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MORE THAN LIKES: HOW NEWS CONTENT INFLUENCES AUDIENCE ENGAGEMENT ON SOCIAL MEDIA

A Master Thesis by

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An image generated by Midjourney's image generation model using the prompt:
"A renaissance painting of people arguing over the content of a tabloid newspaper".

Abstract

This study investigates how the content of news articles influences audience engagement on social media. Addressing research gaps in previous studies, which often rely on limited or biased samples and narrow definitions of audience engagement, this study utilizes machine learning and natural language processing techniques to analyze a comprehensive dataset of news content shared on Facebook over a span of nearly two years. By collaborating with Ekstra Bladet, the largest Danish tabloid media, we are able to examine multiple different dimensions of audience engagement encompassing information selection, emotional responses, sharing, and conversations. Through an empirical analysis of the influence of 11 news content characteristics on eight audience engagement outcomes, the analysis can be summarized in three main findings. First of all, news content characterized by unexpectedness and soft news increases individualistic behaviors, such as clicking on articles, while impact and hard news increase social behaviors, such as sharing and having conversations. Secondly, the emotional framing of news content elicits similar emotional responses among the audience, with positivity and negativity prompting more recognizing and offensive language, respectively, in the comment section. Thirdly, news content related to timeliness and proximity shows limited effects on audience engagement. These findings highlight the multidimensional nature of audience engagement, underscoring that there is no universal influence of news content on audience engagement on social media.

Declaration of Responsibilities

Tobias Priesholm Gårdhus: 1, 2.1, 2.3, 2.5, 2.6, 3.2, 3.4, 3.6, 4.1, 4.3, 4.5, 5.1, 5.3, 6
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Declaration of Third-party Collaboration

As part of the study, the authors collaborated with a third-party, Ekstra Bladet, for data availability. However, no conflict of interest has arisen throughout the process.

Contents

1 Introduction

1.1 Background

News media have always played a central role in a well-functioning democracy. The democratic role of media is to serve as an independent and objective reporter of the truth (Herman & Chomsky 1988:55). A common metaphor is that the media represents the watchdog of democracy by exposing the elite and those in power (Kovach & Rosenstiel 2014:160ff). Furthermore, news media has an important obligation to inform and facilitate public discussion about important societal topics (Aalberg & Curran 2012:3; Habermas 1999). However, in recent years, the role of the media has been questioned due to new digital technologies and possibilities. Perhaps the most significant consequence is the changing relationship between media and their audiences (Richardson & Stanyer 2011; Livingstone 2016:2).

Increasingly, many people turn to social media as their preferred platform for reading and engaging with news content. For the first time in 2022, Danish audiences spent more time on social media than on traditional print, radio, and broadcast media (DR Medieforskning 2022:14). Social media allow users to engage with news content in far more ways than when it was distributed through newspapers, radio, or TV (Jenkins et al. 2013:6ff). Furthermore, media organizations, editors, and journalists no longer hold the monopoly of media production and dissemination; anyone can participate in debates and act as a reporter or commentator (Deuze 2005:451). In many ways, the audiences play a more active role in the relationship with the media. Unlike the days of opinion letters and face-to-face conversations, social media and website analytics allow audience feedback to be tracked and analyzed directly within the newsroom (Richardson & Stanyer 2011; Christin 2018; Ferrer-Conill & Tandoc 2018:436).

The audience engagement can also be seen as a part of a digital public sphere, where individuals discuss news content and exchange arguments. However, this deliberative potential may not always be realized, and some argue that the audience engagement pollutes the public debate more than they benefit it (Papacharissi 2002). As a consequence, media organizations have been shutting down the comment sections on their own websites, and instead used social media platforms such as Twitter and Facebook for social interactions (Reimer et al. 2021:4). Recently, multiple Danish media have taken a step further and decided to remove the possibility to comment on shared articles on their Facebook pages, due to the number of uncivil comments. However, this decision is not without consequences. In addition to hindering the possibility of deliberation, these media sites' posts also reach a smaller audience – reducing the impact of the news content (Albrecht 2022). Rather than completely shutting down conversations around news content, it might be more sustainable to examine what drives different kinds of audience engagement. Following these considerations, there are democratic, societal, and academic reasons to better understand audience engagement with news content on social media.

1.2 News Content and Audience Engagement

It is far from all kinds of news content that audiences engage with on social media. While a minority of posts receive thousands or even millions of clicks, likes, shares, comments, or other types of engagements, most posts only receive a few interactions. Understanding what drives audiences to engage or abstain from engaging with news content on social media is important. On the one hand, audience engagement is an important part of opinion-making, which is a central part of a democratic society (Steensen, Ferrer-Conill & Peters 2020:1665). On the other hand, audience engagement may also affect the production of media content by determining what content is popular and thus also what content is most profitable for the media (Martin 2019). The concept of audience engagement has been defined in many different ways, but generally it refers to an active or intentional orientation towards the news content (Broersma 2019:1). In this study, we argue that audience engagement should be understood as a multifaceted phenomenon encompassing different dimensions related to information selection, emotional reactions, sharing of content, and not least having conversations about content.

Research has identified several factors that influence audience engagement on social media. In a review by Kümpel et al. (2015) three types of factors are identified: users, content, and social networks. This distinction is reminiscent of the classical work on media and audiences by Katz & Lazarsfeld (1955), where they identify five intervening variables between media and audiences: exposure, medium, content, predispositions, and interpersonal relations. In this study, we will focus only on how one of these variables influence audience engagement: the news content itself.

To determine the characteristics of news content that might influence audience engagement, many studies have used the idea of news values. Taxonomies of different news values have traditionally been used as a journalistic guideline of a story's newsworthiness, but it has also been adapted to explain how audiences evaluate the relevance of content (Harcup & O'Neill 2001:7; Eilders 2006). From the original formulation by Galtung & Ruge (1965) to contemporary reformulations of news value theory, the categories of news values have varied greatly, but they often include news content characteristics such as timeliness, unexpectedness, proximity, negativity, and positivity.

1.3 Empirical Gap

The question of how news content influences audience engagement on social media has been approached in various fields within both social sciences, humanities, and natural sciences (Kümpel et al. 2015:8). Although a lot of research has been conducted within this field, we argue that specifically two empirical gaps remain.

First and foremost, most studies have relied on smaller samples of the shared news content. Articles, posts, and comments have mainly been sampled based on different analytical heuristics (e.g., selection for qualitative analysis) or technical limitations (e.g., the restrictiveness of social media platform's data access), while few studies have computationally analyzed a full population of posts and comments over an extended period. Furthermore, some studies have only studied the news content that is most engaged with, but not what is less engaged with (Kümpel et al. 2015:8-9). This limitation often stems from data constraints, where empirical analyses are restricted to the top news articles and their engagement. This approach is particularly problematic, since it only examines what is successful and not what is not successful. To better determine the factors driving audience engagement, the complete population of news articles should be included in the analysis.

A second limitation of previous research is the predominantly simple and narrow conceptualization and measurement of audience engagement. Often, audience engagement is aggregated into basic popularity cues, such as the number of likes or shares (Steensen et al. 2020:1663). However, audience engagement is a multifaceted phenomenon that can be both behavioral and felt (Steensen et al. 2020:1665). While the felt engagement is difficult to capture with quantitative metrics, digital traces enable us to construct different measurements for behavior. Even if we only consider behavioral engagement, there might be a significant difference between a user simply clicking the link, liking a post, sharing it to their own feed or even discussing the content in a comment thread. While quantitative popularity cues are often the focus for media organizations due to their connection to ad revenue, audience engagement may also contain undesired behaviors such as incivilities in the comment sections (Martin 2019:21; Su et al. 2018; Chen et al. 2020). To our knowledge, no previous empirical studies have examined how different news content might drive different dimensions of audience engagement.

1.4 Research Question

This study seeks to close the empirical gaps described in the previous section. Overall, we seek to answer the following research question:

> *How does the content of news articles influence audience engagement on social media?*

1.5 Analytical Contribution

This study aims to bridge the empirical gaps in previous research on the relation between audience engagement and news content by constructing a unique and comprehensive dataset. The creation of our dataset and analysis is made possible by collaborating with Ekstra Bladet - the largest tabloid media in Denmark. Approximately one million people visit their website every day. Ekstra Bladet also publish a printed newspaper and share their articles on various social media such as their Facebook page with over 400,000 followers. While tabloid in style, they cover all areas of society and journalistic practice, ranging from celebrity gossip to award-winning investigative journalism (Journalistforbundet 2023).

By collaborating with Ekstra Bladet, we can construct a more complete dataset that overcomes the empirical limitations of previous research. First of all, we are able to include all articles shared on Ekstra Bladet's Facebook page for almost two years in our analysis. This allows us to analyze a complete population of articles for a longer period – rather than relying on a smaller sample that could contain biases or lack representativeness. To be able to construct measures of audience engagement and news content characteristics for this extensive dataset, we apply computational methods, including machine learning and natural language processing techniques, rather than the manual hand-labelling that most previous studied have relied upon. Secondly, we examine social media engagement by a multitude of different manifestations instead of only relying on a simple and narrow measurement. Our access to Ekstra Bladet's Facebook page allows us to retrieve detailed post and comment data from Facebook, and therefore collect a multitude of features not otherwise available. Instead of only retrieving common popularity cues such as the number of likes, we are also able to collect text content and structure of the comment section, and metrics that are only visible to the Facebook page-owner i.e., number of clicks on the shared link. In this way, our study extends and improves the previous empirical foundation by both including a more complete population of news content and a more comprehensive understanding of audience engagement on social media.

1.6 Data and Methods

Our dataset is constructed by combining two different data sources. The first dataset comes from Ekstra Bladet's database and consists of article content and aggregated user behavior on their website. The second dataset is collected from Facebook and consists of all posts made by Ekstra Bladet's Facebook page, along with information about the engagement for the posts and their comment sections. Our unit of observation is therefore the shared posts for which we construct the features of news content characteristics and audience engagement on Facebook.

The dataset spans over almost two years from the 28th of February 2021 to the 1st of January 2023 and contains 18,350 Facebook posts. In aggregate metrics, our measures of audience engagement encompass approximately 5.5 million comments, 7 million likes, and 230 million clicks on links to the shared articles. As audience engagement is defined as a multifaceted phenomenon, we operationalize its various dimensions on social media into eight different outcomes related to information selection, emotional responses, sharing, and conversations about news content. Similarly, we define 11 news content characteristics mainly derived from news value theory. Utilizing multiple linear regression, we analyze the influence of these 11 news content characteristics on each of the eight measurements of audience engagement on social media.

1.7 Reading Guide

The thesis is structured as follows. Section 2 (Theoretical Background) delves into the existing body of knowledge surrounding audience engagement and news content. We review relevant previous studies, theories, and frameworks that inform our research, and highlight the two research gaps that our study aims to address. Section 3 (Data and Methods) describes the research design, data collection, operationalization of audience engagement and news content, and the analytical methods employed. The last part of Section 3 also outlines important background information about our case of study, Ekstra Bladet. Section 4 (Analysis) presents the results of our empirical analysis structured in four dimensions of audience engagement on social media: information selection, emotional responses, sharing, and conversations. Concluding on Section 4, we present three main findings across the outcomes of audience engagement on social media. In Section 5 (Discussion), we discuss our empirical research in the light of the societal and theoretical implications, the reliability and validity, as well as the generalization of our findings to other cases. Section 6 (Conclusion) summarizes the key findings of the study and highlights limitations of the study along with suggestions for further research in the field.

2 Theoretical Background

In this section, we review and discuss the theoretical background and previous literature related to our study. The research subject of our study has been approached from multiple different disciplines within both the humanities, natural sciences, and social sciences. In the following theoretical and empirical review, we include related research across different scientific approaches, while our own approach is mainly sociological.

The first part (2.1) describes how theories of the relationship between media and audiences have developed until today, and how they are relevant to our study. The second part (2.2) focuses on the consequences of social media and digital technologies and relates this digital evolution to the relationship between media and audiences. These two first parts serve as background information that places our study in a broader theoretical context. Subsequently, the third part (2.3) elaborates on the concept of audience engagement on social media and presents findings from previous studies. In the fourth part (2.4), we consider news content might be understood, and what characteristics of news content might influence audience engagement. In the final part (2.5), we discuss two empirical limitations within previous research, which shows the relevance of our current study.

2.1 Media and Audiences

The relationship between media and audiences is an essential topic within media and communications research (Livingstone 2016:1). The concept of an audience has been central since the first formulations of media theories, and in the current digital age, the concept of audiences is more prevalent than ever (Livingstone 2016:1-2). In this section, we will describe the theoretical developments of the theories about media and audiences, and finally discuss how the idea of audiences has become central to contemporary debates in media studies.

2.1.1 Mass Media and Passive Audiences

The early formulations of theories about media are closely related to the emergence of mass media (Merrin 2014:95). The popularization of broadcasting through radio and television gave rise to the concept of a mass being stimulated with content by a single media producer (Merrin 2014:94). Lippmann (1922) was one of the first to describe the idea of a transmission model where media is sent from the producer to the audience. He emphasized how mass media was shaping public opinion by transmitting cognitive stereotypes to a mass of people (Lippmann 1922). Consequently, he was quite critical of mass media, as it carries the potential to manipulate rather than inform the public. This critical perspective has been continued even more famously in the works of Herman and Chomsky and their idea of manufacturing consent (Herman & Chomsky 1988), as well as in the works of Adorno and Horkheimer on enlightenment as mass deception (Adorno & Horkheimer 2002; Adorno 1991). In both of these approaches, the mass audience is deceived, as the media present them with simplified or biased portrayals of the world, promoting conformity rather than an informed and critical consciousness (Adorno 1991:104).

The concept of a transmission model of media has also been developed within a tradition that is less normative, adopting a more positivistic approach. Prominently, the two mathematicians Shannon and Weaver (1949) summarized the relationship between media and audiences in their sender-message-receiver model. This theoretical model has a clear causal relationship: a sender (e.g., the news media) transmits a message, which is received by the audience and produces a specific effect. Similar to Shannon and Weaver's model, Lasswell (2007) also described a transmission model formulated as a chain of questions: who says what in which channel to whom with what effect (Wanta & Myslik 2019:59-60)? These theoretical models have had a large impact on media studies, and many studies have examined media effects of different kinds of content and audiences, but always with an emphasis on a one-way, causal direction from media producers to media consumers (Wanta & Myslik 2019:59-60).

2.1.2 The Idea of Active Audiences

Most contemporary research within media studies has moved away from the notion of audiences as passive masses without any agency. In the latter half of the 20th century, several different approaches contested the previous understanding of audiences. Different theoretical approaches have argued that audiences should be seen as being more diverse and having more agency. Three of the most important approaches that we will mention here are: 1) interpersonal relations by Katz & Lazarsfeld (1955), 2) the encoding-decoding model by Hall (1973), and 3) Livingstone's (2005) concept of active audiences.

Katz and Lazarsfeld (1955) were among the first to challenge the mass-communication-idea of audiences as a passive receiver. They identify five different intervening variables affecting the relationship between media and audiences: exposure level, medium type, media content, audience predispositions, and interpersonal relations (Katz & Lazarsfeld 1955:20-25). Their work emphasizes the fifth variable, interpersonal relations, since it gives a new kind of agency among the audience members. Readers of a newspaper and viewers of a television shows are not just separate individuals, but they have interpersonal relationships through social networks and group norms, which mediates the influence of the media (Katz and Lazarsfeld 1955:43-44). Katz and Lazarsfeld also introduced the idea of a two-step flow of communication, where opinion leaders – people with especially significant interpersonal influence – distribute and mediate the flow of information from media to the audiences (Katz & Lazarsfeld 1955:32).

Another important contribution within media studies is the works of Hall (1973). He argues that there can never be one single stimuli-effect of a media message, because both the process of media production and media reception are embedded in ideologies (Hall 1973:265). When journalists and media workers produce content, it is encoded with different knowledge and assumptions, and subsequently the media content is decoded by the audience and reacted to according to their structural and cultural position.

In more contemporary research, the idea of active audiences has also been greatly emphasized by Livingstone (2006:9). She argues that audiences are increasingly diversified and situated within specific communities (Livingstone 2006:9-10). This perspective strongly emphasizes that media messages are fully interpreted within communities, and thus the approach has had a strong focus on ethnographic methods (Livingstone & Das 2013:1-2). In its most extreme formulation, there is no inherited meaning in media content, and media content will have completely different meanings for different communities (Philo et al. 2015:464).

Although the approaches of Katz and Lazarsfeld, Hall, and Livingstone are quite different in nature, they all share the common trait of imagining an audience that has some kind of agency – both towards media producers and each other. To some extent, the theoretical approaches to media and audiences can be placed on an axis of how much agency is attributed to the audience, and how unified or fragmented the audience is thought to be (Philo et al. 2015:464). While recognizing that these underlying dynamics are a part of the subject, our study will have a specific empirical focus on the relationship between the news content and audience engagement.

2.1.3 Audiences 2.0

The idea of an audience is both a central pillar in media theory and an essential part of everyday practices in newsrooms (Livingstone 2016:1-2). Nevertheless, many researchers have started to question the contemporary relevance of the concept of audiences. The critique is mainly a consequence of the concept being firmly connected to specific technological mediums: mass broadcasting media such as radio and television (Livingstone 2016:2). Recently, mass broadcasting media has been greatly challenged by digital media. Some argue that this technological evolution also has deep consequences for previous media theories - because they simply no longer fit the digital reality - to such a degree that we need to develop a media studies 2.0 (Merrin 2014).

While it seems exaggerated to discard decades of media studies, there is no doubt that the digital technological advancements have introduced new possibilities for the media ecology and not least for the relationship between media and audiences. Where traditional mass media is characterized by a one-to-many-relationship, digital media allows for a many-to-many-relationship (Livingstone 2016:2). On the internet, anyone can produce content that resembles journalistic content. This basic access to publishing challenges one of the most rudimentary principles of traditional journalism: that the journalist is the gatekeeper of producing, selecting, and exposing content to the audience, which passively consumes it (Deuze 2005:451). While there is a possibility for everyone to take up the job as a journalist, it remains questionable if everyone actually does involve themselves in producing content (Livingstone 2016:2). With technological breakthroughs, there is a tendency make overly enthusiastic proclamations of an entirely new era, but we have yet to see the distinction between news content producers and news content consumers completely vanish (Webster 2014:2; Livingstone 2016:2).

2.1.4 Subconclusion: Media and Audiences

This first part of the theoretical background outlines how the concept of audiences has been central to the interdisciplinary field of media studies. Today, most theories of audiences and media regard the audiences as active and diverse communities. The concept of audiences is even more emphasized and discussed with the invention of new, digital media, where audiences have even more agency. Our study continues in the line of research that understands audiences as active and participating by examining audience engagement behavior with news content on social media.

2.2 Digital Media

In the previous section, we consider how the evolution of digital technologies and especially social media have had significant consequences for the relationship between media and their audiences. In this section, we describe these new digital technologies and news media in a broader sociological context. Lastly, we discuss previous research of the social media, Facebook, which is the specific focus of our study.

2.2.1 Digital Trace Data

When researchers refer to the digital age or the evolution of digital technologies in the 21st century, the concrete technological inventions often concern the exponential increase in computational power and storage capacity (Salganik 2018:3-4). Every second, massive amounts of data are written to huge databases. Included in this stream of data is especially the monitoring of our digital and digitalized behavior – commonly named digital trace data. Digital trace data has several advantages. First of all, they are big i.e., they exist in large quantities (Salganik 2018:17). Furthermore, they are found data meaning that it is real, digital or digitized behavioral data, and therefore also non-reactive to the collection by the researcher (Salganik 2018:24). There are also some disadvantages of using digital trace data. These disadvantages are that digital trace data can be noisy, algorithmically confounded, or incomplete – meaning that relevant features such as background information of the users might not be available (Salganik 2018:35ff). The concept of big data has also been used to describe the accumulation and analysis of digital trace data. However, this term is often used in a variety of ways with no clear singular definition (Sætnan et al. 2018:6).

In the context of news and media, the evolution of digital trace data has also had a huge impact. In the literature, several studies have examined how audience analytics mainly based on these digital trace data have made its way into the newsrooms (Christin 2018; Ferrer-Conill & Tandoc 2018). The implementation of different analytics services and dashboards in the everyday of the journalists, editors, or even specific audience editors have been commonplace in many different media organizations (Ferrer-Conill & Tandoc 2018). Digital trace data and predictive modelling have become especially valuable for media organizations, since it is related to recommendation of advertisements, which is a major source of income for most modern media organizations (Martin 2019:21). Moreover, as the study by Christin (2018) of an American and a French newsroom have shown, digital trace data can be interpreted and used quite differently within media organizations (Christin 2018). The constant interpretation of performance metrics might cause a reactivity among journalists where they adapt their work as they become aware that they are being evaluated of their work (Christin 2018:1386; Espeland & Sauder 2007:1). In this way, the introduction of quantitative feedback based on the digital trace data can have both good and bad consequences, both in terms of making content more relevant to the audience, but it could also decrease the kind of news that are important but might not be among the most popular (Christin 2018:1409). While these studies focus on the effect on audience engagement on the media production, our study focuses on what precedes these evaluations: the measurement of how audiences engage with different news content.

