Social Media Metrics as Predictors of Publishers’ Website Traffic

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Abstract: The relationship between legacy media and social media has become a crucial topic in the discussions about new media. The debate intensified after Facebook announced a reduction in news posts in user timelines in 2018. In the era of the “Like economy”, social media holds significant economic value, prompting media outlets to adopt a “let’s try and see” approach to reach new audiences and increase their online advertising share. The present study, based on a large-scale survey of 50 publishers’ websites, Facebook pages, and Twitter accounts, deepens our understanding of the relationship between legacy and social media as indicators of audience feedback. Through the lens of network gatekeeping and reciprocal journalism theories, it contributes to the development of new evaluation tools that predict publishers’ website traffic based on social media metrics. Results show that Facebook and Twitter metrics can predict publishers’ website traffic indicators at a rate exceeding 60%. This study underscores the importance of social media metrics in evaluating media practices and the need to shift research toward specific indicators to understand the relationship between legacy and social media.

Keywords: news websites; traffic; engagement; analytics; social media; metrics; audience

1. Introduction

The dependence of legacy media on social media (Nielsen and Ganter 2017) has become increasingly prominent in the debate concerning new media. This debate has intensified since 2018 following Facebook’s announcement regarding minimizing news posts on user timelines (Zuckerberg 2018).

Opinions converge on the intermediaries’ hegemony (Siapera 2013) and the ever-growing journalism heteronomy (Tandoc and Maitra 2017); however, in the era of the “Like economy”, the social seems to hold a specific economic value (Gerlitz and Helmond 2013). In the context of threats and opportunities, the media follow a “let’s try and see” approach (Nielsen and Ganter 2017). Furthermore, to reach new audiences and gain a larger share of the growing online advertising (Powers and Vera-Zambrano 2017), journalists and media employ social media because it increases their website traffic (Philips 2012; Ju et al. 2014; Hong 2012). Simultaneously, the increased interest of publishers in audience measurements (Nelson 2018) underlines the need to shift research toward specific indicators as tools for evaluating practices followed by journalists (Zamith 2018).

The present study attempts to respond to this need. Through the lens of network gatekeeping and reciprocal journalism theories, it deepens our current knowledge by scrutinizing the characteristics of the relationship between legacy and social media as indicators of audience feedback, such as likes, retweets, and shares (Tandoc and Vos 2015). Additionally, it contributes to the development of new evaluating tools that function as specific prediction models for publishers’ website traffic based on social media metrics.
With a rare large-scale survey (3-month duration, 16 variables, 50 publishers’ websites, Facebook pages, and Twitter accounts), we analyze relationships between publishers’ website traffic and Facebook and Twitter metrics (page likes and followers, posts and tweets, likes, shares and retweets, comments and Twitter replies). Next, we move to the development of predictive models of traffic indicators of visits, page views, unique visitors, time spent/visit, and bounce rate, based on the Facebook and Twitter metrics.

Our results show that Facebook and Twitter metrics can predict publishers’ website traffic indicators at a rate that exceeds 60%.

2. Literature Review

2.1. Legacy Media Empowered by or Dependent on Social Media

“When we use social media to connect with people we care about, it can be good for our well-being... On the other hand, passively reading articles or watching videos—even if they are entertaining or informative—may not be as good. Based on this, we’re making a major change to how we build Facebook. I’m changing the goal and I give our product teams a focus on helping you find relevant content to help you have more meaningful social interactions.”

With this Facebook post from 11 January 2018, Mark Zuckerberg (2018), the founder and chief executive officer of the largest social networking site, announced a major change in its algorithm: prioritizing friends and family posts on the newsfeed while reducing businesses, brands, and media posts. The Business Insider (2018) article titled “Facebook is trying to prove it’s not a media company by dropping the guillotine on a bunch of media companies” reflects the first reactions of the press:

“That new position is going to be a nightmare for many digital media companies that have grown to rely on Facebook’s News Feed to drive readers to their sites. There is a growing list of media companies that have been forced to drastically change strategy as a result of their reliance on the company’s repeatedly changing algorithm, and this will probably be the final straw for many of them.”

According to Nielsen and Ganter (2017), social media has empowered legacy media. In their case study on the relationship between publishers and platforms, the authors highlight that both local media and established, powerful media organizations depend on digital intermediaries beyond their control. Tandoc and Maitra (2017) describe this relationship as “journalistic heteronomy”, which persists as long as media are digitized. Furthermore, they add that this relationship will likely grow. They also claim that Facebook’s influence on media is such that it forces them to follow its rules to increase their content reach and engagement. Commenting on the competition between media organizations and platforms, Siapera (2013) speaks about Internet platforms’ hegemony.

“Total lack of promotion means no traffic”, Kueng (2017) points out. Van der Wurff (2012) subscribes to the relationship between social and legacy news media as one of “co-opetition”, implying simultaneous cooperation and competition. Hayes and Graybeal (2011) agree, suggesting that, along with the traditional media that engage in this relationship to increase their content reach, social media need legacy news media to achieve a social interaction estimate.

2.2. The “Like Economy” and “Engagement Coin”

As Gerlitz and Helmond (2013) highlight, “In this Like economy, the social is of particular economic value.” They explain that interactions between users are transformed into data, which are then presented to the network of interconnected users to generate an even greater engagement and traffic. The influence of the public has a financial capital character for the media that struggle to maintain their capital stability (Tandoc 2014). In this statement, Tandoc attributes the growing use of audience analytics by editorial boards to increase their news website traffic. Edmond (2017) features public participation...
as an economic strategy, explaining it as a way to extend news content’s life cycle and website traffic.

In the era of the “like economy”, “engagement” is the currency. Based on Deuze, a distinction exists between viewing and other interactions, such as “favoriting” and “liking”, which underline different levels of user experience. Interactive engagement metrics complement traditional audience size measurements, such as circulation or traffic measurements, as assumed by Ksiazek et al. (2014). They encourage better exploration of engagement and interactivity as available indicators increase, including the number of Facebook likes, retweets, shares, and recommendations. Examining a positive relationship between popularity, in terms of both exposure and recommendation, and user-content interaction, they conclude that such indicators may be of greater importance in the future than the content itself. Engagement and its measurable indicators now appear as an alternative to even traditional ratings for television programs (Kosterich and Napoli 2015).

