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Innovación y creación especializada en la agenda Iberoamericana.

Coordinadores
Pedro Aguilar Pérez
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PARTE 2:

CIENCIAS SOCIALES, HUMANIDADES Y DE LA TIERRA

SME platforms: A social traffic analysis before and during COVID-19

María Manuela Gutiérrez Leefmans[1], *María Catalina Gutiérrez-Leefmans*[2]
Rosa María Nava Rogel[3]

Resumen

Esta investigación se centra en las plataformas que ayudan a las pymes ofreciéndoles asesoramiento, coaching, herramientas y contenidos. Tiene el objetivo de conocer si los usuarios se comportan de forma diferente en función de la red social que los lleva a la plataforma, sobre todo antes y durante la pandemia. Es un estudio exploratorio descriptivo de carácter cuantitativo que utiliza la analítica web, específicamente el tráfico social de las plataformas y su duración de visita, profundidad de visita y número de visitantes únicos con un análisis de varianza (ANOVA). Los principales resultados muestran que, antes de la pandemia, los usuarios que permanecían más tiempo en las plataformas procedían de YouTube, mientras que Twitter destacó con la menor duración de visita. El tamaño de la plataforma tiene una correlación positiva con las redes sociales. El tiempo de saturación resultó de dos minutos para las redes sociales y se encontraron diferencias significativas entre las redes sociales por número de visitantes únicos. Durante la pandemia, la mayoría de los visitantes fueron usuarios procedentes de LinkedIn y Twitter, y el descenso general de las visitas refleja las menores expectativas de los usuarios de generar nuevos negocios.

Palabras clave: duración de visita, profundidad de visita, pymes, redes sociales, tráfico social

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Abstract

This research focuses on platforms that help SMEs by providing advice, coaching, tools, and content. It is concerned with knowing if users behave differently depending on the social network that drives them to the platform, particularly before and during the pandemic. It is a descriptive exploratory study of a quantitative nature that uses website analytics, specifically the platforms' social traffic and their visit duration, visit depth, and the number of unique visitors. Analyses of variance (ANOVA) are also performed. Main results show that, before the pandemic, users that stayed longer in the platforms came from YouTube, while Twitter stands out with the lowest visit duration. The platform size has a positive correlation with the social networks. The saturation time resulted in two minutes for the social networks and significant differences among the social networks by number of unique visitors were found. During the pandemic, most visitors were users coming from LinkedIn and Twitter, and an overall drop in visits reflects the lower expectations from users of generating new businesses.

Keywords: SMEs, social media, social traffic, visit duration, visit depth

Introduction

Platforms dedicated to supporting SMEs (small and medium-sized enterprises) and entrepreneurs provide relevant content to foster the creation, growth, and consolidation of their business. Such platforms generate knowledge through blogs with success stories, best practices, and business opportunities. For this reason, in recent years, the number of these platforms has proliferated. Particularly, in Latin America there is great potential for platforms that support SMEs, since due to their quantity, they represent the greatest contributors to the economy of these countries.

According to INEGI (2022), Mexico has more than four million micro, small and medium-sized enterprises, of which the largest market share are the micro companies. A similar scenario is presented in other Latin American countries, where there is great potential for entrepreneurial activity derived from various elements, standing out the factor of having a relatively young population, unlike other regions in the world (GEDI, 2020). Data from the OCDE (2019) states that the vast majority (99.5%) of the companies in the Latin American region are SMEs, almost nine out of ten companies are classified as microenterprises, and SMEs are important generators of employment at the regional level (60% of the formal productive employment).

Therefore, it is important to promote the SME development and optimization with creative strategies based on empirical evidence, as the source of social traffic in terms of the duration of the user visit and the number of page views on the platforms. Unfortunately, little has been explored regarding the traffic generated by social networks in this context. Academic studies regarding the difference among social networks user profiles were not found.