2.2.2 Social Media

In addition to the technical evolution of the capacities of computers, a significant newcoming in the 21st century has been the invention and popularization of social media or social network sites. Social media has many different definitions, but a common trait is that it is a digital service that connects people (Aichner et al. 2021:220). Thus, social media is different from previous media, because it is social – it is many-to-many communication rather than one-to-many mass communication (Livingstone 2016:2). Previous research has identified different uses of social media such as socializing with friends or family, romance and flirting, job seeking or networking, and other kinds of interaction with strangers, organizations, companies, content and much more. The many uses of social media highlight how many different social phenomena have been digitalized or amplified by the invention of social media (Aichner et al. 2021:220).

A lot of research has been devoted to the study of social media, and a few areas of research stand out as particularly prevalent. This is especially evident for the phenomenon of social and political polarization, which has garnered significant attention in social media research. Polarization refers to a division between different groups of people or sets of opinions, and the research area is closely connected to related concepts such as echo chambers or filter bubbles that both refer to a social homophily of ideologies, i.e., that you only interact with other people, who have the same opinions as yourself (Bail 2021). A lot of studies have examined the prevalence of polarization of social media, as it has been hypothesized that political polarization is increased on social media. For example, Bail et al. (2018) find that Twitter users being exposed by statements of the opposite republican or liberal ideology become more extreme in their respective political ideology. In general, they find that users become less moderate in their opinion by being on social media and being exposed to different political statements (Bail et al. 2018; Bail 2021). However, the popularized concepts of echo chambers and filter bubbles have been quite contested, as they represent a too simplified description of the informational exchanges on social media (Bail 2021). For example, a study by Gentzkow and Shapiro (2011) found that the polarization of engagement with news media on social media is lower compared to offline media engagement such as newspaper subscriptions. Thus, polarization might be a problem, but the idea of social media amplifying polarization seems to be more complex than first anticipated. Similarly, Bakshy et al. (2015) found that individual selection when engaging with media content on social media leads to more polarization than the algorithmic sorting of the media content. Another interesting study is Schmidt et al. (2017), who finds that more active users tend to focus on a small number of news sources in their social media feed. Rather than constructing personalized filter bubbles of news content, current research suggests that the social media platform tend to homogenize the news content exposure, so that a small number of news media gain most of the exposure and engagement on social media (Nechushtai et al. 2023:18-19).

Another area of research within social media and news is the impact of misinformation, disinformation and fake news. The increase of misinformation and fake news is often related to polarization as studies have shown how strong political partisanship might drive believing in factual incorrect media content (Bail 2021:109). Previous research has examined how adding warning tags or correction statements might influence the effect of misinformation, but the studies are not in agreement (Muhammad & Mathew 2022:279). Some studies have found that warnings can reduce the spread of misinformation, while other have suggested a backfire-effect – a cognitive confirmation bias, where corrections of misinformation increase the belief in the incorrect information (Nyhan & Reifler 2010; Wood & Porter 2019).

There are many different social media with different specific functionalities, norms and likely also different types of people using them. Currently, social media such as Instagram, Snapchat and TikTok are most popular among younger people, while a social media like LinkedIn is more popular among those with higher levels of education (Auxier & Anderson 2021). The popularity of social media can change quickly, and previous popular sites such as Myspace or Google+ have completely disappeared from the landscape of social media. However, in most countries Facebook remains the most popular and widely used social media (Auxier & Anderson 2021; DR Medieforskning 2022:13; Ortiz-Ospina 2019).

2.2.3 Facebook

Across the world, Facebook remains the most popular social media with close to 3 billion daily active users (Meta 2022). In Denmark, 65% of the population use Facebook on a daily basis (DR Medieforskning 2022:13). According to Facebook itself, the mission of the company is *"Giving people the power to build community and bring the world closer together"* (Meta 2023). To a certain extent, the company's slogan reflects that Facebook have always been a site for managing your social network, and previous research have also shown that the primary uses for joining Facebook are social interaction and social identity-building (Caers et al. 2013:984-985). However, Facebook and especially the company behind Facebook, Meta, have over time developed into an overarching platform by co-integrating with Meta's many other social media and digital services such as Messenger, Instagram, WhatsApp (Helmond et al. 2019). Similar with most other social media, the financial model for Facebook is based on using digital trace data of the users to sell advertisements to over 90 million businesses around the world (Helmond et al. 2019).

Engagement with media and news content is also a vital part of using Facebook. In a Danish context, Facebook is the largest source of news content exposure compared to other social media (DR Medieforskning 2018:48). Especially for young people between 15 and 24 years old, Facebook serves as the primary source for news content (DR Medieforskning 2018:48). However, the relationship between Facebook and media organizations has been complicated. The most significant dispute between Facebook and news media was when the Australian government in 2019 tried to force Facebook to pay media organizations for showing their news content, and Facebook reacted by removing all news content for Australian users (Leaver 2021). While an agreement was eventually reached and Australian news content was reinstated on the Facebook platform, this incident highlighted the dual role of Facebook as both a distribution platform for news content exposure and a potential risk to the business models of media organizations. News organizations often share their content on Facebook, but the underlying goal is commonly to use social media engagement to direct potential audiences away from Facebook and onto their respective websites (Humprecht et al. 2020:1).

2.2.4 Subconclusion: Digital Media

This second part of the theoretical background describes how digital technologies and the invention of social media has had a significant impact on news media and their audiences. Extensive research has been dedicated to studying social media, where a particular focus has been on areas such as polarization and misinformation. Lastly, the relationship between audiences and news media is especially interesting on Facebook, as this social media is the largest and for many serves as a central source of engaging with news content.

2.3 The Many Faces of Audience Engagement

In previous research, the idea of audience engagement has been defined and measured in many different ways. When studying audience engagement on social media, measurements of audience engagement have been everything from reading the news content, liking the post, sharing the article, commenting on the post, and not least the content and tone of the conversations around the article. In the following section, we will discuss how audience engagement can be defined, and how we may think of it as a multifaceted phenomenon in which different kinds of behaviors relate to different kinds of motivations for engaging with the news content.

2.3.1 What is Engagement?

The concept of audience engagement is growing in popularity within both academia and media organizations, and it has become almost a media industry buzzword (Nelson 2021:2350-2351; Lawrence et al. 2018). In some newsrooms, there are job descriptions focusing on audience engagement, and there is a growing industry of audience engagement services and tools offered to journalists and media organizations (Nelson 2021:2351). However, there is often a lack of concrete theoretical definitions of what engagement actually entails (Steensen et al. 2020:1664).

One very broad definition of engagement is that it *"refers to the cognitive, emotional, or affective experiences that users have with media content or brands"* (Broersma 2019:1). The main component of this definition is that engagement is different from simply exposure – it *"denotes an active and intentional orientation toward what users read, view, or hear."* (Broersma 2019:1). However, this is still a quite open and perhaps unprecise definition of engagement (Steensen et al. 2020:1664). Some research additionally distinguishes between felt and behavioral engagement, where felt engagement refers to affective and cognitive reactions, and behavioral engagement means practices that can be observed (Steensen et al. 2020:1665). Thus, felt engagement could be having angry or happy feelings about content or changing attitudes as a result of content, while behavioral engagement could be reading a news article, liking content on social media, sharing news content, or writing comments.

In both academia and media organizations, there have been an emphasis on behavioral engagement, because it is easier to measure and quantify, and behavioral engagement might also be used as a proxy for felt engagement (Steensen et al. 2020:1665). However, even if only behavioral engagement is considered, we argue that there are substantial differences in what the different audience engagement behaviors represent. In their review on definitions of audience engagement, Gajardo and Meijer (2022) argue that previous research has predominantly concentrated on attention and time spent on news content, while less consideration has been given to how the time is spent or the quality of the engagement. They highlight audience engagement as a complex and multifaceted phenomenon composed of different dimensions of behaviors and emotional orientations (Gajardo & Meijer 2022; Steensen et al. 2020). In the following, we will further elaborate how different audience engagement behaviors might relate to various underlying motivations.

2.3.2 Motivations for Engagement

To understand different audience engagement behaviors, we argue that it is important to consider what motivation lies behind. Multiple studies have found that different behaviors such as liking, sharing, or commenting are related to different user motivations (Almoqbel et al. 2019; Kim & Yang 2017). In fact, there is a theoretical approach within media studies that emphasizes how different kinds of media uses are related to different kinds of gratifications, i.e., different sociological or psychological motivations (Ruggiero 2000). Here, the question of what constitutes engagement is not only the study of the kind or extent of engagement, but also what precedes or motivates the actual action of engagement.

The theory of uses and gratifications has been described in many ways, but originates from the work of Katz and Lazarsfeld (See Section 2.1.2). One particular sociological formulation is the theory by Levy and Windahl (1984), who stresses that gratifications should not be understood as the audience being superrational and selective (Ruggiero 2000:8; Levy & Windahl 1984:52ff). Levy and Windahl developed a taxonomy in which audience engagement can be placed within both the audience motivation and the phase of exposure: pre-, under-, or post-exposure of the news content. In this way, one kind of audience engagement might be related to a selective orientation, which happens pre-exposure of the news content. Other kinds of audience engagement such as discussing the news content is oriented towards socializing, and it happens after the exposure of the news content. In this way, they provide a theoretical example of how different kinds of audience engagement might be explained and related to different kinds of motivations.

The uses and gratifications approach might be particularly relevant in the case of audience engagement on social media, as this new form of media makes possible an increased agency of the audiences (Ruggiero 2000:20) (See also section 2.1.3). In line with this, a study by Springer et al. (2015) applies the approach to audience engagement on social media - specifically the behaviors of commenting and reading comments. They identify four dimensions of audience engagement, which relate to different underlying motivations. These dimensions include cognition, entertainment, social-integration, and personal identity, and they divide user behavior into commenting (e.g., commenting) and lurking (e.g., reading) behavior (Springer et al. 2015:800ff). Similarly, a review by Kümpel et al. (2015) identifies three broad motivations for online news sharing behavior: self-serving motives like promoting reputation or gaining social status, socializing and discussing ideas, and altruistic motives of information sharing or seeking (Kümpel et al. 2015:6).

As these studies exemplify, there is not a finite taxonomy or theory of the possible uses and gratifications. Furthermore, the different dimensions of audience engagement behaviors and gratifications might also vary between different empirical cases (Levy and Windahl 1984:57; Haradakis & Humphries 2019). Although focusing on different kinds of audience engagement behavior, both Springer et al. (2015) and Kümpel et al. (2015) discuss gratifications that relate to information seeking, socializing, and self-expression. In relation to our present study, the idea of uses and gratifications serves as a theoretical basis for considering how audience engagement might consist of multiple different dimensions. The reviewed studies use the concepts of motivations and gratifications interchangeably. In our case, we chose to mainly focus on motivations moving forward, as it denotes the desire for an outcome. In our study, the underlying motivations cannot be observed directly, but we only examine behavioral outcomes. In the next four sections, we will further examine which dimensions of audience engagement on social media might exist – focusing on information selection, emotional responses, sharing content, and finally conversations and deliberation – while tying them to other relevant sociological theories.

2.3.3 Information Selection

The most basic form of audience engagement on social media might be to simply expose oneself to the news content. In other words, audience engagement can be to read, view, or listen to news content. There can be many different reasons for choosing to click on a link to an article and read it, but one of them might be to get information or gain knowledge about the content in the article (Kormelink & Meijer 2018). For example, it has been shown how use of media content is related to a greater knowledge of political and current events (Oeldorf-Hirsch 2018:227). The idea that news media play an important role in supplying information to citizens has especially been emphasized in the context of political knowledge as a way of maintaining an informed democracy (Aalberg & Curran 2012:3). It is often emphasized how news media have an obligation to inform citizens to make decisions based on knowledge rather than ignorance or misinformation (Aalberg & Curran 2012:3). However, there might also be differences in the way information and knowledge is obtained from the media. As Eveland (2001) has emphasized with his theory of cognitive mediation, the relationship between exposure to news content and information gain is mediated by a number of motivations about learning from the news (Eveland 2001:574-575). For example, a study by Eveland & Scheufele (2000) found that current affairs knowledge gaps between higher and lower education groups are smaller for users that more frequently read news content. Thus, different users might gain different amounts of knowledge from news content (Ohme 2020). The specific question of retrieving factual knowledge from news content from social media is also relevant in relation to the discussion about misinformation or particular forms of fake news on social (See also Section 2.2.2).

Particularly in the context of engaging with news content on social media, research has discussed whether social media has a paradoxical role for the diffusion of information from news content. On the one hand, the extensive amount of information available creates a broad selection of news content for the user to select and choose to read, but on the other hand, the increased amount of available content might also result in an information overload (Pentina & Tarafdar 2014). Gaining information and knowledge from news content is likely not a linear process, but a complex mechanism of news content contributing to sense-making and information-processing (Pentina & Tarafdar 2014:220).

2.3.4 Emotional Responses

Audiences do not just use news content to get information or knowledge. Another important part of engaging with news content is also the phase where the content is interpreted and a form of reaction to the content might happen (Levy and Windahl 1984:54). As described in Section 2.1.2., Hall is well-known for his ideas about this process of decoding news content (and encoding news content for the journalists and editors). In the process of decoding news content, Hall argued that audiences might respond with either a hegemonic, negotiated, or oppositional position towards the content. Quite simplified, audiences might respond in agreement, partly in agreement, or in disagreement with the news content exposed to them.

Another related line of research has also examined the decoding process in relation to the emotions or feelings that might appear in audiences in relation to certain types of news content. The study of audience emotional reactions has been studied across diverse fields such as psychology, neuroscience, anthropology, and sociology (Dafonte Gómez 2018:2142). An emotional reaction based on exposure to news content is often characterized as different feelings such as anger, sadness, positivity, hope, or happiness (Dafonte Gómez 2018:2143). A related line of research has discussed the idea of emotional contagion, i.e., that emotional states of persons interacting with each other tend to influence each other towards the same emotional state (Hatfield et al. 2014:109). Although emotional contagion is widely used within psychology, the idea of interpersonal contagion or imitation is also a classic sociological concept originating from the work of Tarde (Tarde 1903; Katz 2006). The idea of emotional contagion has also been developed to include that the emotional responses of audiences tend to converge towards the emotional framing of news content that they engage with (Bösch et al. 2018). A study by Facebook has examined emotional contagion on their platform to see if the emotionality of the content on users' feed affects the emotionality of the users (Kramer et al. 2014). They found clear evidence that the proportion of exposure to positive or negative expressions influences the amount of positive or negative posts that the users produced correspondingly. It is important to note that the mentioned Facebook study has been heavily criticized as unethical (Salganik 2018:284; Sellinger & Hartzog 2016).

In the context of audience engagement as emotional responses on social media, Facebook have often been the focus of study, as they in 2016 introduced an option to react to content with a number of different emotions beyond the original like reaction (de León & Trilling 2021:1; Meta 2016). With this technological addition, it became possible to materialize the emotionality through digital manifestations on each Facebook post. Some studies have collapsed the total amount of reactions as a general measure of valence, others have grouped the reactions into groups of positive or negative emotions, while still others argue that they might best be understood as a discrete set of emotional reactions (de León & Trilling 2021:2; Heidenreich et al. 2022).

2.3.5 Sharing is Caring

Long before the invention of social media, Katz and Lazarsfeld described the importance of interpersonal relations and social ties in the audience engagement of news content (Katz & Lazarsfeld 1955:43-44; see Section 2.1.2.). Interpersonal social ties can be mediating in terms of increased exposure of content, but also conformity to social group norms is an influential factor (Katz & Lazarsfeld 1955:52). While sharing of news may serve as a way of spreading information or gaining further information, it may also be rooted in motivations of social status-seeking or social acceptance (Katz & Lazarsfeld 1955; Kümpel et al. 2015:6).

In recent studies with a focus on news sharing on social media, the intention of self-representation or group-identification has been re-examined (Kümpel et al. 2015:6). In a study by Ihm and Kim (2018) based on survey data, they find that individuals with a high motivation for self-presentation are more likely to share news online across both private messaging and public social network sites (Ihm & Kim 2018). Similarly, a study by Thompson et al. (2020) has shown that the perceived credibility of news media is related to the willingness to share content, as sharing low-credibility news content might be damaging to the social status of the individual.

Another perspective on sharing may be to interpret it as a form of gift-giving to maintain social cohesion (Duffy & Ling 2020). The idea of gift-giving is a classical sociological theory dating back to Mauss (2004) in which sharing or giving content is a way of establishing and reproducing social ties. Inspired by Mauss' idea of gift-giving, Duffy & Ling propose the concept of phatic news sharing, that is engagement with news content that is not directed at having longer conversation or the information in the content, but the mere act of activating and maintaining a social connection (Duffy & Ling 2020:83).

In this way, there might also be different motivations for sharing news content. The first kind of sharing described by Ihm & Kim (2018) and Kümpel et al. (2015) relates to broader social status-seeking and self-presentation, while the phatic news sharing described by Duffy & Ling (2020) relates to maintaining social ties between specific individuals.

2.3.6 Conversations and Deliberation

A final dimension of audience engagement is how audiences can engage with news content by having conversations about the content. A growing literature has examined audience engagement as conversations and discussions in the comment sections on social media (Reimer et al. 2021:11). These studies take different theoretical and methodological approaches, ranging from discussions of Habermas' theories to predictive studies of uncivil language. In the following, we present the most important positions from this range, and the related empirical findings that are connected to our area of research.

The research of conversations around news content often takes inspiration from classic theoretical ideas about deliberative democracy – especially the work of Habermas. For media studies and especially sociology, Habermas' theory of deliberative democracy stands as a seminal concept when considering communicative practices. He argues that an open, free, and independent public sphere is essential for a well-functioning liberal democracy. Deliberative democracy is achieved through discussions based on communicative rationality as a form of communication where different viewpoints can be encountered and challenged free of coercion and strategic motives (Habermas 1999). While other forms of communication exist, deliberation is the form of communication that the public sphere should facilitate in a well-functioning society (Habermas 1999; Habermas 2001). Habermas' conception of deliberative communication can be understood as a form of democratic communication that prioritizes inclusivity, rationality, and mutual understanding. Habermas emphasized how the media plays a crucial role in facilitating and providing a platform for public discourse. However, he also recognized the potential pitfalls of the media, such as the potential for media organizations to prioritize profit over the public interest (Wessler 2018:58).

Since the early formulation of deliberative democracy, society and technology have developed along with the institutional and technological situation of the public sphere (Habermas 2006, 2022). This has prompted many researchers to reflect on and investigate the potential and challenges of digital platforms for successful deliberation, and how Habermas' theory of deliberation could be applied or translated to this new reality. Ideally, the internet helps to fulfill deliberative ideals, which can be realized through its openness and reach – in contrast to physical spaces' locality and traditional media's closedness. As such, it is argued that social websites, as a public sphere 2.0, have the potential to realize deliberative ideals in a new and improved egalitarian context (Ruiz et al. 2011). However, it is not naturally given that these digital technologies will realize this potential. As Papacharissi (2002) argues, there are serious concerns which are challenging the success of the virtual public sphere such as polarization, dependency on big tech companies, and not least the quality of online, political discussions (Papacharissi 2002:20).

Drawing on this theoretical foundation, many studies have sought to empirically analyze the deliberative quality of conversations on digital or social media. However, there has not yet been established a coherent approach to empirically measure deliberation, and many different operationalizations have been used (Esau et al. 2017:332). One particular approach that has been developed especially for social media is Esau et al. (2017), who measure deliberative quality by four dimensions: rationality, reciprocity, respect, and constructiveness. In practice, rationality can be whether the discussion is on-topic, and reciprocity relates to the depth of the conversation, e.g., if a comment addresses another comment. The dimension of respect refers to the absence of aggressive or offensive language, while constructiveness captures whether comments contain proposals for solutions or similar (Esau et al. 2017:332).

Other studies have predominantly focused on single indicators of lack of deliberation, such as the respect dimension as a presence of uncivil language and paid less attention to the positive indicators such as constructiveness (Reimer et al. 2021:20f). Specifically, a large body of research has tried to explain what factors influence the amount of incivility in online conversations about news content. For example, Coe et al. (2014) found that uncivil comments increase when weightier topics are discussed. Additionally, Diakopoulos and Naaman (2011) and Gardiner (2018) found that topics related to politics, society, crime and justice, disasters and accidents, the environment, and feminism are more strongly associated with uncivil discourse. The sources cited in an article can also influence comment civility (Coe et al. 2014). Anonymity has a negative effect on civility and comment quality (Fredheim et al. 2015; Santana 2014), and female journalists are particularly targeted with hateful comments (Gardiner 2018). Furthermore, research have also shown that the dynamics of uncivil conversations on social media varies from cultural contexts e.g., between different countries (Humprecht et al. 2020). Different research has also examined the consequences of uncivil conversations for news media and results indicate that audience's perception of news bias and credibility are affected by the content of the comment sections, by enhancing perceptions of bias and diminishing perceptions of favorability (Houston et al. 2021; Kümpel & Springer 2016; Gearhart et al. 2022).

