Exploring the Consistency and Variability of Algorithmic Filter Bubbles: A Comparative Analysis of Instagram Reels and TikTok

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ABSTRACT,
The rise of algorithms on social media platforms such as TikTok and Instagram Reels presents new challenges in digital marketing. The opacity of these algorithms makes them comparable to a black box. This study conducts a quasi-experiment with 31 participants to assess the existence of filter bubbles in relation to gender and time spent on TikTok and Instagram. The findings indicate that both platforms exhibit a filter bubble effect, with Instagram showing a stronger effect compared to TikTok. This research provides a comparative analysis of these platforms' algorithms, offering insights into their influence and what affects them. The results contribute to understanding how personalization algorithms impact digital marketing strategies and user engagement on social media.

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Keywords
Filter Bubble, Social Media Algorithms, TikTok, Instagram, Digital Marketing, Personalization, Advertising Bias

1. INTRODUCTION

Social media platforms began to emerge in the early 2000s. From the pioneering days of MySpace and Friendster to the contemporary dominance of platforms like Facebook, Instagram, Twitter, and TikTok, social media has become an integral part of daily life for over 5.04 billion people worldwide (Kemp, 2024). The revolutionary transformation in communication enabled by social media offers a rich field of study for academics across disciplines (Dwivedi et al. 2018). Additionally, it provides companies with unprecedented opportunities to engage with customers, enhance brand awareness, influence consumer attitudes, and drive sales (Dwivedi et al. 2021). Traditional marketing has long sought to tailor products and advertisements to specific target groups, a concept known as 'one-to-one marketing' (Peppers & Rogers 1997). Today, the advent of big data, algorithms, and AI allows marketers to target individual customer preferences with unprecedented precision. “The personalization concept also entails presenting and using customer information to create an individualized customer experience” (Aksoy et al., 2021). This individualized customer or user experience is what alarmed author and activist Eli Pariser, in 2011 he released The Filter Bubble: What the Internet Is Hiding From You. Explaining that the algorithms that create these individualized user experiences are source filter bubbles that isolate users from information and perspectives they have not already expressed an interest in (*Digital Media Literacy: How Filter Bubbles Isolate You*, z.d.).

1.1 Problem Statement

Despite the widespread use of personal data by social media platforms, the inner workings of the algorithms that create filter bubbles remain largely opaque. Media often refer to these algorithms as the 'secret sauce' behind the success of social media companies (Colett 2007; Kincaid 2010; Oremus 2014; Vanhemert 2013). In-feed advertising is one of the most effective advertising formats in the context of social media (Fulgoni & Lipsman, 2014). Because of the ways in which commercial platforms now tailor and personalize content and in-feed advertisements to individual users, the fear is that ‘the opacity of algorithms and private control of platforms alters the ability of the public to understand what supposedly a part of the public sphere is’ (Tufekci, 2014). The knowledge gap we focus on in this research stems from the fear of algorithms that personalize content (Bucher, 2016) and the possibility of bias in the data and algorithms used for digital advertising (Bach, Bernat, 2022). For this research we focus on the platforms TikTok and Instagram, more specifically, Instagram Reels. The tech company ByteDance founded TikTok in 2016. It is the leading destination for short-form mobile video (TikTok). Instagram launched in 2010 as a photo-based platform, in 2020 they launched Instagram Reels, which are short-form videos designed to entertain, in order to compete with TikTok. We focus on these two platforms due to their current high popularity and similar in-feed advertising strategies.

1.2 Research Question

This study aims to explore the existence of an advertising filter bubble effect and understand the underlying algorithms on social media platforms. This leads to the primary research question:

“*To what extent is there an advertising filter bubble observable and what influences the advertising algorithms on social media platforms TikTok and Instagram?”*

The following subquestions will together answer the research question:

1. What are the basic workings of the algorithms of TikTok and Instagram Reels?
2. What are the objectives of digital marketing through Social Media advertising?
3. To what extent are in-feed advertisements that users encounter relevant?
4. Do the variables ‘time spent on platform’ and ‘gender’ influence the working of the advertising filter bubble?
5. Is there consistency and/or variability in the advertising algorithms of Instagram and TikTok?

1.3 Structure

Chapter 2 of this paper presents the theoretical framework and reviews the current literature relevant to the factors studied. Chapter 3 outlines the research design and methodological approach employed. Chapter 4 presents the findings of the study. In Chapter 5, the results are discussed, with conclusions drawn from the analysis. Finally, Chapter 6 addresses the limitations of the study, provides insights into the expectations, and offers recommendations for future research.

1.4 Contributions

This research explores the advertisement filter bubble and the algorithms it. While existing research focuses on single platforms (Min et al., 2019; Kollyri, 2021; Klug & Strang, 2019; Chen, 2023), this study provides a multi-platform comparison to enhance the understanding of filter bubbles and algorithm dynamics. In addition, as there is little existing literature on filter bubbles and algorithms in in-feed advertising, we aim to extend that literature with this research. The practical relevance of this study is that information on what influences the in-feed advertisement algorithms on different platforms can help advertisers select the best platform to reach certain target groups and give the users of these platforms insight into what parts of their digital footprint may influence these (advertising) filter bubbles. This thesis contributes to the field of social media communication by shedding light on the filter bubble effect of in-feed advertising.

2. THEORETICAL BACKGROUND & HYPOTHESES

2.1 Digital Marketing and Personalization

Digital marketing is defined as an adaptive, technology-enabled process by which firms collaborate with customers and partners to jointly create, communicate, deliver and sustain value for all stakeholders (Kannan and Li, 2017). The initial adoption of digital marketing was in the 1990s with the introduction of the internet and email marketing (Srivastav & Gupta 2021; Shetty, 2022). The introduction of the Web 2.0 in the early 2000s increased online interaction, making digital marketing an attractive option for businesses and other organizations (Ghimp, 2022). It has transformed how businesses and other organizations communicate with their audiences (Chaffey & Ellis-Chadwick, 2019). Corporations now highlight the importance of creating a “digital relationship” with customers (Phillips, 2015) and over the years digital marketing has grown into a fundamental and crucial part of any marketing strategy. Changes in consumer behavior require firms to transform their marketing strategies in the digital domain and rethink how they communicate with their audiences (Tiago & Veríssimo, 2014; Chaffey & Ellis-Chadwick, 2019). According to Puthussery (2020), the main goal of digital marketing is to reach consumers and to encourage them to connect with the product via digital distribution. One of the most popular and commonly used channels in digital marketing are social media platforms, which have opened the door for businesses to communicate with millions of people about products and services (Bala et al., 2018). Social media advertising helps to increase the visibility and recognition of a brand (Nieves-Casasnovas & Lozada-Contreras, 2020; Zhou, 2023). A significant trend in digital marketing is personalization. Personalization is considered crucial for enhancing customer experiences, engagement, and loyalty. The purpose is to adapt a standardized product or service to an individual customer's needs and the goal is to create profit for the producer and increase value for the consumer. A marketer automates personalization on behalf of the customer, making it more refined than customization, that is a request of a customer on its own behalf (Montgomery & Smith, 2009; Arora et al., 2008). Techniques commonly used for personalization include, but are not limited to, data mining, machine learning and artificial intelligence, which help to understand customer needs and to provide personalized recommendations (Fan & Poole, 2006). As one of the most popular channels for digital marketing, social media platforms are also essential for gathering customer data, that businesses can use for personalization. Personalization and in particular personalized advertising on social media positively impact consumer brand engagement and attachment, enhancing perceived quality and brand loyalty (Shanahan et al., 2019). The personalized recommendation systems in place on Social Media Platforms help users find relevant content and connections (Yu, 2012). According to Li (2016), the best advertising framework considers both personal interest (personalization) and the dynamic feed context, resulting in higher click-through rates on social media platforms. We can divide personalized advertising into two categories: (1) content personalization, which adapts the message, and (2) targeting individuals, which exposes the message only to specific individuals (Boerman et al., 2021). In this research we are focusing on personalized advertising, where they are targeting individuals using data on their previous engagements. Examining the existing literature on the variables gender and time spent in relation to personalization in digital marketing, we see that increased time spent on a platform allows algorithms to gather more data on user preferences and behaviors, enhancing the accuracy of personalized content and advertisements (Garcia-Pueyo et al., 2023; Kalyanaraman & Sundar, 2006; Pathak et al., 2023). Gender is often used to personalize content. Algorithms might push content that aligns with gender roles and different studies have shown that men and woman may have different interaction patterns on social media. The personalization algorithm takes this into account, causing men and women to see different types of content that reinforce their existing preferences and beliefs and thus limiting their exposure to diverse viewpoints (Klug & Strang, 2019; Fosch-Villaronga et al., 2021).

2.2 In-feed Advertising

Social in-feed advertising delivers advertisements that seamlessly fit inside a user's feed and allows users to engage in social actions (likes or comments) with the advertisements. This visibility among friends can significantly boost interest in the advertised products or services. Businesses, therefore, focus on maximizing these social actions to promote brand awareness effectively (Wang et al., 2020). It is one of the most effective advertising formats in the context of social media (Fulgoni & Lipsman, 2014). In-feed advertisements vary considerably from one platform to another, as they need to mimic the unique message format of a particular platform and are exclusive to that platform (Murphy & Schram, 2014). It appears in forms similar to the content viewed by users, such as graphics, images, and short videos. The method of in-feed advertising relies on data analysis and precise placement, making it highly targeted and efficient (Deng & Li, 2023).

