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Social Media in Tourism: A Twitter (X) Social Graph Approach to #Alula

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Abstract
The Kingdom of Saudi Arabia launched Vision 2030 to diversify its economy beyond oil-related government revenue and grow tourism investments. This multifaceted road map includes promoting the country as a tourism destination on social media platforms. Alula is a key Saudi tourism destination characterized by mountainous landscapes and archaeological discoveries. This study investigates the dissemination of social media content that promotes #Alula on the Twitter (X) platform in order to examine the effectiveness of social media in reviving the tourism sector by disseminating tourism messages and connecting individuals with tourist destinations. We captured and analyzed the social graph of this hashtag using the social network analysis (SNA) tool – NodeXL - through December 2022. The findings reveal the structure and shape of the social media impact of #Alula on network clusters and influencers. We identified the main clusters, along with the powerful influencers that played a role in cultivating the network. These findings have important implications for the design and management of a social media presence and the promotion strategies for tourism destinations by focusing on cultivating a social network to actively promote a tourism destination and identify key players in such networks as they play important roles in disseminating content. Our findings is of interest to practitioners and academics. Practitioners can focus on incorporating SNA for tourism planning, management, and marketing strategies, while academics can pursue further research, focusing on cultivating social networks and identifying influential factors on network size and traverse.

Key Words: Social network analysis, destination image, destination branding, user-generated content, Saudi Arabia, Alula, Twitter (X)

JEL Classification: M15, M3, M4

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1. Introduction

Saudi Arabia's official Vision 2030 is aimed at strengthening its economy, by increasing non-oil government revenue through tourism (Żemła & Szromek, 2023; Gavurova et al., 2021; Naseem, 2021, Sherbini et al., 2016). This includes investments and initiatives to create, develop, and promote specific tourism destinations through geotourism, cultural tourism, heritage tourism, seniors' tourism, rural tourism, and ecotourism (Abuhjeeleh, 2019; Castanho et al., 2021; Grundey & Vilutytė, 2012; Paço et al., 2012; Schyff et al., 2019). In this study, we identified the ecotourism destination of Alula, to examine its social network structure and shape on the social media platform—Twitter(X). Ecotourism is distinguished from other types of tourism, as it involves three components: its nature-based, environmentally-educated, and sustainably-managed destination (Blamey, 1997; Hoang, Pham, & Tučková, 2022).

Cheng (2024) conducted a systematic review on using social media in tourism, and identified opportunities, challenges, and direction for future research. Social media can be an important tool for promoting tourism (Tran & Rudolf, 2022; Hoang et al., 2023), as it has the power of increasing the reach to create an impact on tourism destinations. It is defined as “a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0 and allow the creation and exchange of user-generated content” (Kaplan & Haenlein, 2010). Hoang, Nguyen, and Pham (2022) found that electronic-worth-of-mouth (eWOM) have positive effects on ecotourism loyalty. There are various social media platforms with different levels of interactivity, reach, richness, crowds, and temporal structures (Munar & Jacobsen, 2014; Skulme & Praude, 2016). Nautiyal et al. (2023) investigate a destination image based on Twitter(X) data, and proposed a hashtag strategy for destination promotion. Twitter(X) is the third most-used social media platform (after Snapchat and Instagram, in that order) in Saudi Arabia (Statista, 2022) with at least 14.6 million active users (Datareportal, 2022). It has attractive features that can be utilized for promoting social tourism messages, to its 238 million daily active users worldwide (Twitter(X), 2022).

Research on social media in the tourism context is still in its infancy, and there is a lack of research on social media and engagement in the context of tourism in the Middle East (Chen et al., 2021; Zeng & Gerritsen, 2014). The present study contributes to this area, by investigating the role of social media in the tourism context in Saudi Arabia, particularly, Alula—a Saudi tourism destination promoted as a distinguished ecotourism destination by the Ministry of Tourism of Saudi Arabia. We used a social network analysis (SNA) tool—NodeXL software—to analyze the data extracted from the Twitter(X) hashtag “#Alula.” SNA enables the conceptualization, analysis, and visualization of social interactions on Twitter(X). Thus, it facilitates the understanding and sharing of knowledge obtained by studying content-rich social networks. It can be employed to examine the ties between the actors and the structures of the networks that constitute social networking platforms, by examining the network structure, particularly its pattern, intensity, and diameter, in addition to other elements that characterize the social network under investigation. Thus, we examine the effectiveness of Twitter(X) in disseminating tourism messages, for destination awareness and connecting individuals with tourism destinations. Various measures can be employed to characterize a specific network, and differentiate it from others (Casanueva et al., 2016). Such measures were employed in the present study, including structure, size, density, group, centrality (degree, closeness, and betweenness), and role.