2.3.7 Subconclusion: The Many Faces of Audience Engagement

In this third part of the theoretical background, we discuss the definition of audience engagement as well as related research on the topic. In this study, we employ a broad understanding of audience engagement as any active and intentional orientation towards news content. Inspired by the uses and gratifications approach and a broader literature review, we understand audience engagement on social media through several dimensions manifested in different behaviors. Here, the dimensions identified are behaviors related to: 1) information selection, 2) emotional responses towards the content, 3) sharing content either for social status or maintenance of social ties, and 4) having conversations about the content.

2.4 Engaging with News Content

The previous sections outline how we understand audience engagement on social media such as Facebook. Audience engagement is a multifaceted phenomenon, and there might also be multiple factors that influence how audience engagement unfolds. As described in Section 2.1.2., everything from exposure, type of medium, audience predispositions, interpersonal relations as well as the news content itself might influence how audiences choose to engage with the content. In this study, we chose to focus on the last factor: the influence of the news content itself. In this section, we will review how news content might be characterized, and which features of news content that might influence audience engagement.

2.4.1 News Value Theory

To explain how audiences relate to news content, many studies have turned to the theory of news values (Eilders 2006). The first and perhaps most prominent description of news values is the taxonomy by Galtung and Ruge (1965). The theory sketches out several characteristics of news content that affect whether a story is considered newsworthy or relevant. The focus of Galtung and Ruge was primarily on news selection and prioritization in the news production phase, but it has become adapted also as an explanation of how audiences estimate the relevance of news content (Harcup & O'Neill 2001:7; Eilders 2006).

The taxonomy of Galtung and Ruge has been contested and developed into many alternative versions, but there are often heavy similarities between the list of news values included in each iteration. Thus, the methodology behind news value theories has been based on diverse foundations such as journalistic practices and opinions (Golding & Elliot 1979) or linguistic or discursive features of the news content itself (Bednarek & Caple 2012; Bednarek 2019). Several of the later studies of news values have emphasized that the taxonomy needs to have a stronger empirical foundation (Harcup & O'Neill 2001:6; Bednarek 2019). Across these studies with very different approaches and methodologies, there are several features that are similar (See Appendix, Section 8.1. for an overview table). In the following two sections, we will first present the common news values that go across the different theories, while the second elaborates on some of the more ambiguous parts of the news value theory.

2.4.2 Common News Values

In both the works of Galtung & Ruge (1965), Østlyngen & Øvrebø (1999), and Bednarek & Caple (2012), there is a common feature of *timeliness*. Timeliness means that there is a marker of something that is happening near to the present. It can be that the story considers something that is new or recent, or perhaps the story is still developing or ongoing. It is almost a literal meaning of news that it is something that is new. The trait of being new is even more accelerated in today's news environment, where news articles can be distributed at an instant, and can become outdated after hours or even less (Liao et al. 2020).

Another feature that is described in both Galtung & Ruge (1965), Østlyngen & Øvrebø (1998), Harcup & O'Neill (2001), Brighton & Foy (2007), and Bednarek & Caple (2012) is *unexpectedness*. News content that has an element of surprise, sensation or in general unusualness is more worthy of attention. A few of the studies also describe consonance as a feature of news content, which generally is understood as the opposite of unexpectedness – something that is in line with expectations.

All studies reviewed describe a feature that can be understood as *proximity*. Proximity can be understood as content that is close to the specific situation and context of the specific audience. As Golding & Elliot (1979) describe, proximity can be both geographical nearness, but also cultural nearness. Geographical proximity entails that news content about domestic events are more prioritized in comparison to news content about events from other nations of the world (Golding & Elliot 1979:636). On the other hand, cultural proximity describes content that refers to common cultural markers for both the journalist and the audience (Golding & Elliot 1979:636). The idea of both types of proximity is that content about an event that has happened close to me, and my everyday life might be more relatable and thus more relevant for me.

In several of the studies of news values, the idea of *personalization* is also described. Personalization means that the content focuses on specific people to describe a larger topic – thus making it more concrete and relevant. By centering around an individual, news content directs attention towards intricate subjects, processes, or institutions, thereby enhancing comprehension or fostering a deeper understanding. Throughout the previous works, it is often distinguished between personalization of elite actors or personalization of non-elite actors. By focusing on elite actors or celebrities, the content might make the content more interesting or simply draw the attention of the audience. On the other hand, non-elite actors can make the audience reflect upon themselves and give a more human face to more complex phenomena, making it more relatable (Bednarek 2019:161-162).

Another news value that is present in almost all of the works is *negativity* or sometimes called conflict. It is a saying in media studies that "the only good news is bad news" meaning that stories about events that are evaluated negatively by the general public have long attracted audiences to read the news content (Harcup & O'Neill 2001:11). This is also related to the idea of a negativity bias, i.e., that negativity across the board tends to gain more attention (Robertson et al. 2023). However, there is an ambiguity in that news content might be evaluated as bad news for some, while other might interpret the same content as good news (Harcup & O'Neill 2001:11). Negativity and its opposite, positivity can refer to both the normative evaluation of the topic in the content, but it can also refer to the sentiment of the language. As an example, most audience might evaluate an environmental catastrophe as a negative topic, while a story about tax cuts could be framed as both positive or negative - depending on the political stance both the news media and its general audience.

Finally, the feature of *impact* or magnitude should be emphasized. It refers to news content that is of high general societal significance which may draw the audience's attention. As Brighton and Foy (2007) writes, it is news content that potentially has a large effect on the audience. The news value of impact can be difficult to define unambiguously, but it might be news content about issues that are relevant in terms of size – something that affects a lot of people – or it might be relevant in terms of estimated important or consequences – something that the audience need to know (Golding & Elliot 1979:635). Across the various definitions and descriptions of impact, it is common that it refers to news content that has a larger societal relevance.

2.4.3 Ambiguities in News Value Theory

The different taxonomies of news values vary depending on which features they include and exclude. Certain features are not applicable to all domains of news content. For example, Golding & Elliot (1979) and Bednarek & Caple (2012) include a news value of *visual attractiveness*, but this feature seems to be mostly relevant for content that includes video or images. Furthermore, some taxonomies seem to mix features relevant for production of news content with features relevant for reception of news content (Bednarek & Caple 2012:50). Specifically, the news values of news media composition or underlying ideological bias (Galtung & Ruge 1965; Golding & Elliot 1979; Harcup & O'Neill 2001: Brighton & Foy 2007) and the impact of external influences (e.g. lobbyism or paid content) (Brighton & Foy 2007) are relevant to selection of news content within the media organization but rarely on audience reception.

The study by Golding & Elliot (1979) and Harcup & O'Neill (2001) include a news value of *entertainment*. Harcup and O'Neill refer to the news value of entertainment as content that is not supposed to provide information to the reader, but merely to entertain (Harcup & O'Neill 2001:13). In many ways, this description is reminiscent of the widely used concepts of hard and soft news. The idea of *hard* and *soft* news originates from the media industry, but it has been embraced also by the scientific community (Reinemann et al. 2012:223). In the scientific literature, there is rarely a consensus about the exact definitions of these concepts. Many definitions often mix news topic, style, or other news value characteristics of the content when distinguishing hard and soft news (Reinemann et al. 2012:225-226). However, when focusing on the topic dimension, hard news is often referring to content about politics, economy, finance and similar topics, while soft news is understood as sports, celebrities, lifestyle, weather and more (Reinemann et al. 2012:231; Kalsnes & Larsson 2018).

There have also been considerations about whether news value taxonomies are dependent on the specific type of medium. In a later study, Harcup & O'Neill have revisited their original taxonomy of news values, and here they add a new feature of *shareability* that is specifically relevant for news content that will be transmitted on social media (Harcup & O'Neill 2017:1481-1482). With shareability, they argue that some content is more likely to generate engagement on social media. Shareability could also be understood as *spreadability* – a concept that has been widely elaborated in the work of Jenkins, Ford & Green (2013). Spreadability or shareability are attributes of media content that appeal directly to sharing, interaction, and circulation within a communication rather than attention from a single isolated member of the audience (Jenkins et al. 2013:4ff).

2.4.4 Subconclusion: Engaging with News Content

While the previous parts of the theoretical background consider audience engagement in general, this fourth part focuses on characteristics of news content that might influence audience engagement. Commonly, various taxonomies of news values have been used to summarize basic features of news content that are hypothesized to influence the importance and relevance of news content. Most of the studies that refer to news value theory are empirical in nature, but they have quite different approaches. By aggregating the most important studies of news values and news content, we identify the following content characteristics that might influence audience engagement: timeliness, unexpectedness, geographical and cultural proximity, personalization, negativity, positivity, impact, hard and soft news, and spreadability.

2.5 Research Gaps

In the previous sections, we present different theories on audience engagement and news content, and findings from relevant empirical studies. Multiple studies have examined audience engagement, and how it might be influenced by specific characteristics of news content. While they provide a foundation for this study, we argue that there are still important research gaps that need to be addressed. Generally, empirical studies of audience engagement and news content have been limited to a few specific contexts and sampling strategies. In a review, Kümpel et al. (2015) find that the majority of studies (69%) investigate Twitter, while only 17% of studies examine Facebook, even though Facebook remains the most popular social media in terms of users (Kümpel et al. 2015:4). Furthermore, there is a lack of studies that are not conducted in an American context (Kümpel et al. 2015:4). In addition to these general shortcomings, we argue that there are two primary empirical limitations within the literature examining the influence of news content on audience engagement on social media.

First of all, previous research has mostly relied on smaller samples of articles. Furthermore, a number of studies have only sampled articles with news content that is highly engaged with by the audiences and rarely content that is less engaged with (Kümpel et al. 2015:8-9). As an example, the study by Bednarek (2019) samples and analyzes 99 of the most widely shared news articles on Facebook. This sampling strategy is quite problematic, since it assumes that the associations for the most successful news content are representative for the rest of the distribution. To examine the relationship between news content and engagement, we cannot only look at what is successful – we need to investigate the whole population of news content (Kümpel et al. 2015:9).

Other studies do not sample based on successful content, but instead select smaller parts of the content at random. However, as most previous studies rely on hand-coding of the news content, the studies are only able to construct very limited samples, e.g., only a single week or only a few news stories each day. In a study by Ziegele et al. (2020), the hand-coding took nine coders two weeks to finish, and they were only able to include approximately 1% of the news content published during the seven random weekdays (Ziegele et al. 2020:872). As the authors themselves note, it is a limitation to use a sample in this domain. The content and engagement are most likely influenced by the entire dynamics of the online discussions and the specific events that occur during or overlap with the short period of a few randomly selected days in a two-week period (Ziegele et al. 2020:885). Other relevant studies such as Salgado & Bobba (2019) and García-Perdomo et al. (2018) also examine the relationship between social media engagement and news values, but they also rely on hand-coding, and therefore they are also limited to a small sample of news content. The use of automated text analysis to do large scale investigations of audience engagement and news content has been suggested to move the field forwards (Reimer et al. 2021:3). Such computational approaches have successfully been applied in the field of market and communications research. However, here the focus has been on the branding or communication style of companies and health organizations, rather than news content (Kite et al. 2016; Barcelos & Munaro 2022).

An exception to the sampling limitation within the field is the study by Trilling et al. (2017), who uses an automated text analysis on a large and complete sample of Dutch news articles. However, they only examine audience engagement as a simple count of total Facebook interactions and do not consider the different dimensions of audience engagement. Recalling Section 2.3., we argue that audience engagement should be conceptualized as a multidimensional phenomenon which may be studied through different specific empirical indicators. We argue that in order to gain a richer understanding of the dynamics of news content and social media engagement, one has to consider and combine multiple perspectives on audience engagement at the same time. Doing this will not only give us a broader view but also allow us to examine the variation between the different engagement behaviors.

To sum up, we argue that there are two overall empirical gaps in the previous research examining the influence of news content on audience engagement. The first challenge is that studies have often used either biased or quite limited samples rather than examining a complete population over a longer period. Secondly, previous studies have not defined audience engagement as a multidimensional set of behaviors but have instead examined only a few selected behaviors often void of theoretical explanations.

2.6 Conclusion: Theoretical Background

In the previous sections, we review and discuss the theoretical background and literature relevant to our present study. As described, the relationship between audiences and the media has been a focal point in the various fields studying media within both sociology, humanities, and natural sciences. To some extent, most theories of media can be placed on an axis of how much agency is attributed to the audience. Following the digital evolution of the 21st century, the idea of an active and agentic audience is more relevant than ever. The increased relevance of audiences is a consequence of digital technologies such as social media giving more potential for a many-to-many relationship rather than a one-to-many relationship between media and audiences. The digital evolution and social media have had many consequences for the relationship between media and audience. This includes the possibilities of using digital trace data to analyze the behavior of audiences within the newsroom, but also potentially harmful phenomena such as increased polarization and misinformation. Although these questions are relevant, our specific focus is the relation between audience engagement and news content on the social media Facebook.

Based on these theoretical considerations, we further discuss how we can define and understand audience engagement on social media. Through a review of empirical studies, we find that it is a widely used concept that has been defined and operationalized in many ways. Inspired by the specific formulation in the uses and gratifications approach by Levy and Windahl (1984), we argue that audience engagement is a multifaceted phenomenon that might be manifested in several different dimensions of behavior, as they related to different kind of underlying motivations. We identify four different dimensions relevant to audience engagement on social media: 1) information selection, 2) emotional responses, 3) sharing, and 4) conversations.

As previous literature has examined, there are many different factors that might influence audience engagement. However, the particular focus of this study is how news content influences audience engagement on social media, and we therefore also consider which characteristics of news content might be relevant. Previous research has mostly been based on the idea of news values, which is a theory that exists in many different forms and taxonomies. We summarize previous theories related to news values into a number of characteristics of news content relevant for audience engagement: timeliness, unexpectedness, geographical and cultural proximity, personalization, negativity, positivity, impact, hard and soft news, and lastly spreadability.

Based on the previous studies, we identify two central, empirical limitations. First, the studies that examine the effect of news content on audience engagement are limited mainly in terms of relying on small and often biased sampling techniques. Secondly, most studies define and measure audience engagement as one or few dimensions and do not thoroughly capture audience engagement as a multi-dimensional set of behaviors. In this study, we explicitly seek to bridge these two gaps by examining multiple dimensions of audience engagement on a complete, larger sample of news content shared on Facebook.

3 Data and Methods

In the following section, we elaborate on the specific research design, the case of study, and extensive process of collecting and constructing the dataset. Afterwards, we present our operationalization, i.e., how we move from theoretical constructs to empirical measurements for the outcome, predictor and control variables. Next, we explain and discuss our choice of regression method that we apply in the analysis. Finally, we examine the background information related to our case of study, focusing on the reliability and potential generalizability of our analytical findings.

3.1 Research Design

In Section 2.5, we identify two central limitations in the previous studies of how news content influences audience engagement on social media. Firstly, previous studies have mainly relied on manual hand-coding of news value characteristics and as a result used samples sizes that are often either biased or quite small. Therefore, there is a need for studies examining the whole population of news content and audience engagement during a longer period. As a second limitation, there is a lack of studies that take all dimensions of audience engagement into account. We argue that audience engagement is a multifaceted phenomenon, and that it should be defined and measured including multiple behaviors of selecting, responding to, sharing, and discussing news content.

This study bridges both gaps by constructing a large dataset in collaboration with Ekstra Bladet – the biggest tabloid media in Denmark. In relation to the first gap, the collaboration with Ekstra Bladet yield access to data through both Facebook and their own internal databases, which means that we are able to conduct the analysis of the whole population of shared articles for approx. 2 years. In order to avoid manual hand-coding of the news value characteristics, we utilize natural language processing methods to algorithmically label the news content characteristics for the 18,350 articles in our dataset. In relation to the second gap, we are able to include measurements of several different dimensions of audience engagement. By gaining elevated access to Ekstra Bladet's Facebook page, we are able to collect link clicks, number of reactions, number of shares and comments as well as the text content and structure of the comment section. All of this information is used to define eight different outcomes of audience engagement based on the dimensions of audience engagement on social media identified in Section 2.3.

3.1.1 Computational Social Science

Our study and methodology draw upon ideas and techniques from the field of computational social science. This approach has changed the ways researchers access and study human behavior and social phenomena (Lazer et al. 2009; 2020). The interdisciplinary field of computational social science combines computational methods, such as natural language processing, machine learning, and network analysis, with traditional social science theories and methods to examine large-scale datasets and uncover patterns that were previously unattainable through manual data collection or traditional statistical analyses (Cioffi-Revilla 2017). This is also strongly connected to and enabled by what we introduced in Section 2.2.1. as digital trace data.

Another premise of computational social science is the ability to use new methods and technologies to shed new light on classical empirical research questions (Lazer et al. 2009). An example of this is particularly within the field of analyzing text and documents such as news articles. Here, social scientists have mostly relied on manual hand-labelling by either domain experts, research assistants, or paid micro-workers such as the service from Amazon Mechanical Turks (Do et al. 2022). Labelling text-corpuses is extensive and tiring work, and outsourcing the labor to low-paid micro-workers elicits both ethical and data quality issues (Fort et al. 2011). For a long time, computational approaches for text labelling have not been of sufficient quality for the complex labelling task needed for sociological research question (Do et al. 2022). However, the technological advances of new Large Language Models (LLM) and specifically the transformers architecture have been shown to be able to performs just as well as expert annotation on complicated labelling tasks (Do et al. 2022:20; Vaswani et al. 2017). For example, these types of models have been applied to sociological questions such as how ideology impacts immigration discourses (Mendelsohn et al. 2021), or how polarization relates to opinion of global warming (Luo et al. 2020). There are a number of advantages of using computational and machine learning based approaches to text-labelling. First of all, once the model is trained, the annotation can be applied to millions of texts in less time than it takes to manually annotate a smaller sample of texts. Thus, it is also possible to annotate entire populations of texts, which increases the validity of the study removing issues about representativity or sampling bias due to outliers or hidden patterns (Do et al. 2022:21). A second advantage is that annotation practices are easier replicated. Machine learning models can be distributed and applied quickly through open-source platforms such as Hugging Face (Wolf et al. 2020), while human annotation practices require comprehensive coding schemes and training sessions to replicate on new texts and documents.

By employing a combination of computational methods and social science theories, this study aims to provide a more comprehensive understanding of how news content affects audience engagement on social media. We argue that the interdisciplinary nature of computational social science and the new computational methodologies allows us to tackle the identified research gaps and contribute to the ongoing scholarly debate on the role of news content in shaping audience engagement on social media.

3.1.2 Case: Ekstra Bladet

To answer our research question, our case of study is the Ekstra Bladet, which is the largest Danish tabloid-media. Ekstra Bladet is an interesting case for several reasons. As Reimer et al. (2021) identify in their review, there are few studies of tabloid media and few studies of media environments that are not Anglo-American (Reimer et al. 2021). Ekstra Bladet is the largest online media in Denmark with more than 1 million daily users, which is a large proportion in a country of 5.8 million people (Ekstra Bladet.dk A; Danskonlineindex.dk). Their Facebook page has 400,000 followers and has a dedicated team sharing and managing content. Besides their digital presence, they also have a printed daily newspaper which has been published since 1904 (Ekstra Bladet.dk B). Ekstra Bladet is a tabloid-media, and its value set emphasizes being *"anti-authoritarian"*, *"provoking"*, and refer to their writing as short, precise for *"everyone to understand"* (Ekstra Bladet.dk A, our translation).

The Danish media system is described as a "Northern" media system that is characterized by a high level of public broadcasting and press subsidies, high journalistic professionalism, but also low political parallelism and ownership regulation (Brüggemann et al. 2014). Ekstra Bladet is sometimes referred to as left-leaning, but compared to other countries the political slant is generally low (Blach-Ørsten & Kristensen 2016:33; Brüggemann et al. 2014). In section 3.5. we will present some further empirical background for our particular case, while section 5.4. returns to the question of how the results from the study may be generalized to other contexts.

3.2 Data

The data used in our analysis consists of all Facebook posts made on Ekstra Bladet's Facebook page in the period from the 28th of February 2021 to the 1st of January 2023 – i.e., a period of 1 year and 10 months. The final dataset consists of 18,350 posts with articles shared by Ekstra Bladet, which in total has received approximately 5.5 million comments, 7 million likes, and 230 million clicks on links to the shared articles. The dataset includes the complete population of articles shared by Ekstra Bladet in the period. To create the dataset, we merge two different data sources: 1) data from Ekstra Bladet about the shared articles, and 2) data collected from Facebook about audience engagement for the shared articles. To our knowledge, this results in one of the biggest and most comprehensive datasets examining the relationship between news content and audience engagement.