2.3. The “Let’s Try and See” Media Approach

The media are transitioning to a “let’s try and see” approach, possibly due to the complex context of threats against the traditional role of gatekeeping in journalism and opportunities for the wider dissemination of news content (Nielsen and Ganter 2017). Legacy media are increasingly exploiting the opportunities provided by new media to reach the public. Simultaneously, many have been voicing their doubts about the strategy direction in the longer run.

It is not the second generation of the web (Web 2.0) that started the dialogue between media and their audience (Lewis et al. 2010). Since the golden era of the press during the 18th and 19th centuries, newspapers were open to readers’ letters, and columns that included such letters constituted a crucial part of media content. While the relationship between journalism and the public became quantified with the development of new technologies, the results of audience measurements increasingly influence the editors’ decisions (Ferrer-Conill and Tandoc 2018). Social media offer wider indicators of audience feedback, such as the number of likes, retweets, and shares (Tandoc and Vos 2015). To this end, Lim (2014) argues that social media users’ attitudes are likely to affect their willingness to pay for digital subscriptions at news outlets.

The influence of the public on editorial decisions is not only about social media. Investigating the news selection criteria in the digital age, Welbers et al. (2015) conclude that news selection is affected by the number of clicks. More specifically, they find that newspaper articles among the top five most viewed were more likely to continue to be covered in the next few days, on both the web and in print. Lee et al. (2014) made a similar conclusion, emphasizing that the number of clicks on a news article was associated with the time the editors placed it on a specific spot on the website. This is an “algorithmic judgment”, usually presented in the form of recommendation lists from news websites to increase traffic and advertising impressions (Carlson 2018).

2.4. The Reciprocal Journalism and the Lens of Network Gatekeeping Theory

Media seem to be transitioning away from employing social media as channels to sharing links “with a top-down, we-tell-you-what-is-important approach to dealing with audiences” (Tandoc and Vos 2015). This shift flattens the hierarchy between audiences and their journalists (Groshek and Tandoc 2017). Simultaneously, issues related to the role of gatekeeping for journalism occupy an increasing proportion of research. Hermida et al. (2012), who examined the relationship between the public, news, and social media, noted that the traditional role of gatekeeping for journalism has diminished; in the era of the intermediaries, this role is being increasingly undertaken by friends, acquaintances, and family. The network gatekeeping theory extends the gatekeeping theory from the limited field of information selection process to the stages of information distribution, protection, and intermediation. It suggests that users act as gatekeepers by disseminating content (Barzilai-Nahon 2008). Wallace (2017) notes
that social media users turn into gatekeepers, not only by posting but also by endorsing published news items, thereby stressing the need to examine the relationship between multiple gatekeeping processes.

In this context, the present study builds on the reciprocal journalism theory (Lewis et al. 2013), suggesting that media should start looking at journalism as a conversation between journalists and the audience. Barzilai-Nahon (2008) describes this more dynamic, two-way relationship between the gatekeepers and the gated, the audience and the media. She suggests that gatekeepers and the gated should not be viewed as monolithic social and political entities, for their gatekeeping and gated roles are changing. This change happens because the gated-produced information takes into account reactions and feedback from gatekeepers. Simultaneously, information produced affects gatekeepers, who change their stance to focus on how information flows within communities.

To have a closer approach to the gated-gatekeepers relationship, that is, to conclude on the extent to which legacy media are empowered by and dependent on social media (Nielsen and Ganter 2017), we should examine the characteristics of this relationship. If “engagement” is the coin in the “like economy”, could it be a form of conversation between audience and media? What would be its value?

Our study builds upon the work of Ksiazek et al. (2014) and Wallace (2017) by investigating the relationship between social media metrics and publishers’ website traffic. Based on estimates that public participation increases website traffic (Edmond 2017; Philips 2012) and that relevant indicators (such as likes, shares, and retweets) cannot be ignored (Tandoc and Vos 2015), we expand the research on social media’s impact on website traffic (Lischka and Messerli 2015; Ju et al. 2014; Hong 2012; Lee et al. 2010). At this point, we should underline that in the case of our research, regression is used to make predictions about the dependent variable based on the observed values of the independent variables without further causal analysis, i.e., whether our independent variable actually affects the dependent variable. In particular, as reported in the literature, multiple regression has two main uses: prediction and causal analysis. In the former, the dependent variables take values from the independent variables, while in the latter, the independent variables are considered causes of the dependent variable (Allison 1999). Therefore, we pose the following question:

RQ1: Which social media metrics have a predictive value on publishers’ websites traffic?

2.5. The Impact of Social Media on Websites Traffic

This big debate on the relationship between social and legacy news media is based on the ability to reach new audiences at a time when traditional advertising revenue is on the decline, while online advertising is growing (Powers and Vera-Zambrano 2017). Journalists consider adopting social media, such as Twitter, to increase readership (English 2014). Philips (2012) confirms this assessment through her research: the social media impact on the diffusion of news is remarkable even at the level of smaller news websites.

As Nah and Saxton report (2012), the ability of an organization to create a more influential website depends on its ability to use platforms like Facebook and Twitter. In recent years, the use of metrics challenges aligning audience and journalist values in the metric-centric social media environment (Tenor 2023). Managers perceive a newfound alignment between audience metrics and professional news selection. Commercial publishers prioritize the shift to subscribers, placing pressure on individual journalists. Public service broadcasting finds the link between journalists’ performance and revenue in commercial newspapers extreme.

Despite growing emphasis on audience engagement, news organizations persist in upholding traditional news values (Walters 2022), reflecting tension between relinquishing and retaining control over content and ethical standards (Lewis 2012). While Hermida (2020) highlights the role of algorithms in acting as gatekeeping mechanisms on platforms by selecting and suggesting news and information, Dodds et al. (2023) point out three
competing influences: journalists’ perceptions, user preferences inferred from software-collected data, and platforms’ pursuit of viral content.

