1} + \beta_3 NewLove_{i,t-1} \\
&+ \beta_4 NewWow_{i,t-1} + \beta_5 NewHaha_{i,t-1} + \beta_6 NewAngry_{i,t-1} \\
&+ \beta_7 NewLikes_{i,t-1} + \beta_8 NewCare_{i,t-1} + \xi_i + \varepsilon_{it}
\end{aligned}
$$

$$
\begin{aligned}
NewAngry_{it} = \beta_0 &+ \beta_1 NewShares_{i,t-1} + \beta_2 NewComment_{i,t-1} + \beta_3 NewLove_{i,t-1} \\
&+ \beta_4 NewWow_{i,t-1} + \beta_5 NewHaha_{i,t-1} + \beta_6 NewLikes_{i,t-1} \\
&+ \beta_7 NewSad_{i,t-1} + \beta_8 NewCare_{i,t-1} + \xi_i + \varepsilon_{it}
\end{aligned}
$$

$$
\begin{aligned}
NewCares_{it} = \beta_0 &+ \beta_1 NewShares_{i,t-1} + \beta_2 NewComment_{i,t-1} + \beta_3 NewLove_{i,t-1} \\
&+ \beta_4 NewWow_{i,t-1} + \beta_5 NewHaha_{i,t-1} + \beta_6 NewAngry_{i,t-1} \\
&+ \beta_7 NewSad_{i,t-1} + \beta_8 NewLikes_{i,t-1} + \xi_i + \varepsilon_{it}
\end{aligned}
$$

The analysis aims to explore the relationship and correlations between Facebook reactions and the emotions they reflect, considering the possibility that these emotions may be influenced by peers.

Herfindahl-Hirschmann Index

For further information about the variation of different Reactions on Facebook posts, this thesis proposes a Herfindal-Hirschmann Index (HHI) calculated to the reactions in each timestep. HHI is a widely used measure in economics of market concentration that can also be adapted to analyze the distribution of reactions to a Facebook post, since the different Reactions reflects to different emotions, and the response from the audience might be scattered or concentrated. In this context, the HHI can provide insights into the ratio of different reactions received by posts and the concentration of engagement among those reactions. By calculating the HHI for the collected posts, the level of dominance or diversity in the types of reactions generated by them can be assessed. Higher HHI value indicates a more concentrated distribution, suggesting that a single type of reaction, such as Like, dominates the posts' engagement. Conversely, a lower HHI value indicates a more diverse distribution, with a balanced ratio of different Reactions. Analyzing the HHI over time can help identify patterns in user engagement.

The time effect on HHI of new shares was tested with an OLS regression:

$$HHI\_new = \beta_0 + \beta_1 Timestep$$

The correlation between HHI and new shares is analyzed with and without the effect of Reactions. HHI and New Shares connection without reactions:

$$New\ Shares = \beta_0 + \beta_1 HHI\_new$$

In addition to analyzing HHI for new shares, the total number of shares was also considered in the dataset. The dataset provided information on the total number of shares for each post, enabling a comprehensive assessment of the sharing behavior on social media. By examining both new and total shares, a more complete picture of the information dissemination and engagement patterns was obtained.

$$Total\ Shares = \beta_0 + \beta_1 HHI$$

5.3 Modeling network structure and information spreading

Building on the results concerning the dynamics of sharing political news on Facebook, an agent-based model (ABM) was created to examine the impact of network characteristics. The agent-based model was developed using the software NetLogo. NetLogo aligns with Wilensky et al.'s (2015) eight main uses of agent-based models. It serves as a versatile tool for simplifying real-world systems to offer descriptions, explaining essential mechanisms, conducting repeated experiments to classify behaviors, establishing analogies, facilitating education and communication, providing focal points for research, supporting thought experiments, and even enabling predictive capabilities within specific contexts.

5.3.1 Modeling social networks

There is limited knowledge available about the social network structure of Facebook, so the model tests three different social network structures used in research to model social network sites: (1) a preferential attachment network (PA), (2) a small-world network structure, and (3) a random network.

Random network model assumes a uniform probability of links between each pair of nodes. However, the random network model does not reproduce some properties of real-life networks, such as having a low distance between nodes (i.e., having long ties), high clustering, and the emergence of hubs i.e. a few people having a large number of connections (Barabási, 2016). To deal with the real-life network characteristics of having clusters and long ties, small world networks were proposed (Watts & Strogatz, 1998). Small world refers to a network which has high clustering (friends of friends tend to be friends), and relatively low average distances between nodes.

High clustering in PA networks is achieved by distributing the nodes on a circle and creating connections between each of them within a certain range on the circle. As the resulting network has high distances, in the next step a small fraction of links is redistributed randomly to create ‘shortcuts’. On the other hand, hubs appear in the preferential attachment model where new links are created with a likelihood based on the node’s existing degree (Albert & Barabási, 2002).

In random networks links are probabilistically formed between nodes with uniform probability. In PA networks connections are distributed according to how many connections the node already has.

To create a more realistic environment, the possibility of echo chambers was incorporated in the model. Echo chambers refer to the phenomenon of groups of like-minded users formed on social media, where there is a bias in the information diffusion toward like-minded users (Quattrociocchi et al., 2021). Homophily of users is one mechanism behind echo chambers, but algorithms of social media may reinforce that (Cinus et al., 2022). Homophily refers to the tendency that connections occur at a higher rate amongst those who share a common interest (McPherson et al., 2001). In this simulation, homophily means that a higher number of links are simulated between those whose political interests are similar. With respect to algorithms, a content-filtering algorithm was considered, where posts are shown with decreased probability to those users whose political attitude is more distant from the sender. To examine the possible interactions, each of the three types of network structures were simulated with and without homophily and with or without preference-based filtering algorithm.

5.3.2 Structure of the simulation

This thesis utilizes agent-based modeling (ABM) to examine information spread on networks, with a specific focus on understanding Facebook users' behavior. The NetLogo code is available at https://github.com/emeseeva/thesis.

In the beginning, a post can be seen by nodes who already have followed the page. Once seen it, they can react to it or share it, as on the real site. Facebook data presented that more than two thirds of all interactions to the posts were “Likes” (Chapter Data). Also, the regression on Facebook data showed that the Reactions in total affect the number of shares in the following timesteps, so in the simulation there are no different reactions, only the sum of them. These outcomes are presented later, in Chapter Results. The result, that reactions propagate future shares, was incorporated in the model by adding reactions as a separate channel which propagates visibility of the post to friends. The fixed effect term in the regression analysis is considered as the attractiveness of the post in the simulation.

The simulation was implemented as follows. Each agent represents a person, a member in a social network. A fraction of agents is selected to be a „follower” of the politician; they are shown the information in the first timestep. Their neighbors are the connected nodes who can see their activities – reactions or shared posts. The number of neighbors of a given agent – the node degree – depends on the network structure. The sender (politician) is modeled as being external to the network. Political attributes are assumed to be one-dimensional: the politician stands at the zero point, and the agents are at different distance from it, modelled by a uniformly distributed ‘interest’ parameter. The politician posts different information having a random attractiveness parameter and political specifics. Sharing happens randomly; based on the attractiveness of the post, its political specifics and the distance between the agent and the politician in the political spectrum. (Specifically, the attractiveness parameter decreased by the political distance between the politician and the agent, decreased by the political specificity of the post is evaluated against a random number). Reacting to the post happens similarly to sharing, but with a higher probability.

Non-follower agents – agents that had not seen the information in the first timestep – are only shown the post if their neighbor shared it or reacted to it. This, however, is not automatic. Posts shared (or reacted) by friends are made visible to users randomly based on their political attitudes. Specifically, their distance from the politician decreased by the political specificity of the post is evaluated versus a threshold thar manipulate content filtering algorithm. In the baseline case, almost everyone can see the post, while in the ‘filtering algorithm’ scenario only those can see whose attitude is close to the politician.

Thus, the simulation consists of the following steps:

1. A [Random / PA / Small Word] network of people is created, having different ‘interest’ towards the sender [with / without] homophily. Some people are selected to be followers of the sender. The attractiveness of the post is set.

2. Followers of the sender see the post.

3. Those who have seen the post and have not reacted yet, decide if they react to it or not, based on their attitude towards the post and the attractiveness of the posts.