The data from Ekstra Bladet contains information from the article content such as title, subtitle, text, and meta-data such as time of publication, thematic section, whether the article is characterized as breaking news or not. We only use regular news articles from Ekstra Bladet, which excludes videos and other miscellaneous content such as links to their front page. The following section describes how the Facebook data for each shared article is collected. In Section 3.3., we describe the exact measurements in our final dataset, including the measurements that we construct based on the text from both articles and comment sections on Facebook.

3.2.1 Collecting Facebook Data

Following the Cambridge Analytica scandal and the public debate about data privacy, Facebook data has been increasingly difficult to get access to - even for academic purposes (Freelon 2018). While Facebook still has an official API (Application Programmable Interface – a structured way in which users and developers can gain access to extract or interact with Facebook data), the availability of the data returned has been greatly restricted in the past five years. Despite having internal access to Ekstra Bladet's Facebook page through our collaboration with the news media, it was still quite challenging to retrieve data for their Facebook page. Here, the main issue is that Facebook's API only returns *"approximately 600 ranked, published posts per year"* (Meta, n.d.), which would greatly reduce the number of posts we could retrieve (Ekstra Bladet has posted approx. 9,000 posts per year). Furthermore, there would be an undesirable hidden sampling bias, since Meta provides no further information about how the posts are ranked, and it is not clearly driven by one measurement such as likes.

After an extensive exploration of the Facebook business moderation and management tools provided to the page owner, we were able to manually export all the posts one week at a time through the legacy version of the Page Insights feature. In this way, we were able to get the post-IDs of all posts, and then afterwards use Facebook's API to enrich with the information about link clicks, reactions, shares, and comments - one post at the time. The Facebook data was collected during a week from the 20th-27th of February 2023. Due to a limit in the Facebook API, our dataset begins on 28th of February 2021, as certain features of the data (e.g., link clicks) only extends back one year. In Figure 1 below, we show an example of a post on Ekstra Bladet's Facebook page, and the different information of audience engagement within the post. All of the empirical measurements of engagement are essentially based on this information for each post. The usernames and profile-pictures have been pseudonymized.

Figure 1: Example of Facebook post

Even with our access to Facebook's API, it is not possible to extract any kind of personal information such as usernames or user-IDs from the comment section. While this limits some of the possible analysis, this alleviates ethical concerns when dealing with digital trace data and lessens the task of complying with the GDPR. However, in terms of data validity, it is a limitation, since we do not know the number of unique users commenting on a post, but only the content of the comments themselves. This limitation is further discussed in Section 5.3.1.

Another concern of using Facebook's API is that we rely on their data quality. During our process of validating the data quality, we found a few cases where e.g., the number of reactions from the API did not match the number of reactions shown on the post in the user interface. We cannot for sure say what causes this inconsistency, as the API is not well documented. However, the differences were often small and did not look systematic, and such noise in data is common in studies of digital trace data and social media (Salganik 2018:37).

3.3 Operationalization

The following sections describe our operationalizations – how the theoretical concepts are defined as empirical measurements. The first section describes how the outcomes, the dimensions of audience engagement on social media, are measured. The second section describes how each of the predictors for news content are operationalized. Finally, we present a range of control variables that we include to adjust for possible confounding effects of our main predictors on the outcomes.

3.3.1 Outcomes

In this study, the main concept of interest is audience engagement on social media. As described in Section 3.1, we seek to include a broad and multifaceted understanding of audience engagement. Therefore, we define audience engagement as a number of different behaviors that are theoretically rooted in different kinds of motivations based on previous studies and theory. We have identified four different dimensions of audience engagement: information selection, emotional responses, sharing, and conversations. In the following, we describe how these four dimensions are measured using eight different outcomes.

The outcome variables are measured either as counts or proportions. Generally, metrics based on the content and structure of the comment-section are treated as proportions while the rest are counts. While the proportions may produce outliers in case of posts with very few comments, the advantage of using proportions rather than counts is that it allows us to account for the overall volume of engagement, and as such avoid post popularity to determine too much of the variance.

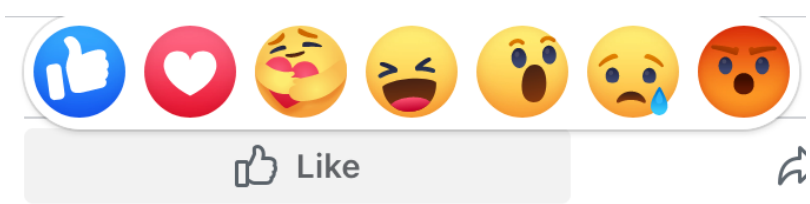
Information Selection

One dimension of audience engagement is the behavior of information selection. In other words, it is behavior where the audience actively chooses to read, view, or expose oneself to the news content. As described in Section 2.3.3., this behavior might be related to a motivation of wanting to obtain information or knowledge about the news content. As an empirical measurement of the dimension of information selection, we use the number of times someone has clicked on the link on the shared article. All posts on Ekstra Bladet's Facebook page contains a link to an article on their website, ekstrabladet.dk. By using meta-tags in the HTML-header on their webpage, Ekstra Bladet defines which title and picture should be used when sharing a link to the page on Facebook. In this way, the post is formatted with the correct title and picture from the article (see Figure 1). To our knowledge, only one other very recent study has used this kind of data in relation to social media engagement (Robertson et al. 2023).

Emotional Responses

Another dimension of audience engagement is tied to the emotional responses to the news content. For this engagement, the underlying motivation might be to interpret or decode the news content and consequentially a specific emotion or opinion might appear. As described in Section 2.3.4., emotional responses usually refer to felt engagement rather than a behavioral engagement. However, Facebook has enabled the manifestation of the felt engagement into behavioral engagement by making it possible to react with an emoji to the content. Therefore, this study uses the total number of reactions on each post as an empirical measurement of emotional responses. From 2016, several reactions representing different feelings were introduced in addition to the traditional like (Meta 2016). Currently, it is possible to react on Facebook with one of the reactions named: like, love, care, haha, wow, sad, and angry. Figure 2 below shows the emojis representing the possible reactions on Facebook. Unfortunately, the care-reaction is not available in the API, from which we collect the data, and therefore we cannot use it in our analysis.

Figure 2: Reactions on Facebook



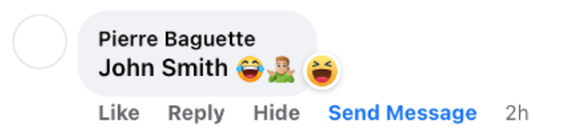
Some studies have examined how different reactions signify and represent different kind of emotional responses to the content, while others combine the total count of reactions as a measure of general valence or emotional arousal (León & Trilling 2021; Heidenreich et al. 2022). Although it could have been interesting to examine how different kinds of emotional responses might differ in their relation to news content, we chose to only include an aggregated count of all reactions as a measure of general emotional valence.

Sharing

Yet another dimension of audience engagement is the behavior of sharing new content. As described in Section 2.3.5., sharing might be related to different kinds of motivations. If sharing is directed towards one's entire social network, it might be related to gaining social status, while sharing behavior directed at a specific person might be related to phatic sharing that is a way of maintaining specific social ties. To capture these two types of sharing, this study includes two different measurements of sharing behavior: 1) the number of times a post has been shared onto a user's feed, and 2) the proportion of mention comments in the comment section.

Sharing a post on Facebook means that the post is shared on your own profile, and it is likely to appear in your friends' feed. It is not directed at specific people, but it will be shown to your entire network of friends. In addition to this, we also introduce a second novel measurement of the proportion of comments that can be understood as a mention comment. When writing a comment to a post, it is possible to tag other users, and they will get a notification that they have been mentioned in a comment. Some comments do not contain any supplementary text other than perhaps an emoji or two, and we argue that these comments are a different type of comment than regular comments – a different method for engaging with content in a specific relational manner. Figure 3 below shows an example of such "mention."

Figure 3: Example of a mention comment



These mention comments represent sharing, but in a different way than when sharing the post to your own feed. Mention comments are directed towards a specific person as a way of telling the person that this content is particularly relevant to the person. In this way, it is reminiscent of the idea of phatic news sharing described by Duffy & Ling (2020), whereas sharing the post to your own timeline might to a larger degree represent a sharing-behavior directed at self-expression, social status, or informational sharing (See Section 2.3.5.).

Conversations: Volume, Reciprocity, and Respect

The final dimension of audience engagement included in this study is the behavior of having conversations about news content. As described in Section 2.3.6., there can be many different motivations related to the behaviors of discussing news content. First of all, there might be motivations that are related to the general behavior of actually having a conversation rather than lurking or keeping opinions to oneself. However, this motivation relates only to the volume of conversations and not the content of the comments or the quality of conversations that is required in the theories of deliberative democracy. The presence of comments and conversations could signify a motivation to express opinion, but it is different motivations that relate to how deep or respectful the conversations are. Furthermore, the behavior of having conversations might also be motivated by sincerity, empathy, or respect to engage with each other, or it might be motivated by disrespect, anger, or strategic motivations. Thus, the dimension of audience engagement of having conversations is operationalized as four different empirical outcomes in this study inspired by the study by Esau et al. (2017): the volume of conversations, the reciprocity of conversations, and the disrespect and respect of the conversations.

The volume of conversations is measured empirically using the number of comments on each post. The count of comments also includes reply comments (when a comment is a reply to another comment or reply rather than a comment on the post itself) and mention comments. This outcome is the measure of the quantity of comments, while the remaining measure different kinds of qualitative indicators. While the measurement of volume is not a part of Esau et al.'s original dimensions, we argue that it is an important prerequisite since it may indicate both that a broader audience is engaged, and more diverse opinions are shared.

The reciprocity can be understood as the depth of the conversation, e.g., to which degree the comments address other comments. To measure reciprocity in this study, we use the proportion of reply-comments out of all comments. Replies are different from ordinary comments, as they are a response to another comment or reply, while comments can only be responses directly to the post. In our analysis, we do not distinguish between replies that are directed at other replies or replies that are directed at comments. The share of replies is generally a representation of how nested the conversation in the comment section is, i.e. how much dialogue takes place.

To measure disrespect and respect of conversations in this study, we use the proportion of comments with offensive language and the proportion of comments with recognizing language. In previous studies, respect has only been understood as the absence of offensive or hateful language, but other studies have argued that positive aspects of respect should also be included such as comments that contain constructiveness, empathy, or recognition (See Section 2.3.6.).

To create a measure of how many comments contain offensive or recognizing language, we use two different models developed by Analyse & Tal (2021) to detect these linguistic traits. Multiple models for detecting offensive language in Danish have been developed (Sigurbergsson & Derczynski 2019), while only one model for detecting recognition in Danish exists. In Analyse & Tal's work, recognition is defined as a complex concept comprised of statements of empathy, praise, or openness, targeted towards another human being (Analyse & Tal 2021b). They draw on a broad range of literature, including Kierkegaard, Hegel, and Honneth, highlighting relationships and respect as important aspects (ibid:14b). As a part of their operationalization, they further define eight forms of recognition: praise and agreement, empathy, acknowledgment of other views and arguments, curiosity, openness, expression of susceptibility or self-doubt, expression of desire for dialogue, trust, and ritual recognition. On the other hand, offensive language is defined as any stigmatizing, offending, stereotyping, or threatening utterances (Analyse & Tal 2021a).

Both models are based on a Danish pretrained version of the transformer model architecture, Electra (Højmark-Bertelsen 2021; Clark et al. 2020). Transformer models are state-of-the-art deep learning architecture for dealing with text data (Wolf et al. 2020). The Electra model is pre-trained on a large quantity of text, where the task is to predict masked words in the text. By doing this, the model gains a numerical representation of text in general, which can then be used for other tasks, such as classification. A standard way of evaluating classification models is by using F1-scores in which zero is the lowest value and a score of 1 would be a perfect model. In our case the macro average F1 score is used as a metric to evaluate the performance of a multi-class classification model. It is calculated by first computing the F1 score for each class separately and then taking the average of all the F1 scores. In other words, macro average F1 score gives equal weight to each class, regardless of its size or distribution. Both models by Analyse & Tal have a performance around 0.8 measured with a macro average-F1-score (Analyse & Tal 2021). Figure 4 and 5 below show examples from our data of predictions of both comments with offensive language and recognizing language.

Figure 4: Example of a comment with offensive language

"You are so ugly which is why no one wants to hire you"

Figure 5: Example of a comment with recognizing language

"John Smith in any case, it seems to have accelerated a lot in the past few months. But yes, I totally agree."

We have manually inspected samples of the predictions from the models, and there are a few nuances to consider. For one thing, a comment can contain both offensive language and recognition at the same time. An explanation of this might be that a comment can contain both anger towards one person and empathy towards another person in the same argument. In addition to this, a limitation of these classification models is that they do not take the context of social relations or the other comments in the thread into consideration. We discuss this limitation further in Section 5.3.1.

Subconclusion: Outcomes

In this section, we described how our multifaceted understanding of audience engagement has been operationalized into empirical measurements. Table 1 below presents an overview of the four dimensions of audience engagement and their eight empirical measurements. The second column describes the possible motivations that we have considered based on previous theory and research. While extensive, this operationalization should not be seen as a coherent theory, since developing a unified framework for understanding behavior and motivations lies beyond the scope of this study. Instead, they represent possible mechanisms which we will discuss in relation to our empirical results. In the next section, we present the empirical measurements of the predictor variables as different measurements of news content.

Table 1: Outcomes

Dimension of Audience Engagement	**Possible motivations**	**Empirical Outcome**
Information Selection	Knowledge gaining or entertainment	Number of link clicks
Emotional Responses	Interpretation or opinion-making	Number of reactions
Sharing	Social status Maintenance of social ties	Number of shares Proportion of mention comments
Conversations	Expression of opinion Reciprocity or dialogue Disrespect Respect or empathy	Number of comments Proportion of reply comments Proportion of offensive comments Proportion of recognizing comments

3.3.2 Predictors

The predictors in the analysis are the news content characteristics from news value theory and related concepts such as spreadability and the distinction between hard and soft news (see Section 2.4.). In most previous studies these news content characteristics have been manually labelled, but in this study, we take a different approach, which allows us to create a much more comprehensive dataset (See Section 3.1). In the following section, we describe how each news content characteristic is operationalized in our analysis.

Timeliness and Unexpectedness

The news content characteristic of timeliness refers to the article containing something that is new, recent, or ongoing. In the articles by Ekstra Bladet, it is common to refer to stories that are ongoing by writing *"LIVE"* in the headline or *"Opdateres"* (Eng: is updated) in the subtitle or accompanying message on Facebook.

To construct this measurement, we use regex (regular expressions - a way of creating structured pattern matching for text content based on a sequence of characters) to check whether the title, subtitle, or message (the added description in the Facebook post) contains any of these words. In the regex-matching, the casing of the letters is ignored. We do not check the body of the article, as it would return too many false positives, where the word could be used in different contexts. Furthermore, the title and subtitle represent a resume of the content, and it is often also where the framing and relevance of the article is most clear (Dor 2003).

For the news content characteristic of unexpectedness, we use a similar approach. Here, we define a regex to check the title, subtitle, or message for any of the words *"chok"* (Eng: shock), *"overraskelse"* (Eng: surprise), *"afsløring"* (Eng: revelation), *"sensation"*, *"usædvanlig"* (Eng: unusual).

Geographical and Cultural Proximity

Geographical and cultural proximity means that the news content is relevant or near the audience by using either geographical or cultural references. In order to measure whether the article content contains such references, we draw on techniques from natural language processing and use a machine learning model trained on the task of named entity recognition (NER). NER is a technique to classify whether each word in a text represents a predefined label such as persons, geographical locations, or organizations. Figure 6 below shows two examples of article titles and subtitles with NER predictions.

Figure 6: Examples of NER classification of title and subtitles

The label PER is persons, LOC is locations, ORG is organizations, and MISC is miscellaneous.

The specific model we use is a transformer-based model trained by Ekstra Bladet, which achieves an F1-score of 0.93 on a test-dataset of articles from Ekstra Bladet. As geographical proximity, we match the predicted geographical locations with a list of Danish geographical entities extracted from Danmarks Adressers Web API (DAWA). Thus, we argue that an article contains content that is geographically near if it contains a Danish geographical location. For cultural proximity, we argue that references to organizations could be used as a novel measurement. Cultural references vary from individuals, and therefore it might be difficult to determine the general cultural proximity of a news story based on the entire possible population of readers. However, when articles reference a specific named organization in the headlines, it could be the name of a sports club, a company, or an interest organization, and to do so might invoke a sense of a shared cultural frame.

The separation of cultural and geographical proximity into two different measurements is supported by our talks with Ekstra Bladet's social media team (see Section 3.5.3. for further elaboration). As an example, one of the social media editors from Ekstra Bladet explained how they would highlight news stories differently: when referring to a news story about an incident in a church in a Danish town, Ribe, they argued the significance of mentioning Ribe to capture geographical proximity. On the other hand, if something happened in a McDonalds in an American city, the fact that it happened in a McDonalds would be emphasized, since this is the cultural reference to which people can relate to. In this case, the Danish town Ribe would match a Danish geographical location, while McDonalds would match the entity of an organization and thus cultural proximity.

Personalization

The referencing of persons in news content refers to both the news values of eliteness and non-eliteness. On the one hand, referencing people that are famous or have high social status might drive relevance in some contexts, and on the other hand referencing non-elite actors, who the audience can relate to, might also drive relevance in other contexts. To measure the references of persons in the article content, we also use the technique of NER. Examining the frequency counts of the extracted matches, we see that they can mostly be interpreted as elite people. Even the persons that only appear once in an article headline or subtitle are often famous to the general Danish public. Therefore, we argue that this measure is primarily an operationalization of personalization (elite). We have tested alternative ways to measure referencing of non-elite person in the text, but the quality was unsatisfying. As a consequence, we do not use the news value of non-elite personalization in this analysis, which is a limitation to the study. Instead, we only include eliteness, which we will just call personalization in the remaining sections.

Negativity and Positivity

The news content characteristics of negativity and positivity can be tricky to operationalize. In previous research, different concepts such as sentiment, emotionality or valence are used. Whether content is positive, negative, or neutral can be understood as both explicit and implicit (Van de Kauter et al. 2015). By explicit, the content itself contains language that can be interpreted as negative or positive. On the other hand, implicit implies that the wording itself can be neutral, but that the content or topic refers to something that is negative or positive. Therefore, we argue that negativity and positivity can both be based on the topic or the style of the news content. For negativity, we are able to construct measures based on both the topic and style, while we are only able to construct measures based on the style for positivity.

The measurement of negativity based on the topic is made using a machine learning model predicting the topics of the article. This model is a transformer-model trained by Ekstra Bladet, and it predicts the highest probable topics of the article out of a list of 21 predefined topics. On a test-dataset of articles, the model achieves an F1-score of 0.81. We define that the news content contains negativity based on the topic when the model predicts any of the topics: catastrophe, conflict and war, or crime. These topics are inherently negative, while we were not able to define any topics as exclusively positive.

To construct a measurement of negativity and positivity based on the style, we evaluate multiple different approaches. Sentiment classification is a large area of research within the field of natural language processing, although it has mostly been applied to texts with explicit expressions such as product reviews or social media, but to a less extent news content (Hamborg & Donnay 2021). As a consequence, no available sentiment classification models pretrained on the domain of news content in Danish, and we therefore choose to use a model pretrained on a different domain. To evaluate which approach would be optimal for this specific task, we labelled a sample of 500 articles from our dataset to use as a test dataset. Previous annotation-schemes for sentiment have been defined as attitudes towards a specific target. We argue that this is less relevant in the domain of news content, and that a more suitable definition is to consider sentiment as the imagined attitude of the author of the text (Hamborg & Donnay 2021:1666). We use this definition for annotating the test dataset. We use only the text from the title and subtitle of the article, as this headline is understood to contain the discursive framing of the article (Dor 2003). First, both authors labelled 100 articles, with an achieved inter-coder-reliability of 70%. We then discussed the diverging cases, and subsequently labelled the 400 remaining articles. The relatively low inter-code-reliability could possibly have been improved if the coders had undergone a more extensive training process, but since producing a high-quality benchmark dataset is not the scope of this study, we found the reliability acceptable.

On this test set, we evaluated five different models: AFINN which is a lexical approach to sentiment analysis (Nielsen 2011), SENDA (Platform Intelligence in News 2022) and BERT Tone (Alexandra Instituttet 2023) which are transformer-based sentiment classification models, ScandiNLI which is a natural language inference model (Nielsen 2023), and finally GPT-3.5-turbo (OpenAI 2023) which is a transformer-based large language model (LLM) that we prompt-engineered for the sentiment classification task. These models represent different approaches to sentiment classification, and therefore we can evaluate which approach is most useful for our specific task and domain. Section 8.2. in the Appendix shows the performance of each model on our test set. ScandiNLI has the highest F1-score (0.70) – just a slightly better performance than GPT-3.5-turbo – and therefore we use this model to predict on our full dataset for analysis. Although the best performing model does not yield an astonishing performance, it is at the same level as the manual labelling of sentiment, and we therefore find it acceptable for the present study.

