informatics

Article

An Evaluation Study in Social Media Research: Key Aspects to Enhancing the Promotion of Efficient Organizations on Twitter

Hani Brdesee [1,*] and Wafaa Alsaggaf [2]

[1] Computer Information Technology, Faculty of Applied Studies, King Abdulaziz University, P.O. Box 80200, Jeddah 21589, Saudi Arabia
[2] Department of Information Technology, King Abdulaziz University, P.O. Box 80200, Jeddah 21589, Saudi Arabia; waalsaggaf@kau.edu.sa
* Correspondence: hbrdesee@kau.edu.sa

Abstract: As social media has shifted from traditional to modern technical patterns, organizations have sought to take advantage of the presence of beneficiaries on social networks. They may serve customers, display ads, and respond to queries on social media accounts such as Twitter. The implementation of these services required a scientific study considering: (1) how to attract beneficiaries, (2) attraction times, and (3) measurement of the impact of that attraction. This study aimed to address these three points through an analysis of data from an educational organization's Twitter account. We found that the interaction rates with tweets increased in the evening, and we identified the best times for the organization to reach more followers. We examined five months of data (an entire semester), analyzing thousands of tweets and their associated impressions, types of responses, integration ratio, and account usage. We also discovered that the quality of tweets had an impact on attracting new followers, particularly when tweeting media such as photos, videos, and other types of content. Finally, this research serves as a resource for educational organizations on new ways to publish accounts and foster organizational growth through electronic media.

Keywords: social media; data retrieval; data analysis; organization presence; Twitter

check for updates

Citation: Brdesee, H.; Alsaggaf, W. An Evaluation Study in Social Media Research: Key Aspects to Enhancing the Promotion of Efficient Organizations on Twitter. *Informatics* **2021**, *8*, 78. https://doi.org/10.3390/informatics8040078

Academic Editor: Jiang Bian

Received: 19 September 2021
Accepted: 15 November 2021
Published: 17 November 2021

1. Introduction

Building relationships with beneficiaries through social media, and the way these channels are managed, is a key element in the success of an organization's reputation. Social media can positively affect the service popularity of organizations and, to a large extent, can influence loyalty [1]. Although social media was initially designed for personal use and to maintain personal interactions, with its development and increasing popularity, it has become a valuable tool for building a community around the organizations. Patrons are more likely to use this type of communication, which is molded around their daily lifestyles, and this ensures greater and more flexible access. The use of such strategies will not only increase the effectiveness of activities in this area, but also has a positive effect on the image of the organization due to convenience and social interaction [2].

Twitter, which is the focus of this research, is a social networking site that allows its users to publish short posts known as tweets. It is possible to follow other people's tweets and comment on them, and tweets can be used and placed within keywords on Twitter, in addition to the ability to search [3]. For tweets on this site, the number of characters is 280, and the site is characterized by its ease of use and its integration with external services. Users can share other tweets on their Twitter accounts through what is known as retweeting, as this is a good option when the user wants to reply to other people's tweets or show their interest in the topic being retweeted. Furthermore, a trend can be defined as a popular topic on Twitter, and some trends are preceded by a sign (#), which is called a hashtag. A keyword or phrase included in the tweet preceded by a hashtag symbol (#) categorizes tweets by topic. When clicking on a specific hashtag, you can view the rest of the tweets that include that hashtag, and this method enables users to follow trending topics on Twitter [3].

This research focused on analyzing the data of one of the parties that serves a large segment of the beneficiaries in an educational institution in Saudi Arabia. The research aimed to understand the most important elements that affect the spread of the institution on Twitter, in order to take advantage of these effective elements by promoting their use, as well as disseminating these elements to similar academic communities. In theory, this research will contribute to increasing the effectiveness of organizations' visibility on social media, thus achieving greater effectiveness of spread. In order to achieve these objectives, this research went through several stages, as shown in Figure 1.

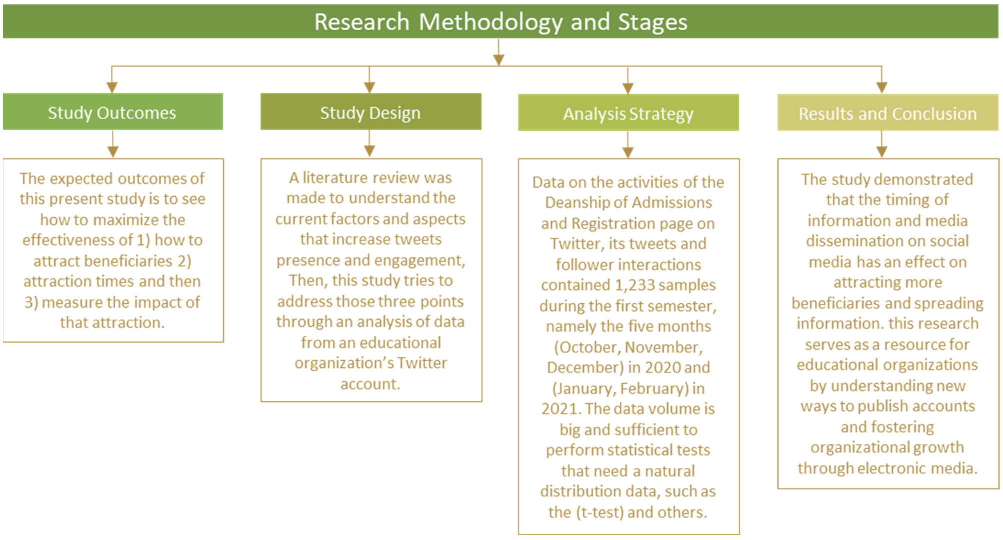

Figure 1. Research methodology and stages.

2. Background

The Twitter account of the Deanship of Admission and Registration at a Saudi governmental university was chosen for this research. For decades, the university has been represented in the Deanship of Admission and Registration, which is responsible for academic advising for students. More recently, the Deanship began working on a comprehensive academic advising program, a large part of which went into effect in 2016 [4,5]. The university's academic advising structure aims to offer an electronic academic advising platform with all possible sources of technical and human resources, plans, and mechanisms.

The university offers a variety of graduate and university degrees, as well as qualifying diplomas, for over 120,000 students at the university's headquarters and branches, with study options ranging from regular to external to distance education. Although the institution has an organizational structure for academic advising, with so many students still attending, the Deanship has taken advantage of electronic services [6–10], particularly social media, namely Twitter and Facebook, to conduct its advising service [11].

In fact, the Deanship has had a Twitter account since the end of 2013. However, there was no mechanism in place to ensure the continuation of the advisory service on the account until 2015, when the Deanship established a unit called the E-communication unit. This unit's function is to respond to current students' questions, and the questions of those expected to be admitted to the institution [11,12]. The Deanship's Twitter account (@Admissionweb) had 9000 followers before the unit was founded, and then the number climbed to almost 400,000 followers by October 2021.

3. Literature Review

Several studies have considered elements of promoting social media accounts for government entities, such as ministries and municipalities, among others. Stone and Can [13] discussed the factors that influence the purpose of municipalities' tweets in the United States of America and how far citizens are engaged with them. The researchers found that interaction with a multiplatform approach and fiscal health can predict the level of engagement with tweets and concluded that median age plays a significant role in predicting the number of tweets that aim for disseminating information and community building. Siyam et al. [14] studied the two-way communication between governments and their citizens, which is also known as e-participation, to identify and predict citizen engagement, such that citizens may express their views and leaders can make decisions accordingly. While the researchers asserted that e-participation increases transparency, trust, and acceptability of government decisions, the study concluded that engagement is affected by post type, as posts with videos and images have the highest impact on engagement, as well as timing of tweets as engagement increases on weekdays compared to weekends. In a similar case study conducted in Florida, USA, Kocatepe et al. [15] explored public engagement with tweets of the Florida Department of Transportation on traffic conditions. The researchers found that engagement with tweets is driven by several factors, such as posting time, tweet analytics, accident information, and demographic variables. The researchers maintained that this can help officials to adjust their plans to improve their social media channels, so that better and faster information can be provided to the public. Stating that Japan has the world's highest Twitter penetration rate, Wang [16] investigated the factors that affect the intensity of Twitter use in the country. The study found that the prime factors are the relational mobility and the intent to share information. Guijarro et al. [17] attempted to identify the key factors for public administrations to use Twitter as a medium from a social marketing perspective. The study concluded that the most influential and effective factors from a social marketing perspective were: (1) the average population age; (2) the presence of a plan to communicate with the population; (3) the number of tweets; (4) the number of followers, retweets, and mentions; and (5) the efficiency of the account.

