

# The Quiet Power of Social Media: Impact on Fish-Oil Purchases in Iceland during COVID-19

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## Abstract

The rise of social media has revolutionized communication and the sharing of information and interests, with a significant impact on purchasing behavior. Consumers increasingly rely on social media for product recommendations and reviews, often finding themselves "accidentally influenced" by other users' posts and advice. This study examines the impact of social media in Iceland during the COVID-19 pandemic when there was a surge of posts giving dietary advice to prevent or treat the virus or its symptoms. One example is the rise and fall of fish oil advice. Using a large-scale dataset from one of the most popular supermarket chains in Iceland and netnography, we apply Data Science to analyze: sales data; Google search trends; Twitter posts from 2019 and 2020 to understand the impact of the online world on purchasing behavior in the offline world. Our results show evidence of the impact of social media on people's purchasing behavior, particularly during a pandemic, and provide a comparison of consumer behavior before and during COVID-19.

## Introduction

In the last decade, social media have become an integral part of our daily lives and have radically changed the way we communicate, gather information and make purchasing decisions (Cao, Meister, and Klante 2014; Wandabwa et al. 2020). With the advent of social media platforms, consumers now have access to a vast amount of information about products and services that were once not easily accessible (Young, Selander, and Vaast 2019).

Social media have a huge impact on purchasing behavior, as consumers increasingly rely on reviews and recommendations from their peers and social media influencers to make informed decisions (Bynum Boley, Magnini, and Tuten 2013; Sogari et al. 2017). Platforms such as Instagram, Facebook and Twitter, have become a powerful marketing tool for companies to showcase their products and services and build brand awareness (Bhanot 2012).

At the beginning of the COVID-19 pandemic, fear and uncertainty dominated people's perception and reaction to this new and unknown disease, which was not yet fully studied, and a cure was not well known. Consequently, in this atmosphere of uncertainty, people were impressionable in ad-

vice on how to avoid and treat the disease, and both true and false news spread quickly using the internet, and in particular social media platforms (Awan et al. 2022; Miyazaki et al. 2023).

Furthermore, there were several such news and advice regarding the relationship between certain diets or supplements that reduced risk of contracting COVID-19. Some of them even went as far as stating that certain diets or supplements, would cure COVID-19. As an example, before COVID-19, there was evidence supporting several micronutrients, like zinc and vitamins C and D, as key components in aiding the immune system when fighting infections (Calder 2020; Gombart, Pierre, and Maggini 2020; Martineau et al. 2017). Numerous other nutritional supplements exist, including omega-3 fatty acids – also known as fish oil –, probiotics, and plant isolates such as garlic (Lentjes 2018).

In Iceland, fish oil stands out as a remarkably popular product. Renowned for its health benefits (de Magalhaes et al. 2016; Gammone et al. 2018), fish oil has been embraced by the Icelandic population for decades. Because of all the benefits it brings, fish oil was widely recommended worldwide to prevent and treat COVID-19.

Iceland's geographic isolation, heightened during the COVID-19 pandemic, underscores a unique context in which fish oil emerges as a popular and enduring supplement, with established purchasing patterns, particularly recording increased sales during the fall (Haraldsdottir et al. 2016). In light of this, the establishment of fish oil as beneficial in the fight against COVID-19 introduces a compelling scenario.

Although its effectiveness, in general, has been proven, research shows that opinion on the effect of fish oil on COVID-19 in particular spread at an incredible speed during the pandemic (Hathaway III et al. 2020).

The purpose of this paper is not to prove or debunk fish oil and its connection to COVID-19. Instead, this article aims to quantitatively assess the potential susceptibility of Icelandic individuals to fish oil promotion in the context of the ongoing pandemic. Through this investigation, we analyze the spread of social media posts regarding the benefits of fish oil versus COVID-19 and its impact on consumer purchasing behavior.

We are guided by the following research question: "*How did social media posts impact the Icelandic population's*

*purchasing behavior during the COVID-19 pandemic?*". To answer the research question, we collected and analyzed different data sources. We had the unique opportunity to collaborate with the second largest supermarket chain in Iceland, which provided us with purchasing data, so it was possible to compare the effects of the online world on the offline one. Besides, we conducted a netnography by extracting the time series of posts published advertising fish oil.

Then, we analyzed the data using different techniques, to show that the increase of fish oil purchasing was not casual but apparently influenced by social media. More information will be detailed in the methods section.

The main contribution of this paper is our conceptualization of social media influence in information systems through a data-driven approach to social media activity and its cultivation in an offline world, crystalized through changes in purchasing behavior.