Nevertheless, the analysis of online user behavior derived from web analytics has become a common practice. Particularly, studies on visit duration (stickiness) and visit depth (page views) have explored the relation of these metrics with different traffic sources. However, few have explored the social traffic source, specifically the difference between social networks. Due to the rising use of social networks in recent years and preferences of certain networks among users, it makes sense to incorporate the social traffic variable to the study of website visit duration and visit depth. Both measures bring insights into consumer behavior and into the understanding of social networks' user characteristics.

The objective of this study is to identify differences in user behavior determined by the three most used social networks before the pandemic, namely Facebook, Twitter, and YouTube, in order to make strategic recommendations. During the pandemic, LinkedIn became the most visited social network but no data on visit duration is available, however, descriptive data on the overall user behavior during this period, reflects that the boom in inquiries to business pages occurred before the pandemic, when there were good expectations of generating business. However, with the arrival of the pandemic, thousands of companies disappeared, which had an impact on the drop in visits to pages specialized in helping companies.

For this study, user behavior is defined as the visit depth and visit duration on the platform. Also, the variable of unique visitors is studied in order to understand if the size of the platform is related to the different social networks. Given the lack of evidence in scientific research on the role of social networks in social trafficking, an exploratory study was carried out (Hernández, Fernández & Baptista, 2014) with the aim of establishing a basis for the development of subsequent research. It is a quantitative field study that was based on social network traffic metrics obtained from SimilarWeb.

Literature review

Social networks and user behavior

Social networks refer to the services and software based on the internet that, according to Ryan (2020) they allow users to exchange, discuss, communicate, and participate in any form of social interaction online. Chaffey and Smith (2022) consider them as the digital media that encourages audience participation, interaction and sharing such as Facebook, Instagram, Twitter, and You Tube, among others.

Various investigations have emerged to find out how social networks can be used to benefit companies. Several authors (van Dam & Van De Velden, 2015; Antelmi et al., 2019; Dolan et al., 2019) coincide in the valuable information given by social media to analyze user behaviors and relate them to firms. Althoff et al. (2017) consider social networking has outcomes in online and offline behavior and that, despite this, it has been understudied. They demonstrate that "the creation of new social connections increases user online activity by 30%, user retention by 17%, and user offline real-world physical activity by 7%" (p.538), which means there is a "cause and effect" result on how social networks affect user's behavior.

Benevenuto et al. (2009) explain the importance of user behavior research related to social networks since it allows the evaluation of systems in order to obtain better results in website design and advertisement policies. They also consider user behavior in social networks models are essential in social studies and viral marketing. Finally, the authors highlight the importance of studying the impact of social network on internet traffic to contribute with valuable knowledge for the design of infrastructure and content.

Specifically, referring to Facebook, van Dam and Van de Velden (2015) show how data from social networks can be used to obtain knowledge from a company. Antelmi et al. (2019) analyze Twitter users and how the use of this social network is turning new generation of consumers to interact more actively. Khan (2017) studies YouTube users' motivation to participate and consume content, concluding in useful recommendations on the kind of content preferred by users. The study of social networks is, therefore, very relevant, as online users tend to select information that supports their opinions (Bessi et al., 2016) and the analysis of clickstream data is a valuable way of understanding user behavior (Schneider et al., 2009). Due to the recent nature of studies comparing user behavior on social networks, ours is an exploratory study.

Visit duration

According to Danaher et al. (2006), the industry considers online 'stickiness' as a standard way to measure visit duration since it improves visitor-to-buyer conversion rate and usually generates online loyalty (Xun, 2015). Visit duration indicates how long a visitor stays on a website (Chaffey & Smith, 2022). It is an important metric to measure online performance, as, according to Prasetio and Harsono, "the longer a visitor stays in a website, it is more likely they will act to fulfill website goals" (2016, p. 1), such as clicking ads, filling out forms or subscribing to a newsletter. A technical definition of website visit duration is the estimated daily visit duration (measured in minutes and seconds) on a specific website (Xun, 2015).

Danaher et al. (2006) find much variation in visit duration across the sites they studied. The authors report that, for the top 50 websites they sampled, the overall visit duration, ranges between a minimum of 0.5 minutes to a maximum of 84 minutes. This result was similar for the number of pages viewed. Insights from their study indicate that entertainment sites are significantly visited longer than portals and so are auction and news sites. Internet service providers (ISPs), on the other hand, are the ones with the shortest visit duration. Therefore, there does not seem to be an "industry average" of visit duration.