Businesses and private organizations have also paid attention to social media, especially the engagement rate. Cao et al. [18] probed the issue of retailers' seeking to actively engage with consumers. The study concluded that social media context has a significant effect on engagement behaviors, as the consumer is more likely to engage with social media platforms when they offer richer content. Wigley and Lewis [19] compared tweets that mention highly engaged companies and those mentioning less-engaged ones to figure out the rules of engagement. The study concluded that tweets reflect less negative mentions for highly engaged companies when dialogue is used for communication, while less-engaged companies usually receive more negative mentions. This view was supported by Bozkurt et al. [20], as they examined how customers' perceptions of brands' social media interactivity influences customer engagement behaviors, such as purchases, referrals, and knowledge, among others. They found that customers tend to buy brand offerings when they perceive that the brand is highly interactive on social networks, and that the positive impact of social media interactivity on customer purchases, referrals, influence, and knowledge varies according to the brand and the type of social media platform. The study also reported that higher engagement on social networks encourages clients to add to the brand value through purchases and suggestions. Wadhwa et al. [21] studied the characteristics of tweets that attracted higher engagement rates for a scientific journal twitter account over a period of two years. They found that tweets with a high engagement rate tended to have photos. In their study, Boujena et al. [22] probed, from a managerial perspective, customer engagement on social media. Their results illustrated the gaps between customer engagement conceptions, customer engagement dimensionality, and the metrics of social media performance beyond customer engagement, maintaining that performance metrics include the reach and number of followers, while suggesting the need to access consumers profiles, aggregate the metrics across social media networks, and track the customer journey online and offline. Aydin et al. [23] explored the means of engaging customers through effective social media channels in Turkey. The researchers found that engagement is affected significantly when posts have videos, images, frequency, and interactivity. Schee et al. [24] studied future lines of inquiry connected to branding outcomes, finding that consumer status, disposition, personality, intrinsic motivation, extrinsic motivation, and cultural dimensions are the major areas specific to consumer factors. The study also concluded that brand engagement is relative to affective, cognitive, and behavioral engagement, and identified six brand outcomes, namely status, disposition, attitude, affirmation, connection, and aversion. In their study on the banking industry, Ferm and Thaichon [25] used social exchange theory (SET) to determine the factors that precede SET's cost–benefit analysis of social media participation, and the extent that these factors have an impact on attitudinal loyalty. The researchers found that attitudinal loyalty is affected by online interaction propensity. While age, gender, and page visit frequency did not exhibit a tangible difference between different groups, groups with higher incomes exhibited higher levels of loyalty. Han et al. [26] explored how the form of tweets affects Twitter user engagement, including the tweet length, hashtags, mentions, pictures, videos, and links. The results showed that some industries, such as luxury and hardware technologies, are digital sensitive and benefit more when the tweets include hashtags and videos or picture URLs, while other industries, such as the software industry, appeared to be more digital insensitive. The researchers recommended that businesses should design their tweets to attract high customer engagement.

Social media channels have always been of interest to academic organizations and educational institutions. Prabhu et al. [27] reported that 85% of radiologists use social media for both private and academic practices, suggesting an approach for research using online social media with four steps, namely: (1) pick your platform(s); (2) create a profile; (3) establish your network; and (4) create, share, and optimize content. Sharp et al. [28] explored the effects of the components and characteristics of tweets during a major medical conference. They found that mentions, multimedia, hashtags, and the number of followers affected tweets and retweets.

While attracting an audience and generating engagement have received much attention from researchers across the world and in different domains, researchers have often been interested in increasing engagement rates. Gligor and Bozkurt [29] explored the concept of social media agility as applied to several domains. They found that perceived social media agility affected customer-based brand equity, both directly and indirectly, through customer engagement. Khan and Ahmad [30] investigated engagement strategies on Twitter in Pakistan, as applied to a group of six micro-celebrities. The analysis included engagement patterns for several variables. They concluded that the content type, language and length, hashtags, mentions, images, links, videos, hour of the day, and day of the week have strong effects on engagement. In their 2016 study, Mahdavi et al. [31] attempted to assess the extent to which shared content becomes popular among audiences, regardless of the source of the content. They performed an analysis of the content of tweets, and then judged its influence on the popularity of the tweets. The researchers found that tweets with social content are more likely to be popular, while tweets with individual content are less likely to be popular. The study also underlined the significance of content-based features, especially the number of retweets.

Numerous studies focused on the timing of tweets. Alwagait and Shahzad [32] maintained that increasing the response to a tweet requires knowledge of the number of online users who may see the tweet and engage with it. Their study focused on Twitter users in Saudi Arabia who engage with tweets according to the 'last seen' status, to determine the best time slots to tweet based on when the percentage of online users is high. They found that most social networking is performed around midnight. Abdullatif et al. [33] suggested an algorithm to find the best time to tweet, maintaining that because of the dynamic nature of social networking, tweets that are hidden to followers decrease engagement and activity. The study proposed a system to discover the best time to tweet based on active followers' behavior. Although the study focused on the architecture of the algorithm itself, rather than stating the best tweeting times, the researchers stressed that the proposed system may assist leaders and individuals in attracting followers and increasing engagement on their tweets. Orellana-Rodriguez et al. [34] discussed the development of strategies to spread news on Twitter. The researchers found that different combinations of features of tweets influence engagement with different news categories, such as politics and sports, suggesting guidelines for individual and corporate twitter accounts to increase engagement, with a special focus on the timing of tweets. The study concluded that while the best tweeting time for individual accounts may differ according to the topic, analysis of corporate accounts showed that there is no best time to tweet to attract more engagement. However, the general trend is that tweets have more audience engagement after 5:00 p.m. on weekdays and weekends. In their 2014 study on the South Korean 2012 presidential race, Ko et al. [35] maintained that information sharing on the day scale is seen as a good measure for engagement, but the hour scale reflects the daily cycle of activity of Twitter users. They found that tweeting/retweeting is related to the in-flow of information from other media. Chong et al. [36] proposed a collective entity linking geocoded tweets that are tweeted at close times. The study showed that events in the same geographical area often result in similar/related entities that are mentioned in spatio-temporal proximity. They concluded that collective linking consistently yields more positive changes than negative changes to the linking quality.

Researchers have also considered sentiments and emotions while tweeting, and their effect on tweet popularity. Sayed et al. [37] analyzed emotional tweets in Arabic during the Arab Spring. The researchers considered the emotions of surprise, happiness, sadness, and anger, in addition to sarcasm. The study proposed a framework to analyze emotional trends over time, at different fine-granularity levels (tweets, expressions, and aspects). The study developed a clustering algorithm that achieved better results than other clustering algorithms. After Twitter released its data corpus on Iran- and Russia-backed accounts, Cheung et al. [38] explored whether emotion-laden tweets reach a wider audience than non-emotional tweets. They found that practical implications vary across people and professions, including those targeting emotions to attain influence, and those subject to such attempts. The researchers also found that civic educational content should include social media literacy.

Building on the previous research results and recommendations for future research, Boujena et al. [22] suggest conducting further studies on engagement in different geographical locations and cultural milieus, while Gligor and Bozkurt [29] maintain that further research should attempt probing means to develop social media agility in cultures other than the United States of America. Further studies on factors that affect performance on social media are recommended by several scholars such as Han et al. [26] and Orellana-Rodriguez et al. [34], who recommend measuring the impact of predictors on engagement, while Stone and Can [13] endorse exploring the drives and influencing factors for using social media platforms to generate more interaction and engagement. This is further supported by Guijarro et al. [17], who suggest further research on analyzing the factors leading to a higher impact of tweets such as content appropriateness, tweet quality, and the tweeting time.

As the literature suggests, increasing engagement with tweets depends on several factors, from the characteristics of the tweet, through its content, and finally to its timing, among other factors. While multiple studies focused on means to boost engagement and even suggested few steps to do so, such as supplementing a tweet with pictures and videos, the timing to tweet in the academic context and probability of user engagement are seen as significant factors for more engagement, which is the motivation for this study.

4. Materials and Methods

In order to develop an initial understanding of the probability of using social media data to enlarge the organization's presence in academia and provide an additional tool for decision-makers, the authors decided to apply a case study to understand university tweets. One of the biggest Saudi Arabian universities was selected, particularly the university's deanship of admission and registration Twitter account. The account has more than 380,000 followers, four times the number of university students. The account is very active, answering hundreds of students' and community visitors' inquiries every day. This excellent response boosts the in-campus activities of Academic Advising (AA) into a broader impact through social media.