2.6. The Need for New Measures

Zamith et al. (2020) highlighted the lack of consensus in measuring success, coinciding with an increased emphasis on social media affordances and reactions when allocating news on digital networks due to the perceived role of social recommendations as the driving force (García-Perdomo 2021). Promoting the argument by Cherubini and Nielsen (2016) that encompasses no “God metric”, Zamith (2018) stresses the need to shift research from the general use of terms such as “analytics” and “metrics” to specific systems and measurements that will help assess journalistic practices. Nelson (2018) further notes the rising interest of the news industry in audience measurements, while stressing that big players consider it worthwhile to explore how audiences engage with media. According to Cherubini and Nielsen (2016), new media growth requires the continued development of new metrics and tools for journalists to understand the changing media environment. In their research on news media development and audience data and metrics used, they discovered that the process is in its nascent stage. MacGregor has been documenting the integration of interactivity into some journalists’ priorities since 2007. He notes that traditional publishers always emphasize numbers of circulation, viewers, or listeners, just as they do on website analytics.

2.7. Measuring Social Media Impact on Website Traffic

Welbers et al. (2015) aimed to launch the development of measurements on the gatekeeping influence of social media editors for news organizations. They report a strong influence of newspapers’ Facebook pages on the diffusion of news content on the social media website. The correlation of native videos on Facebook with the number of interactions was investigated by Tandoc and Maitra (2017). Specifically, they find that native videos predict greater interaction (likes, shares, and comments) but only for a very small portion of variance. Commenting and sharing in a news website environment do not significantly affect traffic, as stated by Lischka and Messerli (2015). A positive correlation between (a) the number of Facebook page likes and Twitter followers and (b) the number of website visitors was recorded by Ju et al. (2014), who spoke about a symbiotic relationship between social and legacy news media. A strong positive correlation between Twitter use and online traffic was recorded by Hong in 2012. Finally, Lee et al. found a positive correlation between the number of comments and the popularity of online content since 2010.

Our study attempted to respond to the need for continued development of new metrics and systems, which may help assess journalistic practices (Cherubini and Nielsen 2016; Zamith 2018). Building on previous studies that suggest the development of prediction models as tools to assess online journalistic practices (Angelou et al. 2020), this study examined the role of several social media metrics as predictors of publishers’ websites traffic. Therefore, the study tries to answer the following question:

RQ2: To what extent are social media metrics capable of predicting publishers’ website traffic?

2.8. The Greek Case’s Special Interest

Despite the low percentage of Internet access in its households (71% compared to 87% of the 28 EU countries), Greece is a country of interest, according to Eurostat (2018). It has high rates of citizens informed by the Internet and by social media in particular (among the population with an Internet connection). Regarding relative indicators, the country is ranked among the highest in comparative terms globally. Greece is one of 3 out of 37 countries where social media news use is higher than TV use (Newman et al. 2018). Based on the 2023 Digital News Report, the most frequently accessed source of news in Greece is online (social media included), which accounts for 81% of sources of news
consumption, followed by social media (61%). These percentages significantly exceed those of TV (48%) and print (15%) (Newman et al. 2023). It is noteworthy that in 2017, Greece was second after Turkey among the 36 countries in the country’s online population informed through the Internet (95%) (Newman et al. 2017). Simultaneously, according to Digital News Report 2016, Greece was the first among the 26 countries in social media use as the main source of news (Newman et al. 2016).

3. Materials and Methods

3.1. Method

The study employed empirical analysis of two datasets for three months (March–May 2018), following a major change in Facebook’s algorithm. The first dataset is a series of traffic indicators extracted from the Online Publishers Association of Greece website (ENED). The Association publishes monthly statistics on the sites of its members, including unique visitors, page views, and visits. The reliability of ENED’s “Measurement Code” is certified by the International Auditing Organization, OJD (ENED (Online Publishers Association in Greek) 2018).

The second dataset, including social media metrics, was collected by employing the Brandwatch platform. Brandwatch (2018), a social intelligence company, provides software solutions, including monitoring data from social media, blogs, forums, and websites. In particular, the “Brandwatch for students” program has been utilized as it provides three-month access to Brandwatch Analytics. However, one needs to take a short exam before they can access these data. Data collected by Brandwatch, alternatively called “social media metrics”, concern the activity on official Facebook pages and Twitter accounts of sample publishers.

3.2. Sample

As a survey sample, the members of the Online Publishers Association of Greece were examined. ENED represents the publishing companies of branded digital content. It was founded in January 2012; it has more than 20 members today. In 2018, there were 79 ENED members’ websites. The Online Publishers Association of Greece includes members who must satisfy certain standards. Analytically, among others, they must produce original content (and not simply copy third-party content), employ at least 10 employees with a dependent labor contract of any form and/or partners on fixed-term independent service contracts, and “their websites must have daily traffic comparable to their counterparts’ places of the already existing members.”

As a prerequisite for sample inclusion, a publisher’s website needs to have a presence across the four most popular social media as of March 2018. According to the 2018 Digital News Report (Newman et al. 2018), the top social media in Greece were Facebook (60% for news use and 78% for all uses), YouTube (36% for news, 79% for all uses), Twitter (13% for news, 24% for all uses), and Instagram (10% for news use, 33% for all uses). In March 2018, out of 79 ENED member websites, 77 had a presence on Facebook (97.47%), 72 on Twitter (91.14%), 60 on YouTube (75.95%), and 50 on Instagram (29%). Consequently, 50 publishers’ websites were included in our sample. The vast majority of the included websites are news-focused, covering a range of topics such as “hard” news, sports news, travel journalism, celebrity and lifestyle journalism, fashion journalism, food journalism, men’s and women’s magazines, and weather news.