2.3 Social Media Algorithms

Definitions of what an algorithm compasses can be found in current literature, as Cormen et al. (2009) notes that "an algorithm is a well-defined computational procedure that takes some value, or set of values as input, and produces some value, or set of values, as output." Therefore, we can say that an algorithm is a series of computational steps that transform input into output. However, the computational procedure responsible for taking values and producing them for each social media platform can be compared to a mysterious black box (Bucher, 2016; Pasquale, 2016). For social media algorithms, data extracted from tracking user interactions with other users' profiles and companies' profiles would be the input, while the in-feed advertisements and contents recommended for this user would be the output (Figueiredo & Bolaño, 2017). Adisa (2023) describes an algorithm as 'a series of instructions designed to solve specific problems, perform tasks, or make decisions.' She explains that in social media, algorithms are rules, signals, and data that govern each platform's operations. An overview of the key signals that are said to govern the operations of TikTok and Instagram can be found in Appendix 1. These algorithms dictate the filtering, ranking, and recommendation of content to users, thereby shaping their choices and the content they encounter on social media. A recurring limitation in the current literature is that algorithms are proprietary, resulting in limited access to the workings behind these algorithms making research on the topic difficult (Bucher, 2016; Figueiredo et al., 2017; Binns et al., 2018; Pasquale, 2016). Both TikTok and Instagram utilize advanced algorithms to personalize content and advertisement for their users. According to De Los Santos and Klug (2021), TikTok's algorithm focuses on maximizing user engagement, often at the cost of privacy, whereas Instagram balances personalization with user privacy and control (Skrubbeltrang et al., 2017). Many papers conclude that TikTok's algorithm generally outperforms that of Instagram in terms of content personalization and user engagement (Bishqemi & Crowley, 2022; Noveria & Karjo, 2023; Lina &Ahluwalia, 2021; Hendriana et al., 2022). However, Instagram users report higher enjoyment and a more balanced flow state compared to TikTok users, helping users to maintain healthy engagement (Roberts & David, 2023). Instagram also offers more user control over content visibility and provides tools for understanding how the algorithm works. This transparency helps users navigate and utilize the platform more effectively, enhancing the overall experience. Mehlhose et al. (2021) mentions that the user recommendation system of Instagram due to its effective identification and promotion of relevant content often outperforms the algorithms of other platforms in terms of user satisfaction and engagement.

2.4 Filter Bubble

The concept of the filter bubble was introduced by Eli Pariser (2011), in his book "The Filter Bubble: What the Internet is Hiding From You". The filter bubble is defined as 'a state of intellectual isolation that allegedly can result from personalized algorithms accommodating content to individual preferences' (Pariser, 2011; Min et al., 2019). People sometimes confuse the term 'filter bubble' with the term 'echo chamber' and use them interchangeably. This is incorrect as there are differences between the two concepts. An echo chamber describes a situation where only certain ideas, information, and beliefs are shared (Dubios & Blank, 2018). Echo chambers arise when individuals seek out information or communities that align with their existing beliefs, leading them to magnify those beliefs without exposure to opposing viewpoints (Nguyen, 2018). Whereas the filter bubble is created by algorithms that personalize content for users based on their online behavior. Algorithms that filter out information that does not align with the users' past behavior create this filter bubble. These personalization algorithms isolate users from contradictory viewpoints (Pariser, 2011). Adee (2016) asserts that personalization algorithms on social media platforms can create a filter bubble effect, exposing users to similar types of advertisements repeatedly. Research suggests that TikTok's algorithm effectively personalizes advertisements based on user interactions, which can lead to the reinforcement of an advertising filter bubble (Yuan et al., 2022).

2.5 Bias and Negative Reputation in Advertising

Advertisements aim to arouse consumer desire and appeal, thereby fostering brand loyalty and boosting purchasing intentions (Mogaji, 2018). Users of social media platforms perceive advertisements as relevant when they effectively address their immediate needs or interests (Zhu et al., 2023). The personalization-privacy paradox emphasizes the friction between the benefits of personalized advertisements and the privacy concerns they raise. Users appreciate relevant advertisements, but the data collection required to create this type of personalization raises concerns. This can lead to a negative perception of an advertisement, even if its content is relevant to the user. (Xu et al., 2011; Sutanto et al., 2013). Research has shown that personalized advertising can cause reactance, ad avoidance, ad blocking, and a decrease in trust in advertisements (Boerman et al., 2021).There is a risk of bias in social media advertising algorithms. Advertising bias simply means that brands make unconscious assumptions to make decisions about who they market to and this bias can be part of the data and algorithms that platforms employ for advertising (Bach & Bernat, 2022). Technological bias can occur when a human cognitive bias or biases in the training data are unknowingly encoded into the system and distributed at scale. (IBM Watson Advertising, 2022).

Several factors contribute to the low level of trust and negative reputation of social media advertising. Firstly, research reveals that social media is the least trusted media channel, a finding that adversely affects the effectiveness of social media advertisements. People perceive social media advertisements as intrusive and manipulative, leading to negative reactions and a reduced trust in the advertised brands (Hahn et al., 2016). Moreover, deceptive or false advertising can lead to a psychological response where consumers or users establish a principally defensive attitude towards advertisements, decreasing the overall effectiveness of advertising as a marketing tool (F. Li & Miniard, 2006).The personalization-privacy paradox (XU et al., 2011; Sutanto et al., 2013), the bias in advertising (Bach, Bernat 2022) and the negative reputation of advertising give thought to what level of personalization and relevance we should consider as to examine to what degree there is the existence of the advertising filter bubble. To establish to what extent an advertising filter bubble is observable, it is important to determine if there is a filter bubble in the first place, a filter-bubble baseline. A mean relevance score of at least 25% seems a safe spectrum in the personalization-privacy paradox, as several studies claim that a medium level of personalization is said to often be the most effective, as high levels of personalization can lead to a feeling of invasiveness and low levels of personalization would not achieve engagement with the user (Walrave et al., 2016; O'Donnel & Cramer, 2015; Zhu & Chang, 2016). This established baseline of 25% will be used to evaluate the in-feed advertisement relevance scores of TikTok and Instagram.

2.6 Relevance and Neutrality

Participants score the in-feed advertisements according to their relevance to them. Therefore, it is important to define relevance. There is little to no agreement or consensus as to exactly what relevance is (Schamber & Eisenberg, 1988). Cambridge dictionary defines relevance as: "*The degree to which something is related or useful to what is happening or being talked about*". Where Mizarro (1997) in 'Relevance: The Whole history' states that it is commonly accepted that relevance is a relation between two entities or groups". Cooper (1973) characterizes relevance as topicality, a notion inherent in utility. Utility, he says, is a "catch-all concept" a "cover term for whatever the user finds to be of value about the system output, whether its usefulness, its entertainment, or esthetic value, or anything else". Information scientists who have adopted and developed cognitive psychology's approaches tend to view relevance judgements as intersubjective and constantly evolving phenomena. They assert that internal factors such as attitudes and prejudices, as well as external factors like needs and situations, can influence users' judgments as individuals. This is in line with the findings of Schambler and Eisenberg (1988). To cover both internal and external factors, I am defining relevance for the participants with these two questions:

1. Have you engaged with this topic in the (recent) past? (internal)
2. Is it about a topic you are normally already interested in? (external)

In addition to relevance, to leave no room for ambiguity, we also defined the term neutral. Labeling items as neutral are often ambiguous and inconsistent between datasets, with phrases like "neither" (Nie, et al 2020a) or "might be correct" (Bowman et al., 2015; Williams et al., 2018). There are two senses in which the relationship between two things can be neutral:

1. True neutral: There are not sufficient strong reasons to satisfy either entailment or contradiction
2. Conflicting neutral: The user finds strong reasons to support both tailment and contradiction

In this research, we define neutral as true neutral. The participant does not consider the in-feed advertisement to be completely relevant or irrelevant to itself.

2.7 Hypotheses

We will test the hypotheses shown in Table 1 to answer to Subquestions 3, 4, and 5.

Research Focus	Platform	Hypotheses
Platform Comparison	Both	H0a: No significant difference in relevance scores between platforms. H1a: Significant difference in relevance scores between platforms.
Time Spent	TikTok	H0b: No relationship between time spent and relevance scores. H1b: Relationship between time spent and relevance scores.
Time Spent	Instagram	H0c: No relationship between time spent and relevance scores. H1c: Relationship between time spent and relevance scores.

Platform Comparison Time Spent	Both	H0d: No significant difference in the relationship between time spent and relevance scores across platforms. H1d: Significant difference in the relationship between time spent and relevance scores across platforms.
Gender Influence	TikTok	H0e: No significant difference in relevance scores between genders. H1e: Significant difference in interest scores between genders.
Gender Influence	Instagram	H0f: No significant difference in relevance scores between genders. H1f: Significant difference in interest scores between genders.
Platform Comparison Gender	Both	H0g: No significant difference in the relationship between gender and relevance scores across platforms. H1g: Significant difference in the relationship between gender and relevance scores across platforms.

Table 1: Hypotheses

3. METHODOLOGY

This section outlines the research design, data collection methods and analytical techniques used in this study.

Through the combination of a thorough literature review and the collection of quantitative data this research aims to answer the already mentioned research question: "*Is there an advertising filter bubble observable and what influences the advertising algorithms on social media platforms TikTok and Instagram?"*

The theoretical framework provides the answers to Subquestion 1: 'What are the basic workings of the algorithms of TikTok and Instagram Reels?' and Subquestion 2: 'What are the objectives of digital marketing through Social Media advertising?'. We answer Subquestions 3, 4, and 5 through quantitative analysis.