Data on the activities of the Deanship of Admissions and Registration (DAR) account on Twitter were obtained through a permission request to the account administrators. Twitter provides the option to download an archive of the data, giving the account admin a compressed file. Usually, Twitter offers complete access to archived data. It also provides a tweet activity dashboard (TAD) service that displays data to help admins optimize their performance on Twitter. They can leverage these insights to inform the ongoing tweeting strategy. They can track the number of impressions, engagements, and earned engagement rate for each tweet they send. It automatically shows the last 28 days of data, but admins can change the date range for tweets they want.

Finally, and most importantly, admins can also export this data as a CSV file from the dashboard. The file includes all tweets information to be analyzed using some advanced analysis models, as proposed in this research. For this research, the authors obtained DAR's tweets and its follower interactions, which included 1233 samples during the first semester (October, November, and December in 2020, and January and February in 2021).

Thus, this research, as it deals with structured data, can be considered quantitative research. An SPSS package was used to analyze the obtained data. The hypotheses mentioned in the analysis section were answered to fill the research gap. However, some qualitative data were extracted from the received data. For example, the authors classified the type of tweet. This variable has several options related to the type of tweet, such as: (admission, registration, exams, College Enrolment Allocation (CEA), transfer, electronic transactions, graduation, general inquiries).

5. Data Analysis

The data volume was large, and sufficient to perform statistical tests that require a natural distribution of data, such as the *t*-test. All variables in the study, along with their types and description, are included in Table 1 below.

Table 1. Study spreadsheet.

Number	Variable	Variable Type	Description
1.	Date	Qualitative	This variable has two options (morning: a.m. or evening: p.m.).
2.	Tweets	Qualitative	This variable has several options related to the type of tweet (admission and registration, exams, CEA, transfer, electronic transactions, graduation, inquiries).
3.	Impressions	Quantitative	This variable indicates how frequently a tweet appears to participants.
4.	Posts	Quantitative	This variable indicates the number of Admission and Registration Deanship posts.
5.	Retweet	Quantitative	This variable indicates the number of a particular post retweets.
6.	Reply	Quantitative	This variable indicates the number of responses per tweet.
7.	Likes	Quantitative	This variable indicates the number of likes per tweet.

Table 1. *Cont.*

Number	Variable	Variable Type	Description
8.	Profile clicks	Quantitative	This variable indicates the number of times the user's profile has been visited.
9.	Click on the link	Quantitative	This variable indicates the number of clicks on the tweet link.
10.	Clicks on tag	Quantitative	This variable indicates the number of clicks on the tweet tag.
11.	Detail expansions	Quantitative	
12.	Watch media	Quantitative	This variable indicates the number of views per tweet.
13.	Media sharing	Quantitative	This variable indicates media sharing number of tweets.

The following research questions will be addressed by using and evaluating this data:

1. When is the best time to tweet for impacts and impressions, and to elicit audience interaction?
2. To what extent do tweets and responses attract browsers to visit the account's homepage?
3. What metrics are used to measure followers' interaction with Tweets? The study was therefore based on the following hypotheses:
   - The first hypothesis: The null hypothesis: the average follower interactions of the Admission and Registration page tweets are not associated with the tweet period (morning or evening). The alternative hypothesis: the average follower interactions of the Admission and Registration page tweets are associated with the tweet period (morning or evening).
   - The second hypothesis: The null hypothesis: there is no correlation between the average number of tweets and browser responses and the average number of follower visits to the account's home page. The alternative hypothesis: there is a correlation between the average number of tweets and browser responses and the average number of follower visits to the account's home page. The analysis and specification method of this data and associations will be provided in the next section of the report.

Analysis and Specification of Data

SpSS v.25 was used to analyze the data, including providing the results in tables, creating graphs, and finding correlations between variables. The answers to the research questions were subsequently deduced, and hypotheses either proven or rejected. The following were the procedures for analyzing data and extracting answers and results:

1. All five months of data were collected in one file, and a new nominal variable called "month" was introduced with five different values: "10" for October, "11" for November, "12" for December, "1" for January, and "2" for February. All data (1233 samples) were evaluated for all months at the same time, and the relativity of each month's sample, in which the month variable was included, was preserved.
2. Quantitative and descriptive analysis of each variable in the study, by calculating frequencies and percentages, a descriptive analysis to find the calculation averages (means), variance, highest value (maximum), and lowest value (minimum), and charting (bar chart, pie chart) of variables to illustrate differences and variations in values. We clarified this in the data descriptive analysis part.
3. A new variable was found, called the sum of scale type, which was the total number of interactions, including replies, likes, retweets, clicking on the profile, clicking on the link, clicking on tags, detail expansions, watching media, and sharing media, for each sample.
4. To conduct the statistical tests required to answer the research questions and prove or reject the hypotheses, the *t*-test was used to answer the first research question, based

on the time and sum of the independent variables, which represented the sum of all interactions per sample. It is worth noting that the *t*-test uses this to compare only two variable averages for a large naturally distributed data set, and that the data in this study met both of these requirements. When conducting this research, the sig coefficient value was found and compared to the α value, which was equal to 0.05. If the sig coefficient value is greater than 0.05, this indicates that there is no statistically significant correlation between the two variables tested. However, if the sig coefficient value is less than 0.05, this indicates a statistically significant correlation between the two variables.

5. Regression analysis, which is a statistical tool, was conducted to build a model that estimated the relationship between an independent variable or numerous independent variables and a dependent variable. An equation was then created to determine the kind of relationship these variables have, addressing the second research question. The number of clicks on the profile was considered the dependent variable, while the tweets and responses variables were the independent variables.

In this test, the correlation coefficient (R), the modified correlation coefficient square, and the sig value, which shows a link if it is less than 0.05, were calculated to demonstrate that the variables were associated with each other. The results were enhanced using the correlation coefficient test.

6. To answer the third research question, all types of interactions were examined; namely replies, likes, retweets, clicking on the profile, clicking on the link, clicking on tags, detail expansions, watching media, and sharing media, as well as the variable that represents the sum of all of them. The objective was also to prove that those interactions were associated with the tweets variable, to determine which indicators allow us to measure followers' interactions with the page.

6. Results

The data included 1233 samples of tweets over five months (October, November, December, January, and February). Each sample comprised the variables specified in the spreadsheet.

First: data descriptive analysis:

Table 2 shows the number of recurrences of both evening and morning tweets in all 1233 study samples during all five months. There were 259 morning tweets on Twitter out of 1232, equal to 21%, and 973 evening tweets out of 1232, equal to 79%.

Table 2. Morning and evening tweets.

		Time			
		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	a.m.	259	21.0	21.0	21.0
	p.m.	973	78.9	79.0	100.0
	Total	1232	99.9	100.0	
Missing	System	1	0.1		
Total		1233	100.0		

The following pie chart shows the distribution of tweets on the Admission and Registration page within five months, and their classification as morning or evening.

We can see from Figure 2 that the majority of tweets on the Admission and Registration Twitter page were made in the evening (p.m.). In the appendices, there are tables analyzing the tweet times for each month. These tables show that in October, 74.4% of tweets were made in the evening and 25.3% in the morning, while in November, 92.6% were made in the evening and 7.4% in the morning. In December, 91.3% of the tweets were made in the evening and 8.7% in the morning; in January, 65.9% of the tweets were made in the evening and 34.1% in the morning. In February, 74.3% of the tweets were made in the evening and 25.1% in the morning. Therefore, we can conclude that evening tweets predominated. However, November had the highest percentage of evening tweets, and the least in the morning, while January had the lowest percentage of evening tweets across the five months, and the highest percentage in the morning.

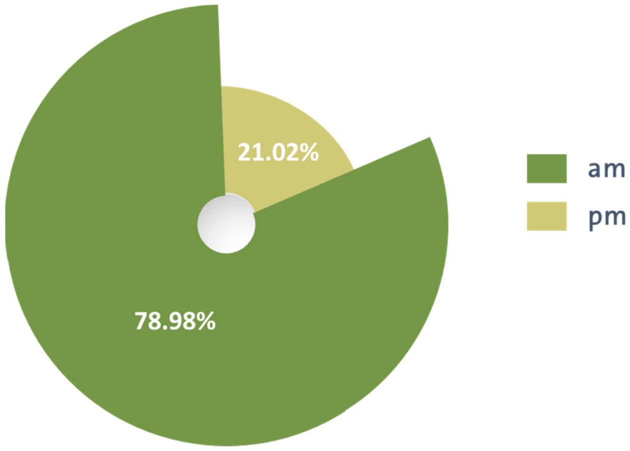

Figure 2. Pie chart representing tweet times.