3.3. Survey Measurements

3.3.1. Traffic—Dependent Variables

To measure traffic, we used five indicators (see Table 1) often encountered in field theory on audience metrics (Napoli 2011; Tandoc 2014; Powers 2018; Zamith 2018) and that are publicly available on ENED’s Code of Measurements (ENED (Online Publishers Association in Greek) 2018).
Table 1. Descriptive statistics of publishers’ website traffic data.

<table>
<thead>
<tr>
<th></th>
<th>1st Month</th>
<th>2nd Month</th>
<th>3rd Month</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>M</td>
<td>SD</td>
</tr>
<tr>
<td>Visits</td>
<td>5,123,278.16</td>
<td>7,281,789.81</td>
<td>5,434,830.54</td>
<td>7,416,152.96</td>
</tr>
<tr>
<td>Page views</td>
<td>15,521,687.58</td>
<td>22,841,235.72</td>
<td>16,416,609.70</td>
<td>22,921,901.93</td>
</tr>
<tr>
<td>Estimated unique visitors</td>
<td>1,451,281.28</td>
<td>1,431,980.38</td>
<td>1,527,402.74</td>
<td>1,473,364.23</td>
</tr>
<tr>
<td>Time spent/visits</td>
<td>633.46</td>
<td>698.34</td>
<td>656.86</td>
<td>697.69</td>
</tr>
<tr>
<td>Bounce rate</td>
<td>62.75</td>
<td>12.48</td>
<td>62.65</td>
<td>12.65</td>
</tr>
</tbody>
</table>

1. Visits. We define the use of a website by a user for 30 min as a visit.
2. Page Views. A request to deliver files to a browser from a server upon request submitted by the browser results in the measurement of a page view.
3. Estimated Unique Visitors. This indicator counts unique and distinct browsers (not individuals) that visited a website within one month. It may be larger or smaller than the actual number of people visiting a website owing to various reasons, such as dynamic/static IP, block of cookies, access through proxy server, and so forth.
4. Time spent/visit. The specific index is defined as the quotient of the time spent on the website in a month by the number of visits during the same time.
5. Bounce Rate. The bounce rate of a website is the percentage of people who visited any page of the website and dropped out of it immediately.

The average number of “visits” collected during the research period by the publishers’ sample websites was approximately 5,236,869 per month. Threefold in number on average were the “page views” that reached 15,790,281 each month. The “estimated unique visitors” averaged around 1,469,155 per month. The time spent/visit average in the survey sample was approximately 637 s or 10.5 min. Finally, the average bounce rate in publishers’ websites was over 62%.

3.3.2. Social Media Metrics—Independent Variables

The independent variables for social media use included indicators mostly referred to in the relevant literature, namely,

(a) page likes (followers) on Facebook and Twitter followers (Hong 2012; Ju et al. 2014),
(b) posts (number) on Facebook page and Tweets (Hong in 2012),
(c) likes for Facebook page posts (Tandoc and Vos 2015; Ksiazek et al. 2014),
(d) shares of Facebook page posts and retweets (Lischka and Messerli 2015; Tandoc and Vos 2015; Ksiazek et al. 2014)
(e) comments on Facebook page posts and replies on Twitter (Lee et al. 2010; Lischka and Messerli 2015). We categorize comments into two distinct types: (a) “audience comments”, referring to those made by the audience under each media post or in response to each media tweet, and (b) “owner comments”, denoting comments made by the media in response to audience comments on each post or tweet.

Facebook Metrics

During the survey period, the sample’s average number of page likes amounted to 173,103 for each page (see Table 2). The number of posts on publishers’ Facebook pages was approximately 1141 per month. The total number of posts likes amounted to approximately 86,899 each month. The total number of shares was much less, approximately 3457. The number of comments on publishers’ Facebook posts was approximately 8498 each month. Finally, the number of publishers’ comments (publishers-audience dialogue) was very low, as the average did not exceed 11 per month.
Table 2. Descriptive statistics of publishers’ Facebook page metrics.

<table>
<thead>
<tr>
<th></th>
<th>1st Month</th>
<th>2nd Month</th>
<th>3rd Month</th>
<th>Average</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>M</td>
<td>SD</td>
</tr>
<tr>
<td>Page Likes</td>
<td>172,066.0</td>
<td>156,990.9</td>
<td>172,905.8</td>
<td>157,910.4</td>
</tr>
<tr>
<td>Owner Posts</td>
<td>1140.8</td>
<td>866.6</td>
<td>1170.7</td>
<td>844.1</td>
</tr>
<tr>
<td>Likes</td>
<td>87,646.6</td>
<td>292,577.9</td>
<td>90,829.2</td>
<td>300,211.3</td>
</tr>
<tr>
<td>Shares</td>
<td>3684.4</td>
<td>5150.6</td>
<td>3627.3</td>
<td>4792.0</td>
</tr>
<tr>
<td>Audience Comments</td>
<td>8377.5</td>
<td>22,217.6</td>
<td>8943.9</td>
<td>23,805.9</td>
</tr>
<tr>
<td>Owner Comments</td>
<td>10.9</td>
<td>38.6</td>
<td>10.7</td>
<td>38.8</td>
</tr>
</tbody>
</table>

Twitter Metrics

The number of followers on the sample’s official Twitter accounts averaged 37,507 per account (see Table 3). The number of tweets published was approximately 682 per month. The total number of retweets amounted to approximately 226. The number of audience’s replies to publishers’ tweets was smaller, at approximately 62. Finally, the publishers’ replies on their tweets (publishers–audience dialogue) were virtually zero, as their average did not approach one per month (0.35). Owing to Brandwatch platform’s limitations at the time of the research, liking as a form of Twitter engagement was not tested; in the case of Facebook, all reactions were included.

Table 3. Descriptive statistics of publishers’ twitter account metrics.