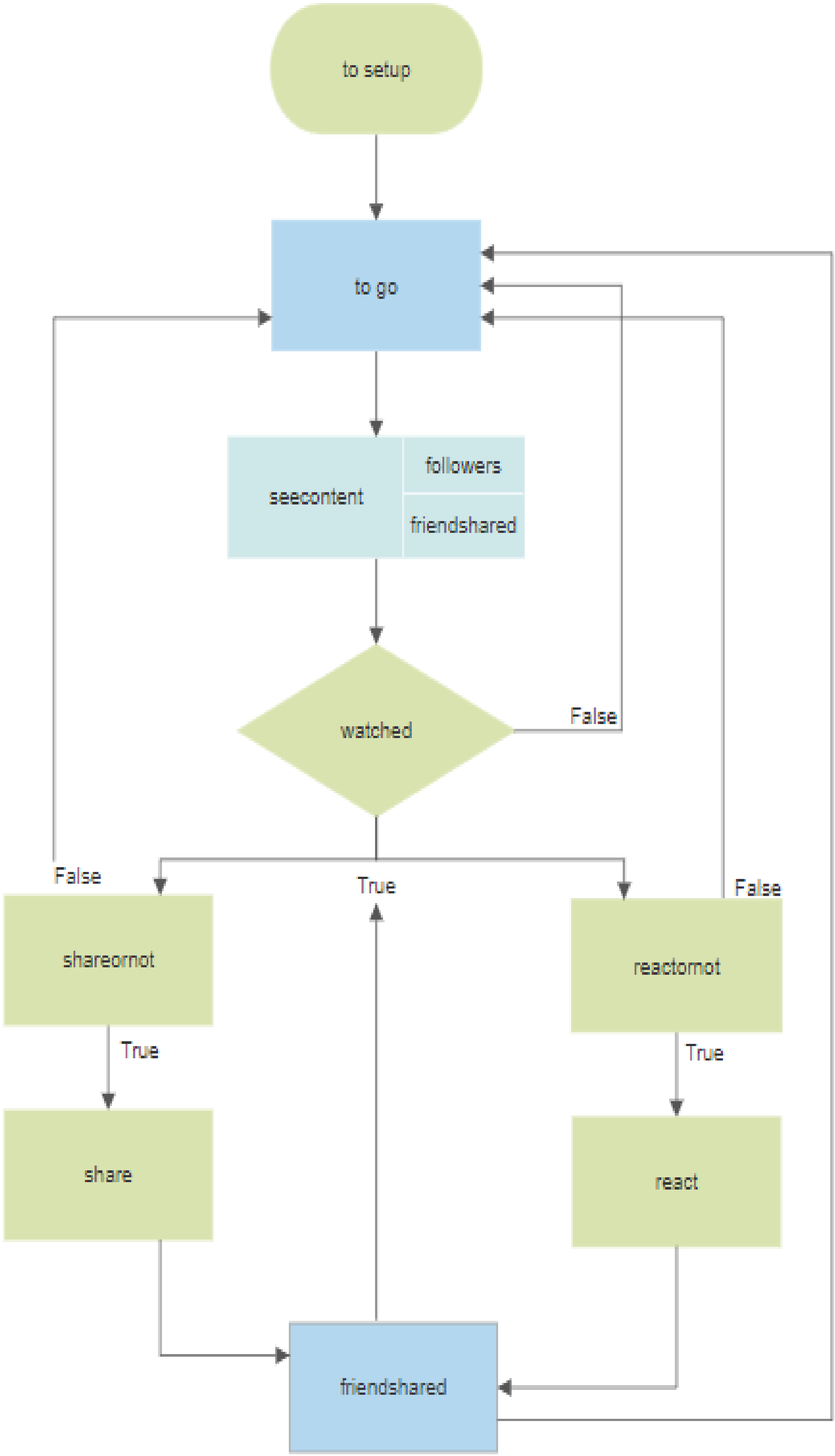
4. Reactions are shown to the connections of those who have reacted to it.

5. Those who have seen the post, and have not shared yet, decide if they share it or not, based on their attitude towards the sender (interest) and the attractiveness of the post.

6. The post is shown to connections of those who have shared it with a given probability. In the case of echo chambers, higher similarity is necessary.

The flow of the steps is on Figure 10.

Figure 10. Steps of the simulation



In the first simulation, the network consists of 400 nodes, of whom 20 are followers of the politician, and 380 are not. Each node has an average degree of 4. Additionally, the simulation was repeated with different settings to compare results. Table 10 shows the version of the settings for the simulation. The number of nodes, and average node degree were modified, and in the case of small world networks the probability of the rewiring of the network is tested in two versions.

10.. Table: Settings of the simulation

Scenario	Network Type	Number of Nodes	Average Node Degree	Number of Followers
A	Small world (p = 0.1)	400	4	20
	Preferential Attachment	400	4	20
	Random	400	4	20
B	Small world (p = 0.1)	1000	4	50
	Preferential Attachment	1000	4	50
	Random	1000	4	50
C	Small world (p = 0.1)	1000	10	50
	Preferential Attachment	1000	10	50
	Random	1000	10	50
D	Small world (p = 0.05)	400	4	20

In Scenario B, the average node degree from Scenario A remains constant, but both the number of nodes and followers are increased proportionally to maintain the same ratio as before. In Scenario C, the node degree is increased by a factor of 2.5. Lastly, Scenario D specifically targets small world networks, testing modifications to the rewiring probability.

5.3.3 Linear regression on the results of the simulation

To compare the influence on information diffusion caused by different network attributes, a linear regression was applied to the number of nodes who shared the information in the simulation. The number of agents that shared the original information was explained by the network type, homophily, the presence of filtering algorithms and the pairwise interactions of these factors. Accordingly, the following equation was estimated:

$$\begin{aligned} TotalShare = {} & b_0 + b_1 SmallWorld + b_2 PA + b_3 Random + b_4 Homophily \\ & + b_5 FilterAlgorithm + b_6 Homophily \times FilterAlgorithm \\ & + b_7 PA \times Homophily + b_8 Random \times Homophily \\ & + b_9 SmallWorld \times Homophily + b_{10} PA \times FilterAlgorithm \\ & + b_{11} SmallWorld \times FilterAlgorithm \\ & + b_{12} Random \times FilterAlgorithm + \varepsilon \end{aligned}$$

Overall, this analysis aims to identify networks and the network attributes where political information and news are likely to spread wider and reach more users.

6 Results

6.1 Online and offline political activities

6.1.1 Synthesis of studies

Bayesian Updating combined evidence for positive, negative, and null effect of the predictor of interest – in this case the online participation – on the dependent variable – in this case the offline participation. The method is employed to evaluate the hypotheses, in this case it tested whether online political participation:

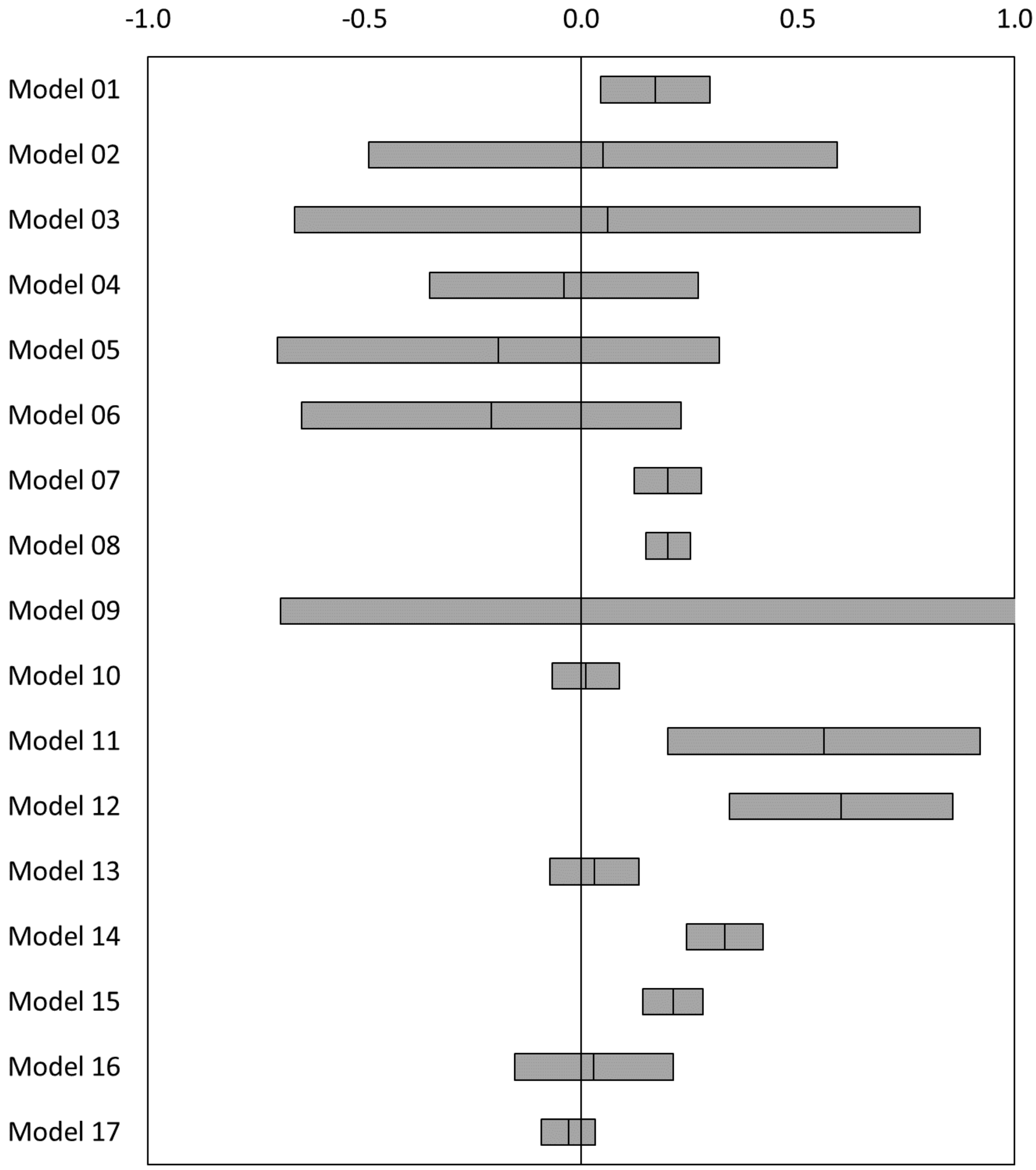
H_0: does not have an impact on offline political participation,