The posts (tweets) shared by the Admission and Registration Deanship page on Twitter were varied (admission and registration, exams, CEA, transfer, electronic transactions, graduation, inquiries). Table 3 shows the frequency of each type over the course of five months.

Table 3. Types and recurrence/frequency of tweets in all months.

		Tweet			
		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	Admission and Registration	273	22.1	22.2	22.2
	Exams	125	10.1	10.1	32.3
	CEA	29	2.4	2.4	34.7
	Transfer	41	3.3	3.3	38.0
	electronic transactions	134	10.9	10.9	48.9
	graduation	39	3.2	3.2	52.0
	Inquiries	591	47.9	48.0	100.0
	Total	1232	99.9	100.0	
Missing	System	1	0.1		
Total		1233	100.0		

The graph below depicts the percentage of each type of tweet (Admission and Registration, exams, CEA, transfer, electronic transactions, graduation, inquiries) for all tweets (1233 tweets) over the course of five months.

As shown in Figure 3, the highest percentage was for the inquiries tweets, at approximately 48%, followed by tweets on Admission and Registration (22%), electronic transactions (11%), and exam tweets (10%). Lastly, the amount of funding (3.3%), graduation (3.2%), and CEA (2.4%) tweets were all close.

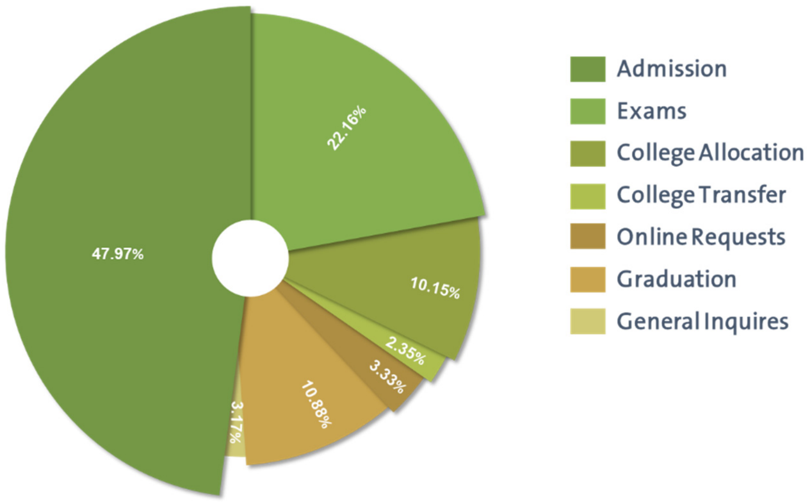

Figure 3. Graph of the types of tweets.

As for the frequency of tweets per month, the tweets in October were distributed as follows (from the highest percentage to the lowest): 66.7% of tweets were queries, 13.1% were admission, and the lowest number were about graduation. In November, the highest recurring type was queries at 56.5%, followed by exams, while graduation, CEA, and funding were the least recurring content, with equal proportions (1.7%).

In December, the most recurring tweets were those on admission and registration at 43.3%, followed by queries at 21%, while the least recurring were funding tweets. In January, the most frequently repeated tweets were queries at 56.8%, followed by admission and registration; the least recurring tweets were those on graduation (1.3%). Finally, in February, the most frequently repeated tweets were those on admission and registration (34.7%), followed by queries (22.8%), while the least recurring tweets were those on CEA.

Based on these statistics, we can conclude that queries were among the most recurrent tweets in all months, ranking first in most months and second in others. Moreover, the frequency rankings for types of tweets varied in the months based on the circumstances of each month, i.e., months at the start of the semester had a higher rate of tweets about admission and registration.

As for the variable number of tweets, their distribution varied over the five months (October, November, December, January, February), and the following table displays the distribution of the average number of tweets over the five months, using the means comparison test.

As the data in Table 4 show, the highest average number of tweets was 1571.11 in November. The average was 1091.41 in December, followed by October with 797.7 tweets, then January with 614 tweets, and the lowest month was February with 322 tweets. The table also shows that the average number of tweets for all months was 888.16 per month.

The figure below depicts the average number of tweets per month, clearly demonstrating that the highest number of tweets was in November, followed by December, October, and January, and February had the least (Figure 4).

With regard to the variable impressions during the five months, these were calculated in the same way as the number of tweets variable. Table 5 shows the impressions averages per month.

Table 4. Number of tweets (average) over the five months (case processing summary).

	Cases					
	Included		**Excluded**		**Total**	
	N	**Percent**	**N**	**Percent**	**N**	**Percent**
Interactions/Month	1231	99.8%	2	0.2%	1233	100.0%

İnteractions

Month	Mean	N	Std. Deviation
January	614.01	308	3460.027
February	322.05	165	1020.875
October	797.70	297	3752.055
November	1574.11	230	5877.707
December	1091.41	231	5518.549
Total	888.16	1231	4162.156

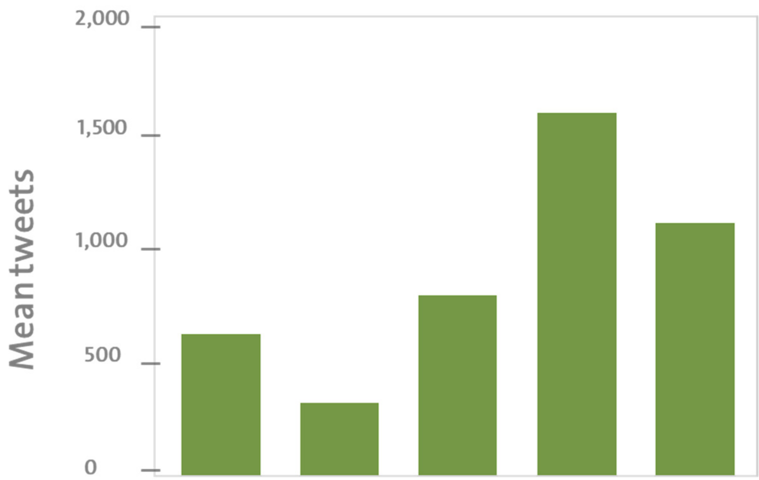

Figure 4. Distribution of the number of tweets over the months.

Table 5. Impressions averages per month (case processing summary).

	Cases					
	Included		**Excluded**		**Total**	
	N	**Precent**	**N**	**Precent**	**N**	**Precent**
Impressions/month	1231	99.8%	2	0.2%	1233	100.0%

Inter Actions

Month	Mean	N	Std. Deviation
January	7373.32	308	25,656.783
February	5513.29	165	14,688.455
October	9092.42	297	32,145.444
November	16,552.68	230	32,614.770
December	12,421.56	231	45,166.616
Total	10,201.15	1231	32,170.876

According to the data in Table 5, the highest impressions average was 16,552 times in November, 12,421 times in December, 9092 times in October, and 7373 times in January, with the lowest average being 5513 times in February. The table shows that the impressions average for the five months was 10,201 per month. We can conclude from these figures that the order of months in impression averages, from highest to lowest, was the same as the order of months for the number of tweets average, indicating a relationship and a correlation between the number of tweets and impressions, and that the more tweets a page has, the more they appear to followers.

Figure 5 is a graph of these numbers that shows the order and differences between the impressions averages over the course of five months.

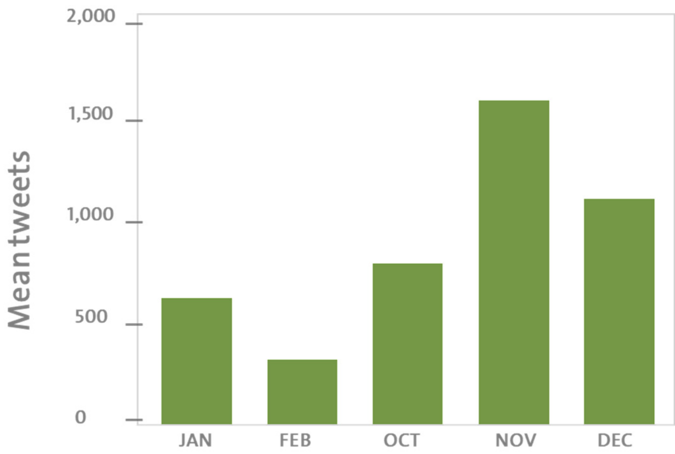

Figure 5. Distribution of impressions by months.

The interaction with tweets was also analyzed, namely, replies, likes, retweets, clicking on the profile, clicking on the link, clicking on tags, detail expansions, watching media, and sharing media, in each of the five months (October, November, December, January, and February). The data in Table 6 depict the distribution of the monthly average number of interactions for each type of interaction.

Table 6. Averages of interactions per month.