<table>
<thead>
<tr>
<th></th>
<th>1st Month</th>
<th>2nd Month</th>
<th>3rd Month</th>
<th>Average</th>
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<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>M</td>
<td>SD</td>
</tr>
<tr>
<td>Followers</td>
<td>37,451.5</td>
<td>70,888.1</td>
<td>37,490.9</td>
<td>70,844.3</td>
</tr>
<tr>
<td>Owner Tweets</td>
<td>694.7</td>
<td>695.0</td>
<td>676.3</td>
<td>670.0</td>
</tr>
<tr>
<td>Audience Retweets</td>
<td>230.2</td>
<td>468.4</td>
<td>218.5</td>
<td>393.9</td>
</tr>
<tr>
<td>Audience Replies</td>
<td>56.2</td>
<td>105.9</td>
<td>59.4</td>
<td>120.7</td>
</tr>
<tr>
<td>Owner Replies</td>
<td>0.2</td>
<td>1.2</td>
<td>0.4</td>
<td>1.7</td>
</tr>
</tbody>
</table>

3.4. Data Analysis

Based on our research questions, we began by providing a simple description of the traffic numbers of publishers’ websites and the social media metrics of their official pages and accounts. Owing to the large sample size and the type of variables (continuous/arithmetic type), we processed the data using Pearson’s correlation. We compared the traffic numbers for the publishers’ websites with the social media metrics.

In the next analysis step, ordinary least squares (OLS) regressions were employed to predict variance in traffic indicators based on social media metrics. We used OLS regression, a method used in similar field investigations (Cha 2017; Nelson and Webster 2016; Park et al. 2020a, 2020b). This technique was found to be more appropriate given the survey data were a panel (time-repeated cross-sectional data). The analysis was controlled for all aforementioned covariates. The method of OLS regression is considered appropriate for the analysis of panel data as the big number of cases (N = 50) improves the precision of the estimates we obtain.
4. Results


Facebook Likes: Tandoc and Vos (2015) argue that indicators of audience feedback, such as the number of likes (see Table 4), retweets (see Table 5), and shares, are almost impossible to ignore. This study shows a positive and strong correlation between the number of Facebook posts’ likes and the number of visits, page views, and estimated unique visitors.

Table 4. Pearson correlations between websites traffic data and Facebook metrics.

<table>
<thead>
<tr>
<th></th>
<th>Page Likes</th>
<th>Owner Posts</th>
<th>Likes</th>
<th>Shares</th>
<th>Audience Comments</th>
<th>Owner Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visits</td>
<td>r</td>
<td>0.646</td>
<td>0.588</td>
<td>0.673</td>
<td>0.623</td>
<td>0.697</td>
</tr>
<tr>
<td></td>
<td>p</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>-0.059</td>
</tr>
<tr>
<td>Page views</td>
<td>r</td>
<td>0.605</td>
<td>0.537</td>
<td>0.678</td>
<td>0.592</td>
<td>0.685</td>
</tr>
<tr>
<td></td>
<td>p</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>-0.050</td>
</tr>
<tr>
<td>Estimated unique visitors</td>
<td>r</td>
<td>0.655</td>
<td>0.587</td>
<td>0.547</td>
<td>0.597</td>
<td>0.577</td>
</tr>
<tr>
<td></td>
<td>p</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>0.540</td>
</tr>
<tr>
<td>Time spent/visits</td>
<td>r</td>
<td>0.079</td>
<td>0.131</td>
<td>0.058</td>
<td>-0.038</td>
<td>0.048</td>
</tr>
<tr>
<td></td>
<td>p</td>
<td>0.337</td>
<td>0.109</td>
<td>0.484</td>
<td>0.648</td>
<td>0.561</td>
</tr>
<tr>
<td>Bounce rate</td>
<td>r</td>
<td>-0.202</td>
<td>-0.188</td>
<td>-0.149</td>
<td>-0.142</td>
<td>-0.106</td>
</tr>
<tr>
<td></td>
<td>p</td>
<td>0.013</td>
<td>0.021</td>
<td>0.069</td>
<td>0.083</td>
<td>0.199</td>
</tr>
</tbody>
</table>

Table 5. Pearson correlations between website traffic data and Twitter metrics.

<table>
<thead>
<tr>
<th></th>
<th>Follower Count</th>
<th>Owner Tweets</th>
<th>Audience Retweets</th>
<th>Audience Replies</th>
<th>Owner Replies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visits</td>
<td>r</td>
<td>0.039</td>
<td>0.303</td>
<td>0.134</td>
<td>0.214</td>
</tr>
<tr>
<td></td>
<td>p</td>
<td>0.638</td>
<td>&lt;0.001</td>
<td>0.101</td>
<td>0.09</td>
</tr>
<tr>
<td>Page views</td>
<td>r</td>
<td>0.005</td>
<td>0.270</td>
<td>0.157</td>
<td>0.242</td>
</tr>
<tr>
<td></td>
<td>p</td>
<td>0.948</td>
<td>0.001</td>
<td>0.056</td>
<td>0.003</td>
</tr>
<tr>
<td>Estimated unique visitors</td>
<td>r</td>
<td>0.095</td>
<td>0.281</td>
<td>0.106</td>
<td>0.137</td>
</tr>
<tr>
<td></td>
<td>p</td>
<td>0.246</td>
<td>&lt;0.001</td>
<td>0.197</td>
<td>0.096</td>
</tr>
<tr>
<td>Time spent/visits</td>
<td>r</td>
<td>-0.020</td>
<td>0.170</td>
<td>0.583</td>
<td>0.548</td>
</tr>
<tr>
<td></td>
<td>p</td>
<td>0.811</td>
<td>0.037</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Bounce rate</td>
<td>r</td>
<td>0.059</td>
<td>0.081</td>
<td>0.024</td>
<td>-0.058</td>
</tr>
<tr>
<td></td>
<td>p</td>
<td>0.471</td>
<td>0.325</td>
<td>0.770</td>
<td>0.477</td>
</tr>
</tbody>
</table>

Shares: Lischka and Messerli (2015) in their research found that commenting and sharing on a news website do not significantly affect traffic. This study generated a different image for the Facebook and Twitter environments. Sharing on Facebook was positively related to the number of visits, page views, and estimated unique visitors; sharing on Twitter (retweeting) was positively related to time spent/visits.