3.1 Sample

A total of 33 subjects participated in this study. This is a relatively small sample due of the time-consuming method required for collecting this type of data. In addition, it turns out to be very hard to find male subjects that have TikTok. Two of the participants are removed from the final sample because they did not encounter any advertisements on one of the platforms. Ultimately, the final sample size consists of 31 participants. A sample of at least 30 participants is recommended when doing quantitative research to achieve sufficient statistical power (Vasileiou et al., 2018). Criteria for selecting the participants are as follows: Each participant must have both applications, TikTok and Instagram on their mobile device. Also, each participant must have the screentime monitor activated on their device. Finally, each participant must identify as a man or a woman, because we test the effect of gender as a variable. All participants must provide informed consent before participating in the study. We ensure confidentiality of participant data by anonymizing responses. We conduct the study in accordance with ethical guidelines for research involving human subjects.

3.2 Methodological approach

Research Design

Quasi-experimental designs allow researchers to study interventions in real-world settings, such as social media platforms. Studying the personalization effects in the actual environment with the advertising content increases the external validity of the findings, making the results more generalizable to the broader user base of the platform (Mena et al., 2020) For this study it is not possible to directly manipulate any variables within the platforms. Quasi-experimental designs are often used to research causal relationships in social media systems, as this type of research design helps in the understanding causal effects without the need for direct manipulation of variables (Oktay et al., 2010). A quasi-experimental design therefore makes it possible to observe and analyze these complex interactions in a more naturalistic context, providing insight into how different factors, gender, and time spent on social media influence algorithmic outcomes. The aim is to establish cause-and-effect relationships between independent variables and a dependent variable. Do gender and time spent on Instagram or TikTok influence the filter bubble present on these platforms? Also, this data allows us to examine to what degree an advertising filter bubble exists on both platforms.

Data collection

We collect the quantitative data for testing the hypotheses two primary methods. First, we gather demographic information through a short survey with the following questions: (1) What is your gender? (2) How much time on average do you spend daily on TikTok? (3) How much time on average do you spend daily on Instagram? Second, we employ systematic observation in a quasi-experiment where participants recorded their observations of in-feed advertisements on TikTok and Instagram according to structured categories: 1. very relevant, 2. relevant, 3. neutral, and 4. irrelevant (Vonk et al., 2007). Each participant used each of the platforms for five minutes. We transform the collected demographic into independent variables and analyze them using various statistical tests to evaluate the hypotheses. The categories 1. Very relevant and 2. Relevant will be merged to create the variable in-feed advertisement relevance score for each platform. Each experiment will take a total of 15 minutes. It must be noted that participants are aware of the observation, which could create a certain bias in their behavior and can lead to the Hawthorne effect.

3.3 Analysis

Statistical Tests

After collection, we organize the data and compile it into a dataset (Appendix 2) to facilitate an in-depth analysis through multiple statistical tests, summarized in Table 2.

H0	Statistical Test	Reasoning
H0a	Welch's T-test	Comparing the two means, the data is normally distributed, no equal variance
H0b, H0c	Simple Linear Regression	Determining if time spent on platform (independent variable) significantly predict the relevance scores of in-feed ads on that platform (dependent variable)
H0d	Comparative Multiple Regression Analysis with interaction term	To test the difference in the effect of time spent on platform on the in-feed ads relevance scores between the two platforms
H0e, H0f	Independent Samples T-Test	Comparing the two means of the male and female group, the data is normally distributed and has equal variance

H0g	Two-way Anova	Examining the interaction effect between the variable gender and platform on relevance scores to determine if there is a significant difference between both platforms

Table 2: Statistical Tests per Hypothesis

Significance level

In this study, we use a significance level of 0.05 for our statistical tests. This threshold is widely recognized and accepted across various fields of research, providing a reasonable balance between the risks of Type I errors (false positives) and Type II errors (false negatives), ensuring that our findings are both reliable and reproducible (Ioannidis, 2005). The 0.05 significance level is particularly important in social sciences where the costs of both types of errors need careful consideration (Muller & Cohen, 1989). Given the relatively small sample size in our study, a more stringent significance level, such as 0.01, might increase the risk of Type II errors, potentially overlooking meaningful effects. Conversely, a more lenient threshold, such as 0.10, might increase the likelihood of Type I errors, leading to spurious findings. Thus, a 0.05 significance level is deemed appropriate to maintain a balance between sensitivity and specificity in our tests (Kim & Choi, 2019).

4. RESULTS

A dataset was created from the collected data. This dataset was analyzed using Excel and Python. As mentioned in chapter 3, different statistical tests were performed to obtain results.

4.1 4.1 Hypothesis testing

Relevance

Calculation shows that the mean relevance scores are 33.75% for TikTok and 47.49% for Instagram. First we tested the data for normality using the Shapiro Wilk test and Levene's test to test for equal variance (Appendix 3). The results for both variables indicated normality, but the assumption of equal variances was not met. Therefore we continued to determine whether the difference between these means is statistically significant with Welch's t-test instead of the Independent Samples t-test (Appendix 4) . The test yielded a p-value of 0.006, lower than the significance level of 0.05. Consequently, we can reject the null hypothesis (H0a), affirming a statistically significant difference between the relevance scores of TikTok and Instagram. Furthermore, Figure 1 displays the notched boxplots that show that the confidence intervals for the means of TikTok and Instagram do not overlap, reinforcing the conclusion that there is a significant difference between the two platforms.

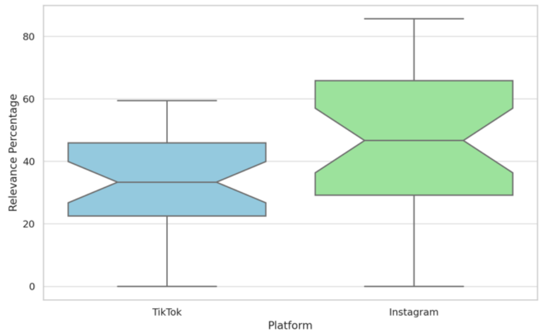

Figure 1: Comparison of the Relevance Scores for TikTok and Instagram (with Notches for CI)

Time spent on platform

Next, we test H0c and H0d. To determine if time spent on a platform significantly influences the relevance scores of in-feed advertisements on that platform, we performed a Simple Linear Regression (SLR) analysis for both platforms. Figures 1 and 2 show the plotted data and Table 3 summarizes these results. To gain a deeper understanding of the data, we repeated this regression analysis for two separate groups per platform, regular users (time spent ≤ 50 minutes) and frequent users (time spent > 50 minutes). The results of these two analyses did not show any significant different outcomes than the total dataset. These results and their visualizations can be found in Appendix 5

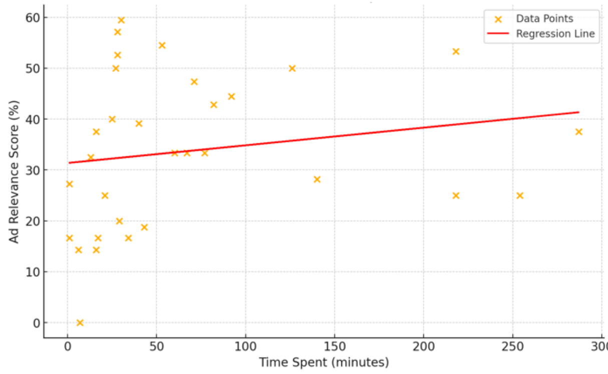

Figure 2: SLR TikTok

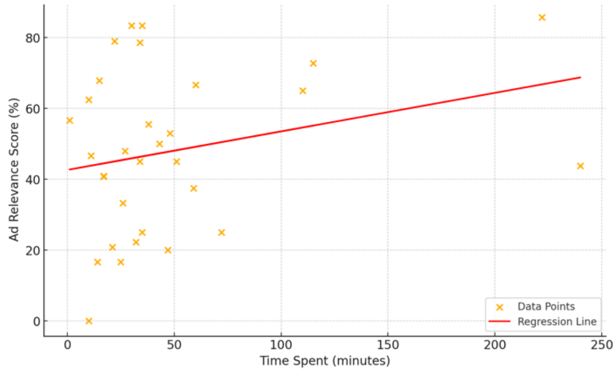

Figure 3: SLR Instagram

Platform	t-value	p-value
TikTok	1.114	0.275
Instagram	1.840	0.076

Table 3: P-Values SLR

The plotted data in Figures 1 and 2 show that there is a positive relationship between the time spent on the platform and the in-feed advertisement relevant scores for both TikTok and Instagram. However, the results from the Simple Linear Regression in Table 3 show that both P-values > 0.05, that indicates that there is no significant relationship between these two variables for both platforms. We fail to reject both H0c and H0d. For TikTok the R-squared value of 0.031 means that 3.10% of the variance in relevance scores is explained by the time a participant spent on TikTok. For Instagram this also means that the R-square value of 0.068 shows that 6.80% of the variance in the relevance scores is explained by the time a participant spent on Instagram. These are both low proportions that indicate a weak linear relationship between time spent on platform and the in-feed advertisement relevance scores.