We penetrate deeper into the social network of the ecotourism destination, Alula, to unveil its main characteristics and how such knowledge can be used to improve the decision-making process to promote tourism and cultivate the social network of the destination image. Hoang et al. (2023) found that factors such as destination image, tourist satisfaction and tourist experience significantly predict destination and ecotourism loyalty. Thus, the objectives of this study are to understand how the social message of tourism is exchanged and distributed, as well as its reach. In addition, this study investigates the size, structure, and connectivity of the social network of Alula, and identified the main nodes/actors and influencers in the network and their degree of centrality (a measure that indicates the degree of importance of nodes/actors). By adopting a network perspective-social graph approach, this study focuses on the relationship among actors, rather than on individual characteristics/attributes (Borgatti & Ofem, 2010).

In the following section, we briefly review using social media and social networks in tourism, followed by a brief introduction to the research context of Alula, an ecotourism destination in Saudi Arabia. Subsequently, we present the research methodology and SNA results. The last section comprises the discussion and conclusion followed by recommendations, limitations, and future research.

2. Literature Review

Social media platforms are frequently used to promote tourism, as well as destination branding and image. On these platforms, tourism knowledge and experiences are shared as subjective evaluations by tourists before, during, and after visiting a destination (Munar & Jacobsen, 2014). Therefore, these platforms have impacts on travel decision-making processes of tourists (Tung & My, 2023). These experiences vary among individuals and rely on factors, such as perceptions, expectations, experiences, and mediated spaces. Thus, shared content can impact the intention (Ballester et al., 2023) and behavior of tourists and shape the image of a destination (Camprubí et al., 2013; Gartner, 1994; Martín-Martín et al., 2023). Munar and Jacobsen (2014) investigated the motivation for creating and sharing tourism content on social media and found that public sharing of content was less frequent than private sharing. Furthermore, they observed that tourists were motivated differently to create and share content on social media for personal, community, and social values. Kitsios et al. (2022) investigated the determinants of users' trust in information shared on social media regarding tourism and discovered that perceived enjoyment and value were the most critical factors affecting user trust in social tourism messages. Zeng and Gerritsen (2014) identified issues, such as language constraints on sharing social content, the consequences of negative word of mouth, and the trustworthiness of this content. Social media can contribute to an increase in destination visits and brand building for tourism destinations (Zeng & Gerritsen, 2014). It can connect potential visitors to tourism destinations through social content, authentic visitor reviews, and shared photographs and videos, to showcase an integrated experience to visitors (Kiráľová & Pavlíčeka, 2015). Tourism content creators, individual or sponsored, share information to be consumed by others with similar interests, and thereby naturally connect in groups/clusters. These connections form "social networks" and feature unique characteristics (Smith et al., 2014). Casanueva et al. (2016) noted that a few studies on tourism have employed this approach. Smith et al. (2014) identified six distinct types of networks on Twitter(X): polarized crowds, tight crowds, brand clusters, community clusters, broadcast networks, and support networks. The variations in theirs structures and shapes reflect the variations in the conversations had on these networks.

In SNA, clusters can be identified by applying mathematical algorithms that assign vertices/nodes (i.e., individuals) to subgroups of densely interconnected users (Clauset et al., 2004). Clustering algorithms dynamically identify the number of clusters, and each vertex/node is assigned to one cluster; thus, there is no overlap between clusters. Clusters can also be referred to as communities, subgroups, and subnetworks in a network, where there is a higher density of edges/connections within groups than between them (Hansen et al., 2020, Hansen et al., 2011). Thus, the present study used communities, subgroups, and subnetworks interchangeably.

In the tourism context, the concept of a "destination image" is dependent on the destination's global impression (Gallarza et al., 2002). Chon (1990) defined image as "the set of meanings by which an object is known and through which people describe, remember, and relate to it". Hoang, Nguyen, and Pham, (2022) fount that destination image has the greatest influence on ecotourism loyalty, along with other factors including tourist satisfaction, eWOM, and social influence. Hernández et al. (2016) evaluated a tourism destination by analyzing its image on Twitter(X). Based on their study, a destination image comprises three interrelated components. The cognitive component comprises the physical attributes characterizing the tourism destination, such as location, weather, and attractions/activities. The affective component comprises evaluations of and feelings toward the tourist destination expressed by visitors and tourists, such as satisfaction and happiness. The conative component comprises the subsequent behavior resulting from exposure to the destination image by visitors or tourists, such as actual visits to the destination and recommendations.