$H_>$: affects positively offline political participation,

$H_<$: affects negatively offline political participation.

Combined studies implied models that supported each of these hypotheses. Figure 3 presents the 99 per cent confidence intervals for each model. Models that are overlapping the line 0, shows no significant results (Model 01, 02, 03, 04, 05, 06, 09, 10, 13,16, 17). Model 01, 07, 08, 11, 12, 14 and 15 supports the positive hypothesis with positive significant results. No study supported the negative hypothesis.

Figure 11. 99 percent Bayesian intervals



After updating the uninformative prior probabilities regarding the seventeen models mentioned earlier, Bayesian Updating provided clear evidence for the positive impact of online political participation on offline participation forms. Posterior model probability of $H_{>}$ hypothesis is 1, while that of $H_{<}$ hypothesis is 0, and for H_0 hypothesis it is also practically 0. Thus, the overall effect is positive, with respect to the studies regarded.

Table 11: Posterior model probabilities for the 17 models with different prior variances

	$\frac{1}{2}\sigma_0^{T2}$	σ_0^{T2}	$2\sigma_0^{T2}$
H_0	1.96E-69	6.46E-72	2.97E-72
$H_>$	1.00E+00	1.00E+00	1.00E+00
$H_<$	0.00E+00	0.00E+00	0.00E+00

Note: Posterior model probabilities after taking into account all the seventeen models of the fourteen different studies. Source: Own calculation.

Table 11 presents the results of the Bayesian Updating analysis, which supports the positive hypothesis regarding the relationship between online and offline political activity. The table also includes information about σ^2, representing the uncertainty of parameter estimation in the final step, *T*. A sensitivity analysis was conducted to validate the results with different parameter estimation uncertainties, further confirming the validity of the positive relationship between online and offline political activity. The findings from the international literature, combined with the results obtained through the Bayesian Updating method, provide strong evidence supporting the connection between online and offline political engagement.

6.1.2 Hungarian context

The findings show a positive association between online and offline political engagements within the Hungarian context, aligning with the results of previous empirical surveys from various contexts presented in Chapter 2.2.2. Table 12 displays the outcomes of the regression, highlighting the impact of the combined online activities variable on combined offline activities.

Table 12: Regression analysis on offline political activities explained by the online political activities.

	Offline activities
Online activities	1.84***
Observations	4,606
R2	0.23726
Adjusted R2	0.2371
F Statistic	1432.16
*Note: *p<0.1; **p<0.05; ***p<0.01*	

Table 13: Regression analysis on offline political activities explained by commenting, liking, and sharing posts online

	Offline activities
Commented on an internet forum on political or public affairs topics	2.4***
Liked posts, events, or videos related to public affairs or politics online	1.35***
Shared posts, events, or videos related to public affairs or politics online	1.77***
Observations	4,606
R2	0.24014
Adjusted R2	0.23965
F Statistic	484.803
*Note: *p<0.1; **p<0.05; ***p<0.01*	

Table 13 presents the outcomes of the regression analysis where the original activities are employed as independent variables, rather than the combined online variable. The results reveal a significant positive impact of commenting, liking, and sharing posts online on the combined offline political participation variable.

Table 14: Fixed effect regression analysis on offline political activities explained by commenting, liking, and sharing posts online

	Offline activities
Commented on an internet forum on political or public affairs topics	2.13***
Liked posts, events, or videos related to public affairs or politics online	2.25***
Shared posts, events, or videos related to public affairs or politics online	1.9***
Observations	4,606
R2	0.22571
Adjusted R2	-1.2257
F Statistic	155.667
*Note: *p<0.1; **p<0.05; ***p<0.01*	

Table 14 shows the results of the repeated regression with fixed effects. Fixed effects control for the individual effect, thus this regression analysis highlights that political interest increase the possibility of both online and offline political participation.

The findings from the Hungarian panel data demonstrate that individuals who engage in online activities such as liking, commenting, or sharing politics-related information are more likely to participate in offline political activities This align with the results of the research of Szabó and Gerő (2021).

Regarding offline and online political participation in Hungary, Szabó and Gerő (2022) argues that in 2021, 8-9 per cent of Hungarian people liked, commented, or shared news online, which is comparable in extent to other political participation forms. They analyzed four types of political participation local, traditional, direct, and online. Local political participation refers to organizing local community events or participation in public forums. Those types of activities are not present in the analysis of the thesis, but traditional and direct forms of participation refer to activities that are present. Traditional forms include contacting national or local politicians; engaging in a political party or movement; or wearing or displaying political badges or symbols. Direct forms of participation refer to signing a protest letter, participating in demonstration, and boycotting certain goods.

Online forms of participation are similar to the definition used in this analysis: posting, liking, commenting and sharing political posts.

The research found that the four forms of participation are relatively strongly related to each other. Particularly strong was the correlation between local and online political engagement. While the correlation between online and traditional participation exhibited the weakest connection, over the period from 2018 to 2021, this correlation experienced a strengthening trend.

These findings suggest that different types of participation actions reinforce each other, similarly to the offline and online political activities analyzed in this research.

6.2 Emotions

6.2.1 Results of analyzing emotional valence

This subchapter presents the results of the analysis about the effect of emotional valence and diversity of a post on the times it was shared over time.

Effect of post-specific sentiment on Shares

To measure emotional valence, the Reactions were analyzed as a proxy for different emotions. The linear regression tested the effect of different Reactions on the total number of Shares on the posts. Table 15 presents the results:

Table 15: Regression on the post-specific effects of Reactions on Total Shares

	Share
Like	0.17012***
Comment	-0.69296***
Love	0.20
Wow	0.95
Haha	0.7711***
Sad	0.54968*
Angry	0.86805***
Care	-1.14
Observations	146
Multiple R2	0.709
Adjusted R2	0.692
F Statistic	41.72
*Note: *p<0.1; **p<0.05; ***p<0.01*	

On the total number of Shares, Likes, Haha, Sad, and Angry Reactions had significant effect. Angry reactions can be understood as straightforward negative emotion and some research use Sad reaction as a negative emotion, too (e. g. Freeman, 2020), but in general the Sad, Haha, and Like buttons have more diverse meanings. Like, being the oldest Reaction button in use, is the most commonly used for various reasons (Larsson, 2015), and Haha and Sad can have different connotations, especially if used ironically, for example. This finding suggests that negative emotion expressed through reactions and the commonly used Like reaction have a significant influence on the spread of the post regarding the sentiment of the posts. The presence of more Comments decreased the number of Shares on a post. This could be a result of comments and shares both being actions that require a higher level of engagement from a user, meaning, when users are actively commenting on a post, they may be less likely to also share it.

General effects of Reactions on Shares over time

To examine the influence of emotions on sharing posts, the following analysis focuses on the valence of emotional Reactions over time. Several factors can influence the Reactions received by a post, including the sentiment of the post (as discussed in the previous subchapter) and other factors such as social influence, and the role of the algorithm. Concerning social influence, the analysis focuses on the impact of Reactions on subsequent Reactions, specifically whether the quantity of a particular Reaction fosters additional Reactions of the same nature. This effect was examined through three distinct regression models: one considering total Reactions, another assessing individual Reactions separately, and a third analyzing Reactions within specific time periods.

All three analyses were performed using fixed effect panel regression and negative binomial regressions with fixed effects. Fixed effects capture the consistent, time-independent variations among the pages that influence the count of new shares, beyond what is explained by the pages themselves. A higher average fixed effect signifies a greater initial value of new shares.