Impact

The news content characteristic of impact refers to content that has significant consequences or extraordinary relevance. In this study, we argue that the concept of breaking news is a good measurement of when content is of significant impact. The concept of breaking news can be traced back to Associated Press in 1906, who coined the concept as *"news of transcendent importance"* (Pennington 2021:214). In the same way, we argue that content labelled as breaking still represents the most impactful or significant news stories. In our dataset, it is defined by the editors and journalists of Ekstra Bladet when an article is considered breaking, and we get that information from Ekstra Bladet's database. There are no formal guidelines or rules for when news content should be labelled as breaking news, which falls in line with the classical idea of breaking news as something that *"you know when you see it"* (Pennington 2021:214). If an article is labelled as breaking news, the article is automatically presented with a yellow background on the website, and users of their app will get a push-notification. However, there are not any automatic differences on the shared article on Facebook, but here the framing is made by the social media editors, who often write "BREAKING" in the accompanying message of the shared link.

A limitation of using breaking news as a measure of impact is that some also interpret breaking news as related to the news value of timeliness. The idea of breaking news is not only that it is of significant societal impact, but also that it has just happened (Pennington 2021:214). However, we argue that in our case most of the news content on Ekstra Bladet has relatively just happened, and that the importance is on what they emphasize when presenting the news content.

Spreadability

The news content characteristic, spreadability is specifically used for news content on social media. Spreadability refers to news content that is optimized for sharing, commenting and remixing in various ways (Jenkins et al. 2013; Harcup & O'Neill 2017). News content with spreadability is content that directly prompts the audience to interact with each other instead of just seeking individual attention (Jenkins et al. 2013:4). To measure spreadability, we check whether the message of the post contains a question mark at the end. Asking a message in the question have previously been shown to drive to greater user engagement (Quesnelle & Montemayor 2020). Furthermore, we argue that the question framing represents a prompt aimed directly at the audience to make them engage and interact with the post.

Hard News

The final news content characteristic included in our study is the difference between hard and soft news. In news value theory, this is often mentioned as the news value of entertainment. As described in Section 2.4.3., hard and soft news is an often used, but also ambiguously defined concept in both media studies and media organizations. In this study, we define hard and soft news in terms of the topic of the news content rather than style or framing (Reinemann et al. 2012:234).

When hard or soft news is defined by topics, it refers to whether the news content address heavier topics of societal relevance such as politics, economy, or science on the one hand or topics related to entertainment such as lifestyle, celebrities or similar on the other. To measure hard news topic in this study, we use the machine learning model trained by Ekstra Bladet to predict topics of the article that we also use for measuring negativity based on the topic. Out of the list of 21 pre-defined topics, we argue that hard news topics are: business, politics, society, health, science, and economy, while the remaining topics are more likely to be soft news topics.

Subconclusion: Predictors

In this section, we described how the news content characteristics are operationalized into empirical measurements. In contrast to previous studies, we do not rely on manual labelling of the news content but use methods from the field of natural language processing to label the news content. The strength of this approach is that it can be used on huge datasets that would not be feasible to label by hand. Table 2 below summarizes the concrete operationalizations of each news content characteristic that we use as predictors in our analysis. All measurements are dummies.

Table 2: Predictors

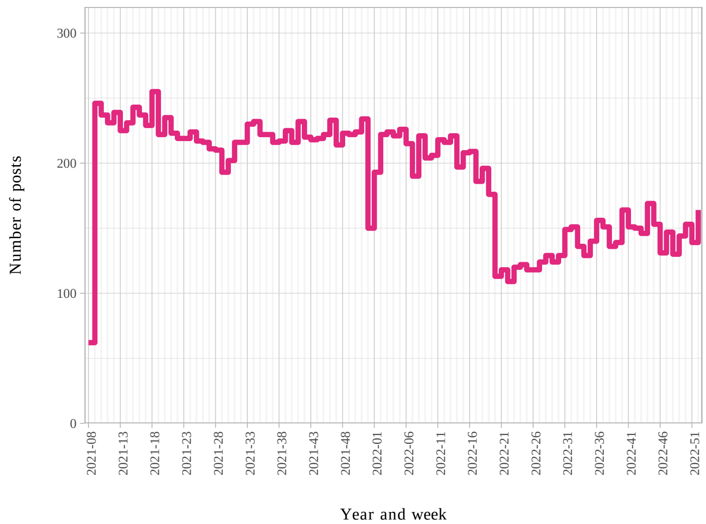
News content characteristic	Empirical measurement
Timeliness	Contains any of “LIVE”, “opdater” in the message.
Unexpectedness	Contains any of “chok”, “overraskelse”, “afsløring”, “sensation”, “usædvanlig”,”mirakuløs”, “opsigt”, ”vild” in title.
Geographical Proximity	Contains a location (LOC) NER-tag matched with a list of Danish locations in either title or subtitle.
Cultural Proximity	Contains an organization (ORG) NER-tag in either title or subtitle.
Personalization (elite)	Contains a person (PER) NER-tag in either title or subtitle.
Negativity (topic)	Has predicted topic of either “konflikt og krig”, “katastrofer”, “kriminalitet”.
Negativity (style)	Has predicted “negative” sentiment (ref. neutral)
Positivity (style)	Has predicted “positive” sentiment (ref. neutral)
Impact	Is “breaking news”
Spreadability	Message contains “?”
Hard news	Has predicted topic of either “erhverv”, “politik”, “samfund”, “sundhed”, “videnskab”, ”økonomi” (ref. soft)

3.3.3 Control variables

In our analysis, we include a few additional measurements that are important to control for. First of all, we control for the fact that the article may be behind a paywall. This restrictiveness to the full content of the article could influence the different levels of engagement. Furthermore, we include two control variables related to different time periods. We control for the time of day, i.e., posts posted PM or AM. We also control for the day of the week, by including a binary variable for weekends or weekdays. We include these control variables, since both engagement and the selection of news articles may vary for both time of day and day of week, which is supported by our talks with the moderators (see Section 3.5.3.).

Another possible source of bias is the internal rules and strategies for selecting of what content to post among the social media editors at Ekstra Bladet. For example, the social media team at Ekstra Bladet changed their social media strategy from the 1st of May 2022 deciding to reduce the frequency of sharing posts on their Facebook page. This can be seen quite drastically in Figure 7 below showing the number of articles posted on their Facebook page per week during the period.

Figure 7: Number of Facebook posts per week



Third parties such as researchers are commonly unaware of such internal, strategic decisions, but nonetheless these decisions might have a significant impact on the dynamics of the audience engagement. This is another example of how our collaboration with Ekstra Bladet has yielded an important background knowledge of our case of study. In order to control for this change in social media strategy, we include a control variable capturing whether the article is posted during the previous or current internal strategy.

In addition to the confounding bias by internal decisions by the media organization, there might also be macro-level influences that affect the influence of news content on audience engagement. For example, the act of holding an election is a significant societal event that has the potential to change the relation between news content and audience engagement. During an election, audiences might engage more intensely with political or societal issues than during other periods (Strömback & Johansson 2007). In the period included in our data, there was a national election, and this event could affect the audience to be more interested in news content about politics than in average during the entire period. Therefore, we include a control variable for whether the article is posted during an election period or not. Table 3 below summarizes the control variables included in our analysis.

Table 3: Control variables

Control Variables	Operationalization
Pay-wall	From Ekstra Bladet's database
Time of day	Is posted from 12.00-00.00 (PM) (ref. posted from 00.00-12.00 (AM))
Day of week	Is posted in the weekend (SAT, SUN) (ref. posted on a weekday (MON,TUE,WED,THU,FRI)
Strategy Change	Article has been posted after strategy change (from 1st of May or later) (ref. before)
Election Period	Article has been posted during a national election period (5th of October 2022 to 1st of November 2022) (ref. outside)

3.4 Methods

In this section, we describe the methods that we use to analyze how news content influences audience engagement. In the first part, we consider different distributions and our choice of regression design as proof of association. In the second part, we describe our methodological approach of evaluating validity through theory-based data analysis.

3.4.1 Regression Design

In order to analyze the influence of news content on audience engagement, we employ eight different regressions – one for each outcome of audience engagement. For all eight regressions, we use a multiple linear regression estimated with ordinary least squares (OLS). To accommodate for heteroscedasticity, we calculate robust standard errors. Multiple linear regression with OLS is perhaps the most common regression model, and while it serves as a versatile tool, there are also a couple of limitations of this regression design. For example, linear regression assumes that a unit increase of the predictor leads to a constant change for the outcome. Thus, it is also assumed that the distribution of the outcomes can be any value from $-\infty \rightarrow \infty$. However, that is not the case for any of our outcomes in the analysis. Instead, four of our outcomes are counts, i.e., they can range from $0 \rightarrow \infty$, but only integer values, and the remaining four outcomes are proportions, i.e., they can range any value from $0 \rightarrow 1$. For example, it is not possible to have a negative number of comments or more than 100% offensive comments on a post. In principle, it might be more suitable to use other kinds of regression models such as Poisson-regression for the count-distributed outcomes, and a Beta-regression for the proportion-distributed data.

Considering the distribution of our outcomes, it is also apparent that all the measurements of audience engagement are far from normally distributed, and often highly skewed towards zero. The distributions of the outcomes tend to be power-law-distribution with a small minority of observations having extremely high values compared to the majority of observations. A limitation of linear regression is that it can be prone to outlier observations that might be too influential on the coefficient estimates (Van der Meer et al. 2010). However, we argue that these outlier observations do not represent data errors, but rather extreme values as part of the distribution, and therefore we should not exclude them from our analysis.

As a consequence of these limitations, the linear model with OLS might not be able to provide the best possible fit for our data. In our analysis, this can be seen in the R_2-values that are quite low. Assessing alternative regression models to potentially achieve a more optimal fit for our outcome distributions would have been valuable. Nonetheless, such an exploration is beyond the scope of the present study. Furthermore, we argue that the linear regression also has an advantage in terms of explainability, as we are able to express the coefficient estimates in absolute values rather than relative values.

As described, our dataset contains all articles shared during the period of analysis, and therefore the analysis is based on the complete population. Usually, this would imply that there is no need to infer from a sample to a population, and statistical significance would be irrelevant. However, we are still interested in generalizing from the population to a superpopulation, i.e., articles shared on Facebook before and after our period of study (see Section 5.4.). Therefore, the analysis will still use measures of statistical significance to evaluate the associations.

3.4.2 Theory-based Data Analysis

While the empirical research design of this study is correlational, the objective of the study is explanatory – meaning that we want to examine whether news content characteristics can causally explain the audience engagement of the shared articles. However, the causal mechanism cannot be fully confirmed based on our empirical setup, and the causal validity of our results should be evaluated based on synergy between theory and empirical results (Aneshensel 2013:20-21; Agresti & Finlay 1997).

Drawing on the approach of theory-based data analysis by Aneshensel (2013), we understand our empirical results as the correlation of measured variables that we use to make probable the underlying mechanisms of the theoretical constructs (Aneshensel 2013:5). Studies using big data and new methods from the field computational social science have been criticized for being too inductive, too correlational, and having a vague theoretical foundation (Cowls & Schroeder 2015). To address these concerns, our study prioritizes a solid and comprehensive theoretical foundation to base our empirical results on more than just correlational estimates. Following Agresti and Finlay (1997), empirical association is only the first of three conditions that must be fulfilled in order to claim a causal relationship. To validate a causal effect, one must also consider a correct theoretical temporal sequence of the phenomena and the elimination of alternative explanations of the association (Agresti & Finlay 1997:302-303). In Section 5.2., we discuss our empirical results in relation to the theoretical temporal sequence, and in Section 5.3. we consider any alternative explanations of the findings.

3.5 Background

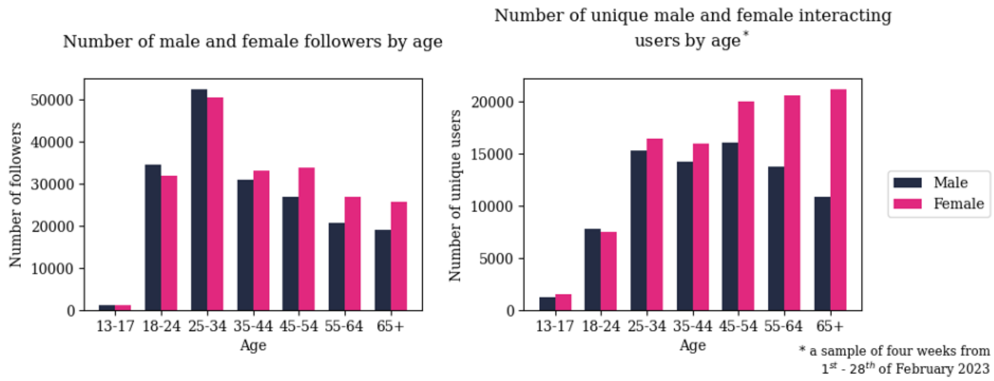
In this section, we examine the background of the case and empirical analysis. While not directly related to our research question, we argue that this descriptive information about the media and audience context is important for the validity of our main analytical findings. First, we consider the demographic distribution of Ekstra Bladet's audience on Facebook. Secondly, we examine a potential selection bias by comparing the characteristics of the articles shared on Facebook with all articles published by Ekstra Bladet. Thirdly, we describe Ekstra Bladet's strategies for engaging with their audiences on Facebook, and finally, we consider how much of the Facebook engagement with Ekstra Bladet's content we capture through their own Facebook page.

3.5.1 Ekstra Bladet's Audience on Facebook

Our specific case of study is the relation between the Danish media, Ekstra Bladet and their audiences on Facebook. In order to interpret the analytical findings and possibly generalize or transfer the findings to other cases, it is important to characterize the specific audience of Ekstra Bladet.

The Facebook page of Ekstra Bladet has a little over 400,000 followers (as per the 1st of April 2023). 48% of the followers are men, while 52% are women. Figure 8 below shows the distribution of age and gender for both followers of the Facebook page and followers actively engaging with content on the page from a sample of four weeks from 1st-28th of February. As we only have access to this aggregated demographic data, and since Facebook's API documentation is inadequate, it is unknown to us how Facebook specifically defines active engagement in this context. However, it is likely that their definition overlaps with the measurements included in our definition of audience engagement.

Figure 8: Ekstra Bladet's Facebook audience demographics



As Figure 8 shows, Ekstra Bladet has very few followers, who are younger than 18 years old, while the most frequent age group is audiences between 25-34 years old consisting of about 25% of all followers. Fewer and fewer followers are found among older age groups, especially for men. There are noticeable different demographic characteristics when considering audiences, who just follow the page and audiences, who actively engage with the content. When it comes to audience, who actively engage with the news content, 43% were males, and 57% were females. Especially for the ages 45 to 65+, there is a large overrepresentation of women compared to men. An explanation of the demographic difference between audiences, who follow Ekstra Bladet, and audiences, who actively engage with the news content, might be that Ekstra Bladet's content might cater more to this specific part of the audiences. However, it might also be a result of different social media usage patterns. For example, younger audiences are increasingly present on different social media than Facebook - especially new social media such as TikTok and Snapchat are increasingly popular − while older audiences still primarily use Facebook as their main platform (DR Medieforskning 2022:14; Slots- og Kulturstyrelsen 2020:26). Furthermore, studies on Facebook behavior have been shown that women generally tend to be more active than men (McAndrew & Jeong 2012).

3.5.2 The Sample of Articles posted on Facebook

In the period of study, Ekstra Bladet published 80,285 articles on their website, but our dataset only contains the 18,350 articles that have also been shared on Facebook. Thus, out of all articles published on the website of Ekstra Bladet, approx. 20% are shared on their Facebook page. As the responsibility for selecting articles to share on Facebook is held by the social media editors, it is possible that there are certain kinds of articles that are more likely to be shared on Facebook, which might represent a potential selection bias. However, it is important to note that the articles shared on Facebook are our population of interest, as the study examines audience engagement on social media specifically. In Table 4 below, we present summary statistics of the presence of news content characteristics that we use as predictors in the analysis while comparing the full sample with the articles posted on Facebook.

Table 4: Descriptive statistics for all articles and only articles shared on Facebook

Variable	Article published on website	Articles shared on Facebook	X2-test
Timeliness			X2=60.168***
... 0	91%	89%	
... 1	9%	11%	
Unexpectedness			X2=104.722***
... 0	95%	94%	
... 1	5%	6%	
Geographical proximity			X2=28.691***
... 0	88%	87%	
... 1	12%	13%	
Cultural proximity			X2=6.118**
... 0	99%	99%	
... 1	1%	1%	
Personalization			X2=0.19
... 0	99%	99%	
... 1	1%	1%	
Hard News			X2=786.276***
... 0	58%	47%	
... 1	42%	53%	
Negativity (topic)			X2=54.648***
... 0	75%	72%	
... 1	25%	28%	
Negativity (style)			X2=212.298***
... 0	78%	73%	
... 1	22%	27%	
Positivity (style)			X2=61.917***
... 0	91%	93%	
... 1	9%	7%	
Impact			X2=1402.972***
... 0	97%	90%	
... 1	3%	10%	

Statistical significance markers: * p<0.1; ** p<0.05; *** p<0.01

As seen in Table 4, most of the news content characteristics have a larger proportion among the articles shared on Facebook. For example, 9.9% of articles shared on Facebook contain the news value of impact - defined as news articles that are breaking news - compared to only 3.4% among all articles published. For the distinction between hard and soft news, 53.2% of articles shared on Facebook are around hard news topics such as politics, economy, health and more, while for all articles from Ekstra Bladet only 41.7% of articles are hard news topics.

From Table 4, it is also apparent that some of the news content characteristics are quite sparse. For example, it is less than 1% of the news content than contains cultural proximity or personalization. Thus, there are only around 110 out of 18350 articles in our dataset that contains cultural proximity.

For most of the news content characteristics except positivity, personalization, and cultural proximity, we see that the articles shared on Facebook contains more of every article trait. While there is a selection process in the journalistic production phase before articles are published, these differences show that there is also a selection process when considering which articles to share on Facebook. Only the most relevant stories become news articles, and only the most relevant news articles are shared on their Facebook page.

Furthermore, it seems that the selection criteria are likely to also be based on the news content features that we include in this study.

3.5.3 Social Media Strategy

As part of the collaboration of the study, we have had access to talk with the people at Ekstra Bladet, who are responsible for posting and moderating content of their Facebook page. The strategies and norms for administering their Facebook page are also relevant to our empirical study as they influence the selection and framing of news content.

Based on our conversation with Ekstra Bladet, the strategy for what articles is posted on Facebook is mostly based on the intuition of the responsible social media editor. According to the editor, the intuition or feeling for what content will be engaged with, is has been developed through experience of posting content for a long time, and they only sporadically use different analytics platforms to gain an understanding of what performs well. Furthermore, there is no written or formal strategy for posting content.

The social media editors describe that they think a lot about what kind of content to post at specific times. According to them, certain content is more favorably received during morning or evening hours, whereas other content is more suitable to post on the weekend rather than a weekday. In terms of determining criteria for selecting articles to share on Facebook, the editors often mention traits that are reminiscent of news value theory such as geographical, cultural proximity, or hard news. They also describe that they often consider when to share articles that are hidden behind a paywall – those that can only be read with a subscription. The descriptions of the social media strategy provided by the social media editors at Ekstra Bladet further emphasize the importance of controlling for variables such as the time of day and week when the article is posted, as well as whether it is hidden behind a paywall (See Section 3.3.3.).

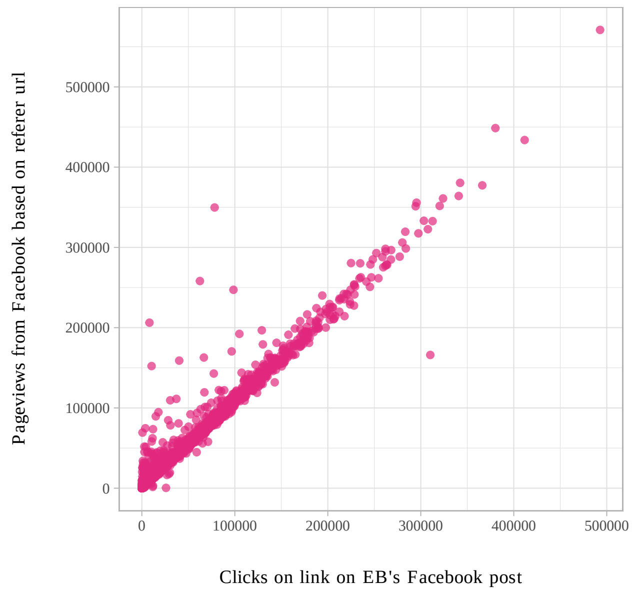
In addition to the social media editors, we have also talked with one of the Facebook moderators who review and delete comments that do not adhere to the rules of communication according to Ekstra Bladet. According to the written description on Ekstra Bladet's Facebook page, they do not accept comments that are spam or that have a commercial nature. As described by the moderator, there is also a great focus on comments that are hateful. There is a rule of thumb that the debate is allowed to be heated, but comments are not allowed to be personal attacks. Comments that do not adhere to these guidelines will be deleted without a warning. On Facebook, it is also possible for moderators to hide comments, so that one the writer can see the comments, but this feature is not consistently used among the moderators. The moderator states that the type of shared articles that require moderation can vary significantly based on what kind of news content that the article contains. The unique insights gained from engaging with the social media editors and the moderator have served as useful background knowledge for our case of study as well as strengthening our choices of empirical measurements.