## Related Work

### The Impact of Social Media on Purchasing Behavior

Social media have significantly influenced customer behavior over time, revolutionizing the way they interact with brands, make purchasing decisions, and engage with products and services (Shirky 2011; Lee and Ocepek 2023).

Social media exert a significant influence on purchasing behavior through its provision of abundant product information and reviews. Users can effortlessly access comprehensive details about products, peruse reviews from other consumers, and compare various options within these platforms. This profusion of information empowers individuals to make more informed decisions when it comes to their purchases (Leonardi 2017). Furthermore, social media platforms have become the domain of influential individuals known as influencers who often endorse and recommend products or services through their substantial followings (Masuda, Han, and Lee 2022; Kurdi et al. 2022). Their opinions carry weight and hold the power to influence the decisions of their followers, resulting in increased sales for businesses (Jansom and Pongsakornrungrungsilp 2021).

Moreover, people are naturally inclined to be influenced by the choices and preferences of others (Bauer and Ferwerda 2023; Ling, Gummadi, and Zannettou 2023). When they witness their peers or admired influencers endorsing specific products, it fosters a sense of validation and trust. As a result, individuals are more likely to make similar purchases, influenced by the actions of those they admire. Regardless of influencers or just regular people sharing content, social media have become a primary source of information, where customers research products, read reviews, compare prices, and gather insights before buying (Masuda, Han, and Lee 2022).

During sudden events like COVID-19, social media became a very important source of information (Han et al. 2020). The pandemic caused confusion and concern about health and wellness among the public (Baines, Elliott et al. 2020). In particular, lots of dietary news - both true and unproven - circulated on the internet (Baines, Elliott et al.

2020). Among those, there were news items stating that certain foods or supplements can protect against or even cure viruses in general and COVID-19 in particular, and as mentioned earlier in this paper, certain supplements would prevent or reduce symptoms. Although some of this news was unproven, the information was still spread through social media platforms and shared widely by netizens citizens of the internet, and they drastically changed customers' purchasing behavior (Roozenbeek et al. 2020).

### The Relationship Between Online Behavior and Offline Behavior During COVID-19

One of the large-scale changes during the pandemic was customers' purchasing behavior and purchasing trends (Mehta, Saxena, and Purohit 2020). A study conducted by (Jílková and Králová 2021) shows evidence of consumers changing their purchasing behavior drastically due to COVID-19, mostly moving to a larger extent towards online purchases and e-commerce. More specifically, various studies indicate that many consumers opted for online shopping in order to avoid going out for an enhanced feeling of safety and to cultivate an increased feeling of protection from the spread of the virus (Sayyida et al. 2021; Gomes and Lopes 2022). Moreover, some people were forced toward e-commerce and buying their groceries online because in some countries many shops were closed due to drastic social distancing measures taken.

In this context, data analysis can play a crucial role in understanding the changes in purchasing behavior as a result of online information (Akter, Ashrafi, and Waligo 2021; Laato et al. 2020). One way that data analysis has been used is to track changes in sales data over time (Carpinelli et al. 2022). For instance, by analysing sales data before and during the pandemic, it was possible to demonstrate that we can identify changes in consumer behavior directly related to the onset of the COVID-19 pandemic (Tyrväinen and Karjaluo 2022). The power of data analysis can be utilized for a wide variety of product categories or for multiple geographical regions to identify specific areas where certain types of information may have had a greater impact on consumer behavior (Fong, Guo, and Rao 2021) and (Hu et al. 2022).

### Research Contribution

Inspired by this type of research, we explore the impact of advertisements online, spread by netizens and their effect on the offline world, where consumer behavior plays a crucial role. Another way that data analysis can be used, is to track online searches and social media platform activity related to COVID-19 and consumer products through a netnography approach, which is coupled with the data analysis herein. By analyzing these types of data sources, for instance internet data and purchasing behavior data, we show that it is possible to identify trends in the types of social media posts that circulated and their impact on consumer behavior (Shah, Zahoor, and Qureshi 2019).

In this study, we had the unique opportunity to analyze the purchasing behavior of an entire nation. Iceland is isolated and was even more so during the pandemic (Cook and Jóhannsdóttir 2021).

In contrast to many other nations where platforms such as Amazon played a pivotal role, Iceland lacked a robust online shopping infrastructure (Kassem 2020). The absence of major e-commerce platforms heightened the complexity of transitioning to online purchasing, a transition that became particularly critical during periods of restricted mobility (Gudmundsson 2010).

One of the very few ways available in Iceland to do shopping online is by using the website of the supermarket you want to refer to.

The limited availability of comprehensive online marketplaces posed challenges for residents accustomed to the convenience offered by platforms like Amazon. Access to a diverse array of products online became a notable challenge, leading to an increased reliance on local businesses and traditional retail channels (Ghersetti, Ólafsson, and Ólafsdóttir 2023).