To determine if there is a difference in the effect of time spent on in-feed advertisement relevance scores between TikTok and Instagram, we tested the null hypothesis (H0d). A comparative multiple regression analysis with an interaction term was conducted, as visually represented in Figure 3. The results from this analysis yielded a p-value of 0.347, which is greater than 0.05. Therefore, we fail to reject the null hypothesis, indicating that the influence of time spent on the platform on in-feed advertisement relevance scores does not significantly differ between TikTok and Instagram.

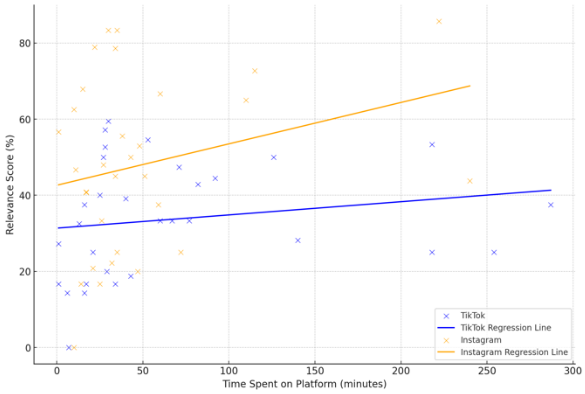

Figure 4: MRA with Interaction term

Gender

To test H0e and H0f, we conducted both the Shapiro-Wilk test for normality and Levene's test for equality of variances. The results indicated that the relevance scores did not significantly deviate from a normal distribution and the variances were equal (Appendix 6), meeting the necessary assumptions for conducting an independent samples t-test. The descriptive statistics can be found in Appendix 7. The results of the independent samples t-test can be found in Table 4. For both TikTok and Instagram, the t-test P-value exceeds 0.05, leading us to reject both H0e and H0f. The outcomes of the independent samples t-test indicate that there is no statistically significant difference between the relevance scores of male and female participants, and that therefore the variable gender does not significantly influence the in-feed advertising algorithms on either TikTok or Instagram.

Platform	t-Test Statistic	t-Test p-value
TikTok	1.114	0.275
Instagram	1.840	0.076

Table 4: Independent Samples t-test

We tested hypothesis H0g to see if there is a difference in the effect of gender on the in-feed advertisement relevance scores between both platforms TikTok and Instagram. After checking the normality and equal variances assumptions we performed a Two-Way ANOVA (Appendix 8), to test the interaction between to independent variables, gender and platform. The results of the interaction term are F-statistic: 0.795 and p-value: $0.376 > 0.05$, indicating that the difference in relevance scores between the platforms does not significantly depend on gender. However, the two-way ANOVA does indicate that for both platforms combined, with a p-value of $0.036 < 0.05$, there is a statistically significant effect of gender on the ad relevance scores, this is interesting as for the separate platforms the results indicated that there was no statistically significant effect. These results indicate that the effect of gender on the ad relevance scores is consistent across both platforms, but this effect only becomes statistically significant when considering the larger combined dataset.

5. CONCLUSIONS

This thesis explored the existence of the in-feed advertising filter bubble on TikTok and Instagram and assessed the potential influence of gender and time spent on these platforms on the algorithms creating these filter bubbles. Social media algorithms dictate the filtering, ranking and recommendation of content to users, thereby shaping their choices and the content they encounter on social media. Algorithms are proprietary and dynamic in their nature, what makes research on the basic workings of the algorithms of TikTok and Instagram (Reels) difficult. This lack of transparency creates challenges for digital marketeers, who try to reach consumers and encourage them to connect with products via digital distribution through these opaque algorithms. By testing multiple hypotheses, the study revealed several key findings. The mean in-feed advertisement relevance score is 33.75% for TikTok and 47.49% for Instagram, both surpassing the earlier established baseline of 25%. These findings indicate the presence of a filter bubble on both platforms, with a significantly stronger filter bubble observed on Instagram compared with TikTok. Furthermore, the analyses showed no statistically significant evidence that gender or time spent on the platform influenced the algorithms behind the filter bubbles. This suggests that there are other factors, not examined in this study, influence these algorithms. The consistency in the impact of gender and time spent across both platforms underscores a similarity in the algorithmic behaviors of both platforms regarding these variables. However, the overall relevance scores highlight a notable difference between the platforms: The mean relevance score for in-feed advertising of Instagram is significantly higher than TikTok's, indicating a stronger filter bubble effect on Instagram. This variability suggests distinct algorithmic strategies employed by both platforms. In conclusion, while gender and time spent on the platform do not seem to influence the algorithms that lead to the formation of filter bubbles, the overall strength of the filter bubbles differs between TikTok and Instagram. This presents implications for digital marketeers that aim to optimize their advertising strategies across these social media platforms.

6. DISCUSSION

6.1 Validity and generalizability

To conduct this research, 33 people participated in a quasi-experiment to gather data on the in-feed advertisement relevance levels of TikTok and Instagram. This research is reproducible, because if someone reanalyzes the data we collected, using the same statistical tests, they will obtain the same results, demonstrating that the analysis in this research was conducted fairly and accurately. Due to time constraints, the study does not demonstrate whether it is replicable, we were not able to conduct the study two or multiple times and therefor fail to determine if the same results would be achieved with new data, reducing the reliability of the research. In addition, the rapid development of these algorithms make replication challenging, as the results are only valid for a limited period, due to the swift pace of technological advancement. These limitations altogether make the validity and reliability of the study lower than expected. The approach we used to test the degree to which a filter bubble was observable on TikTok and Instagram can be replicable as it is a very general approach to keep a score of relevance, which can be found in Appendix 9. Because the research was tested in a real-life setting, we can speak of ecological validity. However, due to the similar nature and layout of TikTok's for you page and Instagram Reels, the study would be replicable for these platforms, but would not be applicable to other platforms.

6.2 Interpreting results and expectations

The research of Eli Pariser (2011), but also my own experience as user of the examined platforms, created the expectation that an in-feed advertisement filter bubble exists on TikTok as well as Instagram. With both platforms surpassing the baseline determined in Section 2.5, this study indicates that there indeed is an advertisement filter bubble on TikTok and Instagram. While most studies conclude that the TikTok algorithm generally outperforms that of Instagram in terms of content personalization, the results of this study are more in line with that of Melhose et al. (2021). The mean in-feed advertisement relevance score of Instagram (47.49%) is significantly higher that of TikTok (33.75%) and therefore indicates that Instagram outperforms TikTok. A difference in the relevance scores aligns with previous research indicating the variability of algorithmic personalization across different social media platforms (Yuan et al., 2022; Min et al., 2019). As mentioned in the theoretical background, prior research on the influence of gender bias on advertising generated the expectation that gender would indeed have an influence on the in-feed advertisement algorithm for each platform. The same holds for the variable time spent on platform, where existing literature provides reasoning for the existing influence of this variable on advertising algorithms. However, the findings of this study do not completely support this. When testing H0g, the results indicated that the effect of gender on the ad relevance scores is consistent across both platforms, but this effect only becomes statistically significant when considering the larger combined dataset. This is consistent with the expectation that the small sample size decreases the statistical power and enlarging the sample size therefore makes it more likely to detect a significant relationship if one exists. These results are in line with the expectation that gender has an influence on algorithms of social media platforms in general.

6.3 Limitations

This study has several limitations. One primary limitation is the small sample size of only 31 participants. A larger dataset can increase the likelihood of finding a significant relationship because of the statistical power that then increases. As already seen with testing H0g, where both TikTok and Instagram data was compiled, generating a statistically significant result, besides a larger sample can average out high variability or noise in the dataset. Furthermore, another limitation is that of the interpretation of the relevancy of in-feed advertisements by the participants. Despite the conceptualization of relevance, interpretations by the participants remain subjective. Because of the recent introduction of social media algorithms in academic literature, we deviated from using only peer-reviewed academic articles, questioning the scientific value of the data collected from the literature. The opacity created by TikTok and Instagram, frequently mentioned in existing literature, as expected induced limitations for this study.

6.4 Implications

This study contributes to the existing literature by performing a multi-platform analysis. It adds to the current knowledge about the inner workings of social media algorithms. It adds to the transparency that is so much sought after in social media algorithms, giving a miniscule insight into this black box. In addition, this study provides empirical evidence of the existence of filter bubbles in in-feed advertising on social media platforms. Empirical evidence is important for theories related to personalized content and the isolating effect personalization has on users of social media platforms. By comparing TikTok and Instagram this paper increases the understanding of how different algorithms can lead to varying degrees of filter bubble effects. As most current literature is on single platforms only, this comparative approach is valuable for developing more nuanced theories in studies on the filter bubble and the algorithms creating them. Looking at practical implications, the knowledge that Instagram provides higher relevance scores and thus is better at personalizing in-feed advertisement to the users preferences help digital marketeers and advertisers prioritize their investments and efforts on platforms where advertisements are likely to be more effectively targeted and more engaging for the users.

6.5 Recommendations for future research

Where this study already makes a start, a recommendation for further research would be to include more social media platforms like Facebook, Twitter and perhaps even YouTube, as there is little current literature on multiplatform analysis regarding algorithms. As mentioned in Section 6.3, increasing the sample size would be a recommendation for further research as this would increase the statistical power of an equivalent study in the future. To gain more insight into the secrets of the algorithms behind social media platforms, investigation of the impact of other demographics and key signals on these algorithms would be a great contribution. If more resources are accessible, a multiplatform study using bots instead of human participants would be very interesting as such research can conduct a longitudinal study that also observes changes in algorithms over time to see how several key signals impact the algorithms. These research ideas can build on the findings of this study and can contribute to a deeper understanding of the complex dynamics of the personalization algorithms on social media platforms.