Most of the studies on visit duration have focused on the relation between it and traffic sources (direct, e-mail, search, referrals, display ads, etc.). An example is the work of Prasetio et al. (2016) who find that the shortest time visit is the one from visitors who come from the search traffic source, and that it is significantly different from the direct and referrals sources of traffic. However, few researchers have studied social traffic, and they have not done it in detail. That is, looking at the different social networks where traffic comes from and analyzed its relation to visit duration.

Visit depth

Visit depth is defined as the average number of pages viewed per visit. Laudon and Traver (2018) define "page views" as the number of pages viewed by visitors on the website. However, it was considered that due to the pages with multiple page views for a single page (caused by web frames) (Laudon & Traver, 2018), the information obtained by this metric could be false (Prasetio & Harsono, 2016). As technology enhancements came into place, others viewed the page view metric as an indicator of website success (Chaffey & Smith, 2022). This means there is still an opportunity to provide more insights into the usefulness of this metric.

Studies on page views have used it as a mediating variable in the relationship between web technologies and product returns (Zhang et al., 2015). A research of a more technical nature studies connection speed and type of visitor (new or returning) (Omidvar et al., 2011). Studies on human-computer interface have focused on the impact of different factors, which include the user type of site, demographics, the presence of functionality features, and text and graphics content among others, on website duration and the number of page views (Danaher et al., 2006). Danaher et al. (2006) conclude that page views are proportionate to both traffic built on the website and visit duration. This is confirmed by Xun (2015), who finds that there is a strong positive impact of page views per user, on visit duration when visiting an e-tailer's website.

Prasetio et al. (2013) correlate social traffic with page views per visit versus direct and referral traffic, incorporating social media as well. Such study finds that, compared to the direct and referral traffic sources, social traffic visitors significantly average less page views per visit. The social media traffic from this study comes from Facebook only and it uses an independent t-test statistical tool. The reason for the increasing importance of page views is that websites often have links from sponsors directing to other websites, which are important system activities (user acquisition-retention and partnerships) of SME platforms' business models (Gutiérrez-Leefmans & Holland, 2019). Hence, the relevance for marketers to study this variable.

Unique visitors

The number of unique visitors is a common metric used by marketing intelligence companies. It is defined as the number of users requesting pages from a website during a month (Chaffey & Smith, 2022). It is a useful way to see how popular a platform is, and it allows a categorization per size. That is, the more unique visitors, the larger the platform is. Unlike other metrics like the number of visits (how many times a platform is visited), the number of unique visitors counts only once the user (distinct individual) that visits the platform.

The unique visitor metric is common in clickstream data literature. Examples are the work of Sashi, Brynildsen, and Bilgihan (2019) on how social media facilitates the process of customer engagement, and the work of Olsen, Kammer, and Solvoll (2020) who analyze audience metrics in the transition of print to digital of local newspapers. The use of this metric to compare websites in terms of size, is therefore a valid approach. The specific relation of size and social traffic seems to have been overlooked in literature. However, the increase on the use of social networks in the last decade brings relevance to this question.

Context

In Latin America, there is a wide use of social networks and even though most of the population in the region has a low socioeconomic level, there is a large scope of its usage. Chile, Uruguay, and Argentina are the countries with the highest percentage of social network users over the total population (Statista, 2020b). The use of social networks in Chile reaches 79% of its population, while in Uruguay 78% of its inhabitants are active users of these type of platforms (Statista, 2020 b). In Latin America, the most active network is YouTube, more than Facebook. In addition, the time allocated in these countries to the use of social networks is more than three hours a day, while in European countries the figure is around one hour (Hootsuite, 2019). This confirms the potential of the social channel for the acquisition of traffic in the region.

According to the Statista Research Department (2020a), it is predicted that in 2021, more than half of the population in Mexico will use social networks. Currently, 84% of internet users in Mexico use social networks and they mainly use Facebook, WhatsApp, YouTube, Instagram, and Twitter, in the order mentioned (IABMexico, 2019).