Another important concept in tourism is "customer engagement (CE)," which boosts loyalty and trust (Harrigan et al., 2017; So et al., 2016). CE is important in hospitality and tourism management because of the nature of this industry, which provides experiences rather than products. It is defined and conceptualized from different perspectives, either behavioral or psychological/emotional, and as a unidimensional and concept (Chen et al., 2021; Lim et al., 2022). Behavioral CE on social networks can be passive, by consuming social content, or active, by creating social content. Although emotional CE comprises the emotions and attachment toward the destination, such as positive feelings and excitement, it is important to consider and incorporate CE to promote tourism as intangible and experience-based. Cheung et al. (2023) found that two forms of interactions—marketer-traveler interaction and traveler-traveler interaction—to be influential factors on destination brand engagement. Furthermore, they found that marketer-traveler interaction was more important than traveler-traveler interaction in driving destination brand engagement. Tran and Rudolf (2022) conducted a systematic review on destination branding and social media in the tourism context from 2011 to 2021. Destination branding is a basic marketing strategy for tourism, that identifies and shapes the image of a destination and how the said destination is perceived and promoted. Destination branding is complex; however, social media plays an important role in creating and sculpting the destination image through strategic planning and implementation.

3. Research Context of Alula

Alula is a UNESCO World Heritage Site, in Saudi Arabia and a tourism destination with hundreds of natural attractions, and historical monuments dating back to more than 200,000 years (Experiencealula, 2023). The Royal Commission for Alula was established in 2017 to preserve and develop Alula as a global tourism destination.

The official Twitter(X) handle of Alula is "@ExperienceAlUla." The account was created in September 2018, has 106,356 followers, and follows 19 accounts. The main profile page contains a link to the destination website, which provides detailed information in Arabic and English. The Alula account uses various hashtags and the secondary account, "@AlUlaMoments," to promote monthly events. We identified and used one Twitter(X) hashtag for data collection, "#Alula," as it was observed to be the most used and relevant to the tourism destination.

4. Method

4.1 Data Retrieval and Analysis

For data retrieval and analysis, we used NodeXL (Social Media Research Foundation, version 1.0.1.510), an SNA tool that can be used to collect social media data from various social media platforms, and is used for data analysis and to generate network metrics, clusters, and visualizations., with validated methodology and algorithms in literature (Hansen et al., 2020; O'Regan & Choe, 2023; Smith et al., 2014).

We directly extracted all #Alula data from Twitter(X) using NodeXL, and captured the changes in the Alula network over one month, from November 29 to December 31, 2022. The detailed analysis was solely based on data from December 31, 2022. A total of 480 users and 1,353 relationships, in the form of tweets, retweets, replies to, mentions, mentions in retweet, were extracted and analyzed as follows. Each circle represents a Twitter(X) user, and lines between users indicate relationships (ties). The relationship identified in our dataset is in the form of 1,353 tweets, 1,316 retweets, 1,025 replies to, 1,276 mentions, and 1,226 mentions in retweet.

Figure 1 shows the analysis of users (vertices), their relationships (unique and total edges), network diameter (size), and density (number of connections between nodes in a network).

Figure 1. **Evolution of Social Network of #Alula over one Month**

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Figure 1(a)

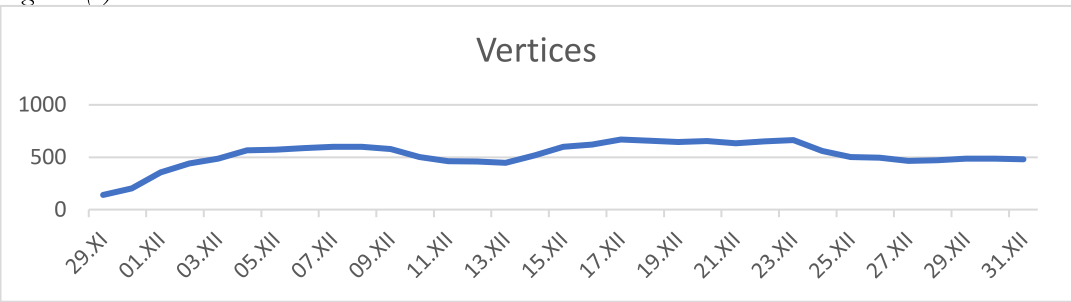

Figure 1(b)