Concerning the attributes of the New Shares dependent variable, the main findings of the negative binomial regressions are discussed here, in Chapter Results, but for the purpose of comparison, the results from the alternative models are available in the Appendix.

Table 17 presents the results of the NB FE regression analysis that examines the individual effects of each different Reaction on the number of New Shares, using the lagged version of each Reaction as explanatory variables. The findings indicate that the number of New Comments in the previous Timestep does not have a significant effect on the number of New Shares. When analyzing the Reactions separately, the New Likes, New Love, New Haha, and New Angry reactions demonstrate a significant effect on the number of New Shares. This suggests that the presence of these Reactions in the previous Timestep is associated with a change in the subsequent number of New Shares. The presence of more New Love and Haha reactions means less New Shares in the following Timestep, but the New Like and New Angry reactions have positive significant effect.

The other Reactions do not show a significant individual effect on the number of New Shares.

Table 16: FE NB regression on different lagged Reactions on New Shares

	New Shares
New Likes$_{t-1}$	0.00868***
New Comments$_{t-1}$	0.01
New Love$_{t-1}$	-0.05683***
New Wow$_{t-1}$	0.03
New.Haha$_{t-1}$	-0.018274***
New.Sad$_{t-1}$	0.02
New.Angry$_{t-1}$	0.023626***
New.Cares$_{t-1}$	0.01
*Note: *p<0.1; **p<0.05; ***p<0.01*	

In the linear model, comparable significant outcomes were observed for New Like and New Angry reactions, with both showing a significant positive influence. Nevertheless, New Love and New Sad reactions did not have any significant effect in the linear regression. In contrast, the New Wow reactions demonstrated a significant positive impact. Similar to pooled in sense that negative facilitates sharing can be the result of algorithm boosting posts with negative feelings too.

To reveal more about the time-related aspect of the Reactions effect on Shares, the second regression incorporates the concept of Time Periods of the posts' lifespan. The Time Period variable is utilized to identify the point in time when a post reaches half of its total shares.

The primary objective of the regression analysis with the Time Period variable is to uncover the time-dependent effects of Reactions: how the impact of Reactions may vary over time. By considering the dynamics and changes occurring across different timesteps, it aims to capture the evolving nature of Reactions and their influence on New Shares. This time-variant approach allows for a more nuanced understanding of the relationship between Reactions and their effects, revealing temporal patterns in the context of Facebook posts.

Table 17: FE NB regression on the number of New Shares with Time Periods

	New Shares
New $Likes_{t-1}$	-0.008373***
New $Comments_{t-1}$	-0.01
New $Love_{t-1}$	-0.03
New Wow_{t-1}	0.02
New $Haha_{t-1}$	0.00
New Sad_{t-1}	0.03
New $Angry_{t-1}$	-0.01
New $Cares_{t-1}$	0.08
Time Period	-1.322652***
New $Likes_{t-1}$*Time Period	0.012208***
New $Comments_{t-1}$*Time Period	0.01
New $Love_{t-1}$*Time Period	0.00
New Wow_{t-1} * Time Period	0.00
New $Haha_{t-1}$*Time Period	-0.01
New Sad_{t-1}*Time Period	-0.03
New $Angry_{t-1}$*Time Period	0.024275*
New $Cares_{t-1}$*Time Period	-0.06
*Note: *p<0.1; **p<0.05; ***p<0.01*	

When incorporating Time Periods into the negative binomial fixed effects regression analysis, it was found that only the New Like and New Angry reactions exhibited a statistically significant effect in addition to the Time Period variable (Table 17). This result is in line with the previous analyses suggesting the importance of Like and Angry Reactions. In the first Time Period, an increase in New Likes was associated with a lower number of New Shares in the subsequent timestep. However, in the second Time Period, the effect of New Likes on New Shares became positive, indicating that an increase in New Likes was associated with a higher number of New Shares. New Angry reactions go together with higher number of New Shares only in the second Time Period. These findings suggest that the influence of New Like and New Angry reactions on New Shares is affected by the specific Time Period. Moreover, the significant negative effect of Time Periods implies that after a post reached half of its total Shares, the number of New Shares in each Timesteps declines.

After examining the impact of different Reactions reflecting various emotions, the analysis also considered the combined effect of total Reactions and Comments on the number of New Shares. This was done to determine if there was a general influence of higher engagement or if the effects were mostly emotion-based. The regression analysis included the total sum of Reactions and Comments received by the post at the previous timestep (t-1), allowing for a study of their influence over time. By incorporating these variables, the analysis aimed to understand how the overall level of engagement in the past affected the subsequent number of shares on the post.

The following Tables show that the overall number of Reactions has a positive significant effect on the number of New Shares, as well in the linear models, but the Comments effect is not present in the negative binomial model.

Table 18 presents the results of the regression analysis for the prior version of New Reactions and New Comments, with a focus on their impact on the number of subsequent New Shares. The findings indicate that only New Reactions variable have a significant positive effect on the number of New Shares, indicating that a higher number of Reactions is associated with an increase in the number of New Shares in the subsequent Timestep.

Table 18: NB FE regression on New Shares by lagged Reaction and Comments

	New Shares
New Reactions$_{t-1}$	0.007377***
New Comments$_{t-1}$	0.00
Observations	9,329
*Note: *p<0.1; **p<0.05; ***p<0.01*	

Consistent with the previous findings, Table 20 reveals that overall only Reactions in the previous Timestep are linked to an increase in the number of New Shares when including Time Period variable into the regression. However, the analysis indicates that this effect diminishes in the second Time Period.

Table 19: NB FE regression on New Shares by lagged Reactions and Comments and Time Period

	New Shares
New Reactions$_{t-1}$	0.006178***
New Comments$_{t-1}$	0.00
Time Period	-0.960124***
*Note: *p<0.1; **p<0.05; ***p<0.01*	

The results indicate that the quantity of New Shares a post receives over time is influenced by Reactions, rather than the broader user engagement encompassing Comments. This observation underscores the significance of emotions, given that the emotional Reactions hold considerable importance.

The alternative models – linear fixed effect panel regressions (Appendix) – found similar results to the negative binomial regressions regarding the overall positive significant effect of lagged cumulative Reactions on additional Shares. Additionally, it shows a positive significant effect of Comments as well. In the linear model, both the number of new Comments and total Reactions correlated with higher number of Shares in the subsequent Timestep in both Time Periods, however, later period decreases the additional interactions significantly. In the analysis of the effects of different types of Reactions the results reinforce the effect of Love reactions, as they increase the number of Shares in the subsequent Timestep. However, in that model Comments were also associated with a significant negative effect. When introducing Time Periods to the regression, the linear model shows significant effect in the case of less Reactions than in the negative binomial model. Like and Angry reactions have lost their significant positive in both Time Periods. Only Love reactions show significant effect: in the earlier phase of the post lifespan, their presence correlated with higher number of additional Shares in the subsequent Timestep, but this positive effect turns negative in the second half of a post lifespan.

6.2.2 Results of analyzing influence

Table 20 presents the Pearson's correlation matrix of the variables in the summarized dataset, as shown in Table 2. The correlations indicate the relationships between different Reactions. In this case, it is observed that the number of total Cares on posts tends to move together with the number of total Likes and Loves on the posts, suggesting a positive association between these reactions. This might be the result of the positive valence these emotions share. Similarly, the Angry and Sad reactions that represent negative emotions, show a positive correlation. These correlations support the result of Eberl et al (2020) regarding Reactions representing the emotions. Interestingly, the correlation between Haha and Angry reactions is strong positive, even though Haha is translated to Hungarian as “Funny (Vicces)” on Facebook, which is not necessary a straightforward negative emotion. One possible explanation is based on Zsolt et al (2021), who argues that in Hungary, anti-elitist attitudes are general, and this phenomenon can unfold in a sarcastic sense of using the Haha reactions regarding political topics.

Table 20: Pearson's correlation of reactions

	Number of posts	Followers at Posting	Number of Likes at Posting	Total Likes	Total Comments	Total Shares	Total Love	Total Wow	Total Haha	Total Sad	Total Angry	Total Care
Number of posts	1.0000											
Followers at Posting	0.7691	1.0000										
Number of Likes at Posting	0.7924	0.9974	1.0000									
Total Likes	0.3647	0.6361	0.6119	1.0000								
Total Comments	-0.0111	0.4973	0.4582	0.7079	1.0000							
Total Shares	0.4832	0.7216	0.7402	0.5216	0.4455	1.0000						
Total Love	-0.0896	0.0949	0.0802	0.7162	0.6081	0.2492	1.0000					
Total Wow	0.0634	0.3084	0.3160	0.5474	0.6460	0.6710	0.7610	1.0000				
Total Haha	0.1659	0.5997	0.5956	0.2639	0.6938	0.6713	0.1484	0.6361	1.0000			
Total Sad	0.2120	0.1904	0.2003	-0.0244	0.1355	0.4227	-0.1858	0.2156	0.3562	1.0000		
Total Angry	0.2577	0.5245	0.5361	0.0462	0.4159	0.7091	-0.1285	0.4831	0.8814	0.6846	1.0000	
Total Care	0.0280	0.2135	0.1985	0.8131	0.6035	0.3045	0.9769	0.7204	0.1227	-0.1729	-0.1396	1.0000

To gain more insight into the relationship between various Reactions, a fixed effects model was employed to examine the effects of Reactions on each other. By employing the FE model, it is possible focus specifically on the relationship between different Reactions. Figure 12 shows the effects of Reactions on each other, based on the significant connections and B values in Table 22. Blue arrows represent positive, red arrows represent negative relationships.