Search engines generate most of the traffic in websites globally; either with organic (43%) or paid (18%) options (Wolfgang Digital, 2019). The same source indicates that referrals from other websites contribute with 7%, social media 5%, e-mails 4%, and paid advertising 1%. Other channels and direct access to the site conform the total traffic (Wolfgang Digital, 2019). Even though social media represents a low traffic source, the data on the wide usage of social networks in the Latin America region indicates an area of opportunity. Wolfgang Digital's (2019) team considers that social networks are undervalued since, although they generate a lower percentage of traffic to websites, the income from these means is significant.

Most of the platforms that form the sample of this study are Mexican, but their users are entrepreneurs and SMEs from several countries in Latin America. Also, most of them are private, as only two are government initiatives.

Methodology

SimilarWeb is a major marketing intelligence company. It employs an automated technique for capturing and indexing public data from more than 200 million website pages and apps every month, similar to how search engines like Google index the web (SimilarWeb, 2020). Due to its automatic data-capture process and use of tracking systems; this type of data (online panel data) is very reliable. As such, SimilarWeb provides detailed information on the actual behavior of the user in a certain period of time.

The construction of the database was accomplished based on the following parameters: (a) identification of web pages that support entrepreneurial initiatives. A search was performed considering the following keywords in Spanish: *emprendedor* (entrepreneur), *pyme* (SME), **consultoría** (consulting), and startup. This was done in early 2019 and the process was repeated in July 2021; (b) using the SimilarWeb marketing intelligence tool, once a platform was located, the links that lead to similar sites within the tool were followed; (c) the search process continued until a saturation point was reached (Glasser & Strauss, 1967). This means the system repeatedly began to suggest the same platforms; (d) with this search, an initial database of 79 platforms was built. However, many of them did not contain data from social networks (too little traffic to be identified by SimilarWeb). The final 2019 base was made up of 40 platforms that contain data from Facebook, YouTube, and /or Twitter. A similar process was followed in July 2021. In this case, the search process led to finding 50 more platforms. From the new ones, 17 resulted also in very low traffic and did not report any data. This led to only 11 new platforms with data on social media traffic, which were added to data from 2019. By unifying the platforms with data from social networks from both end of 2018 and 2021, a total of 51 platforms was considered for the study; (e) with the 51 platforms that made up the sample of this study, a monitoring was performed to collect traffic information from social networks for the last quarter of 2018 and the third and last quarters of 2021. The model used one month of user-centric panel data, a technique that has been used effectively with a similar number of observations (Danaher et al., 2006); (f) the number of unique visitors to each platform and the number of monthly visits were initially extracted from SimilarWeb in order to ensure that all platforms were active; (g) data was extracted from the same source on number of page views, visit duration and percentage of social traffic. Data on social traffic was separated by social network (Facebook, Twitter, and YouTube). Traffic from other social networks (WhatsApp, Pinterest, LinkedIn, Quora, Google+, and Pocket) was not initially included due to unrepresentative traffic. However, for the exercise in July 2021, LinkedIn was added as it resulted in a relevant social network.

The analysis is part of a descriptive exploratory study of a quantitative nature. Using website analytics, the number of unique visitors, the duration and depth of visit (time on site and pages visited) on the platforms were identified, as well as the social traffic to those platforms. Since the present work has an exploratory scope, a hypothesis was not formulated (Hernández, Fernández, & Baptista, 2014). The multifactor analysis of variance (ANOVA) was chosen for this study since according to Yuan and Lin (2006), it is useful in selecting the most important effects and interactions in order to have a precise prediction on the response variable.

The research design is non-experimental, transectional, carrying out the data collection of a single month, with the purpose of discovering differences on the social networks regarding the duration of the visit, the visit depth, and the number of unique visitors to the websites. The statistical software SPSS version 25.0 was used. Correlational analyses were run between variables, and for the significant results, the analysis of variance (one-way ANOVA) was calculated. For the ANOVA analysis the data was grouped into ranges in order to compare each range of average visit time and number of unique visitors (treated as categorical variables, measured with a nominal scale) for each social network. Given that this analysis indicates significant differences, multiple comparisons of Tukey's post hoc test were performed in order to identify where the difference was.