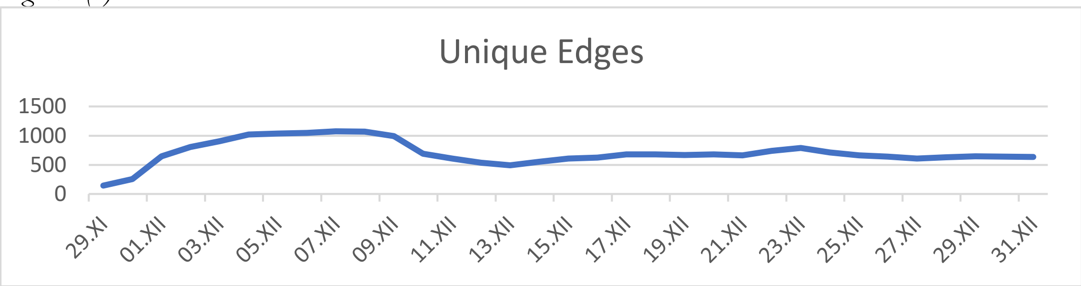

Figure 1(c)

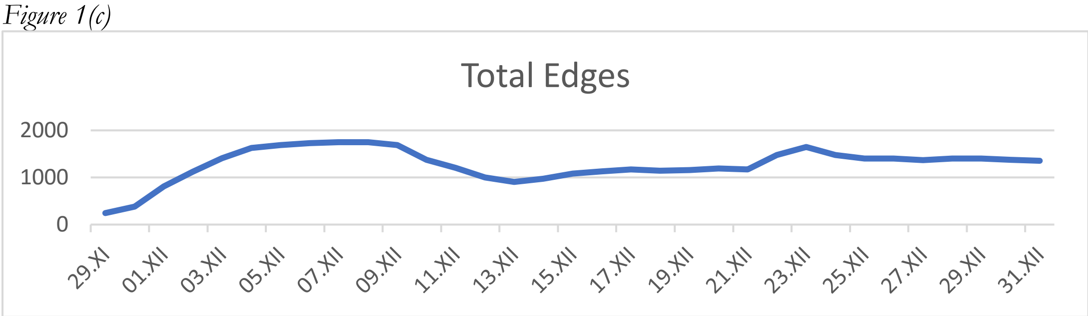

Figure 1(d)

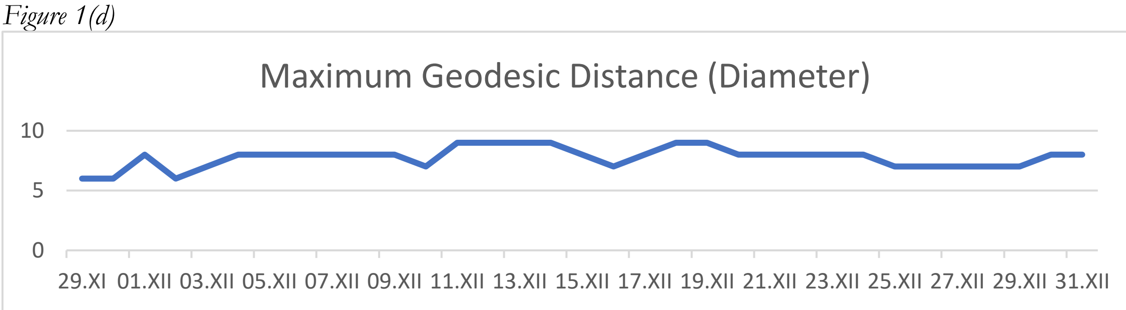

Figure 1(e)

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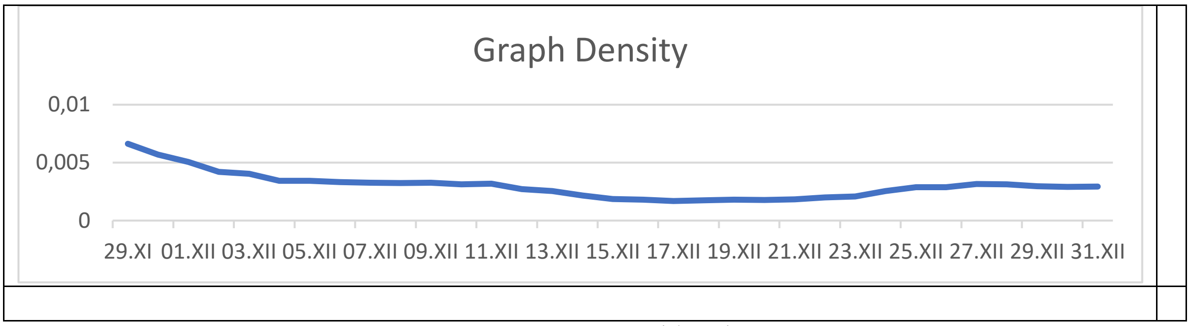