12. Figure Effect of lagged New Reactions on New Reactions

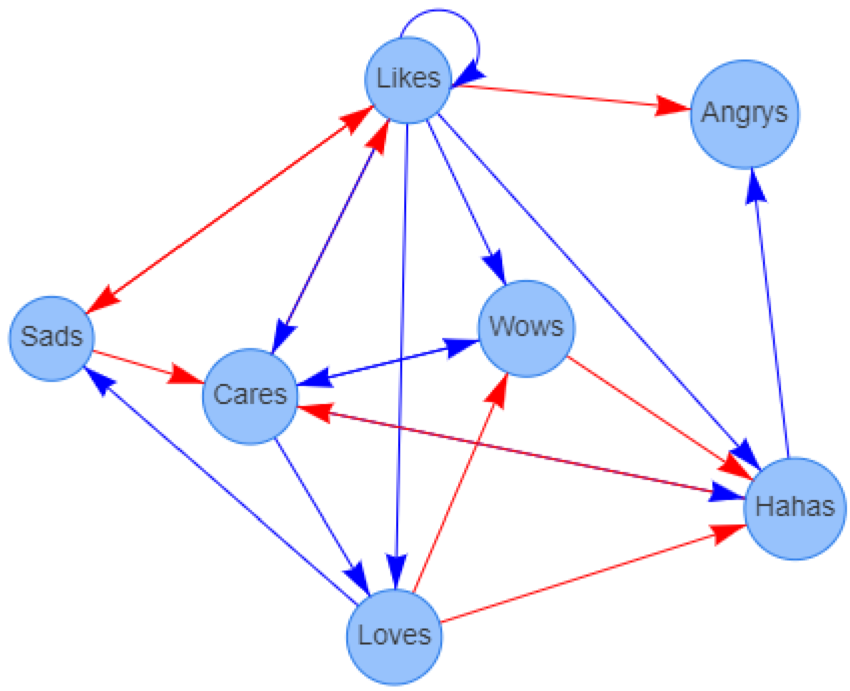


Figure 12 reveals the various relationships between Facebook reactions. Likes tend to positively reinforce more Likes (0.388), while negatively affecting Angrys (-0.06). Likes decreases the number of Sad reactions (-0.003) in the subsequent Timestep, too, and this effect is reciprocal (-0.736). Cares have negative impact on Likes (-2.92); however, Likes increase the number of Cares (0.005). but show a slight positive effect on Loves (0.085) and Wows (0.138). Loves reactions reduce Wows (-0.054). Hahas, when more abundant, tend to increase Angrys (0.134), and decrease Cares (-0.012).

The results of the FE regression models are in Table 21.

Table 21: FE regression results on the influence on Reactions

	New Likes
New Likes$_{t-1}$	0.3880014***
New Loves$_{t-1}$	-0.1990
New Wows$_{t-1}$	0.43521
New Hahas$_{t-1}$	-0.12969
New Sads $_{t-1}$	-0.73614385***
New Angrys$_{t-1}$	-0.0010
New Cares$_{t-1}$	-2.92064926***
Observations	9,513
R2	0.092
Adjusted R2	0.084
F-statistic	106.329 (df = 8; 9430)

	New Loves		New Wows
New Loves$_{t-1}$	-0.03465072	New Wows$_{t-1}$	-0.01925707
New Likes$_{t-1}$	0.00430131***	New Love$_{t-1}$	-0.05389535***
New Wows$_{t-1}$	0.02883	New Likes$_{t-1}$	0.00107228**
New Hahas$_{t-1}$	0.00039	New Hahas$_{t-1}$	0.00225
New Sads $_{t-1}$	-0.0221	New Sads $_{t-1}$	-0.0013
New Angrys$_{t-1}$	-0.0022	New Angrys$_{t-1}$	-0.0014
New Cares$_{t-1}$	0.08518996*	New Cares$_{t-1}$	0.13839746***
Observations	9,513	Observations	9,513
R2	0.007	R2	0.017
Adjusted R2	-0.002	Adjusted R2	0.008
F-statistic	6.93272 (df = 8; 9429)	F-statistic	18.0467 (df = 8; 9429)

	New Hahas		New Sads
New Hahas$_{t-1}$	0.0136203	New Sads$_{t-1}$	-0.0156243
New Love$_{t-1}$	-0.1280331***	New Love$_{t-1}$	0.0629928**
New Wow$_{t-1}$	-0.1538425*	New Wow$_{t-1}$	-0.03168
New Likes$_{t-1}$	0.0073638***	New Haha$_{t-1}$	0.01664
New Sads $_{t-1}$	-0.0115	New Likes $_{t-1}$	-0.0028410*
New Angrys$_{t-1}$	-0.0113	New Angrys$_{t-1}$	0.0141
New Cares$_{t-1}$	0.1901779*	New Cares$_{t-1}$	-0.01
Observations	9,513	Observations	8,985
R2	0.008	R2	0.003
Adjusted R2	0.000	Adjusted R2	-0.005
F-statistic	8.87012 (df = 8; 9430)	F-statistic	3.46947 (df = 8; 9429)

	New Angrys		New Cares
NewAngrys$_{t-1}$	-0.003751	New Cares$_{t-1}$	-0.02445683
New Love$_{t-1}$	0.0748	New Love$_{t-1}$	-0.0150
New Wow$_{t-1}$	-0.11719	New Wow$_{t-1}$	0.08978891***
New Haha$_{t-1}$	0.1340280***	New Haha$_{t-1}$	-0.01183511*
New Sad$_{t-1}$	-0.0240	New Sad$_{t-1}$	-0.01444375*
New Likes$_{t-1}$	-0.0058074*	New Angry$_{t-1}$	-0.0047
New Cares$_{t-1}$	0.02	New Likes$_{t-1}$	0.00500110***
Observations	9,513	Observations	9,513
R2	0.011	R2	0.029
Adjusted R2	0.002	Adjusted R2	0.020
F-statistic	11.1976 (df = 8; 9429)	F-statistic	31.3018 (df = 9; 9429)
*Note: *p<0.1; **p<0.05; ***p<0.01*		*Note: *p<0.1; **p<0.05; ***p<0.01*	

Herfindahl-Hirschmann Index

Analyzing the Herfindahl-Hirschman Index (HHI) in a time-dependent manner can provide information about the structure and dynamics of reactions over time. By analyzing the temporal dynamics of the HHI, patterns in how emotional responses unfold and evolve within the lifespan of a Facebook post can be revealed.

The results of the OLS regression of Timesteps on HHI calculated of the new reactions are in Table 22. The results indicate a statistically significant negative impact of Timesteps on the HHI, suggesting that as time progresses, there is a decrease in the dispersion of reactions, leading to a higher concentration of specific types of reactions, meaning that the reactions become more focused and less diverse over time. This indicates a kind of social consensus formation mechanism about how followers together categorize the original post over time.

Table 22: OLS regression on HHI of new reactions explained by Timesteps

	HHI new
Timestep	0.0004245**
Observations	6,730
Multiple R2	0.001317
Adjusted R2	0.001168
F Statistic	8.872*** (df = 1)
*Note: *p<0.1; **p<0.05; ***p<0.01*	

However, HHI on the total reached Reactions does not have a significant effect on the number of total Shares, as is shown in the next table. This suggests that the concentration or dispersion of Reactions, as measured by HHI, does not significantly impact the overall popularity, or reach of the post in terms of total Shares. Comparing to the results of Table 23, it means that while there is some kind of concentration in the Reactions that increases in later Timesteps, there is no straightforward connection between the congruence of Reactions and overall popularity, measured as number of Shares on a post. This implies that the alignment of Reactions does not increase the overall popularity of a post. Interestingly, this finding contradicts the results obtained by Leong and Ho (2021), who demonstrated that Facebook Reactions can influence how people perceive the dominant opinion climate, and when the opinion climate aligns, it can impact individuals' willingness to express their views.