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9. APPENDIX

Appendix 1 – Key Signals according to Adisa (2023).

Key signals	Explanation	Instagram reels	TikTok
Relevance	The contents relevance is determined by popularity signals like likes, saves and comments	x	
User activity/interaction	Posts you've liked, shared, saved, or commented on convey your content preference	x	x
Content type/video detail	Users who prefer photos see more photos. Same goes for videos. Video quality, captions sounds or hashtags to recommend content		x
Interaction history	Your interactions with an account's posts and frequency influence the appearance of their content in your feed	x	x
Account Information	An account's popularity, including follower count and engagement level, informs content recommendation	x	
Location	Recent and popular content in your region		x
Watch time	The number of replays and completed videos influences your feed		x
Device and account setting	This includes language, device type and country		x

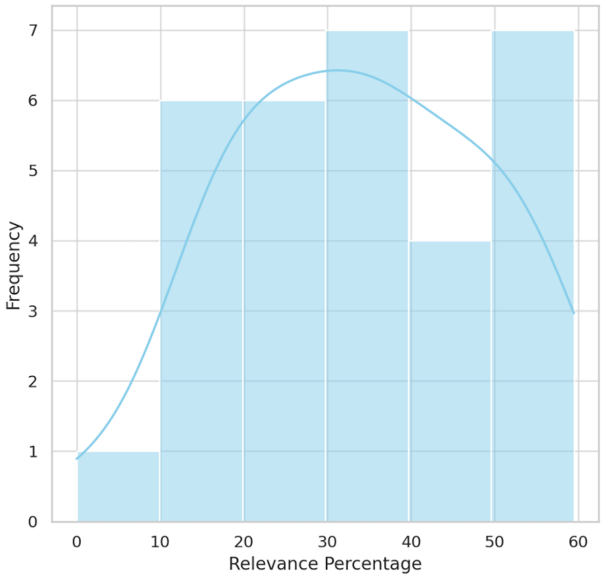
Appendix 2 – Dataset

Participant	gender	average time spent on tiktok (minutes)	average time spent on Instagram (minutes)_	Ad Relevance percentage TikTok	Ad Relevance percentage Instagram
1	female	16	10	37.5	62.5
2	female	29	72	20.0	25.0
3	female	67	32	33.33	22.22
4	female	27	48	50.0	52.94
5	female	25	15	40.0	67.86
6	female	6	27	14.29	48.0
7	female	71	17	47.37	40.74
8	female	126	115	50.0	72.73
9	female	140	110	28.21	65.0
10	female	254	34	25.0	78.57
11	female	28	222	57.14	85.71
12	female	30	240	59.46	43.75
13	female	53	11	54.55	46.67
14	female	17	60	16.67	66.67
15	female	60	43	33.33	50.0
16	female	16	21	14.29	20.83
17	female	40	22	39.13	78.95
18	male	13	35	32.5	25.0
19	male	1	30	27.27	83.33
20	male	218	47	25.0	20.0
21	male	34	51	16.67	45.0
22	male	77	38	33.33	55.56

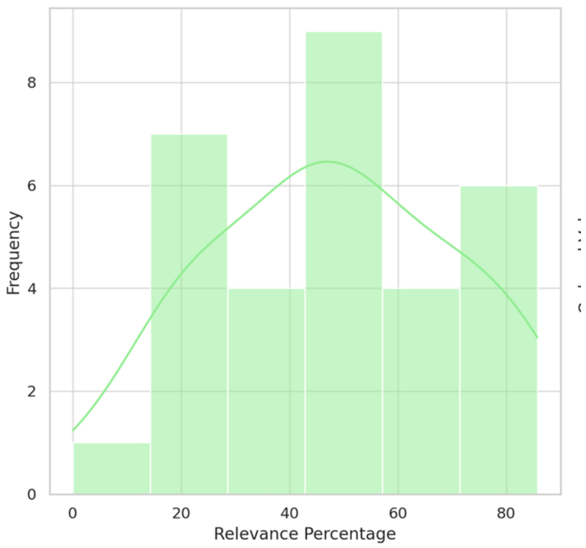
23	male	92	59	44.44	37.5
24	male	82	26	42.86	33.33
25	male	7	35	0.0	83.33
26	male	218	17	53.33	40.91
27	male	287	1	37.5	56.67
28	male	1	10	16.67	0.0
29	male	43	14	18.75	16.67
30	male	28	25	52.63	16.67
31	male	21	34	25.0	45.0

Appendix 3 – Shapiro Wilks & Levene's test H0a + histograms

Test	Statistic	P-Value
Shapiro-Wilk TikTok	0.970	0.507
Shapiro-Wilk Instagram	0.968	0.465
Levene's Test	4.785	0.033



TikTok 1



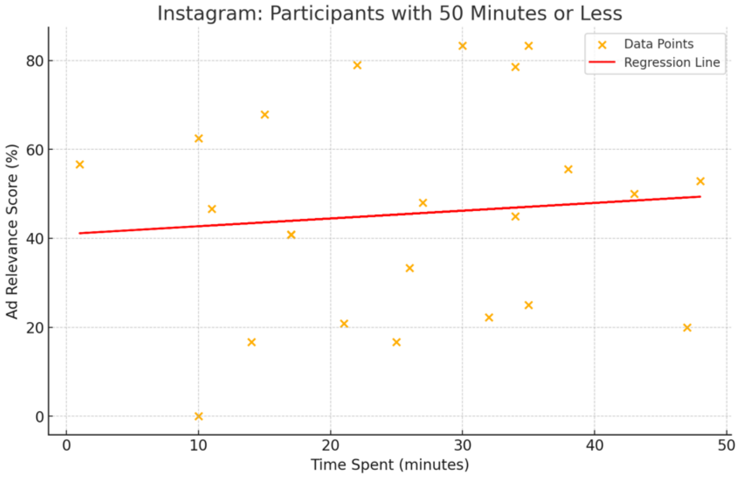
Instagram 1

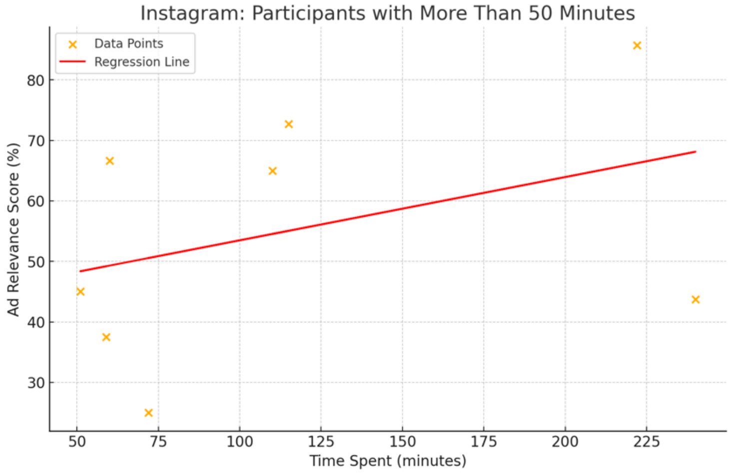
Appendix 4 – Welch's t-test

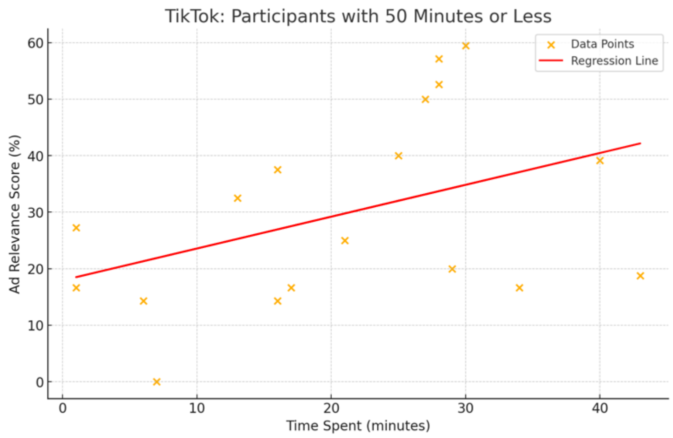
Test	Statistic	P-Value
Welch's T-Test	-2.8798867655966000	0.0057662311029095500

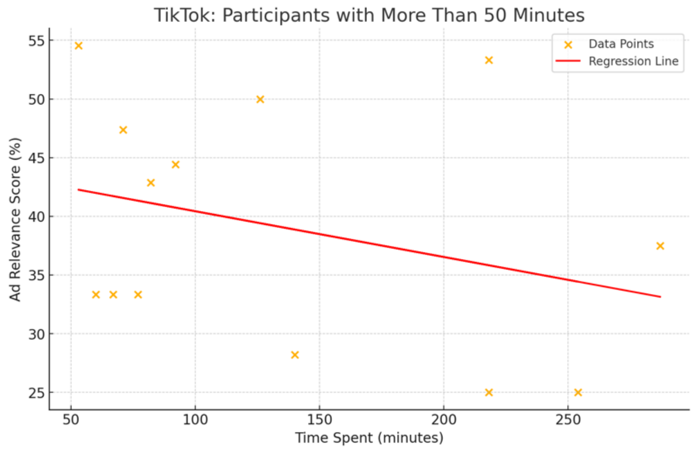
Appendix 5 – Results & Scatterplots Regular Users and Frequent Users