The pandemic was a sudden event that caused both fear and uncertainty and as such, it changed people’s purchasing behavior. Consumers started to buy different products in different quantities, which is why some studies speak of a structural break (Karavias, Narayan, and Westerlund 2022). A structural break might occur when there is a war, a major change in government policy, or some equally sudden events like for instance, a sudden onset of a worldwide pandemic. Certainly, COVID-19 represented a breaking event for the purchasing trends that had existed up to that point, and it is interesting to study how much social media contributed to this change.

## Methods

As stated earlier, we set out to investigate the impact that social media posts about fish oil as a remedy against COVID-19 had on consumer purchasing behavior in the offline world, through their in-store and online purchasing behavior. For that particular purpose, several data sources were utilized: we extracted Twitter data through academic Twitter API to understand the trends of certain types of posts via social media platforms, Google search trend data to see how people reacted to the two pieces of information mentioned above and if they researched further, and the purchasing data, focusing specifically on changes in fish oil purchase trends. The research process was three-fold. First, we conducted our data collection. At this stage, we collected all the data, explained in the section below. Secondly, we conducted data inspection and data analysis. In this phase, Twitter data, Google Trends and purchasing data were inspected as time series, and structural break analysis and correlation analysis were applied to all three data sources. Then, we applied the Granger Causality Test to determine whether there was evidence that social media posts time series had caused a change in the purchasing one. Finally, the results obtained were compared and discussed. Figure 1 shows the research process.

### Data Collection

We divided the data collection into four phases: i) Twitter data collection, ii) Google Trends data collection, and iii)

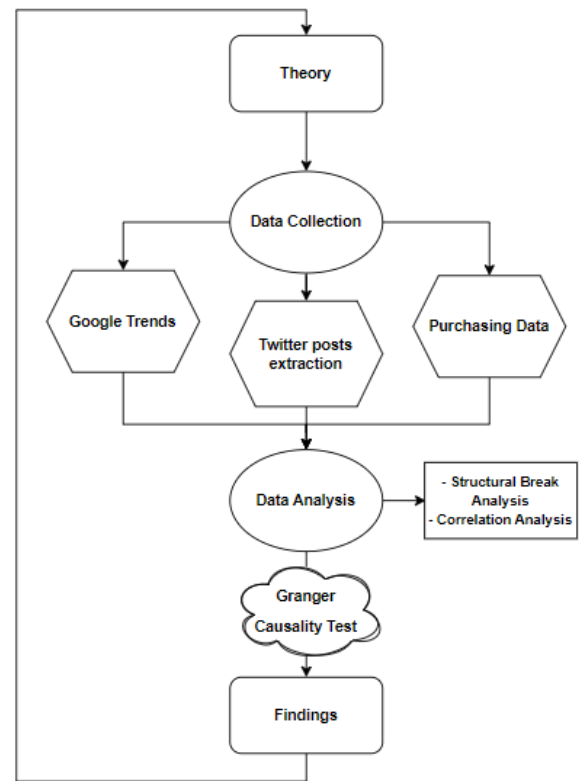


Figure 1: Research Process.

purchasing data collection.

**Twitter Data Collection** In the first phase, we looked for how information spread on social media platforms, focusing on Twitter data. We used the academic Twitter API to extract Twitter posts both in English and Icelandic from the period of 01.01.2019 to 31.12.2020 where we followed the terms and tags with both capital and lower-case initial letters: Fish oil covid; Fishoil covid; Lýsi; #fishoil; #fishoil #covid; #Lýsi. For clarification, lýsi is the Icelandic word for fish oil.

We extracted the data in weekly granularity for two reasons. Firstly, because there were several zeros in the daily granularity; secondly, because the data provided by Google Trends also had weekly granularity and because of that, a comparison between the graphs would yield a more accurate view.

We found 6768 Twitter posts in total from users all around the world. Before analysing the data, we added up the number of all the Twitter posts extracted and analyzed them as a unique time series. Figure 2 shows the number of Twitter posts over time.

Figure 3 shows a few examples of the posts found. It is interesting to notice that there are some verified accounts (the one with the blue badge). This means that the account that published that post is an account of public interest, with a lot of followers and hypothetically a lot of influence.

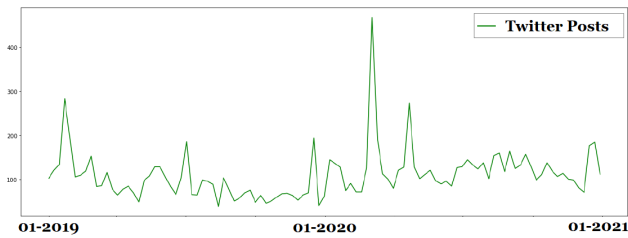


Figure 2: Twitter posts over time.