Table 23: OLS regression on the number of Total Shares of posts explained by HHI

	Shares
HHI	1536
Observations	144
Multiple R2	0.001756
Adjusted R2	-0.005176
F Statistic	0.2533 (df = 1)
*Note: *p<0.1; **p<0.05; ***p<0.01*	

6.3 Effects of network structures

6.3.1 Results of the simulation

Utilizing the insights from the results of the Facebook data analysis the social network simulation aims to test the final reach of information diffusion on different network settings introduced in Chapter 5.3.2. The results of the previous regression analysis indicate that the quantity of New Shares a post receives over time is influenced by Reactions.

Table 24 presents the results of the first version of the ABM. The number of agents who have shared, watched, and reacted to the post in the 100^{th} step of the simulation is presented. Results show that in each network type, a filtering algorithm decreases the number of agents who interact with the post, and decreases its final reach. Additionally, homophily tends to increase interaction with the post if a filtering algorithm is present. Results indicate that the highest average count of individuals who viewed, reacted to, or shared a post occurred within small world networks, particularly those without filtering algorithms and incorporating homophily. On the contrary, the lowest count of nodes engaging in sharing was observed in random and preferential attachment networks, particularly those without homophily and with the presence of a filtering algorithm.

Table 24: Average number of agents at each step who have watched/reacted to/shared the post in the 100th step of 100 iteration Scenario A

Network Type	Homophily	Filtering algorithm	Number of nodes	Average node	Number of followers	Watched	Reacted	Shared
Small world	false	false	400	4	20	203.5	123.5	106.5
Small world	false	true	400	4	20	138.9	65.1	53.9
Small world	true	false	400	4	20	209.3	141.7	119.5
Small world	true	true	400	4	20	179.5	118.0	99.9
Random	false	false	400	4	20	185.9	120.4	90.1
Random	false	true	400	4	20	87.9	31.1	21.0
Random	true	false	400	4	20	177.5	114.2	82.0
Random	true	true	400	4	20	137.9	73.5	49.5
PA	false	false	400	4	20	161.2	82.3	59.8
PA	false	true	400	4	20	81.3	29.2	21.5
PA	true	false	400	4	20	167.8	105.6	77.3
PA	true	true	400	4	20	121.8	70.4	49.6

The results of Scenario B of the simulation have similar results regarding the presence of the filtering algorithm (Table 25).

Table 25: Average number of agents at each step who have watched/reacted to/shared the post in the 100th step of 100 iteration Scenario B

Network Type	Homophily	Filtering algorithm	Number of nodes	Average node	Number of followers	Watched	Reacted	Shared
Small world	false	false	1000	4	50	558.0	295.2	268.5
Small world	false	true	1000	4	50	466.4	216.8	191.7
Small world	true	false	1000	4	50	555.4	407.0	365.5
Small world	true	true	1000	4	50	443.3	308.6	273.8
Random	false	false	1000	4	50	524.0	345.9	282.9
Random	false	true	1000	4	50	331.2	149.5	115.9
Random	true	false	1000	4	50	595.4	441.3	353.6
Random	true	true	1000	4	50	386.4	246.9	192.2
PA	false	false	1000	4	50	537.1	318.7	264.9
PA	false	true	1000	4	50	334.1	150.2	118.8
PA	true	false	1000	4	50	517.1	354.8	289.2
PA	true	true	1000	4	50	321.3	193.2	151.5

The results of Scenario C of the simulation is presented in the table below, in Table 26.

Table 26: Average number of agents at each step who have watched/reacted to/shared the post in the 100th step of 100 iteration Scenario C

Network Type	Homophily	Filtering algorithm	Number of nodes	Average node	Number of followers	Watched	Reacted	Shared
Small world	false	false	1000	10	50	703.8	410.9	364.9
Small world	false	true	1000	10	50	472.6	232.2	200.2
Small world	true	false	1000	10	50	563.5	466.8	416.7
Small world	true	true	1000	10	50	501.7	393.1	344.4
Random	false	false	1000	10	50	612.3	358.3	265.1
Random	false	true	1000	10	50	470.6	199.3	134.7
Random	true	false	1000	10	50	478.8	331.9	232.5
Random	true	true	1000	10	50	392.6	285.0	199.6
PA	false	false	1000	10	50	549.3	299.7	224.4
PA	false	true	1000	10	50	415.0	180.8	126.6
PA	true	false	1000	10	50	562.0	386.1	286.2
PA	true	true	1000	10	50	362.5	237.0	164.8

In each setting, the lowest number of interactions was observed in cases of preferential attachment without homophily but with filtering algorithms. On the other hand, the highest number of shares in each setting was achieved in small world networks, especially with homophily and without filtering algorithms. The impact of increased average degree is positive overall but differs through different conditions.

Regarding the small world network, the modified rewiring probability is presented in Table 27 below. The original and the rewired small world network scenarios are similar, as in both cases, the filtering algorithm caused the less interactions, and the homophily the most. However, the differences are smaller in the rewired network. Compared to Scenario A, where small world networks performed the most interactions in the presence of homophily, without filtering algorithm, in Scenario D, after modifying the rewiring probability, the most watches happened without homophily. In the case of reactions and shares the results were similar to the original network.

Table 27: Average number of agents at each step who have watched/reacted to/shared the post in the 100th step of 100 iteration Scenario D

Network Type	Homophily	Filtering algorithm	Number of nodes	Average node	Number of followers	Watched	Reacted	Shared
Small world	false	false	400	4	20	242.1	148.7	129.3
Small world	false	true	400	4	20	139.5	62.6	52.8
Small world	true	false	400	4	20	197.6	150.7	130.1
Small world	true	true	400	4	20	183.0	115.9	96.0

To sort out the above differences, and get a clearer overview, linear regression models were run.

Regarding network type, the coefficients of small world and preferential attachment (PA) networks were measured, and random networks served as a reference category, as the linear regression contained the network types as dummy independent variables.

Table 28: Linear regression on the total number of agents who shared the post in the simulation for Scenario A

	B
Intercept	181.82***
Small World	-16.81
Preferential Attachment	-54.21*
Homophily	-29.99
Echo chamber	-90.93***
Homophily and Echo chamber	26.77*
Homophily in Preferential Attachment	12.61
Homophily in Small World	19.38
Echo Chamber in Preferential Attachment	17.8
Echo Chamber in Small World	14.69
Observations	1200
Multiple R2	0.08634
Adjusted R2	0.07943
*Note: *p<0.05; **p<0.01; ***p<0.001*	

Results in Table 28 show that after one hundred timesteps, in preferential attachment networks there are significantly less agents who shared the information than in random or small world networks. Between random and small world networks, no statistically significant difference was detected. Although both homophily and filtering algorithms may be viewed as mechanisms that restrict diffusion, homophily did not cause statistically significant decrease in shares on its own. Filtering algorithm was shown to have such a negative impact. Further, the presence of homophily was shown to counteract the negative effect of filtering algorithms; if both were introduced in the networks, it resulted in more total shares.

Linear regression about the second version is presented in Table 29. The simulation involved an increase in both the number of nodes and followers, and the outcomes supported the constraining impact of the filtering algorithm.

Table 29: Linear regression on the total number of agents who shared the post in the simulation for Scenario B

	B
Intercept	371.5***
Small World	-105.2075
Preferential Attachment	4.07
Homophily	73.995
Echo chamber	-163.725**
Homophily and Echo chamber	-0.3233
Homophily in Preferential Attachment	-45.06
Homophily in Small World	16.035
Echo Chamber in Preferential Attachment	22.31
Echo Chamber in Small World	79.925*
Observations	1200
Multiple R2	0.06588
Adjusted R2	0.05882
*Note: *p<0.05; **p<0.01; ***p<0.001*	

The outcomes of the linear regression applied to Scenario C of the ABM simulation further supported the constraining impact of the filtering algorithm (Table 30). Unlike the previous version, modifications were made to the node degree in this case. Interestingly, within the context of small world networks, homophily exhibited a contradictory effect: it led to more shares overall. The baseline impact of homophily is nonsignificant and negative, but with a magnitude nearly identical to the significant effect of homophily in small world networks. Furthermore, the positive interaction effect of homophily in small world network was present in previous models as well, although it was not statistically significant in those cases.

This is not a straightforward effect since homophily, much like the filtering algorithm, is typically considered a restrictive mechanism.