Platform	Participant Group	R-squared	Adjusted R-squared	F-statistic	Prob (F-statistic)	Intercept (const)	Slope (x1)	p-value (Slope)
TikTok	All	0.031	-0.002	0.9409	0.34	31.3667	0.0347	0.34
TikTok	50 Minutes or Less	0.095	0.012	1.149	0.307	44.3297	-0.039	0.307
TikTok	More Than 50 Minutes	0.384	0.287	3.953	0.066	20.9758	0.2014	0.066
Instagram	All	0.068	0.036	2.124	0.156	42.6358	0.1087	0.156
Instagram	50 Minutes or Less	0.146	0.004	1.028	0.35	43.0335	0.1045	0.35
Instagram	More Than 50 Minutes	0.316	0.184	2.396	0.156	47.4318	-0.1653	0.156









Appendix 6 – Shapiro Wilk's & Levene's test for gender

Test	Platform	Gender	Statistic	p-value
Shapiro-Wilk	TikTok	Female	0.942	0.341
Shapiro-Wilk	TikTok	Male	0.969	0.867
Shapiro-Wilk	Instagram	Female	0.950	0.450
Shapiro-Wilk	Instagram	Male	0.951	0.582
Levene	TikTok	Both	0.035	0.853
Levene	Instagram	Both	0.0208	0.652

Appendix 7 – Descriptive statistics

	TikTok Female	TikTok Male	Instagram Female	Instagram Male
count	17.0	14.0	17.0	14.0
mean	36.48647058823530	30.425	54.5964705882353	39.926428571428600
std	15.113969920729200	15.040336406835100	20.095575676369800	24.321641710511800
min	14.29	0.0	20.83	0.0
25%	25.0	20.3125	43.75	21.25
50%	37.5	29.885000000000000	52.94	39.205
75%	50.0	41.520000000000000	67.86	52.92
max	59.46	53.33	85.71	83.33

Appendix 8 – Two Way Anova

Source	Sum of Squares	df	F-value	p-value
Gender	1649.8605862022200	1.0	4.612318757129580	0.0359335647779157
Platform	3135.225679032260	1.0	8.76477705338819	0.0044430230376395700
Gender * Platform	284.4771852534550	1.0	0.7952789881114940	0.3761934869946500
Residual	20747.029647899200	58.0		

Appendix 9 – Quasi experiment and short survey form

Participant number:

Exploring the Consistency and Variability of Algorithmic Filter Bubbles: A Comparative Analysis of Instagram Reels and TikTok

Hi, the main aim of my research is to "prove" the existence of a "filter bubble" effect in advertising and to understand the workings of the algorithms involved on different platforms, what results in the following research question:

"Is there an "advertising filter bubble" observable and do different variables influence the advertising algorithms on social media platforms Instagram Reels and TikTok?"

To answer this research question, I am conducting this quasi-experiment, collecting data from different users of Instagram and TikTok. First you will be asked to fill in a few short questions, to collect demographic data I will later on use as different independent variables. The second part is the actual "experiment". First you will scroll through Instagram Reels for 5 minutes. You will then score each ad that comes along the following values:

- Very relevant to me
- Relevant to me
- Neutral to me
- Irrelevant to me

The term "relevance" is defined as:

- Is the ad about a topic you are normally interested in?
- Have you engaged with this topic in the (recent) past?

To clarify this, I will use myself and what is relevant to me as an example. I have played hockey my entire life and still do, thus an ad about hockey falls under something I am normally interested in, but this could cover many other topics. Then an example of something I have engaged with in the (recent) past, I have been trying to find dresses for a prom, so ads about dresses cover a topic I have (recently) engaged with in the past. Personally, I have had nothing to do with horses my whole life, nor have I engaged with horse content any time in the (recent) past; therefore, content about horses would fall under the neutral or even irrelevant category.

Questions about demographics:

Gender:

Average time spent on tiktok (daily average):

Average time spent on Instagram (daily average):

Ad	Very relevant	Relevant	Neutral	Irrelevant
1				
2				
3				
4				
5				
6				
7				
8				
9				
10				
11				
12				
13				
14				
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This table can be copied and used for TikTok as well as Instagram

Appendix 10 – Literature matrix

Theme	Source	Definition	Research objectives / Problem	Methodology	Findings	Limitations or weaknesses	Implications or suggestions future research
Filter bubble/ Echo chamber							
	Eli Pariser, (2011) “The Filterbubble: what the Internet is hiding from you”. Guide books, ACM Digital Library.	Filter bubble The personalized ecosystem of information that an individual is exposed to online	Investigate how personalization algorithms filter information and create individual filterbubbles that limit the diversity of content. Understand the societal impact. Raise awareness	Literature review Interviews with experts from various fields. Case studies with specific examples to illustrate the impact of filter bubbles	Online platforms use algorithms to customize content on user behavior, creating a personalized information bubble. Personalization leads to echochambers. There is a lack of transparancy and control. Filter bubbles can polarize a society.	Rapid technological changes may find findings outdated quickly. Scope of platforms is limited. Subjectivity in interpretation by author of data and intervviews. To much anecdotal evidence	Broader platform analysis. Increase the use of quantitative and empirical methods. Adopt interdisciplinary approaches.
	Min, Y. , Jiang, T., Jin, C., Li, Q. & Jin, X. (2019). “Endogenetic structure of filter bubble in social networks” . Royal Society Open Sience, 6(11).	Filter Bubble An intermediate structure in social networks that not only forms dense communities of users with similar preferences but alsoexhibits an endogenetic unidirectional starlike structure	Examine internal organisation of filter bubbles in social networks. Analyze how these structures contribute to polarization. Utilize AI technologies to study the dynamics of filter bubbles	Social bot deployment Data collection and analysis from these bots to identify patterns and structures	Filter bubbles in social media networks are not just dense communities but exhibita n endogenetic inidirectional starlike structure. The structural formation inherently excludes non preferred information. Using bots and AI	Scope focusing on Weibo. Short experiment period	Long term studies to observe sustained impact. Broader platform analysis. Investigate how individual user behaviors contribute tot he formation and maintenance of filter bubbles

					provided a controlled and privacy-protective method		
	Dubois, E., Blank, G. (2018). “The echo chamber is overstated: the moderating effect of political interest anddiverse media.”. Information, Communication & Society, 21(5), 729-745	Echo chamber an environmentwhere individuals are exposed predominantly to information and opinions that reinforce their existing beliefs, leading to an amplification of their viewpoints.	Evaluate echo chambers and whether they significantly affect polarization Identify moderating factors	Survey and data analysis	Most people use multiple media outlets which reduces the risk of echo chambers. Those with high political interest are less likely tob e in echo chambers duet o diverse media consumption	Scope focussing on the UK. Short term data	Future research should include a global perspective and research how individual beaviors influence echo chambers
	Nguyen, C. T. (2018) “Echochambers and epistemic bubbles”. Episteme, 17(2) 141-161	Echo chamber a social structure where members are conditioned to distrust any external voices or sources of information	Clarify differences between echo chamber and epistemic bubbles Analyse mechanisms Investigate Impact on beliefs Propose intervention strategies The problem is the detrimental effect of echochambers and epistemic bubbles	Conceptual analysis, literature review,case studies and comparative analysis Philosophical argumentation	Echo chambers discreditoutside sources, fostering distrust in external information, while bubbles merely exclude outside voices. Echo chambers are more harmful. Both contribute to polarization. Isolation mechanisms. Echo chambers isolate by promoting distrust.. Bubbles isolate through omission of perspectives	Study relies heavily on conceptual and philosophical analysis. Need for empirical data.	Future research should include empirical research with a broader scope

	Adee, S.(2016). "Burst the filterbubble". New Scientist, 232 (3101), 24-25.	A state of intellectual isolation that can result from personalized searches when a website algorithm selectively guesses what information a user would like to see based on information about the user, such as past click behavior and search history	Identify the problem, Assess impact and propose solutions	Literature review Expert interviews Case studies Proposed solutions and user behavior analysis	Social media algorithms create personalized content bubbles limiting viewpoints. These bubbles can increase polarization. Users can seek mitigation strategies. Platform recommendations	Lack of empirical data Focus on major platforms limiting applicability	Future research needs to include empirical data, platform diversity, investigates user engagement and explore ways to increase algorithmic transparancy
In feed advertising	**Source**	**Definition**	**Research Objectives and problem**	**Methodology**	**Findings**	**Limitations or weaknesses**	**Implications or suggestions future research**
	Wang Et al, (2020) Social Influence does matter: User Action Prediction for In-Feed advertising, Proceedings of the …. AAAI Conference on Artificial Intelligence, 34(01), 246-253	A form of digital advertising where ads are seamlessly integrated within a user's content feed	To develop and enhance methods for accurately predicting user interactions with advertisements embedde within their social media feeds. Problem/pad adressedSocial influence on user actions, Data sparsity, and need for advanced prediction models	End to end approach, integrating datacollection, graph-based modeling and machine learning	The significant impact of social influence on the accuracy of user action prediction in in-feed advertising.	Datasets not representative of all social media platforms. Scaleble issues to very large datasets for graph based techniques Privacy and ethical concerns	Broader dataset inclusion Incorporation of additional factors needed Optimazation for scalability. Future research should focus on Realtime prediction systems. Cross disciplinary approach will give more comprehensive model
	Fulgoni, G., Lipsman, A. (2014),	A form of native advertising	To explore how social media can	Comprehensive, comparative	Social media significantly	The complexity of integratin	Future studies should