Figure 3: Some of the Twitter posts related to fish oil and COVID-19 during 2020.

**Google Trends Data Collection** In the second phase, we looked for the potential impact that news and posts on fish oil benefits had on internet searches, by analysing Google searches in Iceland between 2019 and 2021 for key terminology related to fish oil. During this phase we analyzed the following words with both capital and lower-case initial letters, in various combinations: Lysi; fish oil; Omega-3 and Cod liver oil.

Then, we combined all the searches and illustrated that in Figure 4 where we show the Google Trends day by day, both with initial capital letters and lower-case letters. We found 4589 Google searches in total for the selected period.

**Purchasing Data Collection** The purchasing data analyzed in this paper is numerical and represents daily sales

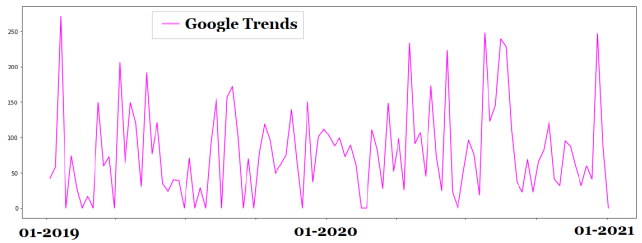


Figure 4: Google searches over time.

of fish oil of all brands sold in Iceland for two years: 2019 and 2020. The data was obtained thanks to our collaboration with the Icelandic second largest supermarket chain and it is from on-site and online purchases. The data included the features of date (in format dd-mm-yyyy) and quantity sold, for a total of 33707 purchases in 732 entries. Figure 5 shows the time series data obtained.

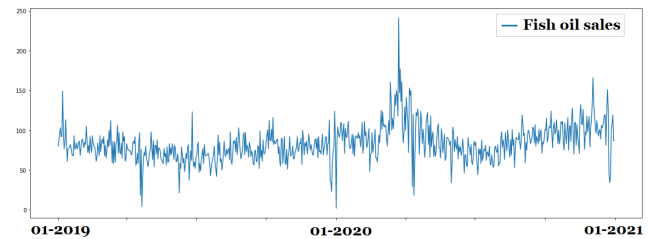


Figure 5: Items of fish oil sold daily over time.

Before conducting data analysis and comparison between the time series, we aggregated the purchasing data in weekly granularity.

Table 1 illustrates the total data points identified for each data source. Following the adaptation of all three datasets to a weekly granularity, the data points are distributed across a total of 54 entries per dataset.

Data Source	#data points
Twitter posts	6768
Google Trends	4589
Purchasing data	33707

Table 1: Overall data points for each data source.

### Structural Break Analysis

The first part of our data analysis focuses on investigating whether there are significant changes in the time series data during the time when fish oil recommendations on social media were prominent. To embark on that analysis, we first analyzed the stationarity of the time series. We performed the Augmented Dickey-Fuller test, a statistical significance test widely recognized and frequently used. There is a hypothesis test involved with a null hypothesis and alternate hypothesis, and as a result, a test statistic is computed, and p-values reported. From the test statistic and the p-value, an

inference can be made as to whether a given series is stationary or not, as we can read from (Prabhakaran 2022).

A structural break is an analysis type that is used to illustrate an abrupt change in a time series. This change could involve changes in mean or a change in the other parameters of the process that produces the series (Muthuramu and Maheswari 2019). Structural break analysis is used to determine when and whether there is a significant change in the data, which is what our research question calls for in this particular paper. In the present study, we looked for structural changes by performing a linear regression model on the following formula:

$$model = LinearRegression(Data \sim \frac{1}{length(Data)}) \quad (1)$$

Then, we evaluated the coefficient significance to ensure that the linear model created was consistent. We calculated the breakpoints and took the number of breakpoints with the minimum Bayesian Information Criterion (BIC), which is a metric commonly used to compare the goodness of fit of different regression models, as assumed by (Zach 2021).

### Correlation Analysis

Before conducting the correlation analysis, a normality test of the data was carried out. In order to put together the three data sources, we transformed the purchase data to a weekly granularity, like the Google Trends and the Twitter data. Then, we conducted a Shapiro-Wilk normality test to see whether we should use parametric or non-parametric tests to calculate the correlation between our data. The Shapiro-Wilk test turns out to be much more accurate than other tests for small datasets (Mishra et al. 2019), so we chose this one because we have a time series with weekly granularity and only 54 entries for each dataset.