Results and Discussion

Results from data extracted before the pandemic, indicate that Facebook is the social network that generates most traffic to the platforms, with almost half of the total traffic (49.72%), followed by YouTube with 18.89% and Twitter with 13.36%. Other social networks (not included in the analysis because of their low volume) complete the rest of the social traffic source (Table 1). Users stayed on the platforms for an average of one and a half minutes and navigated almost two pages per visit on average.

Table 1. *Descriptive statistics of variables*

	N	Minimum	Maximum	Mean	Std. Deviation
Facebook	50	0	1	0.49719	0.3212953
Twitter	50	0	1	0.133578	0.26108
YouTube	50	0	1	0.188958	0.2626531
Avg. Visit Duration (time)	50	00:00.0	05:46.0	01:32.7	01:01.8
Pages	50	1	4.4	1.9862	0.78092
Valid N (listwise)	50				

Source: based on results from SPSS 25.

When the data was analyzed, the normality could not be corroborated; therefore, the Spearman correlation, being a non-parametric measure, was used to identify any significant relationship among the variables. All the correlations between Facebook, YouTube, and Twitter resulted negative and significant, which indicates that users reach the platforms from either one of the social networks. Although, as a fact, a same user can reach the platforms from different social networks, in average the user behavior can be different.

The correlation between visit duration and visit depth turned highly significant, which, reasonably, means that users that spend more time on the platforms visit more pages. The analysis between the number of page views and different social networks did not result in any significant correlation. Therefore, no further analysis could be made on this variable. However, the Spearman correlation between visit duration and the specific social network of Twitter resulted in a significant negative correlation, meaning that Twitter users stay the least time on site. In this case, both Facebook and YouTube did not correlate significantly with the visit duration variable (Table 2).

Table 2. *Spearman correlation of visit duration among social networks*

	Facebook	Twitter	YouTube
Facebook	1.000	.007	.060
Twitter		1.000	-.339*
YouTube			1.000
*. Correlation is significant at the 0.05 level (bilateral).			

Source: based on results from SPSS 25.

For a more understandable comparison, the observations were grouped into ranges, both the average time per visit and the social traffic registered. For the average visit time on the pages, a comparison was made of the means of each range in each of the social networks (Table 3). It can be observed that users who reach the pages through Facebook are present in all the ranges of average visit time. Being the most consulted social network in Mexico and Brazil, the results found in the sample are consistent with what happens at the macro level. The table also shows the percentage of social network traffic source according to visit duration, from where is clear to see that YouTube users are the ones that spend more time on the platforms and Twitter users spend the least.

Table 3. *Average visit time by range*

	Facebook		Twitter		YouTube	
	Average Time visits	% Visits	Average Time visits	% Visits	Average Time visits	% Visits
Less than 20 seconds	2,246.0	47%	1,445.8	29%	410.0	9%
From 20 to 30 seconds	2,770.0	57%	693.0	15%	417.0	9%
From 40 to 60 seconds	3,456.5	70%	554.3	11%	350.0	7%
From 60 to 70 seconds	38,452.5	44%	4,017.9	39%	11,942.5	13%
From 70 to 90 seconds	1,492.0	31%	596.4	12%	1,303.8	28%
From 90 to 100 seconds	6,785.4	53%	2,289.6	4%	3,348.6	16%
From 100 to 110 seconds	20,251.0	46%	-	0%	82,333.0	49%
From 110 to 120 seconds	6,265.5	99%	95.5	1%	-	0%
From 120 to 140 seconds	**380,181.7**	70%	**90,868.3**	8%	**173,716.0**	22%
From 140 to 150 seconds	18,027.5	76%	2,744.0	7%	597.0	12%
From 150 to 170 seconds	43,476.5	43%	243.3	5%	84,914.8	32%
From 170 to 180 seconds	12,725.0	72%	2,272.3	6%	529.7	11%
From 180 to 200 seconds	25,466.5	86%	-	0%	-	0%
From 200 to 210 seconds	881.5	19%	-	0%	2,460.0	50%
More than 210 seconds	823.0	17%	-	0%	2,295.5	48%
Total	**37,468.3**	**50%**	**6,840.7**	**13%**	**23,208.9**	**19%**

Source: based on results from SPSS 25.