	Digital Game Changers. , Journal of advertisin g Research, 54(1), 11-16.	embedded directly within a users social media feed or contentstr eam	facilitate the transition to effective mobile and multi platform advertisin g measurem ent. Theu ai mto identify the impact of social media on advertisin g strategies, evaluate the effectiven ess of multi platform campaign s, and highlight the opportunit ies and challenges with measuring advertisin g performan ce across platforms. It adresses challenges such as data fragmenta tionand the need for consistent measurem ent techniqus	analysis data from multiple platforms and case studies	enhances measurem ent of advertisin g effectiven ess across mobile and multiplatf orm campaign s. It highlights the need for integrated metrics that can capture user engageme nt. In-feed ads are more effective duet o their seamless integratio n with content, leading to higher engageme nt and positive brand attitudes	g data across multiple platforms, this can lead to inconsiste nt metrics and difficultie s in standardiz ing. Rapid technolog y changes can quickly find some findings obsolete	focus on broader datasourc es, real-time analytics, and ethical considerat ions in data use to improve the accuracy and applicabili ty of advertisin g effectiven ess assessmen ts
	Deng, J. & Li, L. (2023). In-feed Advertisin g, Pricing and Privacy Informati on Utilizatio n Strategies of short video platforms, EAI.	Advertise ments that are seamlessl y integrated into the content feed of short video platforms	To develop a comprehe nsive understan ding of in-feed advertisin g pricing strategies on short video platforms, particularl y focusing on how these platforms use users privacy informatio n while	Theoretic al and empirical approach. Modelcon struction, simulation and validation	Increased privacy concerns initially decrease the utilization of privacy informatio n and platform profits but can reverse at higher levels. Platforms benefit from positive cross-network	Different weakness es the most important: The study relies on simulated data, limiting its applicabili ty to real world scenarios. The study may not account for rapid techonolo gical developm	Incorporat e real data to validat and improve model. Explore the impact of privacy regulation s. Extend the research to various digital platforms. Account for new technologi es like AI and machinele

			addressing privacy concerns Problem adressed: critical issue of balancing effective advertising with user privacy concerns		externalties, where increased user advertiser interactions enhance profitability	ents. Findings may not be transferable to other digital environments. Yhe model underemphasizes factors like content quality and does not consider long term effects.	arning and integrate behavioral factors.
	Murphy, T and Schram, R. (2014), “What is it worth? The value Chasm between Brand and Influencers”, Journal of Brand Strategy (3:1), pp 31-40	Ads that are seamlessly integrated into a user’s social media feed or content stream. These ads are designed to appear as a natural part of the content	To evaluate the effectiveness of in-feed advertising on social media platforms. Specifically investigating how consistency and sociability of in-feed ads impact consumers perceptions. The study seeks to determine whether in-feed ads can mitigate negative perceptions and enhance engagement by appearing less intrusive.	Experimental design to assess the impact of in-feed advertising features	They found that in-feed ads, when designed with high consistency and sociability, significantly reduce perceived intrusiveness and ad clutter. These features also decrease ad avoidence .and are thus more effective	Findings may not apply to other platforms Variability among different demographic groups not fully explored. Short term focus. Controlled experiment may not fully reflect real world conditions	Suggestions: -study in-feed ads across different platforms -examine long term effects -consider impact on various demographic groups - replicate under real wold settings
Relevance	Source	Definition	Research objective and problem	Methodology	Findings	LImitations and weaknesses	Suggestions
	Schamber, L.& Eisenberg, >m. (1988). Relevance : The Search for	Relevance is a multidimesional concept that hinges on human	To critically examine existing definitions of relevance in	Review existing definitions: systemoriented, user-oriented,	Relevance is a multidimensional concept influenced by cognitive	Subjectivity because of reliance on individual judgements.	-Develop better methods for measuring subjective relevance

	a Definition. Annual Meeting of the American society for Information Science	judgment. Their user-centric approach posits that relevance depends on both internal(cognitive) and external (situational) factors	information retrieval systems and propose a new, user-centric approach. Problem is the lack of consensus on the definition and critique existing approaches as too system focused	multidimensional and cognitive approaches. They explore within the context of the sense-making methodology at Syracuse University	and situational factors. Relevance judgements are subjective yet can be systematically measured.	Complexity of the model (different factors). Difficulty to systematically measure subjective relevamce. Generalization may be difficult	-Reduce complexity in the model -expand testing and conduct studies to understand relevance judgement over time
	Mizzaro, S. (1997). "Relevance: The Whole history". Journal of the American Society for Information Science, 48(9).	Relevance is a complex, multidimensional concept that varies depending on several factors, including the context of the user's information need, the charachteristics of the infromation, and the interaction between the user and the informationsystem	To provide a comprehensive historical review of the concept of relevance in information science and retrieval. The problem is the lack of a comprehensive and unified definition of "relevance"in the field of infromation science.	Historical analysis Framework development leading to critical examination and synthesis to a unified understanding	There is an evolution over time. It is a dynamic multifaceted concept influenced by cognitive and situational factors. He emphasizes on user centric judgements. Literature review about the subject	The complexity of the concept, the subjectivity of user centric aspects lead to inconsistent relevance judgements. Historica bias	Enhance methods for measuring subjective relevance consistently and make relevance concepts easier to apply. Examine changing contexts and incorporate cognitive and psychological science
	Cooper, W. S. (1973). On selecting a Measure of retrieval Effectiveness. Journal of the American society of Information Science, 87-100	The user's subjective evaluation of the usefulness of the information retrieved by the system	To develop a practical method for evaluating information retrieval systems. He aims to approximate user's subjective evaluations of system utility, proposing both ideal and compromise measures, and validating these	Combination of theoretical exploration and practical experimentation	The ideal measure is based on user's subjective evaluation. Implementing is impractical duet o complexity and subjectivity	This research relies on user's subjective evaluations, which can vary and are hard to quantify, they are impractical to implementand face validation challenges in real-world scenari''s.	Future research should develop objective measures, enhance validation techniques, explore contextual factors and refine user-centric models

			through experimentation and analysis. The main problem is finding a practical measure that accurately reflects the user's evaluation				
Digital Marketing	**Source**	Definition	**Research Objectives and problem**	**methodology**	**Findings**	**Limitations and weaknesses**	**Implications or suggestions future research**
	Kannan, P.& Li, H.(2017). "Digital marketing: a framework, review and research agenda", International Journal of research in Marketing, 34(1), 22-45	The use of digital technologies to facilitate the marketing of goods and services, leveraging online platforms, social media, mobile applications and other digital mediums to reach and engage customers	Develop a framework, review existing research and set a research agenda. The problem is the lack of a comprehensive framework that integrates various elements of digital marketing	Framework development, literature review and issue identification	Digital technologies significantly affect various stages of the marketing proces, enhancing consumer engagement, data analytics and personalized marketing strategies	Findings may become outdated. This research may not provide sufficient solutions for managing and leveraging data. Privacy concerns need more attention.	Should focus on cross-channell marketing strategies, the role of AI and ethical issues
	Srivastav, P. & Gupta, H. (2021)."Role and applications of digital marketing in digital era: a review. IEEE.	The practise of leveraging digital technologies, platforms, and dat analytics to promote products and services, engage with customers, and drive conversion.	Examine digital marketing's role in reshaping business strategies. Identify implications on consumer behavior, businessmodels and marketing strategies. Study the impact of integrating advanced technologies like AI and data analytics	Literature review Surveys and interviews, casestudies, empirical analysis and modeltesting	Digital marketing significantly improves engagement by leveraging personalized content. The use of AI and data analytics enhances the ability to target specific customers. Leading to higher conversion rates. Businesses are increasing	Scope of datacollection from a developing economy. Representativeness of sample size and diversity of respondents Focus on AI. Context of COVID pandamic	Future research should include other regions. Longitudinal studies Integration of technologies addressing ethical issues, examine the impact of AI and machine learning in digital marketing

					ly adopting digital-first strategies. There are ethical concerns		
	Shetty, S. K. (2022). “Analysing Financial services performance using a powerful digital marketing platform”. International journal for multidisciplinary research, 4(5)	The process of establishing and maintaining consumer relationships through online activities to facilitate the exchange of ideas and products	Evaluate digital marketing impact Investigate the role of digital marketing in building and maintaining consumer relationships Analyze engagement and conversion. Understand how digital marketing aligns with business objectives	Literature review Surveys and interviews with industry professionals Data analysis and case studies	Digital marketing enhances consumer engagement, increases conversion rates, improves customer relationships and aligns well with business objectives	Geographical scope, sample size and data privacy concerns	Conducting longitudinal studies with broader geographical scope, exploring advanced technologies and develop an ethical framework
	Chaffey, D. & Ellis-Chadwick, F. (2019). “Digital marketing: Strategy, Implementation & Practice”. Pearson UK	The use of online channels, platforms, and technologies to promote products and services, engage with customers, and achieve business objectives	Offer an in depth understanding of digital marketing strategies, with practical insights	Literature review, casestudies, datadriven insights			
	Philips, E. E. (2015, november 17). “Retailers scale up Online sales distribution networks”. The Wallstreet Journal Retrieved june 16th 2024	Use of online platforms and tools to enhance consumer engagement and sales	Explore how major retailers are expanding their e-commerce distribution capabilities				