3.5.4 Audience Engagement on Other Parts of Facebook

Another question about the coverage of our dataset is whether it captures all parts of the audience engagement on Facebook. The news articles are not only engaged with on Ekstra Bladet's Facebook page but may also be engaged with through the shared posts or direct link sharing in private messages. In our data, we are not able to include those kinds of audience engagement on social media. However, by using supplementary data from Ekstra Bladet, we are able to briefly examine how much audience engagement with the news articles exists on their Facebook page in comparison with other parts of Facebook.

When visiting an article on Ekstra Bladet's website, the referrer (the URL of the previous website from which the link was clicked) is tracked, enabling us to calculate the number of pageviews from persons, who have clicked to the article page from facebook.com. By comparing the number of pageviews from all of Facebook with the number of link clicks on the shared article, we find out that ~88% of all clicks from Facebook to these articles are from the posts on Ekstra Bladet's Facebook page. In Figure 9 below, we show the number of link clicks on the posts compared to the number of pageviews from Facebook to each article.

Figure 9: Scatterplot of Facebook pageviews and clicks on shared link



As seen in Figure 9, only a few articles have a larger proportion of pageviews to the article that does not come from the shared link on Ekstra Bladet's Facebook page. There are also a few articles that have more link clicks than pageviews of the article. The reason for this is likely that users might click on the shared link, but because of internet connection or server issues the request to the article doesn't load – thus not being registered on Ekstra Bladet's website. There are a few articles that have almost twice the number of link clicks than article pageviews. During the period, a few events have caused quick, but massive spikes in pageviews on Ekstra Bladet's website, which in a few cases has caused the website to be unable to load correctly. These few outliers represent these cases - for example the death of reality star Sidney Lee, and the heart attack of football player Christian Eriksen.

Based on this measurement, we argue that most of the audience engagement with the articles happens with and on the posts from Ekstra Bladet's own Facebook page. There is of course also the question whether the observed audience engagement can be generalized onto other audiences or other social media than Facebook. However, this is a question of discussion that we will return to in Section 5.4.

3.6 Conclusion: Data and Methods

In this section, we describe the data and methods we employ in the study to answer our research question. To bridge the two empirical limitations from previous studies, this study uses a comprehensive dataset that we were able to collect by collaborating with Ekstra Bladet – the largest Danish tabloid media. The dataset has two primary qualities corresponding to each of the previously described limitations of previous research. Instead of only relying on a sample of news content that could suffer from unknown biases or missing representativity, we are able to include the entire population of articles shared on Ekstra Bladet's

Facebook in almost a period of two years. The ability to include the entire population of 18,350 shared articles is also possible, because we utilize machine learning techniques rather than manual hand-coding to label the news content characteristics. The second quality of the dataset is that we are able to access a multitude of features of audience engagement on Facebook by collaborating with Ekstra Bladet. In this way, audience engagement is operationalized as a multifaceted phenomenon with eight different empirical measurements of four different dimensions of audience engagement on social media. To analyze our research question, we employ eight multiple linear regressions estimated with OLS and robust standard errors. In each of the regression, our 11 predictors of news content characteristics are included as well as five control variables mitigating confounding effects of time, paywall access, and relevant consequential events such as an election and an internal strategic change at Ekstra Bladet. Finally, we consider some different important background factors, including information about the demographic distribution, potential selection bias, and Ekstra Bladet's strategies for engaging with followers and moderating content.

4 Analysis

In the following section, we present the answers to our research question: *"How does the content of news articles influence audience engagement on social media?"*. As we discuss, there is a gap within studies trying to answer this question, as most studies have relied on small samples of shared news content which might suffer from bias or non-representativity. Our study bridges this gap by including all articles shared on Ekstra Bladet's Facebook page for one year and 10 months. In addition, very few studies have treated audience engagement as a multifaceted phenomenon. Our study does not just operationalize engagement as simple popularity cues, but incorporates several dimensions of audience engagement including measures of informational selection, emotional responses, sharing, and conversations around news content. In this way, this study extends previous research by also examining how different kinds of news content might result in different kinds of audience engagement on social media. In the next sections, we describe the results for each of the measures of audience engagement, while discussing its theoretical implications.

4.1 Clicking on the Shared Link

As described in Section 2.3.3., one dimension of audience engagement is information selection, which we measure through the choice of clicking on the news article shared in the post. In the Facebook post, the audience is exposed to a snapshot of the article content in form of the title, a picture, and an accompanying caption written specifically for the Facebook post. In this way, clicking on the link to read the article on the website of Ekstra Bladet might represent a selection by the user of relevance based on the immediate exposure. Table 5 below shows descriptive statistics for the number of link clicks on each post.

Table 5: Descriptive statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Link clicks	18,350	11,840	27,002	0	1,024	9,829	492,849

As seen in Table 5, a link to the shared article on average gets approximately 11,800 clicks. However, there is a very large variance between the posts with the most and least clicks. The number of clicks on the shared link ranges from zero to almost half a million clicks, and the standard deviation is more than double as large as the mean. The distribution is heavily skewed with the majority of posts having a relatively small number of link clicks, while a minority of posts get a very high number of link clicks. Table 6 below shows the results of a regression of our predictors of news content on the number of link clicks as the outcome.

Table 6: Linear regression model

	Link clicks
Intercept	
Intercept	13535 (471)***
Predictors	
Timeliness	456 (627)
Unexpectedness	3957 (806)***
Geographical proximity	−392 (587)
Cultural proximity	−3281 (2528)
Personalization	−188 (2087)
Negativity (topic, ref. neutral)	374 (471)
Negativity (style, ref. neutral)	1313 (455)**
Positivity (style, ref. neutral)	−2340 (786)**
Impact	−2544 (675)***
Spreadability	−4353 (590)***
Hard News (ref. soft news)	−5286 (426)***
Control variables	
Posted time PM (ref. AM)	245 (399)
Posted time, weekend, (ref. weekday)	−346 (450)
Pay-wall article	4277 (3312)
Strategy Change	5724 (471)***
Election Period	−4680 (1155)***
Num. obs	18350
R^2	0.02
Adj. R^2	0.02

***p < 0.001; **p < 0.01; *p < 0.05

As Table 6 shows, several news content characteristics significantly influence the number of link clicks. The results show that unexpectedness and negativity based on the style have a positive influence on the number of link clicks, while positivity, impact, spreadability, and hard news have a negative influence on the number of link clicks.

The strongest positive influence on the behavior of clicking on the link is if news content contains unexpectedness. These articles receive on average almost ~3,900 more likes than other articles. This finding emphasizes that the audience information selection is highly driven by curiosity – when news content is framed as surprising or sensational, audiences are stimulated by a need to know. To some extent, this is in line with concepts such as "click-bait"-style headings used by many news organizations, but in particular tabloid news (Bazaco et al. 2019).

The strongest negative influence on the behavior of link clicks is news content that contains hard news rather than soft news. Articles about hard news topics such as politics, economy, etc. receive on average ~5,300 fewer link clicks than articles with soft news topics such as entertainment or lifestyle. Similarly, news content that contains high impact – identified as breaking news content – is associated with ~2,500 fewer link clicks. This finding suggests audiences more often choose to read lighter news content.

We also see that positivity of the article content is negatively related to link clicks, indicating that news content with positivity on average receives ~2,300 fewer link clicks compared to neutral news content. On the other hand, a negative framing seems to be associated with a higher number of link clicks, but here the effect size is smaller at ~1,300 more clicks. This finding is in line with previous research, providing further evidence for a form of negativity bias, where more attention is paid towards content that has a negative nature (Robertson et al. 2023). However, quite interesting and in contrast to the framing of the articles, the content pertaining to negative topics seem to have no significant impact on the number of link clicks.

Finally, if the post contains spreadability, meaning that the accompanying caption is framed as a question, it is negatively related to link clicks, on average receiving ~4,400 fewer clicks on the article. This result falls in line with the argument of Jenkins et al. (2013) that content related to spreadability is perhaps not directed at gaining attention from individuals, but rather to invoke interpersonal behaviors.

The results are interesting in relation to previous literature on seeking, selecting and obtaining knowledge from news content (See Section 2.3.3.). Many previous studies have emphasized the importance of news content in learning and gaining factual information in order to have an informed democracy. As our results suggests that the audience more often choose to read news content with soft news topics and news content that is not breaking news, one might consider, if it is problematic that the public prefers entertainment instead of reading about heavier and important societal issues. Based on our results, the behavior of selecting to read content might be more related to entertainment or curiosity than gaining factual knowledge or learning about societal conditions. This motivation of entertainment and curiosity may be particularly tied to the media's tabloid style and their audience. However, it is also important to note that we cannot know from this empirical basis if the audience obtain the same knowledge from softer or heavier topics, but we can only see that the softer topics are more popular when controlling for the other types of news content characteristics.

4.2 Emotional Responses

As described in Section 2.3.4., a behavior of audience engagement might also be reacting to news content. While there may be different reasons for reacting to a post, we argue that it could be seen as an emotional response by the user. While an emotional reaction usually exists as a feeling within the individual, it may be digital manifested as actual behavior on Facebook, where it is possible to indicate your emotional response to a post. We measure emotional responses as the sum of all types of reactions, which might represent a general emotional valence. Table 7 below shows descriptive statistics for this outcome of the number of reactions.

Table 7: Descriptive statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Number of reactions	18,350	588	1,329	0	69	562	41,961

A post receives on average 588 reactions. However, there is also a large variation as the standard deviation is 1329, and the number of reactions ranges from 0 to a maximum of 41961 reactions. This indicates that the variable follows a power law distribution, where a lot of the observations are distributed at the lower end, while a few observations are far to the right creating a long tail to the right. The 75%-percentile is 562 reactions, which interestingly enough is lower than the mean of 588. Thus, 75% of the posts have fewer than 562 reactions, while the remaining top 25% has a much larger number of reactions. Table 8 below shows the results of the regression of news content on number of reactions as the outcome.

Table 8: Linear regression model

	Number of reactions
Intercept	
Intercept	470 (23)***
Predictors	
Timeliness	−2 (31)
Unexpectedness	−54 (40)
Geographical proximity	20 (29)
Cultural proximity	−28 (124)
Personalization	77 (103)
Negativity (topic, ref. neutral)	−53 (23)*
Negativity (style, ref. neutral)	−33 (22)
Positivity (style, ref. neutral)	198 (39)***
Impact	524 (33)***
Spreadability	−59 (29)*
Hard News (ref. soft news)	5 (21)
Control variables	
Posted time PM (ref. AM)	36 (20)
Posted time, weekend, (ref. weekday)	10 (22)
Pay-wall article	−343 (163)*
Strategy Change	246 (23)***
Election Period	−174 (57)**
Num. obs	18350
R^2	0.02
Adj. R^2	0.02

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

As seen in Table 8, several news contents characteristics have a significant influence on the number of reactions. The news content characteristic of impact has the largest coefficient size, which shows that impactful news content – measured as breaking news – receives ~500 more reactions than regular news content. Thus, news content with high impact drives a higher emotional response. While impact is negatively related to the behavior of clicking on the link (see previous section), it is related to an increase in reactions. While news content with high impact, such as breaking news, has a negative influence on the number of people reading an article, it has a positive influence on the number of emotional responses. From the perspective of media's important role in an informed democracy, it might be problematic that the audiences would rather read about soft news and low impact news content, but as this result show, news content with high societal impact on the other hand drives more emotional responses. The audience might often choose to read news content for entertainment purposes, but high impact content might still leave a stronger emotional impression on the audience than other types of content.

In addition, Table 8 also shows that articles containing positivity receive ~200 more reactions than those with neutral sentiment. On the other hand, articles with negativity defined by the style receive 53 fewer reactions than neutral news content. In this way, our results suggest that news content with positivity influences audience reactions more than news content with negativity. In line with the idea of emotional contagion, the emotional framing of the article seems to influence the emotional response of the audience. However, the results here are in contrast to the previous literature, as emotional contagiousness can be seen for content containing a positive framing but not for content containing a negative framing. Yet, it is important to bear in mind that our aggregated measure of reactions captures the general valence of the emotional response, and that more fine-grained associations might be found for particular emotions such as negative news leading to more negative reactions.

The results also show that news content characterized by spreadability receives 59 fewer reactions. While having a smaller negative influence than for link clicks, reacting may be seen as an individual form of engagement and is as such not increased by the spreadability. None of the remaining characteristics of news content have an influence on the number of reactions.

The number of reactions, which has been used more commonly as a measure of audience engagement, is not influenced by news content in the same way as the number of link clicks was. Comparing the relation between the news content characteristics and these two outcomes, it is clear that the news content does not have a universal effect on audience engagement on social media. In this way, these results emphasize that audience engagement is a multifaceted phenomenon.

4.3 Sharing

In this section, we consider the dimension of audience engagement on social media related to the behavior of sharing. As mentioned, we differ between two different forms of sharing behaviors. The first is seen as a way of sharing information through the implemented share button, which allows a user to share the post to their own feed with the possibility of adding their own accompanying text. The other is a more interpersonal, targeted way of sharing measured through mention comments. Where the first kind of sharing might relate to sharing for social status or spreading information to one's entire network, the latter is a way of sharing which is directed to a specific other person that might be related to the idea of phatic news sharing. In Table 9 below, we show descriptive statistics for the two outcomes: number of shares and proportion of mention comments.

Table 9: Descriptive statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Number of shares	18,350	25	61	0	2	23	1,879
Prop. of mention comments	18,350	0.065	0.097	0	0.0067	0.081	1

From Table 9, we see that a post is shared on average ~25 times. However, there is also a large variation among the posts, where the standard deviation is ~61 ranging from a post being shared between 0 times and a maximum of 1879 times. In the comment sections of the posts, there is 6.5% mention comments on average. For the proportion of mention comments, there is also a large standard deviation of 9.7%-points. While some posts do not have any mention comments, other posts have only mention comments. Table 10 below shows the result of news content on the two outcomes of sharing.

Table 10: Linear regression models

	Number of shares	Prop. of mention comments
Intercept		
Intercept	16 (1.059)***	0.068 (0.002)***
Predictors		
Timeliness	2 (1.411)	0.008 (0.002)***
Unexpectedness	−1 (1.813)	0.001 (0.003)
Geographical proximity	2 (1.320)	0.011 (0.002)***
Cultural proximity	−4 (5.687)	−0.009 (0.009)
Personalization	−7 (4.694)	−0.033 (0.008)***
Negativity (topic, ref. neutral)	−7 (1.059)***	0.008 (0.002)***
Negativity (style, ref. neutral)	−1 (1.024)	−0.017 (0.002)***
Positivity (style, ref. neutral)	−7 (1.767)***	0.008 (0.003)**
Impact	6 (1.517)***	−0.013 (0.002)***
Spreadability	−1 (1.326)	−0.001 (0.002)
Hard News (ref. soft news)	19 (0.957)***	−0.003 (0.002)*
Control variables		
Posted time PM (ref. AM)	0 (0.897)	−0.001 (0.001)
Posted time, weekend, (ref. weekday)	−3 (1.012)**	−0.005 (0.002)**
Pay-wall article	−7 (7.450)	0.014 (0.012)
Strategy Change	4 (1.060)***	0.006 (0.002)***
Election Period	−4 (2.597)	−0.000 (0.004)
Num. obs	18350	18350
R^2	0.03	0.01
Adj. R^2	0.03	0.01

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

As Table 10 shows, two different news content characteristics, hard news and impact, have a positive impact on the number of shares – measured as sharing to your entire social network. News content with hard news topics has the largest influence on the number of shares. Those articles on average receive ~19 more shares than articles with soft news. Furthermore, news content with high impact measured as breaking news is on average shared ~6 more times. These findings indicate that sharing to your entire social network might be important for your social status, and that the audiences find societal relevance important when considering what kind of news content, they want to be associated with (Thompson et al. 2020; See also Section 2.3.5). It is possible that users who share news content to their entire social network see themselves as a kind of opinion leaders that distribute and curate the most important news to their network (See Section 2.1.2). However, we do not know the specific motivations for the users who share, but only that they tend to share more news content with impact and hard news topics.

On the other hand, some types of news content have a negative influence on the number of shares. News content with negativity based on topic gains ~7 fewer shares, while news content with positivity based on style also receives ~7 fewer shares, compared to news content with neutral sentiment. Interestingly, news content with negativity based on the style is not significantly different than those with neutral sentiment in regard to the number of shares. Nonetheless, this kind of sharing seems to be negatively influenced by emotionally laden news content. Following the idea that this type of engagement is related to social status, an explanation might be that those who spread news content do not wish to be associated with emotionally laden content.

The rest of the news content characteristics (timeliness, unexpectedness, geographical and cultural proximity, personalization, and spreadability) have no significant impact on the number of shares. The fact that spreadability – identified as news content framed as a question – is not associated with a higher number of shares may be because of the way people wish to associate and engage with the specific content. Here people are perhaps looking to spread a specific piece of information, pose their own questions, or frame it in their own way, all actions which may be less relevant if the original post is already framed with a specific question. This finding goes against the argument by Jenkins et al. (2013) about spreadability leading to more sharing of the content.

For the other outcome of sharing – the proportion of mention comments – Table 10 shows quite different results than for the number of shares. The coefficients for the proportions represent differences in percentage points and are all rather low, and as such we are not able to explain much of the present variance. However, looking at the news content characteristics, the highest positive influence on the proportion of mention comments is geographical proximity. On average, news content with geographic proximity has a 1.1%-points larger proportion of mention comments. Individuals residing in the same geographic area as the news story – here identified as any location within Denmark – may possess more familiarity and understanding of the local context, making them more likely to activate social ties through mention comments. Geographical closeness is often common between friends – people tend to live near their social network – and this might explain that geographical markers influence this directed, interpersonal kind of sharing (Almquist 2016). The news content characteristics of timeliness and negativity based on the topic also have a significant positive influence on the proportion of mention comments, but the effect sizes only show a 0.8%-points larger proportion of mention comments.

As Table 10 shows, there are also several news content characteristics that have a negative influence on the proportion of mention comments. News content with personalization has the largest negative influence on the proportion of mention comments. On average, news content with personalization – measured if the title or subtitle of the article contains a named person – receives -3.3%-points smaller proportion of mention comments. As outlined in Section 3.3.1., our measure of personalization mostly captures names of famous people such as politicians, professional athletes, or other celebrities. Thus, having a focus on elite persons in the article seems to be something that is not used to activate or maintain social ties to a larger degree.

The news content characteristic of impact also has a significant negative influence on the proportion of mention comments. This kind of news content receives -1.3%-points smaller proportion of mention comments. Compared with the other kind of sharing, news content with impact influences a higher number of shares to your entire social network, but a lower proportion of mentions comments. An explanation of this could be that news content with high societal impact might drive a need for sharing with your entire social network rather than just one specific social tie.

News content with positivity and negativity based on the topic on average gain 0.8%-points more mentions comments, which is a rather small difference. News content with negativity based on the style gain -1.7%-points smaller proportion than the neutral ones. As the effect size for positivity and negativity based on the topic is smaller than 1%-points, the results suggest that emotionally laden news content, both positive and negative, generally seems to decrease or not really influence sharing behavior. Here, the results show some similarity to the first kind of sharing, where emotional valence of the news content also has a negative influence. In this way, the positivity and negativity of the news content seems to decrease both sharing towards your entire social network and directed, interpersonal sharing.

In conclusion, there are noticeable differences between the two outcomes of sharing behavior included in the analysis. News content with impact increases sharing with your entire social network, while having a negative influence on the interpersonal sharing. Geographical proximity increases the latter but does not have an influence on the former. Furthermore, emotionally laden news content, both positive and negative, seems to have a negative or no influence of both types of sharing.

4.4 Conversations

As described in Section 3.3.1., the dimension of audience engagement related to having conversations about news content is measured by four different outcomes representing the volume, reciprocity, respect, and disrespect of the conversations. The following section consists of two parts. The first part analyzes the volume and reciprocity of the conversation, while the second part analyzes the respect and disrespect measured by recognizing and offensive language.

4.4.1 Volume and Reciprocity

In this section, we examine the results for two outcomes of how the audience engages in conversations about the news content: the volume of conversation measured by the number of comments, and the reciprocity of the conversation measured by the proportion of reply comments out of all comments. The first represent a general volume of comments and conversations, while the second relates to the depth of the conversations – whether audiences enter in dialogue rather than one-way utterances. Table 11 below shows descriptive statistics for these two outcomes.