Report									
Month	**Retweets**	**Replies**	**Likes**	**Clicks on the User's Profile**	**Clicks on the Link**	**Clicks on the Hashtag**	**Detail Extensions**	**Media Views**	**Media Tweets**
January	1.51	5.36	3.85	57.35	41.10	6.32	313.05	185.45	185.45
February	1.26	2.57	2.74	44.64	22.16	3.84	162.93	81.90	81.90
October	2.23	4.17	4.43	58.25	36.45	4.34	315.32	416.70	372.48
November	4.48	5.45	9.27	129.67	135.24	11.27	726.01	665.64	552.70
December	2.03	6.20	5.82	70.99	42.91	11.73	467.59	484.13	484.13
Total	2.30	4.87	5.22	71.93	55.37	7.45	399.63	373.13	341.36

Table 5 shows the difference in the ratios of the nine interaction averages. The highest interaction recorded in October was for media views, with an average of 416 times, followed by media tweets, averaging 372 times, and the lowest interaction recorded this month was retweeting. In November, the highest interaction was for detail expansions, with an average of 726 times, followed by watching media, at an average of 665 times, and the lowest interaction recorded in November was for retweeting. In December, the highest interaction was also recorded for detail expansions, followed by media sharing and media watching, all with the same average (484 times), while the lowest interaction was recorded for retweeting again. The highest recorded interaction in January was for detail expansions, with an average of 315 times, followed by media sharing and media watching interactions with the same average, and the least recorded interaction was retweeting. Finally, February recorded the highest interactions, with an average of 162 times for detail expansions, followed by media sharing and media watching on the same average, and retweeting as the least. The highest-recorded interactions across all months were similar: media watching, media sharing, and detail extensions, with the least common interaction being retweeting across all months. The following graph shows the differences between responses, likes, and retweets across the months (Figure 6).

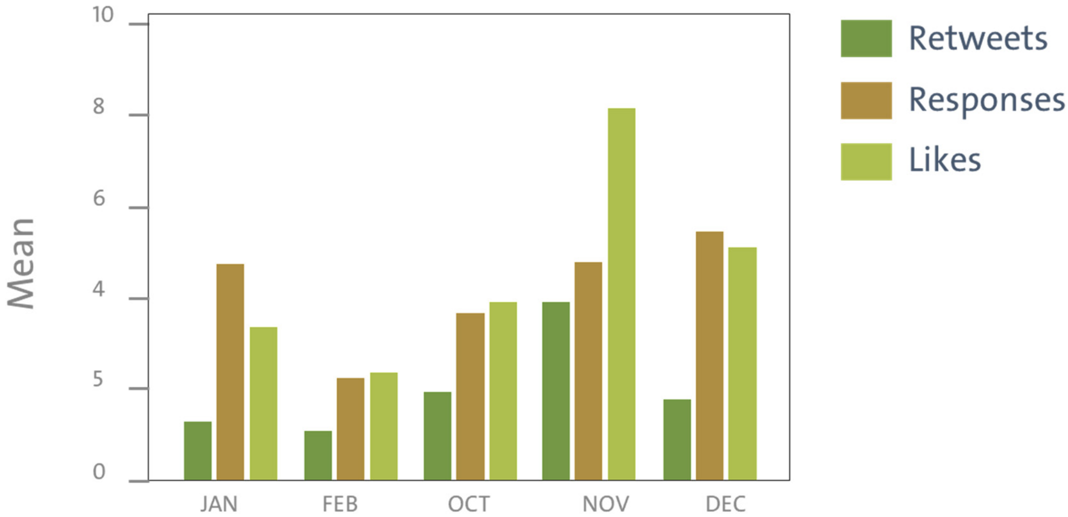

Figure 6. Comparison of average retweets, responses, and likes across months.

Figure 6 depicts the average number of people's interactions with the Admission and Registration page tweets (retweets, responses, and likes). The graph shows that November had the highest average of likes, then December, October, January, and finally, February. The average response numbers were similar in December, November, January, and October, and were the lowest in February. Finally, among these three methods, retweeting had the lowest average, with the highest average in November and close averages in December and October, and lower averages recorded in January and February. Figure 6 also shows other forms of interactions (average number of clicks on the link, average clicks on the profile).

As Figure 7 shows, clicking on the profile was more common and frequent than clicking on the link. The highest value for both was in November, but they converged in other months, and their lowest values were in February. The graph below depicts the average number of clicks on tags over the last five months.

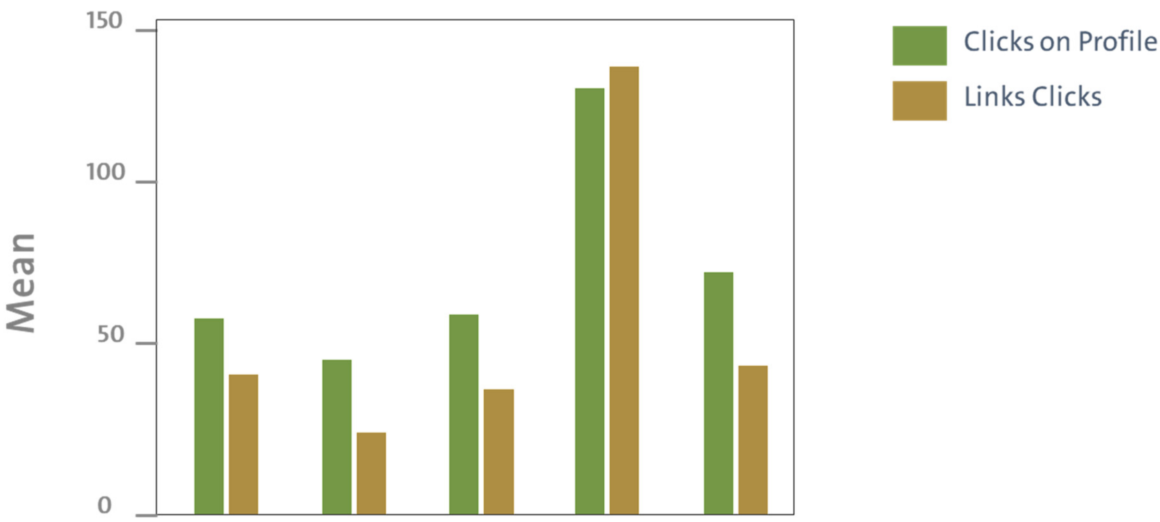

Figure 7. Average profile clicks and link clicks.

Figure 8 shows that the highest average was recorded in December, followed by November, then January, with averages converging in October and February. The graph below shows the averages of detail expansions, media views, and media tweets over the five months.

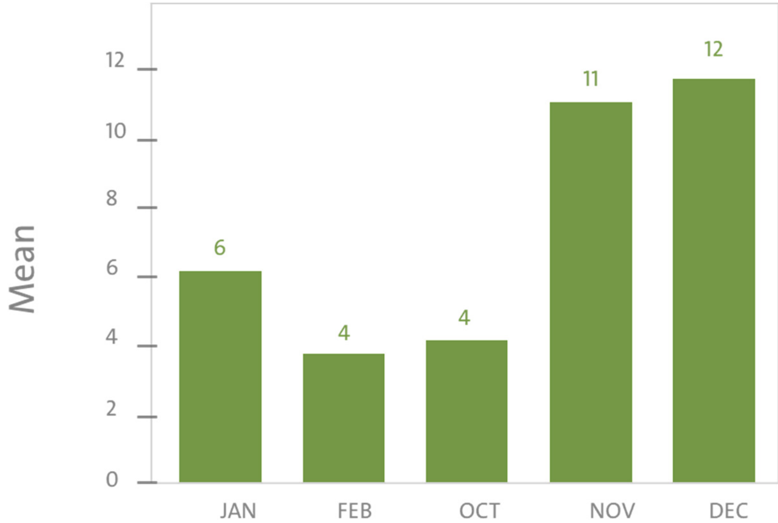

Figure 8. Comparison of clicks on tags during each month.

The first research question: "When is the best tweeting time to impact impressions and elicit audience interaction?".

The variable (sum), which represents the collection of all interactions of all kinds in the five months based on time (replies, likes, retweets, clicking on the profile, clicking on the link, clicking on tags, detail expansions, watching media, sharing media), is displayed in a graph with the number of tweets in all months in Figure 9.