	Tiago, M. T. P. M. B. & Verissimo, J. M. C. (2014). “Digital Marketing and social media: Why bother?”. Business horizons, 57(6), 703-708	The use of internet-based applications to implement innovative forms of communications an co-create content with customers	Understand how firms utilize digital marketing and social media. Identify benefits and challenges Provide insights to enhance digital marketing engagement	Combination of qualitative and quantitative research	Digital marketing enables firms to implement innovative forms of communication and co-create content with customers. Firms face pressure to adopt digital marketing. The need for relationship based interactions to improve digital marketing effectiveness	Consumer based research may limit the comprehensiveness of insights from the firm’s perspective	Future research should include broader industry en geographical scope and focus on emerging technologies and the integration of digital channels
Algorithm	**Source**	**Definition**	**Research objective and problem**	**methodology**	**Findings**	**Limitations and weaknesses**	Implications or suggestions for future research
	Bucher, T. (2016). “Neither black nor box: Ways of knowing algorithms. In Springer E books (pp 81-98)	A set of rules or instructions designed to perform a specific task or solve a specific problem, often embedded within software and systems that influence various aspects of daily life	Investigate the way in which algorithms are pervceived as opague. Understand algorithmic knowledge and analyze the impact of algorithms on society. The central problem is the difficulty in understanding and making sense of	Literature review and theoretical analysis. Specific case studies to provide practical examples and support analysis	Bucher concludes that comprehending algorithms requires recognizing their multifaceted nature and the interplay between technical, social, and epistemological factors. Theu are not transparant, they have significant social impactand hold substantia;l power.	Conceptual complexity of algorithms, limited access to proprietary algorithms and their dynamic nature. Fragmented perspectives (technical, social and user centric views often do not align. Generalizing is difficult with casestudies	Future ressearch needs more open access. Interdisciplinary research is advised and methodologies that can adapt to evolving nature of algorithms

			algorithms				
	Figueiredo, C. & Bolano, C. (2017). “Social Media and Algorithms: Configuration of the lifeworld Colonization by new media. International Journal of Information Ethics, 26	A set of computational rules or procedures used by social media platforms to filter, prioritize, and recommend content to users	Understanding algorithmic influence on user’s lifeworld. Examine social and ethical implications. Advocate for responsible design	Literature review Case studies and qualitative analysis	Social media algorithms play a critical role in shaping what users see and interact with, thereby influencing their perceptions of reality and their social interactions. Algorithms tend to prioritize content that aligns with user’s existing beliefs and preferences (echochamber) It can have impact on mental health because of exposure to certain content. There are ethica land democratic concerns	Popprietary nature of algorithms makes research difficult to fully understand their workings. The rapid evolution. Subjectivity of qualitative data. Difficult to generalize across different platforms and contexts.	Future research should focus on interdisciplinary research. Develop transparancy initiatives Longitudinal impact studies and establish an ethical framework
	Adisa, D.(2023, october). “Everything you need to know about social media algorithms. Sprout Social. Retrieved Atril 10, 2024 from sproutsocial.com	A series of instructions designed to solve specific problems or perform tasks.	Objective article is to explain how social media algorithms work, their importance in content curation and user engagement and how marketeers can adapt their strategies to optimize content	Key findings outlined: Algorithm function, User engagement, Platform specific algorithms and optimization			

			performance				
	Cormen, T.H., Leiserson, C. E., Rivest, R. L. & Stein, C. (2009). "Introduction to Algorithms". MIT Press	A well defined computational procedure that takes an input and produces an output. An algorithm is a finite sequence of well defined computer-implementable instructions, typically used to solve a class of specific problems or perform a computation	Provide comprehensive detailed introduction to the field of algorithms and data structures. Serve as reference Teach algorithmic thinking	Conceptual approach with mathematical proofs and formal techniques and practical real world applications	Broad range of topics with detailed explanations and examples		
	Pasquale, F. (2016). *The Black Box Society: The Secret Algorithms That Control Money and Information*. Harvard University Press.	Algorithms are a set of rules or instructions given to a computer to help it perform tasks. These tasks are often involved in decision-making processes that are automated and that rely on data input to produce outputs.	The book focuses on the lack of transparency and accountability in the use of algorithms. The aim is to shed light on this problem by addressing several issues: The opacity, the lack of oversight, its impact on society and the information asymmetry that occurs.	In this book the author uses different methodology. It combines legal analysis, case studies and critical theory.	The findings emphasize on the impact of opaque algorithms on society. The author calls for urgent changes to increase transparency, ensure accountability and protect individuals from the negative consequences of these algorithms	The book has a limited focus on the positive aspects of the use of algorithms. The author advocates for more transparency, but may underestimate the practical challenges, as transparency in highly complex and proprietary systems can be difficult.	The author highligts the critical need for further research into the transparency and ethical implications of the algorithms.
Personalization	**Source**	**Definition**	**Research objective and problem**	**methodology**	**Findings**	**Limitations and weaknesses**	**Implications or suggestions future research**
	Arora, N. et al	The process	To explore	Literature review	Personalization and	Collecting and using	Future research

	(2008). "Putting one-to-one marketing to work: Personalization, Customizatio, and choice. Marketing Letters, 19(3), 305-321	where a company uses previously collected customer data to determine and implement the most suitable marketing mix fora n individual customer.	and summarize the key challenges and knowledge gaps in understanding the decisions that both firms and customers make within context of personalization and customization in marketing. It adressess the problemof complexities of implementing effective one-to-one marketing strategies	and analysis. Casestudies and cross-disciplinary analysis	customization boost customer satisfaction and loyalty. Key issues include data collection, privacy concerns and implementation costs. Overpersonalization can lead to decision fatigue	personal data gives privacy issues. Generalizatiuon issues across other industries may be difficult	should focus on the long term effects of personalization, balancing privacy and personalization, optimal personalization levels, developing measuring techniques and context specific applications
	Montgomery, A.L., & Smith, M.D. (2009), "Prospects of personalization on the internet". Journal of interactive marketing, 23(2), 130-137	The process of adapting a standardized product or service to meet the individual needs of customers.	Review past research on personalization in interactive marketing. Analyze current applications of personalization and identify key problems and challenges in implementing personalization strategies. The main problem is the complexity of implementing effective personalization strategies	Comprehensive literature review	Personalization significantly enhances customer value and profitability by tailoring products to individual needs.. The study highlights the advancements in personalization through internet technologies but also idetifies major chalenges such as privacy high cost of implementation and difficulties in measuring	Privacy issues and rapid technological advancements can quickly outdate results	Future research should focus on keeping up with rapid technological changes and better measuring techniques

	Fan, H. &Poole, M.S. (2006). "What is personalisation? Perspectives on the design and implementation of personalization in information systems. Journal of Organisational Computing and Electronic Commerce, 16(3-4), 179-202	Tailoring or customizing content, services, or interactions based on individual preferences, behaviors, or characteristics of users.	To explore and define the concept of personalization in the context of computer-mediated communication. Classify types of personalization. Examin benefits and challenges	Literature review and conceptual analysis	They have come to a definition, Identified three types Content, Interface and functional personalization. Rulebased or machine learning approaches. They give insight in benefits like user satisfaction and challenges like privacy and complexity	Relies to heavily on literature review. It lacks empirical data It focusses on system design and not user perspective	Future research should include empirical studies, consider rapid technological changes and integrate user perspectives
	Shanahan, T. Tran, T.P. & Taylor, E.C. (2019). "Getting to know you: Social media personalization as a means of enhanced brand loyalty and perceived quality. Journal of retailing and Consumer Service, 47, 57-65.	The process of tailoring products, services, and experiences to meet the individual preferences, behaviors and needs of users.	Understanding personalization, How this creates value for business and consumers and objective is to examine applications across different sectors	Literature review Case studies Interviews and surveys	It gives a definition and three types of personalization: Content, Product and Service personalization.Benefits are better customer experience, increased engagement, better conversion rates and data utilization. Challenges are Privacy, technical complexity, resource intensive and over personalization	Bias and scope literature review. Generalizability difficult with casestudies	Do empirical studies in diverse contexts. Investigate the impact of new technologies like AI. Study different User demographics
	Yu, S. J. (2012). "The dynamic competetive recommen	The tailoring of product recommendations and services to	Develop a competitive recommendation Algorithm	Algorithm design Datacollection and analysis.	More accurately predicting user preferences thantraditi	-Data dependency of the algorithm Computational complexit	Yu suggests several areas for future research to adress

	dation algorithm in social network services. Information Sciences, 187, 1-14	individual users based on their preferences, behavior, and interactions	Enhance user experience Increase sales and engagement	Simulation and testing	onal methods Increased user satisfaction Boosting of sales anduser ingagement Positive impact on business	y, privacy concerns and scalability and implementation challenges	the limitations and enhance understanding of these kind of algorithms
	Li, Y., Zhang, D. Lan, Z. & Tan, K. (2016). “Context-aware advertisement recommendation for high speed social news feeding. IEEE.	Context aware advertising: delivering personalized ads based on realtime contextual information, such as user location, time of day, device type, and user behavior	Develop a context-aware algorithm, Enhance user engagement and measure effectiveness	Algorithm development, Real time data collection, Experimental set up by implementing the algorithms within a social news feed and compare with traditional advertising	Personalized ads are more relevant leading to higher user engaggement. Increased click through rates. Enhanced user satisfaction and better business performance	Privacy concerns, developing and implementing context-aware algorithms is complex and resource-intensive. Scalability can be challenging duet o computational demands (outdated)	Future research should focus on dataprivacy solutions, algorithm optimization, Cross platform integration and long term user perception studies