Comments by the audience: The present study found a positive correlation between the number of audience comments on both Facebook and Twitter (audience replies) and the number of visits and page views on publishers’ websites. This aligns with the research by Lee et al. (2010) and records a positive correlation between Facebook audience comments and the number of estimated unique visitors, as well of Twitter audience replies and the time spent/visit.
Comments by publishers: Extending the research, the results showed a negative correlation between the number of Facebook owner comments and the bounce rate, as well as a positive correlation between the number of Twitter owner replies and time spent/visit in publishers’ websites. This finding is particularly important because it shows that the development of a dialogue between the media and the public on social media platforms predicts improvement in website traffic. Specifically, it can increase audience loyalty; the audience will consume more content as the bounce rate decreases and the time spent/visits increases.

Social Media Metrics as Predictors of Publishers’ Website Traffic

RQ1 asked which social media metrics had a predictive value on publishers’ website traffic. We ran comparable ordinary least squares (OLS) regression models. All ten regression models included traffic indicators as criterion variables and all Facebook and Twitter metrics as predictors. The risk for multicollinearity was assessed for each model and was deemed acceptable: no high R2 in excess of 0.8 and no high pairwise correlations among explanatory variables in excess of 0.8 or other indicators were observed (Gujarati and Porter 2009).

The initial results show that Facebook metrics have a predictive value with respect to the number of visits (Model 1), page views (Model 2), estimated unique visitors (Model 3), time spent/visit (Model 4), and bounce rate (Model 5). All regression models were significant ($p < 0.001$), accounting for over 60% of the variance in each case. The only exception is Model 4, which was not statistically significant ($p > 0.05$), accounting for just 6.6% of the variance in the time spent/visits variable. The results are summarized in Table 6. By analyzing the regression results, it is initially observed that the $\beta_1$ and $\beta_2$ coefficients are positive and statistically significant when the number of website visits, the page views, and the number of estimated unique visitors are determined as dependent variables. Subsequently, an increase in the total number of page likes and the number of posts on Facebook predicts an increase in the number of websites’ visits, page views, and estimated unique visitors. On the contrary, an increase in the number of owner comments on Facebook predicts a decrease in the number of visits to the websites because $\beta_6$ is negative and statistically significant ($\beta_6 = -20,067.856, p < 0.05$).

| Table 6. Regression results on the impact of Facebook metrics on the publishers’ website traffic. |
|---------------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|
| Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
| **Visits** | **Page Views** | **Estimated Unique Visitors** | **Time Spent/Visit** | **Bounce Rate** |
| $\beta$ | $p$ | $\beta$ | $p$ | $\beta$ | $p$ | $\beta$ | $p$ | $\beta$ | $p$ |
| (Constant) | $-1,369,739.684$ (720,956.880) | $0.059$ | $-1,772,425.082$ (2,418,894.047) | $0.465$ | $-23.273$ (152,983.914) | $1.000$ | $460.490$ (110.333) | $<0.001$ | $68.632$ (2.027) | $<0.001$ |
| Page Likes | 19.611 (3.236) | $<0.001$ | 53.210 (10.856) | $<0.001$ | 4.564 (0.687) | $<0.001$ | 0.001 (0.000) | 0.047 | $-<0.001$ (0.000) | 0.154 |
| Owner Posts | 2417.512 (537.318) | $<0.001$ | 5737.470 (1802.764) | 0.002 | 576.624 (114.017) | $<0.001$ | 0.143 (0.082) | 0.085 | $-0.004$ (0.002) | 0.011 |
| Likes | 4.466 (4.933) | 0.367 | 32.770 (16.549) | 0.050 | 0.397 (1.047) | 0.705 | 0.000 (0.001) | 0.960 | $-<0.001$ (0.000) | 0.094 |
| Shares | $-72.110$ (148.856) | 0.629 | $-31.889$ (499.431) | 0.949 | $-1.169$ (31.587) | 0.971 | $-0.047$ (0.023) | 0.040 | $-<0.001$ (0.000) | 0.491 |
| Audience Comments | 63.415 (72.633) | 0.384 | $-23.184$ (243.691) | 0.924 | 3.892 (15.412) | 0.801 | 0.002 (0.011) | 0.881 | $-<0.001$ (0.000) | 0.123 |
| Owner Comments | $-20,067.856$ (10,032.623) | 0.047 | $-65,792.625$ (33,660.614) | 0.053 | $-3784.117$ (2128.879) | 0.078 | $-1.069$ (1.535) | 0.487 | $-0.077$ (0.028) | 0.007 |
| F ($p$) | $47.766$ (<0.001) | 37.247 (<0.001) | 37.093 (<0.001) | 1.672 (0.132) | 4.000 (0.001) |
| R² | 0.667 | 0.610 | 0.609 | 0.066 | 0.144 |
Model 5 presents an important finding: the impact of the Facebook owners’ comments on the website’s bounce rate is negative and statistically significant ($\beta = -0.077, p < 0.05$).

To finally answer RQ1, we present the results of the regressions models in Table 7, which indicate that Twitter metrics predict the number of visits (Model 6), page views (Model 7), estimated unique visitors (Model 8), time spent/visit (Model 9), and bounce rate (Model 10). All models are significant ($p < 0.001$) except Model 10 ($p > 0.05$).