Table 30: Linear regression on the total number of agents who shared the post in the simulation for Scenario C

	B
Intercept	430.85***
Small World	56.28
Preferential Attachment	-16.14
Homophily	-66.94
Echo chamber	-164.81**
Homophily and Echo chamber	55.44
Homophily in Preferential Attachment	33.76
Homophily in Small World	81.75*
Echo Chamber in Preferential Attachment	-27.98
Echo Chamber in Small World	-36.89
Observations	1200
Multiple R2	0.07807
Adjusted R2	0.0711
*Note: *p<0.05; **p<0.01; ***p<0.001*	

Small world networks with echo chamber and homophily showed different significant effects in the analyses. When modifying the rewiring probability of the small world networks from 0.1 to 0.05, the results supported the effects from the first and second version of the simulations. Table 31 presents the results which shows that filtering algorithm continued to demonstrate a decreasing impact on the total shares, while homophily exhibited no significant effect. However, similar to the initial version of the simulation, the introduction of homophily to the network altered the direction of the filtering mechanism's effect in Scenario D, ultimately leading to an increase in total shares.

Table 31: Linear regression on the total number of agents who shared the post in the simulation for Scenario D

	B
Intercept	247.75***
Echo chamber	-119.14**
Homophily	-42.82
Homophily and Echo chamber	42.55*
Observations	1200
Multiple R2	0.06281
Adjusted R2	0.05571
*Note: *p<0.05; **p<0.01; ***p<0.001*	

The simulation results provide insights into the influence of different network structures, filtering algorithms, and homophily on the total shares of posts and highlight the interplay between network characteristics and filtering mechanisms, suggesting that these factors collectively shape the extent of information dissemination on social media platforms. The findings indicate that small world networks with homophily and without filtering algorithms consistently lead to the highest number of shares across various scenarios The presence of the filtering algorithm tends to restrict the total shares, although in presence of homophily, its negative effect is decreased. Homophily's impact varies depending on the network structure; in some cases, it contributes to more shares, while in others, its effect is less pronounced. It exhibits a negative trend, particularly in denser networks (Scenarios A & C), although this isn't the case in larger networks with lower density (Scenario B) and larger small-world networks (Scenario C). On the other hand, filtering mechanisms inherently have a negative impact, but homophily tends to alleviate this effect under certain network conditions (Scenarios A & D). However, it's worth noting that these two factors never accentuate each other's effects.

7 Conclusions

The research in this thesis investigated online political engagement, focusing on the role of social media, particularly Facebook, in shaping political interactions and information dissemination. The primary objective was to explore the network structures and emotions that influence sharing behavior of political content on social media, examining its impact on the connection between online political participation and real-world outcomes. The investigation acknowledges the general significance of social media in political activities, while recognizing the potential cultural and platform-specific variations that can affect the validity of data analyses. Thus, this research concentrated specifically on the Hungarian context.

The results of this thesis support the presence of connection between online and offline political activities, based on literature comparison, and also on Hungarian national survey. This underscores the importance of analyzing online activities is not only theoretical, but is also grounded in the Hungarian context. In Hungary, the correlation between the number of shares on political posts and the offline popularity of political figures has been proved (Bene, 2019), so regarding social media activities, sharing was in the focus of the study. Sharing is also a technique political actors use in campaign to mobilize voters, thereby the importance of analyzing sharing behavior is important from both standpoints. Thus, the analysis focused on the factors of emotions and network structure that can affect the shares on a Facebook post.

About the emotions, valence and diversity was analyzed in the thesis. Prior research found significant connections between emotional valence and shares of a post (Hansen et al., 2011). Positive (Berger et al., 2010; Stieglitz & Dang-Xuan, 2013), negative (Heimbach & Hinz, 2016; Stieglitz & Dang-Xuan, 2013) and neutral (Hoang et al., 2013) emotions were linked in the literature to message spread on social media, showing that there is no consensus about the effect of emotional valence in the scientific literature yet. Diversity, as introduced in Freeman (2020), in the context of emotions refers to post evokes a diverse range of emotions, that might elicit interest from wider audience or decrease it by fragmenting user activity.

Regarding valence, this thesis distinguished between post-specific and general factors that can affect the shares on social media. Post-specific factor refers to the sentiment, the emotional content of a post. Building on the research by Muraoka et al. (2021), the research used Facebook Reactions as indicators of a post's emotional content, and found that negative emotions did increase the number of shares on a post. Specifically, in the regression analysis, besides the generally used Likes, the more Haha, Sad, and Angry reactions were associated with higher number of Shares. The effect of Haha reactions appears to be outlier, yet overall they exhibit a positive correlation with Angry reactions, implying that they might be used ironically. These results support the theory that regarding the valence of emotions, posts evoking negative emotions tend to get shared more on social media platforms.

However, on social media there are other factors that might affect the number of Shares on a post besides the sentiment. This analysis used fixed effect regression to control for the post-specific characteristics, to analyze the general effect of Reactions on the number of Shares. General effects refer to the social influence of the presence of Reactions that can serve as cues for other users, and the unknown mechanism of the algorithm behind Facebook, which also influences user behavior and interaction. These factors may vary over time, so the analysis applied a regression on the number of additional Shares explained by the Reactions from the previous Timestep. When the post's sentiment is omitted from the analysis and a fixed-effect regression is employed, the influence of other reactions on future shares, than in the analysis of the post-specific effects, becomes significant. Both Like and Angry reactions continue to increase Shares in the subsequent Timestep, while Love and Haha reactions exhibit a decrease. This observation might support the idea that – beyond the general Like reaction – posts reaching more of the Angry reactions tend to reach a larger audience, potentially influenced by algorithmic mechanisms or peer engagement, while the presence of Love reactions causes lower reach.

The time is also an important factor in sharing behavior, as the analysis proved that after a post reached half its total shares, the additional number of new shares overall decrease, but the effect of negative emotions is still present: the presence of Angry reactions increased the additional number of shares in the following timesteps even in the second half of a post’s lifespan. This highlights the already proved importance of negative emotions: even in the case of the natural/general lower user engagement later in time, negative emotions still can generate activity. It indicates that the impact of negative emotions on the number of shares becomes more significant in the later stages of a post's lifespan. This suggests that over time, the influence of negative emotions in encouraging sharing behavior becomes more pronounced.

Like reaction is the only reaction that has a significant effect in both Time Period: at first, they have a negative effect, which turns around for the second half of a post’s lifespan. It suggests that first, reacting to a post might replace other activity, but those who later react to a post might be more engaged and thus more likely to perform activities with higher effort. The regression analysis with the division into Time Periods provided additional insights into the temporal aspect of this effect.

For further understanding of the Reactions’, the diversity of Reactions was examined. Drawing from the affective affordance theory, which suggests that Reactions on Facebook have the potential to trigger a cascade-like effect by influencing one another, the analysis aimed to explore the interplay and mutual influence of different Reactions. the analysis reveals an interesting pattern regarding the impact of Likes on subsequent Reactions. In general, the presence of more Likes tends to have a positive effect on the number of following Reactions, indicating that Likes can serve as a form of positive social influence, encouraging other users to engage with a post emotionally. However, in the case of Sad and Angry reactions, the presence of more Likes is associated with a decrease in the number of subsequent Angry or Sad reactions. This suggests that Likes might express a positive emotion, and at the same time it may act as a form of social reinforcement, potentially mitigating the expression of negative emotions, particularly Sad and Angry reactions.

To analyze emotional diversity in depth, a Herfindal-Hirschmann Index was introduced on the different Reactions. The measurement borrowed from economics makes it possible to measure whether the more equivocal posts or the vaguer posts get more Shares. Interestingly, the analysis reveals that the overall HHI does not have a significant effect on the total number of Shares. These results contradict with the conclusion of Leong and Ho (2021), who has shown that congruence with the opinion climate, as reflected by Facebook Reactions, might encourage people to express their views, which could potentially have an impact on a post's popularity as well. However, when analyzing HHI over time, results show that as time progresses, there is a decrease in the dispersion of additional reactions, which might indicate a kind of social consensus formation mechanism about how followers together categorize the original post over time.

Lastly, the aim was to examine the impact of network factors that previous research has shown to influence sharing: network structure, homophily and echo chambers as filtering algorithms. Since the network structure of Facebook is restricted from researchers, and the algorithm that displays different content to members is also undisclosed, we have limited knowledge about the factors behind actual news diffusion. Therefore, the thesis presented an agent-based model that used the insights gained from the empirical analysis.

In social media environment, the information diffusion is influenced by the algorithm that is linked to the friends' interactions to the information (Bucher, 2012). As it was analyzed in the previous subchapter, interactions regarding a post on Facebook can mean expressing emotions via reaction buttons, commenting and sharing. In the focus of the analysis is sharing, it was explained by other reactions in the regression model in the subchapter 6.2.1 and it showed a significant effect on the number of shares, thus it was implanted into the ABM.