The correlation analysis was conducted between the three time series. We used Spearman's correlation, a non-parametric method used when the data do not meet the assumptions of parametric tests, such as when the data are not normally distributed or when there is a non-linear relationship between variables (Akoglu 2018).

### Granger Causality Test

The Granger causality test is a statistical hypothesis test used to determine whether one time series can be used to predict another time series (Seth 2007). It is named after Clive Granger, who was awarded the Nobel Prize in Economic Sciences in 2003 for his work on this concept (Blinowska, Kuś, and Kamiński 2004).

The Granger causality test helps to understand whether changes in one variable can be used to predict future changes in another variable. However, it is important to note that the term "causality" here does not imply a true cause-and-effect relationship in the way it is commonly understood in philosophy or physics (Maziarz 2015). Instead, it suggests that one variable provides some information about the future behavior of another variable.

Given two time series X and Y, the Granger test is based on the F-test to decide between two hypotheses:

- Null Hypothesis (H0): The past values of variable X do not Granger cause (predict) variable Y;
- Alternative Hypothesis (H1): The past values of variable X do Granger cause (predict) variable Y.

If the p-value < 0.05 it is possible to reject the null hypothesis (suggesting Granger causality), otherwise or confirm it (suggesting no Granger causality) (Shojaie and Fox 2022).

## Results

### Structural Break Analysis

After the Augmented Dickey-Fuller test, all the time series turned out to be stationary, so no changes were necessary, and we could proceed with the analysis. We computed the linear regression model with Equation 1. Then we proceeded with the search for structural changes.

**Twitter Posts** The number of structural breaks with the minimum BIC for the Twitter posts time series was equal to 2, so we took two breakpoints in our model. Each breakpoint has both the date component and the quantity sold because it is a specific point in the graph. The two breakpoints corresponded to the following dates: 26.02.2020 and 31.03.2020. Figure 6 shows the time series of Twitter posts and purchases (aggregated at a weekly level) with the structural breaks of the Twitter posts' time series.

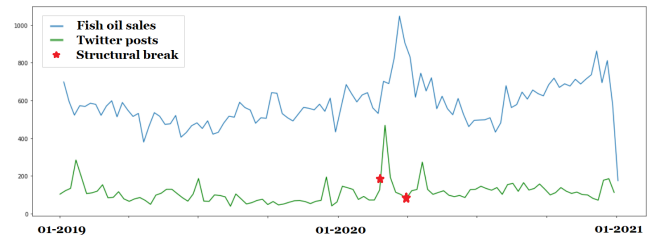


Figure 6: Twitter posts time series (green) with the structural breaks (red stars) compared to the purchasing time series (blue).

As we can see from this image, the two graphs display the same trend, especially at the beginning of 2020. The structural breaks in the Twitter posts' time series correspond almost entirely to the points where the sales graph also changes. The highest peak in the Twitter time series occurs in the week starting from 08.03.2020, while the purchasing time series' peak is in the 22.03.2020 week. We notice how the peaks and troughs in the Twitter posts graph are slightly earlier than in the sales graph.

The discrete consistency observed suggests a potential association between individuals' actions and consumption of posted news. In particular, the peak of substantial purchases aligns closely with the peak of Twitter posts. This correlation leads one to explore the plausible influence exerted by social media posts and news published online on individuals' behavior, a phenomenon also recognized by previous research (Lin et al. 2020).

**Google Trends** The Google search yielded no relevant results, as there was no change in the number of searches by Icelandic Google users for the terms indicated in the Data Collection section. Figure 4 shows minimal changes between 2019 and 2020 but the trend graph does not display a consistent number of searches over time. To determine whether this increased search volume is correlated with actual consumer purchases, we attempted to calculate the structural breaks in the time series. However, the number of structural breaks with the smaller BIC was equal to zero. This result indicates that there are no structural breaks in the Google Trends time series, meaning that there is no significant change in the graph.

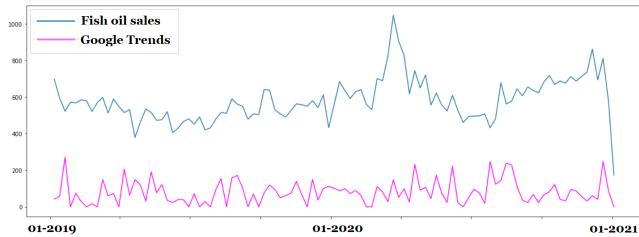


Figure 7: fish oil purchasing and Google searches time series.

Figure 7 depicts two graphs that exhibit dissimilar trends. Google searches for fish oil remained low. The disparity between the two graphs may suggest that at the beginning of COVID-19, people increased their purchases of fish oil without conducting any additional research.