Table 11: Descriptive statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Number of comments	18,350	289	589	1	31	313	17,327
Prop. of reply comments	18,350	0.43	0.19	0	0.31	0.57	0.97

As seen in Table 11, both of these outcomes have a large variance as number of comments ranges from 1 comment to 17,327 comments on a post, and the proportion of reply comments ranges from 0% to 97%. On average, the posts in our dataset receive 289 comments, where approx. 43% are reply comments, i.e., comments on another comment. In Table 12 below, we present the results of the regressions of news content on each of these two outcomes.

Table 12: Linear regression models

	Number of comments	Prop. of reply comments
Intercept		
Intercept	209 (10.183)***	0.379 (0.003)***
Predictors		
Timeliness	22 (13.568)	0.003 (0.004)
Unexpectedness	−33 (17.436)	−0.015 (0.006)**
Geographical proximity	−1 (12.699)	−0.005 (0.004)
Cultural proximity	−28 (54.696)	−0.008 (0.018)
Personalization	−9 (45.148)	0.014 (0.015)
Negativity (topic, ref. neutral)	−133 (10.183)***	0.018 (0.003)***
Negativity (style, ref. neutral)	28 (9.844)**	0.005 (0.003)
Positivity (style, ref. neutral)	−61 (16.995)***	−0.034 (0.005)***
Impact	106 (14.591)***	0.005 (0.005)
Spreadability	138 (12.756)***	−0.027 (0.004)***
Hard News (ref. soft news)	134 (9.209)***	0.089 (0.003)***
Control variables		
Posted time PM (ref. AM)	−7 (8.629)	−0.003 (0.003)
Posted time, weekend, (ref. weekday)	−58 (9.734)***	−0.007 (0.003)*
Pay-wall article	−12 (71.649)	0.012 (0.023)
Strategy Change	127 (10.194)***	0.036 (0.003)***
Election Period	−34 (24.978)	0.009 (0.008)
Num. obs	18350	18350
R^2	0.04	0.08
Adj. R^2	0.04	0.08

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

As Table 12 shows, there are several of the news content characteristics that have a significant influence on the two outcomes. For the first outcome, number of comments, both negativity based on style, impact measured as breaking news, spreadability, and hard news content seems to have a positive relationship with the number of comments. Moreover, unexpectedness, negativity based on the topic, and positivity have a significant negative influence on the number of comments. For the second outcome, the proportion of reply comments, both negativity based on the topic, hard news topic seems to have a positive influence, while unexpectedness, positivity, and spreadability has a negative influence.

Specifically, news content about hard news topics such as politics and economy on average receives ~130 more comments compared to soft news topics. Furthermore, news content about hard news topics also has on average 8.8%-points larger proportion of reply comments than news content with soft news topics. Interestingly, the audience engagement of commenting on the post seems to be very differently related to the news content characteristics compared to the behavior of clicking on the link to read the article (See Section 4.1.). While the news content characteristics of hard news topics and impact were negatively related to link clicks, they were positively related to number of shares, and also positively related to number of comments. This result might indicate that the behaviors of link clicking and commenting are related to different kinds of motivations for audience engagement. News content with soft topics and with less societal impact might drive more link clicks as they serve purposes of entertainment and individual information selection, while news content with hard news topics and with high societal impact drive an urge to express opinions and have dialogues with other members of the audience. Related to the idea of deliberative democracy, we argue that it is valuable that news content with high societal relevance also seems to stimulate more public conversations and fosters more reciprocity, which are important forms of participation in an informed public sphere.

In addition, the results for news content with negativity and positivity show that the volume and reciprocity of conversations might be related to different kind of motivations for the specific behavior. Negativity based on the topic – e.g., if the article is about war, disasters, or crime – is negatively related to the volume of comments, but positively related to the proportion of reply comments. Thus, news content with negative topics influences less conversations, but a higher degree of reciprocity and dialogue between the audiences engaging in the conversation. On the other hand, news content with positivity drives both less volume of conversations, and less reciprocity in the conversations. The results also show a difference between negativity based on the topic and negativity based on the style of the content, as the latter is only slightly or not related to volume and reciprocity of conversations.

Another interesting result is that spreadability is positively related to the number of comments, but negatively related to the proportion of reply comments. Particularly, a post with the accompanying caption framed as a question on average receives 138 more comments, but 2.7%-points smaller proportion of reply comments than other captions. While the spreadability is not related to either link clicks, number of shares, or proportion of mention comments, it seems to drive more comments to the post. However, while spreadability drives a larger volume of comments directly to the posts, it decreases the behavior of engaging in dialogue, as it is negatively related to the proportion of reply comments. The idea of spreadability has been emphasized especially by Jenkins et al. (2013), who argued that news content should be designed to optimize spreadability. However, our results indicate that spreadability only drives the volume of comments and less reciprocity of comments, and therefore spreadability might not be a universally effective way of optimizing the framing of news content.

4.4.2 Respect and Disrespect

In this section, we analyze the results for the next two outcomes of how audiences engage in conversations: the disrespect measured by the proportion of comments with offensive language and respect measured by the proportion of comments with recognizing language. Both of these engagement characteristics are important, as they particularly relate to the quality of conversations. As described in Section 2.3.6., the theoretical idea of deliberative democracy highly emphasizes respect as a prerequisite for a good democratic debate around news content. Table 13 below shows descriptive statistics for both of these outcomes.

Table 13: Descriptive statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Prop. of offensive comments	18,350	0.064	0.069	0	0.014	0.095	1
Prop. of recognizing comments	18,350	0.12	0.12	0	0.061	0.14	1

As Table 13 shows, the average proportion of offensive comments in a comment section is at 6.4%, with a standard deviation of 6.9%-points, a min of 0% and a max of 1%. The average proportion of comments containing recognizing language is 12.1%, with a standard deviation of 12.3%-points and a min of 0% and a max of 1%. Compared to the average of other nation-wide Danish media, Ekstra Bladet on average has a lower proportion of recognizing comments (12.1% compared to 13-15%) and a slightly higher proportion of offensive comments (6.4% compared to 5%) (Analyse & Tal 2021a; Analyse & Tal 2021b). Table 14 below presents the results of the regression of news content characteristics on the outcomes representing disrespect and respect.

Table 14: Linear regression models

	Prop. of offensive comments	Prop. of recognizing comments
Intercept		
Intercept	0.044 (0.001)***	0.149 (0.002)***
Predictors		
Timeliness	−0.003 (0.002)*	0.003 (0.003)
Unexpectedness	0.003 (0.002)	−0.003 (0.004)
Geographical proximity	−0.005 (0.001)**	0.002 (0.003)
Cultural proximity	−0.004 (0.006)	−0.008 (0.011)
Personalization	0.023 (0.005)***	0.017 (0.009)
Negativity (topic, ref. neutral)	0.030 (0.001)***	−0.007 (0.002)***
Negativity (style, ref. neutral)	0.016 (0.001)***	−0.014 (0.002)***
Positivity (style, ref. neutral)	−0.013 (0.002)***	0.040 (0.003)***
Impact	0.008 (0.002)***	0.040 (0.003)***
Spreadability	−0.009 (0.001)***	−0.032 (0.003)***
Hard News (ref. soft news)	0.021 (0.001)***	−0.051 (0.002)***
Control variables		
Posted time PM (ref. AM)	0.001 (0.001)	0.000 (0.002)
Posted time, weekend, (ref. weekday)	−0.004 (0.001)***	0.013 (0.002)***
Pay-wall article	0.012 (0.008)	−0.022 (0.015)
Strategy Change	−0.003 (0.001)*	−0.003 (0.002)
Election Period	0.002 (0.003)	−0.005 (0.005)
Num. obs	18350	18350
R^2	0.11	0.08
Adj. R^2	0.11	0.07

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

As Table 14 shows, almost all news content characteristics - except unexpectedness and cultural proximity - have an either positive or negative influence on the proportion of comments containing offensive language. For the proportion of comments with recognizing language, news content with negativity, spreadability, and hard news topic have a negative influence, while news content with positivity or high impact such as breaking news have a positive influence.

As the results in Table 14 show, news content with hard news topics on average has 2.1%-points larger proportions of comments containing offensive language. This is similar to the findings for previous research such as Coe et al. (2014) (See Section 2.3.6.). However, we are also able to add to this, as our results also show that news content with hard news topic has a 5.1%-points lower proportion of recognizing comments than soft news topics. The theoretical explanation may be that when the topic of discussion is of high societal importance, the discussion might also be more passionate and heated, which may have people turn to both offensive language and recognizing language rather than neutral language. Considering the topics constituting hard news, those articles may be more about political sensitive subjects such as immigration, religion, or ideology, which may have a negative impact on the tone (Coe et al. 2014).

In addition, the results in Table 14 show that news content with negativity based on the topic receives 3%-points larger proportion of comments with offensive language. Similarly, news content with negativity based on the style of the content receives 1.6%-points larger proportion of comments with offensive language. Furthermore, news content with positivity receives -1.3%-points smaller proportion of offensive comments. The exact reverse relationship is found for the proportion of comments with recognizing language. Here, news content with negativity receives -0.7%- and -1.4%-points smaller proportion of comments containing recognizing language, while news content with positivity receives 4%-points more comments with recognizing language. While some of these coefficients are quite small, they do indicate the presence of emotional contagion, i.e., that the emotional responses among the audiences tend to be similar to the emotions encoded in the news content (See Section 2.3.4.). In this way, the results also reinforce the importance of the media in shaping the public debate, as negativity or positivity compared to more neutral framings of the news content seems to drive more or less respectful conversations about the news content. This question is further discussed in Section 5.1.

Another characteristic of news content that influences more comments with offensive language is personalization. When news content contains personalization – i.e., that there is a distinct focus on named persons – the conversation contains on average 2.3%-points larger proportion of comments with offensive language. As Coe et al. (2014:673) have suggested, an explanation of this mechanism could be that personalization creates partisan cues. In other words, the focus on elite actors in the news content might drive a division between proponents and opponents of said person, and that these dynamics increase incivility and disrespectful language.

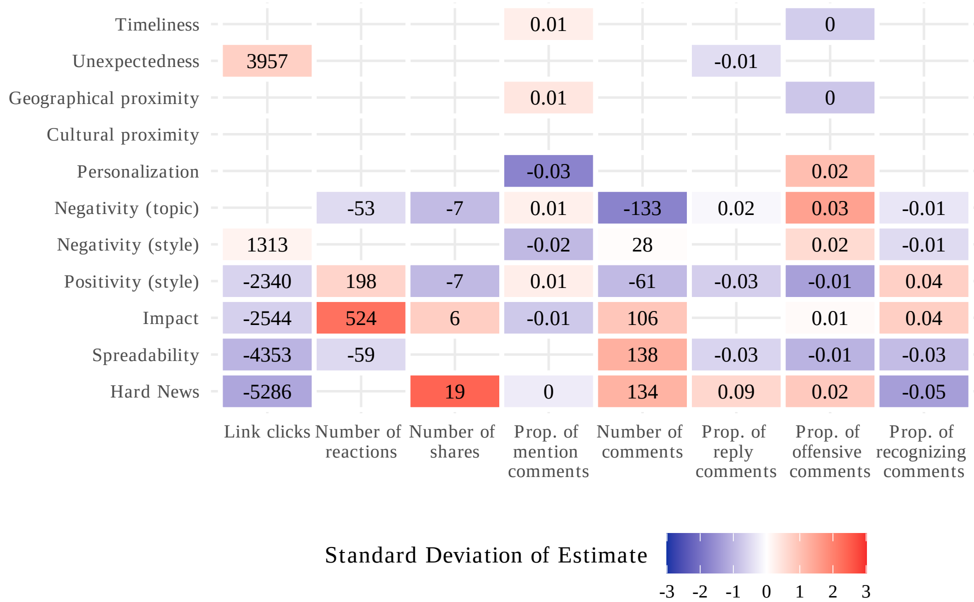
The results also show that news content with impact influences a larger proportion of offensive comments. News content with high impact measured as breaking news in average receives a 0.8%-points larger proportion of comments with offensive language. However, the same kind of news content also receives a 4%-points larger proportion of comments with recognizing language. Thus, independently of other news content characteristics, news content with high societal relevance and impact influences both a more disrespectful and respectful conversation. While at first, this may seem paradoxical, it is important to note that the two characteristics are not mutually exclusive, but the reference category is a neutral conversation. An example to explain such as case from our data is three breaking news articles about the kidnapping and murder of a 22-year-old woman in the beginning of February 2022 . This story exemplifies news content that is both tragic and infuriating, and thus might influence the audience to both express empathy as well as anger towards the news content. Other kinds of such examples from our data include articles about the death of famous persons and victories or losses in sports events, which might influence both kinds of audience engagement.

Finally, news content containing spreadability drives a -0.9%-points smaller proportion of comments with offensive language as well as a -3.2%-points smaller proportion of comments with recognizing language. Recalling the results from Section 4.4., spreadability leads to a higher volume of conversations, but less reciprocity and also less offensive and recognizing language. This further supports the interpretation that spreadability only drives more conversations, but not necessarily more elaborate conversations or emotionally laden responses.

4.5 Conclusion: Analysis

In the previous sections, we present the results of our analysis. As our analysis entails eight different outcomes and 11 predictors, we focus on the significant coefficients, since a full review of all coefficients and control variables is too extensive for the scope of this study. Figure 10 below, shows all significant coefficients, color-scaled to show the most impactful coefficients.

Figure 10: Summary of regression models



Each column represents a regression model. Only coefficients with a p-value < 0.05 are shown. For each model, the color corresponds to how many standard deviations the coefficient is from zero.

The analysis seeks to answer the research question: *"How does the content of news articles influence audience engagement on social media?"*. As our results have shown, the content of news articles does indeed impact the audience engagement on Facebook. However, it is also clear that the effect of news content varies greatly across different kinds of audience engagement behavior. News content might drive more of a certain behavior, while driving less of another behavior. Summarizing across the results from the regressions, we argue that there are three main findings of our analysis: 1) soft news and unexpectedness drive individualistic behavior, while news content with larger societal relevance drives more social behavior, and 2) the sentiment of the news content drives a similar sentiment in audience discussions, and 3) timeliness and proximity have no or only small effects on any kind of audience engagement.

First of all, news content with unexpectedness and soft news topics influences individualistic audience engagement such as clicking on the link to read the article, whereas news content that holds greater societal relevance encourages more social audience engagement such as sharing or having conversations around the news content. The news content characteristics with the largest positive influence on the behavior of clicking on the link is unexpectedness, while the largest negative influences are hard news topic, spreadability and impact. On the contrary, news content with impact or hard news topics generally gains more comments and a larger proportion of reply comments compared with soft news or not breaking news content. In conclusion, these results suggest that articles about soft news or unexpectedness lead to more individualistic audience engagement in form of link clicks, which might represent a motivation for curiosity or entertainment rather than a motivation of having deeper social interactions and deliberations among the audience members. On the other hand, the results also suggest that articles of larger societal relevance such as impact or hard news topics are associated with more social audience engagement such as sharing and discussions on the comment section.

Secondly, the results show that the negativity or positivity also influences the negativity or positivity in the audience engagement in the comment sections. Thus, a negative sentiment in the article drives a larger proportion of comments with offensive language and a smaller proportion of comments with recognizing language, while a positive sentiment in the article drives a smaller proportion of comments with offensive language and a larger proportion of comment with recognizing language. While hard news leads to more conversation volume and reciprocity, the results also show that hard news are associated with a larger proportion of comments with offensive language, and a smaller proportion of comments containing recognizing language. As such, the presence of substantial and political issues often comes with the price of increased incivility. We also find that positive news content and especially impactful news content increase the volume of emotional valence as measured by aggregated reactions, however the association is not found for negative news content. Nonetheless, we argue that the findings about negativity and positivity can generally be tied to the idea of emotional contagion; the emotional framing and content of an article may influence the emotional responses of the audience.

Finally, across all outcomes of audience engagement, the results show mostly small or no effects of timeliness and proximity (both cultural and geographical). These predictors are only significantly associated with the proportion of mention comments and proportion of offensive comments, but the effect sizes are rather small. At first, the conclusion of this might be that these news content characteristics do not have an effect on the audience engagement when controlled for other news content characteristics. However, there might also be methodological limitations behind these findings, which we discuss further in Section 5.3.1 for proximity and in Section 5.4. for timeliness.

Concluding on these results, our most essential finding is that the characteristics of news content do not have a universal influence on audience engagement. Based on news value theory, previous studies and literature have primarily expected an increase in audience engagement for any of the news content characteristics. Nonetheless, our findings show that news content characteristics might not have an effect on all dimensions of audience engagement, and they might even decrease specific kinds of audience engagement. This contributes to an understanding of audience engagement as a multifaceted phenomenon, which may be affected in heterogeneous ways by different kinds of news content.

5 Discussion

In the previous section, we presented our results in order to answer our research question. In this section, we discuss the implications that these findings may entail, the limitations of the analysis, as well as future directions. First of all, we discuss societal implications in terms of the pivotal democratic role of news media facilitating public, political discussions. Secondly, we argue that the findings point towards a further theorization about what causal mechanisms that drive the heterogenous effects of news content on audience engagement that we identified in our empirical analysis. Subsequently, the reliability of the measured effects is discussed, especially in relation to the concerns of granularity, context, and algorithmic confounding. Finally, we also consider how our findings might generalize to other contexts.

5.1 Societal Implications

As mentioned in Section 1.1., the Facebook pages and comment sections of Danish news media have been extensively discussed in recent years. Social media like Facebook have been praised for providing the audience with more agency, as they facilitate new possibilities for discussing and deliberating news content. On the other hand, the comment sections on social media like Facebook have also been notorious for uncivil language and possessing qualities opposite of constructive deliberation as imagined by sociologists like Habermas (See Section 2.3.6.). Recently, the solution to poor conversation quality around news content on social media have been to shut down the ability to comment (Reimer et al. 2021:4). At first sight, the shutdown of comment sections might be an effective and cheap solution, as it removes the possibility for negative content while also removing the otherwise necessary expenses for content moderators. On the other hand, removing the public debate in itself may be damaging from a societal and democratic perspective. If news media do not provide a public space for citizens to engage and discuss important societal issues, it might erode the potential for all voices to be heard and damage the legitimacy of democratic processes. Furthermore, removing the ability to comment may limit the exposure of news content – thus neglecting the obligation of news media in an informed democracy. Therefore, it is crucial to find ways of promoting sustainable public conversations around news content on social media rather than just removing the possibility for discussion entirely.

The results of this study indicate how certain types of news content might yield a more constructive deliberation than other types of news content. Our analysis found that news content with hard news topics and high impact sparked a higher volume and reciprocity of conversations among the audience, but it also resulted in more offensive language. Furthermore, the emotional framing of the news content also resulted in more emotional responses among the audience, and thus negativity also sparked more offensive language in the comment sections. In this way, the journalistic framing of the news content seems to influence how the deliberation unfolds in Facebook's comment sections. To promote better deliberation, it is worth considering whether news content can be framed in a way that encourages more volume and reciprocity without incivility in online conversations. For example, our results suggest that it might be good to avoid negative framings of news content, as negativity drives uncivil conversations in the Facebook comment sections. For the hard news topic that also yields a higher volume and reciprocity of conversations, increased focus on moderation may be a necessity.

A challenge here might be that media organizations also have an economic motivation for their journalistic framing of news content. The source of revenue for all media companies – whether their economic model is ad-based or subscription-based – is to generate link clicks in order to move audiences from Facebook to the media's own website (Martin 2019). At a societal level, not only the quantity but also the quality of engagement may be important for providing a space for public political deliberation. As an example, studies have shown that uncivil comments may decrease the perceived legitimacy of the news content and media (Houston 2011; Kümpel & Springer 2016; Gearhart et al. 2022). Furthermore, our results indicate that the types of news content that influences more link clicks is not the same news content that influences more social behavior among the audience such as sharing and commenting. Therefore, media organizations might have to strike a balance between optimizing their content for engagement quantity to increase revenue and engagement quality to increase deliberation and social behavior.

5.2 Theoretical Future Directions

From the results of our empirical analysis, a central finding is that news content does not have a universal effect on audience engagement. Instead, news content has varying effects on different dimensions of audience engagement behavior. Following this finding, the question follows: what then is the theoretical explanation of how a specific news content characteristic drives either more or less of a specific dimension of audience engagement? The present study is only based on correlational evidence, so in order to determine the validity of the study it is important to have a strong theoretical argument about the mechanism that drives the identified correlations (See Section 3.4.2.).

Many of the studies reviewed provided only vague descriptions about the underlying causal mechanisms, while others mainly draw on psychological concepts. In many studies, the objective seems to be simply to explain the digital traces on Facebook as an outcome in itself, instead of considering the digital trace behavior as a manifestation of underlying social mechanisms. We argue that our approach of supplementing with sociological theories may help gain a more comprehensive understanding of what drives the influence of news content on audience engagement. This includes both grand theories of deliberation and communicative action (i.e., Habermas), but also more micro level theories about reciprocity and social cohesion (e.g., Mauss). However, the inquiry of our study has been mainly empirical, and therefore we have not tried to actively develop the theories of audience engagement and news content. To do this properly would require more empirical studies and a combination of translating older theories into new contexts, while also developing new theoretical concepts that better explain the phenomenon.