About network structure, three network types; small world, preferential attachment, and random networks, that are widely used to model complex social networks, were compared. The simulation confirmed the importance of weak ties in social networks; the most people were reached by the shared news in small world network scenarios, corresponding to prior research (Centola, 2010; Pegoretti et al., 2012). A novel element in the analysis is, however, that small-world networks overperformed the preferential attachment (Albert & Barabási, 2002) networks too in term of the final reach of information. When comparing the different network scenarios, it was observed when network density was relatively low. This result may come from the specificity of the model that sharing is not automatic, but depends on the political alignment of the user. Therefore, if a central person is very negative towards a politician, it will not share the information, despite many of their friends did. Thus, high centralization in our model may stop the diffusion process, if the central person happens to be skeptical, while in less centralized or more dense networks the information easier bypasses easier.

Note that the underlying mechanism of interactions in the simulation is somewhat different to the most widely used models. In contrast to standard diffusion models, such as SIR or SIS, the propensity of people to get the "infection" is heterogeneous; some people have more affinity towards the news and others less – depending on their political attitudes. In comparison to the network externality model (e.g., Pegoretti et al., 2012) in this case of news sharing, preferences of the actors do not depend on the behavior of their peers, which is a different situation from other political actions, such as the success of a protest activity, where there such an interdependence is present. These specificities may explain the different results compared to previous studies.

Emergence of echo chambers became to the forefront of social media research recently (Del Vicario et al., 2016; Quattrociocchi et al., 2021), which this thesis approaches by introducing homophily to the networks together with a bias in the social media algorithm that filters content according to its fit to the attitudes of the agents. An interesting result of the simulation is that in case when the diffusion of news is limited by a content filtering algorithm, homophily enhanced diffusion of the news, especially in small world networks, instead of limiting that. This result is in contrast with what was expected based on earlier studies arguing that homophily and computer algorithms amplify each other in creating echo chambers (B. Jiang et al., 2021) and showing that diverse connections boost diffusion (Cota et al., 2019). About this result it can be argued that in case of bounded diffusion opportunities, when the news itself is not very attractive, and the filtering algorithm does not allow it to be seen to politically distant agents, homophily does not act as a limiting factor, but as an enhancing factor of diffusion. This happens because the connections between similar people create a path, on which the politically interested agents can be reached by the news. In this setting, without homophily, the spread of the news stops early, and agents, who are politically interested, but distant in the network from the source are not reached. Results show that homophily has a positive effect in case echo chambers is present, especially in network types where diffusion is low in average support this interpretation.

These findings offer novel contributions to the scientific research in this topic, as they confirm the connection between online and offline political engagement, especially in the context of Hungary. Moreover, the study provides real-world evidence supporting the idea that negative emotions play a role in how information spreads on social media on Hungarian Facebook. Additionally, the research highlights how homophily cause different effects in different types of social networks, while supporting the importance of small world networks in information spreading.

The analysis also applies diverse and less common methodologies in the field of sociological research about online political engagement, thus it provides new statistical evidence of the analysis of the research questions. Bayesian Update is introduced to analyze the studies about the connection of online and offline political participation, to compare the results of research with different designs of the field. The regression analyses of the Facebook data introduce a temporal dimension to the examination of Reactions' influence on post sharing. This allows for a more comprehensive understanding of how reactions evolve and interact over time, providing insights into the temporal aspects of user engagement with political posts on Facebook. This is a significant difference from other studies about Facebook Reactions' effect on Shares, as they mainly utilize cross sectional data. However, the time-dependency of the effect of Reactions on Shares may be presumable, as the Crowdtangle Data Codebook states that posts on many social media platforms tend to display more variability early in their lives than later. Unlike cross-sectional analyses, which examine reactions at a single point in time, this study considers the temporal dimension of posts too, and thus able to confirm the varying effect of Reactions over time. This temporal approach sets this study apart from many other investigations focused on cross-sectional data, which overlook the dynamic nature of Reactions' effects over time. The method of ABM to investigate virality on social media is widely used, but the simulation used in this analysis utilized the results of the regression analysis of Facebook data, thus aims to model social media more precisely.

Secondly, the research utilized dataset containing posts from Hungarian political figures on Facebook. While obtaining political data from Facebook is often challenging, particularly due to platform restrictions, Facebook holds substantial significance within the Hungarian context. Analyzing this dataset allows for the exploration of the hypothesis that negative emotions encourage more sharing, while also mitigating potential confounding factors stemming from divergent user behaviors across different platforms and cultural settings. This context-specific analysis provides a targeted examination of how reactions impact political posts within the Hungarian political landscape. Furthermore, the study reinforces the theoretically grounded proposition of negative emotions' role in information propagation on social media within this culturally and geographically specific context.

The empirical research highlighted in this thesis underscores the critical role of sharing information on social media in political information dissemination. However, there are some limitations of this research that are introduced in the following.

The introduction of Bayesian Updating to analyze online and offline political activity, while is an appropriate method to compare research with different designs, faces challenges in collecting studies due to variations in data sources, and published results. Additionally, like other meta-analytical approaches, Bayesian updates inherit the methodological limitations of the source studies, such as the influence of unobserved variables. Also, the focus on studies with published regression parameters excludes potentially important studies. Further research could offer a more comprehensive analysis by including a broader range of studies from diverse cultural and time horizons.

The Facebook analysis of this thesis used the Facebook Reactions given to a post to define a post's emotional content. Previous research, such as Muraoka et al (2021) and Freeman et al (2020) used this method, however, only in the case of straightforward emotions (such as Angry and Love). Utilizing Facebook Reactions as indicators of portrayed emotions requires further research to establish a strong correlation between the sentiment of posts and the emotions elicited from users, especially regarding the generalizability for different cultural settings.

The analyses of Facebook Reactions captured the differences between content-related and other effects of Reactions on the number of Shares a post, by using a fixed effect in the regression models. However, the difference between the non-content-related effects, such as social influence and the impact of the algorithm cannot be revealed with this method. Additionally, the mechanism of the algorithm behind the Facebook is unknown, which makes determining these effects difficult.

Other limitations of this analysis lie in the scope of the data and the analysis timeframe. The dataset used in this study was limited to a specific time period, which may not fully capture the long-term effects and dynamics of emotions and network structures on information sharing.

Moreover, while the agent-based model utilizes results from the Facebook data analysis, it simplifies complex social interactions and existing social network structures. Furthermore, certain outcomes were dependent on the specific simulated network settings, highlighting the potential need to broaden these scenarios to achieve a more comprehensive mapping of these factors.

8 Appendix

Appendix 1. Fixed effect panel regression on different lagged Reactions on New Shares

	New Shares
New $Likes_{t-1}$	0.01
New $Comments_{t-1}$	-0.0518493*
New $Love_{t-1}$	0.1886358*
New Wow_{t-1}	0.05
New $Haha_{t-1}$	0.04
New Sad_{t-1}	-0.08
New $Angry_{t-1}$	0.01
New $Cares_{t-1}$	-0.08
Observations	8,985
R2	0.0027159
Adjusted R2	-0.0059561
F Statistic	3.2101 (df = 8; 9430)
*Note: *p<0.1; **p<0.05; ***p<0.01*	

Appendix 2. FE panelregression on the number of New Shares with Time Periods

	New Shares
New $Likes_{t-1}$	-0.02
New $Comments_{t-1}$	0.06
New $Love_{t-1}$	0.8585711**
New Wow_{t-1}	-0.13
New.$Haha_{t-1}$	0.02
New.Sad_{t-1}	-0.01
New.$Angry_{t-1}$	0.07
New.$Cares_{t-1}$	-0.03
Time Period	-0.57
New $Likes_{t-1}$*Time Period	0.02
New $Comments_{t-1}$*Time Period	-0.06
New $Love_{t-1}$*Time Period	-0.532088**
New Wow_{t-1} * Time Period	0.12
New $Haha_{t-1}$*Time Period	0.00
New Sad_{t-1}*Time Period	-0.04
New $Angry_{t-1}$*Time Period	-0.04
New $Cares_{t-1}$*Time Period	0.02
Observations	9,422
R2	0.0049183
Adjusted R2	-0.0046934
F Statistic	2.7391 (df = 17)
*Note: *p<0.1; **p<0.05; ***p<0.01*	

Appendix 3. FE regression on New Shares by lagged Reaction and Comments with Time Period

	New Shares
New $Reactions_{t-1}$	0.049004***
New $Comments_{t-1}$	0.0737804***
Time Period	-2.4720435***
Observations	9,513
R2	0.090242
Adjusted R2	0.075863
F Statistic	309.615
*Note: *p<0.1; **p<0.05; ***p<0.01*	

Appendix 4.FE regression on New Shares by lagged Reaction and Comments

	New Shares
New Reactions$_{t-1}$	0.012***
New Comments $_{t-1}$	-0.05*
Observations	9,436
R2	0.002
Adjusted R2	-0.006
F Statistic	7.777*** (df = 2; 9,436)
*Note: *p<0.1; **p<0.05; ***p<0.01*	

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