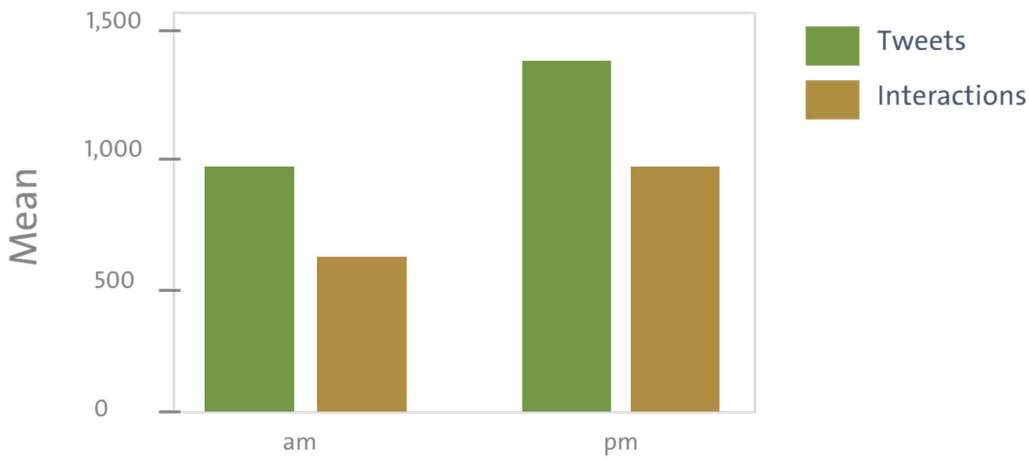

Figure 9. Graph of the number of tweets and interactions during the morning and evening periods.

As the graph shows, the number of tweets in the evening (p.m.) was greater than in the morning (a.m.), and this was true for all types of interactions with these tweets. In order to confirm the existence of a statistically significant correlation, and thus answer the first research question, the *t*-test was used, as explained in the data analysis section (Table 7).

Table 7. Two independent samples for tweets.

Time	Mean	Std. Devation	*t*-Test	Sig
a.m.	970	0.408	22,162.64	0.000
p.m.	1450	0.502		
Two independent samples for intraction				
Time	**Mean**	**Std. Devation**	***t*-Test**	**Sig**
a.m.	640	1.790	3027	0.000
p.m.	965	12.61		

7. Means

As shown in the preceding tables, the sig values were equal to 0.00 and less than 0.05, indicating a statistically significant difference between time (a.m.–p.m.) and total interactions and the same for the difference between time (a.m.–p.m.) and Tweets. That is, the evening period sees the highest interaction with followers of the Admission and Registration Deanship's page. As a result, the number of interactions was proportional to the time of the tweets. Accordingly, and based on the sig value, the first null hypothesis was rejected and the first alternative hypothesis, which states that "the average interactions of the tweets by followers of the Admission and Registration page is related to the time of participation (morning or evening)", was accepted.

As shown in Figure 9, the highest number of interactions was during the evening (p.m.). Therefore, the best tweeting time for impacts and impressions, and eliciting audience interaction, is the evening period, as determined by the descriptive analysis and the *t*-test results.

Research question 2: To what extent do tweets and responses attract browsers to visit the account's home page?

To answer this question, a regression analysis test was performed between clicks on the profile as the dependent variable, and the tweets and response variables as the independent variables. This test was performed on the file containing data for all months, i.e., each variable represented the total data in all months. Table 8 shows the results of this test.

Table 8. Regression test variables.

Variables Entered/Removed [a]			
Model	**Variables Entered**	**Variables Removed**	**Method**
1	Responses, Tweets		Enter

[a]. Dependent variable: clicks on the user profile.

Table 9 shows the results of the R, R square, and ANOVA tests. The table shows the variables that took part in the regression test, where the dependent variable was clicks on the user's profile and the independent variables were tweets and responses. This was intended to investigate the nature of the connection between them, and the extent to which tweets and responses affect the followers' visits to the Admission and Registration personal page.

According to the table above, all the independent variables affect the dependent variable except the number of signs in sig (0.532). As for the R square value, which is the average correlation coefficient square value, it was 94.2%, indicating that responses and tweets (independent variables) can interpret 94% of the dependent variable data (clicks on the profile). The most important value in the ANOVA table is the sig value, which was equal to 0.00 and less than 0.05. This indicated that the connection was statistically significant. In other words, the results of the regression analysis had a strong correlation of up to 90% (R value) between clicks on the profile, responses, and tweets. Furthermore, the independent variables were able to explain 81% of the change in the dependent variable (R square value).

Table 9. Regression test results for profile clicks, tweets, and responses.

Model Summary						
Model		R	R Square	Adjusted R Square		Std. Error of the Estimate
1		0.971	0.942	0.942		907.18953
ANOVA						
Model		Sum of Squares	df	Mean Square	F	Sig
1	Regression	3,926,750,541.210	4	981,687,635.303	1192.826	0.000
	Residual	240,313,912.716	292	822,992.852		
	Total	4,167,064,453.926	296			
Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig
		B	Std. Error	Beta		
1	(Constant)	−23.000	55.537		−0.414	0.679
	Impressions (x1)	0.003	0.005	0.026	0.626	0.532
	Retweet (x2)	501.599	25.148	1.261	19.946	0.000
	Replies (x3)	19.441	4.599	0.127	4.227	0.000
	Like (x4)	−91.904	13.331	−0.428	−6.894	0.000

To enhance the regression analysis outcome, the correlation coefficient was calculated between the variables, responses, tweets (tweets), and the number of visits to the Admission and Registration Deanship account's home page over the course of five months, and the following are the results of this test (Table 10).

Table 10. Correlations.

Correlations **						
		Y	**X1**	**X2**	**X3**	**X4**
	y	1.000	0.866	0.962	0.780	0.915
	x1	0.866	1.000	0.871	0.881	0.865
	x2	0.962	0.871	1.000	0.750	0.973
	x3	0.780	0.881	0.750	1.000	0.737
	x4	0.915	0.865	0.973	0.737	1.000
Sig. (1-tailed)	y	.	0.000	0.000	0.000	0.000
	x1	0.000	.	0.000	0.000	0.000
	x2	0.000	0.000	.	0.000	0.000
	x3	0.000	0.000	0.000	.	0.000
	x4	0.000	0.000	0.000	0.000	.
N	y	297	297	297	297	297
	x1	297	297	297	297	297
	x2	297	297	297	297	297
	x3	297	297	297	297	297
	x4	297	297	297	297	297

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

8. Correlations

As shown in the table above, all sig values were equal to zero, and the Pearson correlation values between tweets and clicking on the profile were equal to 0.898, and to 0.768 between responses and clicking on the profile. The positive reference for both values indicated a positive correlation, indicating that the more tweets and responses, the more clicks on the home page profile. The correlation coefficient value between tweets and clicking on the profile was greater than the correlation coefficient between clicking on the profile and responses (0.898 > 0.768), indicating that clicking on the profile in conjunction with the tweets was more common than for the replies.

To answer the second research question, the regression test results (R = 0.905) showed a very strong and positive correlation between clicking on the profile, responses, and tweets. They were able to interpret 81% of the variable of clicking on the profile.

Therefore, based on the regression and correlation test results, and because the sig values in all tests were equal to zero, the second null hypothesis was rejected, and the alternative hypothesis, which states that "there is a correlation between the average number of tweets and browser responses and the average number of followers accessing the account's home page", was accepted.

Research question 3: What are the measurement indicators of followers' interaction with tweets?

To answer this question, and based on our current findings, all types of interactions, including replies, likes, retweets, clicks on the profile, clicks on the link, clicks on the tag, watch details, watching the link, and sharing the link with tweets (tweets), were indicators of followers' interactions with the page. The sum variable, which represented the sum of all nine interactions across all months, was an indicator of followers' interactions with tweets. Referring to the tables and charts in the descriptive analysis section, all ratios and graphs showed a positive correlation between impressions and tweets and total interactions (sum), as well as each interaction individually, across all months. The table below displays the correlation coefficient values for total interactions (sum), impressions, and tweets across all months (Table 11).

Table 11. Correlation coefficients between total interactions and impressions and tweets.

Correlations				
		Impressions	**Tweets**	**Sum**
Impressions	Pearson Correlation	1	0.819 **	0.823 **
	Sig. (two-tailed)		0.000	0.000
	N	1231	1231	1231
Tweets	Pearson Correlation	0.819 **	1	0.980 **
	Sig. (two-tailed)	0.000		0.000
	N	1231	1231	1231
Sum	Pearson Correlation	0.823 **	0.980 **	1
	Sig. (two-tailed)	0.000	0.000	
	N	1231	1231	1231

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

As displayed in the table, all sig values were equal to zero, i.e., less than 0.05, indicating that interactions were positively related to the number of tweets and impressions; that is, the higher the average number of tweets (tweets), the more impressions, and thus the more followers' interactions. As a result, the variable (sum) served as an indicator for measuring the interactions of the audience or followers with the page's tweets.