**Purchasing Data** For the purchasing data, minimum BIC was obtained with 3 breakpoints, that corresponded to the following dates: 18.04.2019, 11.03.2020, 21.06.2020. The resulting model with the corresponding breakpoints is shown in Figure 8 below.

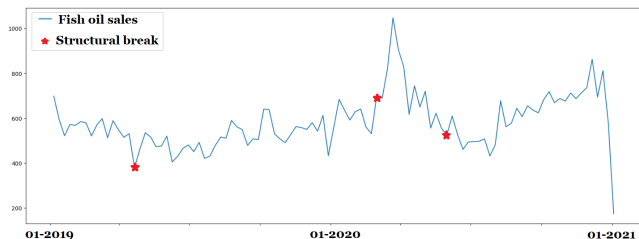


Figure 8: Structural breaks of the purchasing data.

In Iceland, fish oil is usually widely used during the winter to protect the immune system, so it is common for the purchasing trend to increase during the autumn and decrease during the summer. However, Figure 8 shows that there is an abrupt increase in fish oil purchasing that starts in March 2020. Our analysis shows that this can be supposedly attributed to the spread of posts suggesting the use of fish oil online. We then see that around the summer of 2020, there is a decrease in purchases, which brings us back to the usual pattern of purchases decreasing during the warmer seasons.

## Correlation Analysis

The normality test we carried out depicted that our data was not normally distributed. Table 2 shows the correlations between the time series.

The Spaerman's correlation value between fish oil purchases and Twitter posts resulted in  $r = 0.301$ , which is considered as a medium positive correlation value according to (Keskin 2013). With the significance level of ( $p < 0.01$ ) for fish oil purchases and the number of Twitter posts published over time, the result is that there is a medium positive correlation between them.

Google searches proved not to be statistically significantly correlated with either of the other time series. This result demonstrates again the commonality between trends on Twitter and in purchasing, and the difference with the trend in searches on Google. This might indicate that people did not research any further information about the benefits of fish oil.

## Granger Causality Test

We applied Granger's test by first evaluating the pair  $(X, Y) = (\text{Twitter posts, Purchasing data})$  and then  $(X, Y) = (\text{Google Trends, Purchasing data})$ . Table 3 shows that there is a causality between the publication of certain Twitter posts and the purchasing behavior of Icelandic customers. Indeed, the p-value for that pair is less than 0.05, and therefore we can say that there is predictive information: significant Granger causality suggests that past values of the variable X (Twitter posts) contain information that helps predict future values of a variable (Purchasing behavior). In other words, changes in X may provide insights or improve forecasts for Y (Tjøstheim 1981).

It is crucial to emphasize that Granger causality does not establish a true causal relationship in the traditional sense. It merely demonstrates statistical predictability. Other factors or variables not considered in the analysis could be responsible for the observed relationship (Stern 2011).

However, the many different analyses performed in this study also reinforce the result obtained from this last test, as we can see that in every analysis performed there is always a significant result between the Twitter time series and purchasing one.

## Discussion

Within the scope of shedding light on the way social media impact on people's beliefs and behavior, attention and attention-grabbing has become a crucial factor. Attention has become recognized as one of the essential critical resources for influence. As a large portion of the media today is driven by clicks, there is a wave of clicks that comes with successfully grabbing the readers' attention (Conway, Kenski, and Wang 2015; Wells et al. 2020). Since clicks and attention are valued over correctness, there is an epidemic of false or misleading information ongoing through social media, so there is a need to examine further and contribute with empirical findings (Baines, Elliott et al. 2020). Parallel to the focus on clicks and attention-grabbing, there is ideological polarization. Ideological polarization outlines the

	Purchasing data	Google Trends	Twitter posts
Purchasing data	1	0.199	<b>0.301*</b>
Google Trends	0.199	1	0.108
Twitter posts	<b>0.301*</b>	0.108	1

\*. Correlation is significant at the 0.01 level (2-tailed).

Table 2: Spearman’s correlations.

<b>Granger Causality Test</b>	Res.Df	Df	F	Pr(>F)
Twitter Posts - FishOil Purchasing	21	-2	5.8266	<b>0.01063*</b>
Google Searches - FishOil Purchasing	21	-2	2.6871	0.09383

\*. Significant at the 0.01 level

Table 3: Granger Causality Test.

strengthening of the existing beliefs of netizens which are reinforced by the repetition of similar information within a closed system, also known as filter bubbles (Au, Ho, and Chiu 2021; Tomlein et al. 2021) or echo chambers (Cinelli et al. 2021). Although these concepts represent slightly different phenomena, they all resemble each other in terms of their impact. When information enters into reinforced repetition within a closed loop system, the beliefs of the netizens are further reinforced and certain types of news are, by extension, more difficult to break (Au, Ho, and Chiu 2021; Tomlein et al. 2021).