### Table 7. Regression results on the impact of Twitter metrics on the publishers’ website traffic.

<table>
<thead>
<tr>
<th></th>
<th>Model 6</th>
<th>Model 7</th>
<th>Model 8</th>
<th>Model 9</th>
<th>Model 10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visits</td>
<td>$\beta$</td>
<td>$p$</td>
<td>$B$</td>
<td>$\beta$</td>
<td>$p$</td>
</tr>
<tr>
<td>(Constant)</td>
<td>2,968,136.714 (2,968,136.714)</td>
<td>0.001</td>
<td>10,166,232.622 (2,679,869.698)</td>
<td>&lt;0.001</td>
<td>999,654.841 (170,851.325)</td>
</tr>
<tr>
<td>Follower Count</td>
<td>3.711 (9.968)</td>
<td>0.710</td>
<td>-12.897 (31.006)</td>
<td>0.678</td>
<td>2.816 (1.977)</td>
</tr>
<tr>
<td>Owner Tweets</td>
<td>2933.215 (1004.231)</td>
<td>0.004</td>
<td>6583.870 (3123.593)</td>
<td>0.037</td>
<td>628.405 (199.140)</td>
</tr>
<tr>
<td>Audience Retweets</td>
<td>2916.829 (2108.271)</td>
<td>0.169</td>
<td>-5874.873 (6557.635)</td>
<td>0.372</td>
<td>-526.752 (418.073)</td>
</tr>
<tr>
<td>Audience Replies</td>
<td>14,564.395 (6906.760)</td>
<td>0.037</td>
<td>53,531.160 (21,483.009)</td>
<td>0.014</td>
<td>1160.626 (1369.619)</td>
</tr>
<tr>
<td>Owner Replies</td>
<td>-364,518.620 (349,745.010)</td>
<td>0.299</td>
<td>-1,196,789.075 (1,087,858.140)</td>
<td>0.273</td>
<td>-53,876.091 (69,354.866)</td>
</tr>
<tr>
<td>F ($p$)</td>
<td>3.992 (0.002)</td>
<td>3.748 (0.003)</td>
<td>37.151 (0.010)</td>
<td>37.685 (&lt;0.001)</td>
<td>1.090 (0.369)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.122</td>
<td>0.115</td>
<td>0.099</td>
<td>0.567</td>
<td>0.036</td>
</tr>
</tbody>
</table>

The results show that an increase in the number of tweets predicts an increase in the number of visits to the websites ($\beta_1 = 2933.215, p < 0.05$), the page views ($\beta_1 = 6583.870, p < 0.05$), and the number of estimated unique visitors ($\beta_1 = 628.405, p < 0.05$).

Another important finding is the predictive value of retweets ($\beta_3 = 1.018, p < 0.001$) and audience replies ($\beta_4 = 1.736, p < 0.001$) on the time spent/visit variable, with Model 9 presenting a particularly high determination coefficient (in relation to the rest of the models) equal to 0.567. In the same model, it can be noted that an increase in the number of followers and tweets predicts a marginal decrease in the time spent/visit indicator. Finally, no statistically significant predictive value of Twitter metrics on the bounce rate of the publishers’ websites is observed.

### 4.2. Publishers’ Website Traffic Prediction Models Based on Social Media Metrics

RQ2 asked to what extent social media metrics are capable of predicting publishers’ website traffic. Results showed that 4 out of 10 models were significant ($p < 0.001$).

The first model can predict the variance of the number of visits to a publisher’s website based on Facebook metrics at 66.7%. Our second model can predict the variance of the number of page views of publishers’ websites based on Facebook metrics at 61%. The third model can be used to predict the variance of the unique visitors’ indicator based on Facebook metrics at 60.9%. Finally, the ninth model can predict the number of time spent/visit to publishers’ websites based on Twitter metrics for over 56% of the variance.

### 5. Discussion

Our study found that approximately 60% of the variance in publisher websites’ visits, visitors, and page views could be explained by Facebook metrics. Simultaneously, Twitter metrics predicted approximately 60% of the variance in the time spent/visit website indicator. In addition, Facebook and Twitter audience engagement metrics were strongly correlated with publishers’ websites traffic indicators. Our study integrates two central theories—Reciprocal
Journalism and Gatekeeping—to explore the dynamic relationship between media outlets and their audience. Rooted in Reciprocal Journalism (Wallace 2017), our research underscores the multifaceted influence of the public, emphasizing active engagement through comments on social media. The study reveals a robust correlation between audience interactions, especially comments, and subsequent impacts on media websites, aligning with theories of mutual exchange (Groshek and Tandoc 2017; Lewis et al. 2013).

In parallel, our study, grounded in the Gatekeeping and Network Gatekeeping Theory (Barzilai-Nahon 2008), unveils the evolving role of social media users as network gatekeepers. Their active involvement in disseminating content on platforms like Facebook and Twitter not only forecasts news impact on social media but significantly influences media websites’ traffic indicators. This direct and measurable impact extends from the news source to dissemination, reflecting the profound role of public engagement.

5.1. Reciprocal Journalism Concept

The study findings extend our knowledge, as the public influences the distribution of media content not only by posting or endorsing published news (Wallace 2017) but also by commenting on the content. Our results showed that the number of comments on media posts on social media was related to the impact of their websites. In addition, the number of public comments on media tweets had a higher predictive effect on the number of visits, page views, and time spent/visit.

In light of the reciprocal journalism concept, the present study shows that the development of journalists’ interactive relationship with the public is a critical indicator of the media site’s website traffic. These findings confirm a mutual exchange among media and audiences on which the theory is based (Groshek and Tandoc 2017; Lewis et al. 2013).

On Facebook, news commentary by the media had the greatest predictive power for the number of visits and abandonment rate of their websites. However, only a few media comment on their posts on social media, encouraging the interactive relationship with the public. The media selects the classic approach of journalistic practices for the diffusion of content from the top (journalists) to the bottom (audience) and one-way communication. While our study has established a clear correlation between audience engagement on social media and website traffic, a more nuanced exploration of these relationships within the framework of reciprocal journalism is warranted. Specifically, delving deeper into the nature of interactions, such as the tone, sentiment, and thematic elements of audience comments, can provide additional insights into our observed patterns. Understanding how media outlets reciprocate audience engagement, fostering bidirectional communication, would contribute to a more comprehensive grasp of the reciprocal journalism concept as demonstrated in our study. This deeper examination sheds light on the mechanisms at play and underscores the authenticity of the reciprocal relationship between media outlets and their audience, offering valuable insights from our empirical findings.

5.2. Gatekeeping and Network Gatekeeping Theory

Through the lens of gatekeeping theory, our results show that social media users may influence the traditional role of journalists in the process of defining the messages promoted to the public. Users play an active role through engagement, at least in disseminating content on social media channels. The findings seem to confirm the network gatekeeping theory (Barzilai-Nahon 2008), as users act as network gatekeepers by disseminating content. Facebook and Twitter users expand the news coverage. The same happens when a news item is liked or commented on; such actions increase the item’s visibility.