As Facebook is the most used social network, it includes users of all kinds: from those who have little time to consult the pages, such as those who analyze and delve into its contents. In the case of Twitter, the finding that users that come from that social network stay at most three minutes on the platform, stands out. After that, no users are registered. A possible interpretation of this is that Twitter users are usually more dynamic, requiring accurate and quick-to-digest information. As a result, they are willing to use up to three minutes to satisfy their need for information. In this case, the three minutes reported appear in the ranges of 90 - 100 seconds, 140 - 150 seconds and 170 - 180 seconds. As for YouTube, in the range of 100 to 110 seconds, 150 - 170 seconds, traffic of users who access these platforms is higher than Facebook's. This may be due to the fact that the users of such network are more visual, which affects the time they are willing to use to find information on the SME support pages. However, users who access the platforms either via Facebook, Twitter, or YouTube reach their maximum point within two minutes. Subsequently, the ANOVA was calculated to determine the significant differences between the ranges for each social network for the averages of time duration (Table 4).

Table 4. *ANOVA significant differences among social networks ranges for average time duration*

	F	Sig.
Facebook	2.151	.033 *
Twitter	1.131	.367
YouTube	.947	.523
*. The media difference is significant in the level of 0.05.		

Source: based on results from SPSS 25.

The only significant difference that this statistic shows is that of users reaching the platforms from Facebook. This could be due to the large number of users that use this network to access the pages. The ANOVA analysis indicates there is a significant difference. In order to identify exactly where the difference is, Tukey's post hoc test was performed to complement the analysis.

The multiple comparison from Tukey's post hoc test (Table 5) shows that, in the range of 120 to 140 seconds, there are significant differences with most of the other ranges. This corroborates the two-minute saturation point.

Table 5. *Multiple comparisons for Facebook (Tukey's post hoc test)*

Range	Compared to	Sig.	
From 120 to 140 seconds	Less than 20 seconds	.008	*
	From 20 to 30 seconds	.049	*
	From 40 to 60 seconds	.008	*
	From 60 to 70 seconds	.006	*
	From 70 to 90 seconds	.004	*
	From 90 to 100 seconds	.005	*
	From 100 to 110 seconds	.073	
	From 110 to 120 seconds	.053	
	From 140 to 150 seconds	.070	
	From 150 to 170 seconds	.027	*
	From 170 to 180 seconds	.022	*
	From 180 to 200 seconds	.082	
	From 200 to 210 seconds	.047	*
	More than 210 seconds	.047	*

***. The media difference is significant in the level of 0.05.Source: based on results from SPSS 25.**

To analyze the number of visits to platforms, they are grouped by ranges. It is highlighted that not all the ranges had data, for example, there were no 6,000 visits from any social network. Therefore, not all the ranges are mentioned. For the same reason, not all the ranges have the same proportion. Nevertheless, it is not a crucial requirement for this type of analysis.

For the number of unique visitors to the SME platforms, a comparison of the means of each range in each of the social networks was made (Table 6).

Table 6. *Average of unique visitors by range*

	Facebook		Twitter		YouTube	
	Unique visitor	%	Unique visitor	%	Unique visitor	%
Less than 5,000	2,296.4	57%	818.5	20%	915.5	23%
From 7,500 to 8,500	6,717.5	99%	95.5	1%	-	0%
From 13,500 to 17,000	4,257.5	55%	-	0%	3,503.5	45%

From 17,000 to 24,500	15,376.5	87%	-	0%	2,368.5	13%
From 38,000 to 39,500	28,045.7	73%	10,532.3	27%	-	0%
From 45,000 to 56,500	37,412.0	75%	5,724.0	11%	7,001.0	14%
From 200,000 to 360,000	154,766.0	55%	-	0%	125,583.0	45%
More than 540,000	**426,243.7**	53%	**90,868.3**	11%	**284,745.3**	36%
Total	37,468.3	55%	6,840.7	10%	23,208.9	34%
*. The media difference is significant in the level of 0.05.						