Furthermore, since governmental policy-making, news agendas, social movements and election campaigns are run in online settings and through social media platforms in combination with trusted news outlets, it has become increasingly vital to study the correctness of the information spread online (Freelon et al. 2022; Wells et al. 2020) and to try to limit the influence that certain information can have on the users. Moreover, most of the research out there examines the way social media news spread and its evolution, but there is a gap regarding how the impact of social media information spread in online settings can impact the offline world. In this paper, we contribute to that particular gap with our study of the online world, through a netnography of how one news spread, while also studying behavior in offline settings through our purchasing behavior data derived from the supermarket chain. Through that data, we are able to contribute with novel findings on how online information impacts our offline behavior. With that said, it is now time to examine our methodological approach, to tackle our problem area, which we did here.

Google Trends shows a lack of interest in fish oil searches. Both purchasing and Google data were only collected for Iceland, so we can see how the nation reacted to the news. The analysis of Google Trends showed that people did not bother to look for the truthfulness of news read on social media, but trusted them blindly and started to buy more fish oil. This is one of the most worrying circumstances because it is the time when false information can spread fastest and create negative consequences for people (Pomerance, Light, and Williams 2022).

Another reason why people were highly influenceable during COVID-19 is due to the high levels of uncertainty and

anxiety that people experienced (Millroth and Frey 2021; Chen et al. 2023). When people are anxious or uncertain, they are more likely to seek out information to help them make sense of what is happening around them (Millroth and Frey 2021).

Further cause that contributed to people’s susceptibility to certain types of news read on social media was the sheer volume of information that was available during the pandemic. Figure 8 shows precisely how the biggest peak is in March 2020, when the pandemic started to spread around the world and there was such a large amount of information every day (Millroth and Frey 2021). The structural break analysis reveals how abrupt changes in the graph of purchases and the graph of Twitter posts almost match. The fact that there is a structural break in the Twitter data and not in the Google Trends is really interesting because it shows how much people believe what they read and do not search further (Pennycook and Rand 2021). It is important to see that also the correlation analysis confirms what we interpreted from the structural break analysis because we can see in Table 2 that fish oil purchasing is related to Twitter posts but not to Google searches. Moreover, in the Granger causality test, there is a significant result between the Twitter posts and the purchasing time series, but not between the Google searches and the purchasing ones.

These results suggest a strong likelihood that social media significantly influences our lives, potentially leading to a reduced inclination to thoroughly research online news due to implicit trust (Akram and Kumar 2017). In the contemporary landscape, the emergence of influencers appears to play a role in influencing our decisions or purchases, even if we may not be fully conscious of it (Akram and Kumar 2017).

### Limitations

Like all research, this study contains some limitations. Although the data comes from one of the largest supermarket chains in Iceland, with a large geographical spread, we are referring only to one supermarket chain out of four that we can find in Iceland. Because of that we also do not make claims for generalizing for the world based on these findings from Iceland. Moreover, data comes from only one social media which means that the analysis and the data itself could include biases. To counteract this limitation, we could

have analyzed all the data from all the supermarket chains in Iceland and all the most popular social media, but due to complexity, that was not possible. Since our data is derived from a very popular supermarket chain and one social network that is widely used in Iceland, we can assume that the present study is an acceptable approximation of the impact of social media on the Icelandic population during COVID-19.

### Future Work

Our study paves the way for further research in multiple directions. Firstly, we intend to broaden our analysis by examining various social media platforms to enhance the scope of our work. Additionally, we aim to delve into other case studies by differentiating between ordinary users and influencers, while employing social network analysis techniques. This will allow us to investigate the dissemination of social media posts promoting specific product types across the network and compare the outcomes with the tangible influence on purchasing behavior. Finally, it would be interesting to get a worldwide perspective by analyzing other markets besides Iceland.

### Conclusions

In this study, we had the unique opportunity to analyze data from one of the biggest supermarket chains in a single country concerning a major event that impacted society as a whole. We investigated the relationship between social media and its impact on behavior considering all of Iceland as a case study. We zoomed in on one particular product, *fish oil*, whose effectiveness against the virus circulated through websites and social media at the start of the pandemic. We took a data-driven approach and collected data from various sources, including purchases of fish oil through a statistical analysis combined with internet searches and visibility on social media platforms through a netnography approach. We answered our research question “*How did social media posts impact the Icelandic population’s purchasing behavior during the COVID-19 pandemic?*” by showing that the publication of Twitter posts provided some information about the Icelandic customers’ purchasing behavior.