Our results demonstrate that liking, sharing, and commenting largely predict news impact, not only on social media platforms but also on news websites. More specifically, the increase in engagement on Facebook and Twitter predicts an increase in the traffic of media websites and specifically of the indicators of visits, page views, and unique visitors. These data measure the direct and measurable influence of the public on the news—from the source of the information to its diffusion on relevant channels. However, the role of the
public in gatekeeping is not limited to them. It also indirectly affects the agenda-setting process, given that analytics actively affect decisions made in newsrooms. Thus, the news and topics that attract more traffic or greater engagement are more likely to be selected by journalists to channel more information with new posts and news.

5.3. The Need for New Metrics

This study addresses the need to develop tools to help media that pursue a more speculative approach (i.e., “let’s try and see”, Nielsen and Ganter 2017), as well as new metrics (Cherubini and Nielsen 2016) and specific systems and measurements that help assess the practices in journalism (Zamith 2018).

Our findings enrich previous research that concerned models predicting traffic based on the size of the media audience on social media (Angelou et al. 2020), for they presented eight prediction models of publishers’ website traffic based on social media metrics. The first four statistically significant models showed that Facebook metrics could predict over 60% of the variation in visitor indexes, page views, and unique visitors and about 14% of the bounce rate. The other four statistically significant models could predict the fluctuation of traffic indicators related to visits, page views, and unique visitors. Regarding the time spent/visit index, the predictive power of Twitter indicators exceeded 56%.

5.4. Implications

This study has implications for the future: prediction models can be used by practitioners to evaluate the tactics they apply. Because the potential traffic to their websites based on their social metrics is higher than the real numbers, they should consider other factors responsible for the reduced impact. Conversely, if the potential traffic to their websites is lower than the real numbers, they can positively evaluate the practices they apply.

For quality journalism in light of reciprocal journalism theory, the present study showed that the development of an interactive relationship between journalists and the public is a critical indicator of website traffic.

For subscription-based models trying independency, as public participation is considered a means to extend the life cycle of news content and website traffic in general (Edmond 2017), publishers should adopt new ways to better integrate the social media engagement experience to their own platforms. Accordingly, users will remain the gatekeepers (Wallace 2017), but the media may begin to reduce their dependence on likely changes in the diffusion of their news on third-party platforms.

5.5. Limitations

Our research has some limitations. To conduct a large-scale study, our sample was an extract of general content publishers. More specific surveys covering exclusively news media organizations can shed light on any variations or commonalities. In its effort to investigate the relationship between the use of social media platforms and website traffic, our study did not examine the content, i.e., whether it was popular. Furthermore, it did not analyze the other parameters that lead to different user behaviors in terms of interactivity (Bobkowski et al. 2018; Al-Rawi 2017).

The survey sample includes Greek online publishers; therefore, the results cannot be generalized. Similar surveys in other countries could answer the question regarding these results being applicable in general or due to specific characteristics of the target audience in these countries. Furthermore, our survey sample may well include media with different profiles and strategic aims in terms of content production and audience reach. While our sample was not so heterogenous, it did not include only news sites. Hence, for the current research, we were limited to a “first picture” on publishers’ website traffic prediction models based on social media metrics.

The dataset of social media metrics was collected by employing the Brandwatch platform. Due to the platform’s limitations, we were unable to study the total group of
Greek online publishers’ websites. Hence, we decided to study the most social-media-savvy media, supposing that they would give us more useful data.

One notable limitation of this study is the temporal nature of the data utilized. The dataset employed for our analysis reflects a specific timeframe, and as such, the findings may not fully encapsulate the most recent developments in newsroom practices. We acknowledge that the media landscape is subject to continuous evolution, and the data’s age could impact the generalizability of our conclusions to the current media environment. To address this limitation, we emphasize that our study serves as a snapshot of practices during the specific period covered by the dataset.

Finally, we found very few publishers’ (owners’) comments on Facebook and replies on Twitter. More research is therefore necessary to find the results of the media efforts to develop a dialogue with the public.

5.6. Future Extensions

Four major directions for future research emerge to develop prediction models of publishers’ website traffic based on social media metrics.

Our research results do not imply the direction of causality in the relationship between social media engagement and media website traffic, although it can be assumed through the lens of network gatekeeping and reciprocal journalism theories. This relationship could therefore work both ways, as increased website traffic may in turn affect social media metrics. The potential existence of this feedback loop may be interesting to study in future targeted research on this topic, which could help to better understand the issue.

Furthermore, this research should be extended to other highly popular social media platforms, such as YouTube and Instagram.

In social media metrics variables, both on Facebook and Twitter as well as on other platforms, the type of content should be added. For example, content with video, text, links, or photos may lead to different engagement and consequently affect website traffic. Beyond quantitative correlations, a qualitative lens is crucial for unraveling the reciprocal relationship between social media and website interactions. Reciprocal journalism, at its core, implies a symbiotic connection where audience engagement and journalistic content interact synergistically. Future research should delve into the nature of social media interactions, examining the tone and themes of audience comments. Additionally, it could explore how media outlets reciprocate, fostering bidirectional communication. By scrutinizing the mechanisms and challenges of reciprocal journalism, future research could provide a nuanced understanding of how these interactive practices contribute to the dynamics between media outlets and their audience.

Finally, the practices of media organizations on social media platforms need further investigation. Future research should highlight the effects of media responses on user reactions, comments, and posts, given that social media, to be social, must run a two-way communication.

6. Conclusions

A shift in media strategy from a “we-tell-you-what-is-important approach to dealing with audiences” (Tandoc and Vos 2015) to a more dynamic two-way relationship through social media can benefit their audience loyalty and influence expansion. Using publishers’ website traffic prediction models proposed, this study may contribute to the development of new tools for media organizations to assess their online, specifically social media, practices.

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