Source: based on results from SPSS 25.

In all ranges of the unique visitors, the predominant social network is Facebook, although it tends to decrease proportionally, this means that the more unique visitors the platform has, the less it tends to be due to the traffic coming from Facebook users. In the case of Twitter, it should be noted that users who arrive from this social network access the SME platforms in a limited way (in the range of less than 5,000 unique visitors, which is the least), in an intermediate way (from 38,000 to 56,500), or broadly (in the upper ranges of more than 540,000 unique visitors). As for YouTube, the number of unique visitors received from this social network increases exponentially after the 540,000 monthly unique visitors. This could be due to, for example, the fact that such platforms are already well positioned, and they invest more on interactive content with more views.

The ANOVA analysis was calculated to determine the significant differences between the ranges of unique visitors for each social network (Table 7).

Table 7. *ANOVA significant differences among social networks ranges for unique visitors*

	F	Sig.
Facebook	8.827	.000*
Twitter	2.352	.035*
YouTube	8.925	.000*
*. The media difference is significant in the level of 0.05.		

Source: based on results from SPSS 25.

In this case, significant differences were obtained for the three social networks analyzed. Therefore, multiple comparisons from Tukey's post hoc test were developed to determine in which ranges of unique visitors such differences existed (Table 8).

Table 8. *Multiple comparisons for Facebook, Twitter, and YouTube (Tukey's post hoc test)*

Range	Compared to	Sig.		
		Facebook	Twitter	YouTube
More than 540,000	Less than 5,000	.000*	.003*	.000*
	From 5,000 to 5,500	.000*	.130	.000*
	From 7,500 to 8,500	.000*	.131	.000*
	From 13,500 to 17,000	.000*	.130	.000*
	From 17,000 to 24,500	.000*	.130	.000*
	From 38,000 to 39,500	.000*	.140	.000*
	From 45,000 to 56,500	.000*	.188	.000*
	From 200,000 to 360,000	.033*	.130	.104
*. The media difference is significant in the level of 0.05.				

Source: based on results from SPSS 25.

For Facebook, significant differences were found between the highest range (more than 540,000 unique visitors) and all the others ranges. In contrast, for Twitter, only a significant difference was observed between the highest and lowest rank. For YouTube, significant differences were found between the highest range of unique visitors and most of all other ranges, except for the penultimate.

From the 79 web pages that were originally being followed in December 2018, 30 disappeared by December 2021, which reflects the lack of interest in generating businesses during such period. Data retrieved during the pandemic indicates that most of the social networks reduced their traffic from December 2018 to December 2021, except LinkedIn. On average, they reduced by 55%. Most of the social networks reduced their traffic from June 2021 to December 2021, except LinkedIn and Twitter. On average, they reduced by 28%. Although LinkedIn is a slightly more expensive network than the others, it was the only one that had growth from December 2018 to December 2021 (17%) together with Twitter from June 2021 to December 2021 (22%). Twitter does not have a high percentage of traffic, but it is the only network along with LinkedIn that reflects a growth from June to December 2021. In fact, Twitter was the fastest growing with 48%. Despite its decrease, Facebook is still the network that generates the most traffic with 67% of total traffic. YouTube was the second network with the most traffic in December 2018 with more than 20% of the total visits but by the end of 2021, it is in third place with a little more than 6% of the visits.

Conclusions

The usefulness of online panel data has been demonstrated in this study. Online panel data is rich as it is not self-reported data as when a user completes a survey, it provides actual data on users' behavior. The data collection and analysis done allowed to derive interesting insights regarding differences among social networks. Given that an increase in the use of social networks was observed during the pandemic, this paper analyzes the results before and after this period, using data with a difference of two and a half years.