The acquired results suggest a considerable likelihood that consumers were influenced by social media platforms, manifesting a perceptible alteration in their offline behavior as evidenced by an increased consumption of fish oil compared to the established pre-pandemic consumption patterns.

In our analysis, we present the presence of numerous breakpoints, which show that especially in March and April 2020, when COVID-19 began to spread throughout Europe and with it the fear of contracting the virus, different claims spread on social media platforms and fish oil sales significantly increased. Usually the purchase of fish oil increases during the fall, so it is surprising to see such a large increase in sales in the spring of 2020, which leads us to assume an influence dictated by social media. Correlation analysis and Granger causality tests continued to confirm the hypothesis we had from the Structural breaks. The effects we have shown are on changing purchasing behavior, but social media platforms may affect the population in many other ways.

### Ethical Statement

In this study, we paid the utmost attention to people’s privacy. We did not include personal names or accounts in our analysis. In addition, in the example figures, we deleted user identity features (name, photo, and user ID) to maintain anonymity. No consent to extract the data was necessary.

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## Ethics Checklist

1. For most authors...
  - (a) Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socio-economic divide, or implying disrespect to societies or cultures? Yes
  - (b) Do your main claims in the abstract and introduction accurately reflect the paper's contributions and scope? Yes
  - (c) Do you clarify how the proposed methodological approach is appropriate for the claims made? Yes
  - (d) Do you clarify what are possible artifacts in the data used, given population-specific distributions? NA
  - (e) Did you describe the limitations of your work? Yes
  - (f) Did you discuss any potential negative societal impacts of your work? No, because this paper is a descriptive study analyzing only one event and the subsequent reaction of people to this event. We are not making any claims about the veracity of the news spread

- on social media, but we are only analyzing the effect it had.
- (g) Did you discuss any potential misuse of your work? No, it is not relevant in this work.
  - (h) Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? No, because the data is aggregated and hence traceable to individuals, also the Twitter data is public.
  - (i) Have you read the ethics review guidelines and ensured that your paper conforms to them? Yes, and the present article respects all of them.
2. Additionally, if your study involves hypotheses testing...
- (a) Did you clearly state the assumptions underlying all theoretical results? Yes
  - (b) Have you provided justifications for all theoretical results? Yes
  - (c) Did you discuss competing hypotheses or theories that might challenge or complement your theoretical results? Yes, in the results section we explained that there could be other reasons why fish oil purchase increased. Also, in the limitations and future work sections we explained that analysis of other social networks could complement our results.
  - (d) Have you considered alternative mechanisms or explanations that might account for the same outcomes observed in your study? Yes, we explained in the results section that there could be other reasons why fish oil purchases increased, although there is always a correlation with Twitter data that led us to conclude that there was an actual influence of social media.
  - (e) Did you address potential biases or limitations in your theoretical framework? Yes, in the limitation section.
  - (f) Have you related your theoretical results to the existing literature in social science? Yes, in the discussion section.
  - (g) Did you discuss the implications of your theoretical results for policy, practice, or further research in the social science domain? Yes
3. Additionally, if you are including theoretical proofs...
- (a) Did you state the full set of assumptions of all theoretical results? NA
  - (b) Did you include complete proofs of all theoretical results? NA
4. Additionally, if you run machine learning experiments...
- (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? NA
  - (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? NA
  - (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? NA
  - (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? NA
  - (e) Do you justify how the proposed evaluation is sufficient and appropriate to the claims made? NA
  - (f) Do you discuss what is “the cost“ of misclassification and fault (in)tolerance? NA
5. Additionally, if you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
- (a) If your work uses existing assets, did you cite the creators? Yes, every statement is carefully cited.
  - (b) Did you mention the license of the assets? NA
  - (c) Did you include any new assets in the supplemental material or as a URL? NA
  - (d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? No, because it was not necessary to ask for any consent. The extracted data are public or anonymous. Purchase data are anonymous and were collected through collaboration with the supermarket chain; Google and Twitter data are easily extracted through the Internet. In Figure 3, we deleted the names of accounts that published certain posts.
  - (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? No. Our data do not contain offensive content, and have been appropriately anonymized so as not to contain personally identifiable information.
  - (f) If you are curating or releasing new datasets, did you discuss how you intend to make your datasets FAIR (see FORCE11 (2020))? NA
  - (g) If you are curating or releasing new datasets, did you create a Datasheet for the Dataset (see Gebru et al. (2021))? NA
6. Additionally, if you used crowdsourcing or conducted research with human subjects...
- (a) Did you include the full text of instructions given to participants and screenshots? NA
  - (b) Did you describe any potential participant risks, with mentions of Institutional Review Board (IRB) approvals? NA
  - (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? NA
  - (d) Did you discuss how data is stored, shared, and de-identified? NA