9. Discussion

Previous studies discussed the impact of social media such as Twitter on organizations of all kinds, including governmental, private, educational, and many others. They reviewed the impact of tweets on the organizations and the issues that affect the increase of this impact. Increasing engagement with tweets is considered one of the main critical issues. It depends on several factors that many studies have examined within all organizations with limited research on academic perspectives. Those factors are varied from the types of the tweet, tweet content, tweet with media included, and tweet posting time. Unlike previous research, this research focuses on three main questions within an educational institute that serves a large segment of the Saudi Arabian beneficiaries.

The first research question is: when is the best time to tweet for impacts and impressions and elicit audience interaction? As determined by the descriptive analysis and the *t*-test results, there was a clear difference in the number of tweets and interactions between the morning and evening periods. The majority of the tweets (79%) were in the evening, implying that the times of the tweets were related to followers' interactions with the Admission and Registration page. The result is in line with the other study that found that most social networking is performed around midnight, focused on Twitter users in Saudi Arabia. A uniform cultural background may play an essential role in the similarity of the results regarding the tweet post time. Moreover, many other researchers have emphasized the effect that post time plays on increasing engagement with tweets. For example, in government entities concerning the participants' age [13], they found that timing of tweets significant as engagement increases on weekdays compared to weekends [14]. Additionally, an hour of the day and day of the week of tweet posts strongly affects engagement [30]. Our results contradict the claims of Orellana-Rodriguez et al. [34], who found that while the best tweeting time for individual accounts may differ according to the topic, analysis of corporate accounts showed that there is no best time to tweet to attract more engagement. Therefore, organizations have different factors that affect their participants' engagements. Thus, every organization needs to address the factors related to its culture, environment, type of services it offers, and other aspects.

Regarding the second research question of our study, to what extent do tweets and responses attract browsers to visit the account's homepage? By performing a regression analysis test between clicks on the profile as the dependent variable and the tweets and response variables as the independent variables, very strong and positive correlation between clicking on the profile, responses, and tweets was found. They were able to interpret 81% of the variable of clicking on the profile, indicating that clicking on the profile in conjunction with the tweets was more common than for the replies or responses. The results might suggest and recommend increasing the number of tweets to achieve more significant follower interaction with the Twitter account of the Admission and Registration Deanship. In fact, the number of tweets has been found to be significantly positively related to the total interactions with followers. In agreement with research from a social marketing perspective, the number of tweets, followers, retweets, and mentions are identified as crucial factors for public admirations to use Twitter as a medium in marketing [17]. Moreover, purchasers are more likely to engage with social media platforms when they offer richer content and are highly interactive on social networks [18,20].

Regarding this study's third and last question, what metrics are used to measure followers' interaction with tweets? From different views of past studies such as Wadhwa et al. [21], who studied features of tweets that attracted higher engagement rates for a scientific journal Twitter account over two years, they found that tweets with a high engagement rate tended to have photos. The forms of audience interaction with the page's tweets were classified into nine types as follows: replies, likes, retweets, clicking on the profile, click on the link, clicking on tags, detail expansions, watching media, and sharing media. The three interactions of watching media, sharing media, and detail expansions had the highest percentage of interactions across all months, while the retweet interaction was the least popular among followers. Moreover, customer engagement is affected significantly when posts have videos or images [23].

Furthermore, businesses have drawn recommendations on how important it is to design their tweets to attract high customer engagement [29]. They found that different industries have different requirements; for example, hardware technologies are digital sensitive and have an advantage more when the tweets consist of videos or pictures than the software industry. Hence, it is essential to consider the tweet design with respect to the organization's type. For our study, all interactions were indicators of followers' interactions with the page. Finding a variable that represented the sum of all these interactions (the variable (sum)) was a strong indicator. This discussion described all types of interactions with the tweets. It also proved to be related to the number of tweets and impressions when calculating the correlation coefficients. We recommend using it when studying interaction indicators and follower interactions with the page.

Consequently, our results build on existing evidence of the impact of tweets time on increasing engagement of participants. Additionally, the data contribute a clearer understanding of all indicators of followers' interactions. However, the generalizability of the results is limited to educational institutions as they share the exact requirements, participant type, and objectives. Likewise, these results should be considered when considering how important the organization's context is on designing the best tweets that fit the objectives.

10. Conclusions

Educational organizations may have a presence on social media, but this study aimed to understand how effective that presence is. This efficiency is achieved by tweeting at the optimal time on social media. This study focused on the account of a governmental university, specifically one of Saudi Arabia's largest universities, and analyzed the data of the Deanship of Admission and Registration account, which has approximately 400,000 followers, for five months. The study demonstrated that the timing of information and media dissemination on social media has an effect on attracting more beneficiaries and spreading information. There was also a discrepancy in tweet quality between the five months based on the month sequence during the semester. In fact, some semesters had a higher percentage of Admission and Registration tweets at the end or beginning of the semester, while other types of tweets, such as graduation, CEA, and transfer-related tweets, had a lower percentage in most months.

The number of tweets, impressions, and interactions varied by month, with November having the most and February having the fewest, due to differences in working hours and the distribution of holidays across semesters. As a result, we recommend continuing to publish tweets and maintaining the highest rate of tweets and interactions at all times of the year, and in different months. The results revealed a significant correlation between the average number of clicks on the Admission and Registration Deanship's profile and tweets and responses from followers. Therefore, we recommend increasing the number of tweets and responding to followers' comments on tweets to increase interaction and the outcome of responses, which will increase the number of clicks on the profile and thus attract new participants.

This study relied on statistical analyses of some data, which is considered one of the study's limitations.

11. Academic and Practical Implications

Therefore, we recommend that in the future, artificial intelligence and machine learning could be used to analyze tweet text and understand the classification of inquiry topics and interactions received from beneficiaries. The researchers also suggest that this study could be expanded in the future by analyzing similar calculations from other universities, to verify and confirm the findings. The research provides insights for decision makers in the educational institutions that wish to enhance their presence in social media.