As expected, Facebook is the social network that attracts most entrepreneurs and SME owners to the platforms. However, a different behavior is observed between users from different social media platforms. Twitter users are the ones who spend a shorter time in the platforms. Twitter users are generally those who have the least time to stay, or are used to very specific content, which, if not found, they will leave the page. Users coming from Facebook stay less than one minute and up to three minutes in the platform. Likewise, there is a different behavior in YouTube users, who spend the highest average time visit. This means that these users are more attracted to the content in the platforms. A particular finding from the study is that either via Facebook, Twitter or YouTube, the average time visit reaches its maximum point within two minutes. Therefore, content should be designed for this specific length, otherwise most visitors will lose interest.

Although it is known that there are different profiles among the social network users, the findings of the study help to explain such differences and confirm the pertinence of including different content through different landing pages depending on the social network that generates the traffic. This is, for example, more specific information with careful use of keywords for users coming from Twitter. For Facebook, content marketing managers should focus on generating general content of an average length of their time visit. A suggestion for users coming from YouTube is to generate more interactive content (including videos, photos and in general, rich media) as well as more specific and specialized content, given that we know that these users spend more time on site.

Another finding is that, although Facebook generates more traffic to the platforms, it can be inferred that the traffic that comes from YouTube is of a higher quality, as users stay longer in the site. This could mean that these are more interested users or that the type of content offered via this social network, allows more features. Therefore, SME platforms should be investing in advertising as well as in more quality content in this social network. As for the number of unique visitors, results show that, for platforms that have many, Twitter does not bring an aggregate value, but it does for the platforms with few or medium number of unique visitors. For Facebook, results show that its marginal utility is not that representative for the platforms that have many unique visitors. On the contrary, platforms with many unique visitors clearly have more traffic from YouTube.

It can be said that all three social networks bring traffic to platforms and should be considered in the communications strategy. Nevertheless, more specifically, smaller platforms (with fewer unique visitors) have more traffic from Twitter and Facebook, so they should consider specially these two networks. Medium-sized SME platforms should also focus on Facebook and Twitter, and platforms with a high number of unique visitors should definitely not neglect their YouTube content.

Derived from the analysis of 2021 results, we can tell that LinkedIn became an important source of traffic for SME platforms. It could be that due to the economic crisis generated by COVID-19, users looking for job opportunities were attracted to such platforms more than normal users spending time in other social networks. Being the second social network source of traffic in 2021, Twitter's short format may be the reason for entrepreneurs' preference. The overall decline in the use and survival of SME platforms during the pandemic is an interesting finding that reflects the pandemic crisis and its effects.

These results are relevant for the region given the massive use of social networks in Latin America, but also since the study is focused on platforms that have the objective to help entrepreneurs and SMEs in the region to grow and subsist.

The study contributes to online consumer behavior literature since, as an exploratory study, it provides the path for conceptual development of constructs that could lead to a user behavior model based on social networks. Another contribution is to the social media literature, as an important difference among users from different social networks emerged. This is not only relevant for digital marketing strategy studies but could be useful for other disciplines. And third, as stated by Benevenuto et al. (2009), understanding how users behave on social networking sites helps to improve interface and content distribution systems design. It also contributes to strengthen the use of website analytics as a viable data source to bring insights into the digital challenges that SME platform owners face. Marketing practices such as advertising and promotion are transformed by social media unique characteristics and its popularity (Vinerean et al., 2013). This holds true as the differences observed bring out the possibility of developing marketing strategies accordingly.

Successful strategies should be translated into a higher number of unique visitors, and therefore, a greatest market share. As mentioned before, LinkedIn may result in a more expensive social network, however, SME platforms could considerate generating partnerships with the social network as it proved to be attractive during times of crisis.

Some limitations to consider are that Clickstream data contributes broadly to the user behavior study on online social networks. However, its data is limited by the collection duration, and the fact that the behavior of inactive users in the duration is not monitored. Also, further studies could collect data from a wider set of months if possible. Another limitation identified earlier, is that the data is restricted by the monitoring locations (Schneider et al., 2009). As a new line of research, this study arises the question whether the observed behaviors remain after the pandemic. Also, it would be useful to research the social network users' profiles since it would give more insights to develop better and more targeted content in landing pages.

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