As outlined in Section 2.4, the theoretical understanding of news content for previous studies has primarily relied on the idea of news values. However, it is worth questioning whether the idea of news values is the most appropriate categorization of news content when considering how audiences choose to engage or not engage. As an example, our results show different effects of whether negativity was measured based on the topic or style of the news content. In other words, the results differed whether the negativity existed in terms of the content or the framing of the content. The fact that the same theoretical concept measured in two different ways yields different results, may point towards the theory being underspecified or unprecise. To some extent, the theoretical difference between content and journalistic framing might exist for all of the news values. As other studies have argued, news value theory also often mixes news values related to the production and reception of the news content (Bednarek & Caple 2012:50). In general, news values are quite ambiguous, and it is rarely a coherent and well-defined theory. Therefore, a future endeavor could be to reformulate the idea of news value theory that includes a broader understanding of engagement and the mechanisms that connects them to the news content.

Another theoretical consideration is how the temporal process of audience engagement might look like. As Levy & Windahl (1984) argued, different kinds of audience engagement behavior are related to different phases that are either pre-, during, and post-exposure of the news content (See Section 2.3.2.). In the same way, the predictors in our analysis are related to these different phases. Clicking on the link might be related to the selection-phase before reading the article, while commenting or sharing the article would be related to the post-exposure phase. However, the point of exposure on social media is not always as clear cut as for TV-watching for which Levy & Windahl developed the theory. On social media, the chronology may not be as linear, since the audience might read the title and preview of the article, and subsequently, they might choose to click to read to the article, but they could also just go directly to commenting, sharing or other kinds of behavior. In this way, other people's previous engagement with the post - such as the reactions or comments - may also influence current engagement. As audiences on social media interacts in a many-to-many relationship rather than a one-to-many relationship as for mass-media, the different dimensions of audience engagement might also interact, mediate, or amplify the effect from news content characteristics. On social media, news content is almost always encapsulated with other audience engagement behavior, and interpersonal influence through the imitation or contagion of previous audience engagement to the news content might be unavoidable when new audiences are exposed to the news content (Katz 2006:7). It might be relevant to consider how the temporal and interacting dynamics of news content exposure might be different for social media compared to traditional sources of news consumption.

5.3 Methodological Limitations

In this section, we discuss limitations and future directions in terms of our methodological approach. The concerns here are related to the reliability and robustness of the measurements and empirical findings presented in the study. First, we discuss the granularity of our observations, and how more contextual information might improve our measurements. Second, we discuss how platform algorithms in Facebook might have a confounding effect on the audience engagement.

5.3.1 Granularity and Context

In this study, the unit of observation is on the level of the news article, which means that we use the aggregated measurements of audience engagement for each shared news article on Facebook. As a consequence of data availability from Facebook, we do not have access to personal data of the audience. This is a limitation for our study; mainly because we are not able to connect the identities across engagement traces, e.g., the users writing comments. As such, we do not know how many unique users have contributed to the comments on a post. Without user identification, we are unable to tell if the conversations consist of the same two users arguing back and forth or many different users are engaged. For American news audiences, a study found that 80% often click on shared news content on social media, while only around 6% often share or discuss news content on social media (Mitchell et al. 2016). Similarly, other studies have emphasized that it might be a minority of the audience, who produces a majority of the audience engagement (Papacharissi 2002:13; Richardson & Stanyer 2011:985). However, the literature is inconclusive as to whether the minority of highly engaging users is problematic or whether they might serve as digital opinion leaders spreading the news content in their social networks (Katz & Lazarsfeld 1955:32; Nisbet & Kotcher 2009:340).

The lack of user information also means that we cannot examine interpersonal relations or subcommunities among the users engaging with Ekstra Bladet's content, but we are limited to examining the audience of Ekstra Bladet as an aggregation. We know from the work of Katz & Lazarsfeld (1955) and Livingstone (2005) that audiences consist of multiple communities or social networks that might differ in their engagement with the news content. An example of this might be the measurements of geographical and cultural proximity. Both of these measurements show small or no effects on the dimensions of audience engagement in our analysis, which calls into question whether the lack of effects might be a result of too broad measurements. While we measure geographical proximity as national or international content, proximity might also create relevance on a more granular level, e.g., on a regional or city-level. Similarly, cultural proximity might also be quite subjective, and there might be large differences in the cultural references for the 400.000 followers of Ekstra Bladet on Facebook. For these reasons, this present study could very well be elaborated by having a more granular user-perspective.

Another consideration about our methodology is that our measurements might be dependent on their context. This applies to all engagement metrics, as they may be influenced not only by the news content itself but also by previous engagements. To properly capture this relationship would require timestamped data for all the different types of engagement, which is unfortunately not possible with Facebook's current API. In our case, this potential dependency is especially interesting for the comment sections. The measurement of whether a comment contains offensive language or not can be very dependent on the context. The task of determining if language is offensive can be quite difficult for both humans and computers as it is often ambiguous and subjective (Davidson 2022). Certain comments can easily be defined as offensive language – they might contain a slur or threat – while other comments might require an interpretation of the underlying intention and full context. Language only becomes meaningful in social and cultural embeddedness – some slurs have even become reclaimed by certain ethnic or LBGTQ+ communities (Davidson 2022; Sap et al. 2019). Thus, an appropriate prediction of offensive language might also require background information about the individual, who made the comment and the potential target of their utterance, e.g., their age, gender, ethnicity, or social class. The interpersonal relationships of the audience might also be relevant in determining the offensiveness of a comment – insults and offensive language is usually more acceptable among friends, where it may be considered as banter rather than an offensive comment. Furthermore, offensive language is also a politized issue that relates to questions of the boundaries of the freedom of speech, especially in relation to moderating or deleting offensive comments on social media (Davidson 2022; Mchangama 2022:349). In terms of reliability, the ambiguity and subjectivity of determining offensive language may as such especially be a challenge in relation to the machine learning models that we use to predict offensive and recognizing language. While the models applied have an acceptable performance compared to human annotation, they still do not achieve perfect scores (See Section 3.3.1.). The significance of these misclassifications might be more problematic, if there are systematic errors or particular biases embedded within them (Sap et al. 2019). To achieve higher accuracy, reliability, and fairness of these models, it might be relevant to include additional context including the post itself, the other comments, and the interpersonal relationships as input besides the single comment in question.

5.3.2 Algorithmic Confounding

An important limitation of using digital trace data from social media and digital platforms is the algorithmic confounding (Salganik 2018:35). On Facebook and most other social media, the algorithms of the platform are black boxes. This implies that only Facebook has direct access to the algorithm, leaving researchers to rely on qualified guesses about the consequences for social behavior on the platform. Facebook's algorithmic design could potentially have a significant influence on determining the content users encounter on their news feed. The algorithm is optimized to predict what kind of content that users would like to see and engage with based on real-time and historical data (Gillespie 2014). One of the metrics that the algorithm considers when determining relevance might be audience engagement measurements such as link clicks, reactions, shares, and comments. A study by Bakshy et al. (2015) shows that users' previous engagement with news content is heavily prioritized in Facebook's sorting algorithm. A similar finding was found for news content in Google search, where the most import aspect of present engagement is found to be the users' previous engagement (Robertson et al. 2023).

However, when the algorithm mainly relies on audience engagement, it might lead to a feedback-loop in which audience engagement in itself becomes self-reinforcing (Salganik et al. 2006). In this way, the algorithmic enhancement might lead to a so-called Matthew-effect in which news content with a lot of engagement receives even more engagement (Merton 1968). This amplification and diminishment might result in unequally distributions of news content exposure, and thus also audience engagement. This effect might explain some of the skewedness of our empirical measures of audience engagement.

The algorithmic prioritization of previous audience engagement might also yield increased inequality among the users within the audience. For example, users that often engage with news content will be shown more news content, while less engagement users might be shown less news content (Kümpel 2020:1084). In this way, the algorithmic confounding might also contribute to the disproportionate audience engagement with news content (See Section 5.3.1.).

The algorithmic bias on Facebook does not just impact our measurements of audience engagement, but it also has societal consequences. As DeVito (2017) has shown, Facebook's selection of news content is optimized primarily towards social interaction or personal preferences, which considerably differentiates from the news values that journalists and editors often use to prioritize news content (DeVito 2017:766-767). Especially, the news values representing news content of high societal relevance such as breaking news or politics might not be directly prioritized by the Facebook algorithm.

In light of these findings, it becomes evident that the lack of transparency surrounding social media algorithms presents a significant challenge for researchers seeking to understand the relation between news content and audience engagement. While we can make informed assumptions about the potential impact of these algorithms based on existing literature and empirical observations, there is a further need for understanding the inner workings of these platforms. Future studies could very well analyze how Facebook's algorithm operates, what signals it prioritizes, and how it determines which content is shown to users – especially in the context of news media.

5.4 Generalization of the Case

Our study is based on an extensive dataset for a single media, Ekstra Bladet, and their audience engagement on a particular social media, Facebook. As described in Section 3.1.2., Ekstra Bladet is a particular case, and it is therefore relevant to discuss how our results generalize to other cases, both in terms of kind of news media, other social media, and other countries than Denmark.

Ekstra Bladet is a tabloid media, and as such they have a particular journalistic style and cater to a specific audience (See Section 3.5.1.). Undoubtedly, our results reflect that we use a single news media such as Ekstra Bladet as our case of study. Collaborating with a larger and more diverse range of media organizations might lead to other results for the different kinds of news media. Here, the main difference may be that news media often vary in terms of their news content characteristics. At Ekstra Bladet, timeliness is an especially important news value, while other media might give more priority to background articles that do not rely on timeliness at all. There are also large differences in the topics that news media cover – e.g., business media like Børsen might almost exclusively cover topics considered as hard news. Furthermore, there might also be significant differences in terms of writing style. For example, Ekstra Bladet describes themselves as anti-elite with a short and understandable writing, while a media like Weekendavisen uses a much more formal style to address their audience. These examples suggest that our findings might primarily generalize to other tabloid news media, who represent the same way of reporting news and cater to similar audiences. However, several studies have argued that the broader media landscape has shifted towards a more tabloid content and style, especially since the introduction of online based news reporting (Bird 2009). This tendency has been formulated as the notion of tabloidization. The process of tabloidization is exemplified by the introduction of click-bait headlines, a focus on visual presentation including large pictures as dominating eye-catcher for almost all online news stories, as well as a larger focus on soft news. In this way, Ekstra Bladet might be a more typical case of online news media, who are more and more similar to the classic tabloid media, than first anticipated. We argue that the examination of differences between news media is an important direction for further research.

In addition to the type of media, it is also important to consider the type of social media platform. Our case of study revolves around the audience engagement on Facebook, because it is the largest and most significant social media (See Section 2.2.2.). However, the influence of news content on audience engagement might be different on other social media platforms. Social media differ greatly both in their user populations, their technological and algorithmic affordances, as well as the internal norms – all of which may influence the dynamics of audience engagement and news content. In terms of technological affordances, the different ways of reacting and commenting are especially relevant. Comparing Facebook with a social media like Twitter, there are significant differences in possible audience engagement behaviors. On Facebook, there is a range of different reactions, while Twitter just has the ability to like. In Facebook's comment sections, the deepest level of reply is limited to second level replies. In contrast, Twitter's reply system allows for infinite nesting of replies. On Twitter, there is a limit on the length of a comment, but there is no such limit on Facebook. Based on these considerations, we argue that our findings might not generalize to other kinds of social media. However, we also argue that the size and importance of Facebook makes it a relevant case of study in itself.

Finally, there is also a question of whether our findings generalize to other contexts than Denmark. As shown in previous research on media systems, the Danish media system is generally similar to other Northern European media systems (Brüggemann et al. 2014). These media systems are characteristic especially in that they have a high level of press subsidies, and generally a low political slant (Black-Ørsten & Kristensen 2016:33; Brüggemann et al. 2014). In other countries such as Great Britain, Italy, or the United States, the political orientation of journalists is more pronounced, and the boundary between news reporting and political commentary is more blurry (Brüggemann et al. 2014). Especially relevant for audience engagement on social media, there is also great differences in how much social media are used for engagement with news content. In Denmark, social media is widely used for engaging with news content, while it is less common in other countries such as Germany, France, or Japan (Nielsen & Schrøder 2014). All of these country differences show that media and audiences are highly embedded in cultural and societal practices, and therefore we do not assume that our findings will generalize to all cultures around the world (Humprecht et al. 2020). However, we argue that such universal statements are also rarely fruitful as research goals – instead comparative empirical studies should examine how the influence of news content on audience engagement on social media might differ between cultural and societal contexts.

6 Conclusion

The relation between the media, their content and the engagement of the audiences is important to understand for both media studies and media organizations. The idea of audience engagement is even more emphasized and discussed with the invention of new, digital media, as they contain increased possibilities for feedback, participation, and engagement with news content. Audience engagement on social media might be influenced by many different factors – one of which might be the characteristics of the news content itself. Previous studies have primarily used characteristics derived from news value theory related to the framing, style and topic of the content. In this light, the present study seeks to answer the question of how the content of news articles influences audience engagement on social media.

The relevance of our study is based on two empirical gaps, which we have identified from on a review of previous studies. Firstly, previous studies of news content and audience engagement on social media have relied on smaller samples of news content that might suffer from bias or lack of representativity. Secondly, previous studies have had a narrow definition of audience engagement relying for example on simple popularity cues - rather than examining audience engagement as a multifaceted phenomenon.

Our study bridges both empirical gaps by collecting an extensive dataset in collaboration with Ekstra Bladet – the largest Danish tabloid media. Our empirical approach has two important qualities. Firstly, by using computational techniques from machine learning and natural language processing rather than relying on manual hand-labelling to create our measurements, we can include the entire population of shared news content on Facebook over a period of almost two years. Secondly, we conceptualize audience engagement as a multidimensional phenomenon encompassing information selection, emotional responses, sharing, and conversations. By collaborating with Ekstra Bladet and gaining access to data from their Facebook page, we are able to operationalize these four dimensions into eight different empirical measures. Following these two improvements, our study elaborates on the empirical foundation of news content and audience engagement on social media in two directions, by including a more complete population of observations and a more comprehensive definition of audience engagement.

6.1 Findings

In the empirical analysis, we examine the influence of 11 news content characteristics inspired by news value theory on eight different outcomes related to multiple dimensions of audience engagement on social media. Across the results from our eight different regression models, we identify three main findings. Firstly, our results show that news content with unexpectedness and soft news topic drive individualistic behaviors such as selecting to click on the link to the article. On the other hand, news content with a larger societal relevance such as breaking news and hard news topics drives more social behavior such as sharing and having conversations about news content. We argue that these differences may stem from different motivations, where soft news and unexpectedness drives a motivation to satisfy curiosity or entertainment, while societal relevance drives an urge to deliberate and interact with others. Secondly, we find that the emotional framing of the news content influences similar emotional responses among the audience. Positivity and negativity within the news content drives more reactions, negativity drives more comments with offensive language, and positivity drives more comments with recognizing language. We argue that this represents the idea of emotional contagion – i.e., that the emotional valence of the news content may spread to the audience and influence their engagement. Finally, our results also show that news content containing timeliness and proximity, both geographical and cultural, has no or very limited effects on any kind of audience engagement. The lack of association for these news content characteristics might suggest that they are generally irrelevant in the case of audience engagement on social media, but it might also be caused by methodological constraints. In conclusion, our results confirm that news content does not have a universal effect on audience engagement. Certain characteristics of news content might have a positive influence on one dimension of audience engagement, while it may have negative or no influence on other dimensions of audience engagement. Our findings underscore the multifaceted nature of audience engagement, highlighting how specific features of news content can elicit varying responses.

6.2 Limitations and Future Directions

In addition to our findings, it is important to consider the limitations of the study both in regard to data and theory, but also how future research may bridge these gaps and build on our results. We discuss three different concerns related to reliability, validity, and generalizability. First of all, there are important constraints imposed by the availability of data. As with many other studies examining social media, our study suffers from a lack of user-level data. For example, we cannot know the unique number of users commenting on a post. Furthermore, having user-level data could shed further light on especially social and conversational relationships and how these relationships may serve as a motivator or mediator of audience engagement. Additionally, timestamped data could potentially provide a more elaborate understanding of how the engagement with news content evolves over time. Another limitation related to our data stems from our use of digital trace data. On the one hand, digital trace data has benefits in terms of being available in a large amount and representing actual behavioral data. On the other hand, digital trace data also has disadvantages, especially in relation to algorithmic confounding. Secondly, on a theoretical level, our study might also suffer from a theoretical foundation that is rather fragmented and sometimes ambiguously defined, both in regard to news value theory and audience engagement. We argue that a more coherent and elaborate theoretical framework is needed to better understand what characteristics of news content is relevant to explain audience engagement on social media and which underlying causal mechanisms are at play. Thirdly, we argue that our findings may generalize to similar tabloid media on Facebook, but that future studies could examine whether our findings may hold true for other kinds of news media, other social media platforms, or cultural contexts.

6.3 Contribution

Our study contributes to the research of media and audiences on social media by elaborating on two central limitations regarding the reliance on smaller samples and the simplistic definition of audience engagement. However, our findings also direct attention to larger societal issues about the evolving relationship between media organizations, audiences, and social media like Facebook. In the current digital age, the conceptualization and importance of audiences has never been more debated within media studies. Simultaneously, audience behaviors are constantly analyzed within the newsroom in order to optimize news content. At the same time, media organizations are seriously reconsidering their presence on social media like Facebook, as they seek to find a balance between gaining traffic to their websites and reducing uncivil conversations around their news content. Based on our findings, a possible solution might be to pay attention to how specific kinds of news content influences certain kinds of audience engagement. Rather than forfeiting digital audience engagement, we argue that a better understanding of how to stimulate a higher quality of audience engagement on social media will be beneficial for both media and society at large.

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8 Appendix

8.1 Litterature Overview of News Value Taxonomies

Table 15: Litterature overview of news value taxonomies

Paper	Timeliness	Unexpectedness	Proximity
Galtung & Ruge (1965)	Frequency	Unexpectedness	Meaningfullness
Golding & Elliot (1979) (:632-643)			Proximity (geographical/cultural)
Østlyngen og Øvrebø (1998)	Timeliness	Sensation	Identification
Harcup & O'Neill (2001)		Surprise	Relevance
Brighton & Foy (2007) (:26)		Topicality; Unusualness	Relevance
Bednarek & Caple (2012)	Timeliness	Novelty	Proximity
Bednarek (2019)	Timeliness	Unexpectedness	Proximity

Paper	Personalization (non-elite)	Personalization (elite)	Soft news
Galtung & Ruge (1965)	reference to persons	reference to elite nations; reference to elite persons;	
Golding & Elliot (1979) (:632-643)	Personalities	Elites	Entertainment
Østlyngen og Øvrebø (1998)			
Harcup & O'Neill (2001)		The power elite; celebrity	Entertainment
Brighton & Foy (2007) (:26)			
Bednarek & Caple (2012)	Personalization	Prominence	
Bednarek (2019)	Personalization	Eliteness	

Table 16: Litterature overview of news value taxonomies (Continued)

Paper	Negativity	Impact	Opposite of timeliness
Galtung & Ruge (1965)	reference to something negative;	Threshold	continuity
Golding & Elliot (1979) (:632-643)	Drama; Negativity	Importance; Size	
Østlyngen og Øvrebø (1998)	Conflict	Relevance	
Harcup & O'Neill (2001)	Bad news; Good news	Magnitude	Follow-up (subjects)
Brighton & Foy (2007) (:26)		Expectation; Worth	
Bednarek & Caple (2012)	Negativity	Impact; Superlativeness	
Bednarek (2019)	Negativity	Impact; Superlativeness	

Paper	Newspaper agenda (not content)	Text complexity	Opposite of unexpectedness
Galtung & Ruge (1965)	composition		Unambigiuity; consonance
Golding & Elliot (1979) (:632-643)	Bias/objectivity	Brevity	
Østlyngen og Øvrebø (1998)			
Harcup & O'Neill (2001)	Newspaper agenda		
Brighton & Foy (2007) (:26)	Composition		Relevance
Bednarek & Caple (2012)			Consonance
Bednarek (2019)			Consonance

Table 17: Litterature overview of news value taxonomies (Continued)

Paper	Visual attractiveness	External (not content)
Galtung & Ruge (1965)		
Golding & Elliot (1979) (:632-643)	Visual attractiveness	
Østlyngen og Øvrebø (1998)		
Harcup & O'Neill (2001)		
Brighton & Foy (2007) (:26)		External influences
Bednarek & Caple (2012)	Aesthetic Appeal	
Bednarek (2019)		

8.2 Evaluation of Sentiment Models on Test Data

Table 18: F1-score on test data

Model	Weighted Average F1-score
AFINN	0.50
ScandiNLI	**0.70**
SENDA	0.57
BERT Tone	0.58
GPT-3.5-turbo	0.67