Author Contributions: Conceptualization, H.B. and W.A.; methodology, H.B. and W.A.; validation, H.B. and W.A.; formal analysis, H.B. and W.A.; investigation, H.B. and W.A.; resources, H.B. and W.A.; data curation, H.B. and W.A.; writing—original draft preparation, H.B. and W.A.; writing—review and editing, H.B. and W.A.; project administration, H.B. and W.A.; funding acquisition, H.B. and W.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Deanship of Scientific Research (DSR), King Abdulaziz University, Jeddah, Saudi Arabia. The authors, therefore, acknowledge the DSR for its technical and financial support. The author is also thankful to King Abdulaziz University of Saudi Arabia for supporting this research by providing the research environment, data and funds.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Secured and private datasets were analyzed in this study.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. CommBox. The Role of Social Media in Customer Service, Social Media Guide. CommBox. 2021. Available online: https://www.commbox.io/ar/the-role-of-social-media-in-customer-service-a-social-media-guide/ (accessed on 10 September 2021).
2. Edan, O. The Impact of Using Social Media in Customer Relationship Management Performance: A Field Study on Private Jordanian Universities Student View Point. Master's Thesis, Middle East University, Amman, Jordan, 2015. Available online: https://meu.edu.jo/libraryTheses/5870d1e394922_1.pdf (accessed on 5 September 2021).
3. Twitter. Using Twitter Everything You Need to Know So You Can Use Twitter Like a Pro. Twitter. 2021. Available online: https://help.twitter.com/en/using-twitter (accessed on 10 September 2021).
4. Assiri, A.; AL-Ghamdi, A.; Brdesee, H. From Traditional to Intelligent Academic Advising: A Systematic Literature Review of e-Academic Advising. *(IJACSA) Int. J. Adv. Comput. Sci. Appl.* **2020**, *11*, 507–517. [CrossRef]
5. Noaman, A.; Madbouly, A.; Brdesee, H.; Fouad, F. Assessing the Electronic Academic Advising Success: An Evaluation Study of Advisors satisfaction in Higher Education. In Proceedings of the INTED2017, 11th Annual International Technology, Education and Development Conference, IATED, Valencia, Spain, 6–8 March 2017.
6. Brdesee, H. A Divergent View of the Impact of Digital Transformation on Academic Organizational and Spending Efficiency: A Review and Analytical Study on a University E-Service. *Sustainability* **2021**, *13*, 7048. [CrossRef]
7. Brdesee, H. Outstanding Development in Student E-Services: A Case Study of The Scientific Recommendation System. In Proceedings of the ICERI2019, 12th Annual International Conference of Education, Research and Innovation, IATED, Seville, Spain, 11–13 November 2019; pp. 1095–1102.
8. Brdesee, H. A mixed method analysis of the online information course withdrawal system. *J. Behav. Inf. Technol.* **2018**, *37*, 1037–1054. [CrossRef]
9. Brdesee, H. An Online Verification System of Students and Graduates Documents and Certificates: A Developed Strategy that Prevents Fraud Qualification. *Int. J. Smart Educ. Urban Soc.* **2019**, *10*, 1–18. [CrossRef]
10. Alsaggaf, W.; Asad, S.; Algrigri, N.; Alsaedi, N.; Brdesee, H. An electronic students attendance system using indoor positioning and mobile apps technologies. In Proceedings of the INTED2017, 11th Annual International Technology, Education and Development Conference, IATED, Valencia, Spain, 6–8 March 2017.
11. Brdesee, H.; Alsaggaf, W. Academic Advising and Social Media: A Case study on the Twitter Account of the Deanship and Registration of King Abdulaziz University. In Proceedings of the The Conference of Academic Advising in Higher Education of the Gulf Cooperation Council States: Reality and Hope, Jakarta, Indonesia, 2–3 November 2015; pp. 253–267.
12. Brdesee, H.; Madbouly, A.; Noaman, A.; Ragab, A. A comprehensive data mining framework used to extract academic advising knowledge from social media data. In Proceedings of the INTED2017, 11th Annual International Technology, Education and Development Conference, IATE, Valencia, Spain, 6–8 March 2017.
13. Stone, J.A.; Can, S.H. Factors Influencing Tweet Purposes and Citizen Engagement with Municipal Twitter Accounts. *Online Inf. Rev.* **2021**, *45*, 501–516. [CrossRef]
14. Siyam, N.; Alqaryouti, O.; Abdallah, S. Mining Government Tweets to Identify and Predict Citizens Engagement. *Technol. Soc.* **2020**, *60*, 101211. [CrossRef]
15. Kocatepe, A.; Ulak, M.B.; Lores, J.; Ozguven, E.E.; Yazici, A. Exploring the reach of departments of transportation tweets: What drives public engagement? *Case Stud. Transp. Policy* **2018**, *6*, 683–694. [CrossRef]
16. Wang, S.S. To tweet or not to tweet: Factors affecting the intensity of Twitter usage in Japan and the online and offline sociocultural norms. *Int. J. Commun.* **2016**, *10*, 24.
17. Guijarro, E.; Santadreu-Mascarell, C.; Blasco-Gallego, B.; Canós-Darós, L.; Babiloni, E. On the Identification of the Key Factors for a Successful Use of Twitter as a Medium from a Social Marketing Perspective. *Sustainability* **2021**, *13*, 6696. [CrossRef]

18. Cao, D.; Meadows, M.; Wong, D.; Xia, S. Understanding consumers' social media engagement behaviour: An examination of the moderation effect of social media context. *J. Bus. Res.* **2021**, *122*, 835–846. [CrossRef]
19. Wigley, S.; Lewis, B.K. Rules of engagement: Practice what you tweet. *Public Relat. Rev.* **2012**, *38*, 165–167. [CrossRef]
20. Bozkurt, S.; Gligor, D.M.; Babin, B.J. The Role of Perceived Firm Social Media Interactivity in Facilitating Customer Engagement behaviors. *Eur. J. Mark.* **2021**, *55*, 995–1022. [CrossRef]
21. Wadhwa, V.; Hussain, I.; Bilal, M.; Wallace, M.B.; Berzin, T.M.; Chiang, A.L. Tu1073 factors increasing tweet engagement rate for the gastrointestinal endoscopy (GIE) journal twitter feed. *Gastrointest. Endosc.* **2020**, *91*, AB533. [CrossRef]
22. Boujena, O.; Ulrich, I.; Manthiou, A.; Godey, B. Customer Engagement and Performance in Social Media: A Managerial Perspective. *Electron Mark.* **2021**, 1–23. [CrossRef]
23. Aydin, G.; Uray, N.; Silahtaroglu, G. How to Engage Consumers through Effective Social Media Use—Guidelines for Consumer Goods Companies from an Emerging Market. *J. Theor. Appl. Electron. Commer. Res.* **2021**, *16*, 768–790. [CrossRef]
24. Vander Schee, B.A.; Peltier, J.; Dahl, A.J. Antecedent Consumer Factors, Consequential Branding Outcomes and Measures of Online Consumer Engagement: Current Research and Future Directions. *J. Res. Interact. Mark.* **2020**, *14*, 239–268. [CrossRef]
25. Casper Ferm, L.-E.; Park, T. Customer Pre-Participatory Social Media Drivers and Their Influence on Attitudinal Loyalty within the Retail Banking Industry: A Multi-Group Analysis Utilizing Social Exchange Theory. *J. Retail. Consum. Serv.* **2021**, *61*, 102584. [CrossRef]
26. Han, X.; Gu, X.; Peng, S. Len Tiu Wright (Reviewing editor) Analysis of Tweet Form's effect on users' engagement on Twitter. *Cogent Bus. Manag.* **2019**, *6*, 1–9. [CrossRef]
27. Prabhu, V.; Lovett, J.T.; Munawar, K. Role of social and non-social online media: How to properly leverage your internet presence for professional development and research. *Abdom. Radiol.* **2021**, *46*, 5513–5520. [CrossRef]
28. Sharp, S.P.; Mackenzie, D.G.; Ong, D.S.Y.; Mountziaris, P.M.; Logghe, H.J.; Ferrada, P.; Wexner, S.D. Factors Influencing the Dissemination of Tweets at the American College of Surgeons Clinical Congress 2018. *Am. Surg.* **2021**, *87*, 520–526. [CrossRef]
29. Gligor, D.; Bozkurt, S. The Role of Perceived Social Media Agility in Custo9BHmer Engagement. *J. Res. Interact. Mark.* **2021**, *15*, 125–146. [CrossRef]
30. Iqbal Khan, S.; Ahmad, B. Tweet So Good That They Can't Ignore You! Suggesting Posting Strategies to Micro-Celebrities for Online Engagement. *Online Inf. Rev.* **2021**. ahead-of-print.
31. Mahdavi, M.; Asadpour, M.; Ghavami, S.M. A comprehensive analysis of tweet content and its impact on popularity. In Proceedings of the 8th International Symposium on Telecommunications (IST), Tehran, Iran, 27–28 September 2016; pp. 559–564. [CrossRef]
32. Alwagait, E.; Shahzad, B. Maximization of Tweet's viewership with respect to time. In Proceedings of the 2014 World Symposium on Computer Applications & Research (WSCAR), Sousse, Tunisia, 18–20 January 2014; pp. 1–5. [CrossRef]
33. Al Abdullatif, A.M.; Alsoghayer, R.A.; AlMajhad, E.M. An algorithm to find the best time to tweet. In Proceedings of the International Conference on Computer Vision and Image Analysis Applications, Sousse, Tunisia, 18–20 January 2015; pp. 1–13.
34. Orellana-Rodriguez, C.; Greene, D.; Keane, M.T. Spreading the news: How can journalists gain more engagement for their tweets? In Proceedings of the 8th ACM Conference on Web Science, Association for Computing Machinery, New York, NY, USA, 25 May 2016; pp. 107–116. [CrossRef]
35. Ko, J.; Kwon, H.W.; Kim, H.S.; Lee, K.; Choi, M.Y. Model for Twitter dynamics: Public attention and time series of tweeting. *Phys. A Stat. Mech. Its Appl.* **2014**, *404*, 142–149. [CrossRef]
36. Chong, W.H.; Lim, E.P.; Cohen, W. Collective Entity Linking in Tweets Over Space and Time. In *Lecture Notes in Computer Science, Proceedings of the Advances in Information Retrieval, ECIR 2017, Aberdeen, UK, 8–13 April 2017*; Jose, J.M., Hauff, C., Altingövde, I.S., Song, D., Albakour, D., Watt, S.N.K., Eds.; Springer: Cham, Germany, 2017; Volume 10193. [CrossRef]
37. Sayed, A.M.; AbdelRahman, S.; Bahgat, R.; Fahmy, A. Time emotional analysis of arabic tweets at multiple levels. *Int. J. Adv. Comput. Sci. Appl.* **2016**, *7*, 336–342.
38. Cheung-Blunden, V.; Sonar, K.U.; Zhou, E.A.; Tan, C. Foreign disinformation operation's affective engagement: Valence versus discrete emotions as drivers of tweet popularity. *Anal. Soc. Issues Public Policy* **2021**, 1–18. [CrossRef]