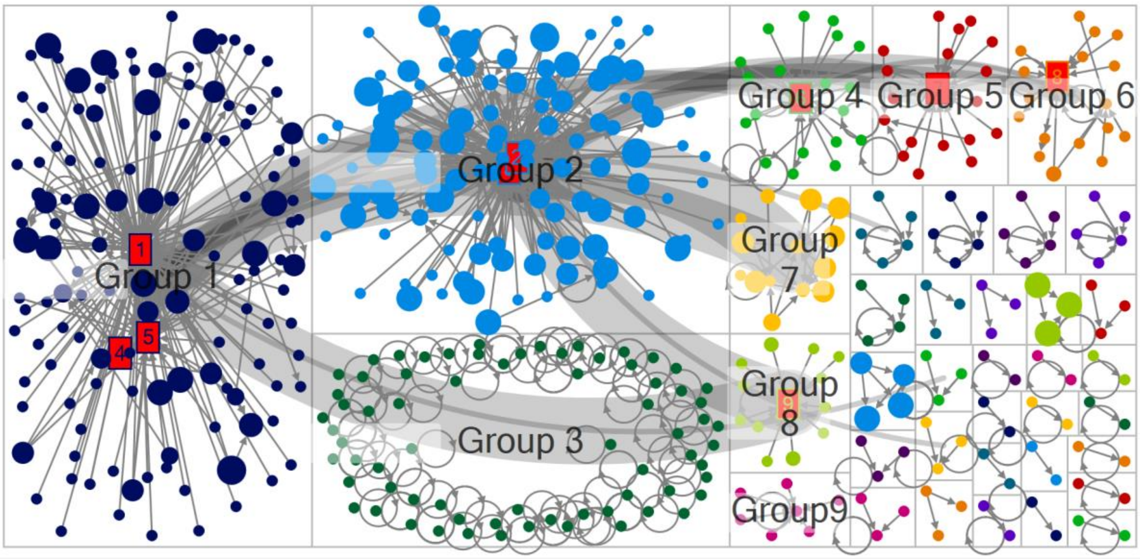
Source: own elaboration

5 Results

5.1 Social Network Analysis Results

Figure 2 shows a visual mapping of the social network of #Alula between users that tweeted, retweeted, or were mentioned in tweets. The network was constructed using the Harel–Koren Fast multiscale algorithm, with the force-directed layout option. We grouped the network into clusters using the Clauset–Newman–Moore method, and each cluster was presented in its own rectangle. In this network, there were 480 Twitter(X) users, with 1,353 connections (unique edges and edges with duplicates) among them.

Figure 2. **Social Network Analysis of "#Alula" on December 31, 2022**



Source: own elaboration

After examining the social networks of #Alula, we classified it into "community clusters" (Smith et al., 2014). In the community clusters, #Alula had multiple smaller clusters/groups, with their own centers, audiences, influencers, and information sources. The main characteristic of community structures is that "they feature a collection of medium-sized groups, rather than a crowd of mostly unconnected Twitter users" (Smith et al., 2014). There are several densely connected clusters/groups of relatively equal size in a community cluster, in addition to numerous small isolated clusters and individuals. Therefore, there were many hubs, each with its own crowd.

The various shapes of groups and clusters in the network revealed the existence of various groups and roles that each individual plays in the network. Table 1 summarizes the network groups and their characteristics. Based on the network visualization, we identified eight main groups or clusters. Outside these major groups were smaller groups with just 88 vertices, who had a few connections to other users or a self-loop edge, which indicated that a "tweet" is not a "reply-to" or "mention." The presence of multiple isolated small clusters indicated that the topic was public, and discussed among these clusters on a narrow scale. There were also a few connections across the divide that functioned as bridges between the clusters and groups.

Table 2 lists the most frequent uses of hashtags in the entire #Alula network. The frequency of the use of the top hashtags in the network ranged from 892 to 33. The number of used hashtags and the frequency of use varied among groups, and there were common as well as unique hashtags used by groups.

The top links (URLs) shared in the network were shared at frequencies ranging from 18 to 3. This indicated a weak link-sharing behavior in the network. The most frequently shared link was about an online article on Construction Week (Middle East), titled "Saudi Alula: RCU promotes sustainable, smart public mobility in new deal." This article illuminates the project collaboration with France's RATP Dev, to develop the mobility network of Alula.

Overlapping was observed among the clusters/groups in hashtags and links sharing, which was an indicator of sharing the common interest and being involved in the same social conversation topic of #Alula. In the social network of a community structure, people are involved in the same conversation, but with variations in perspectives.

Table 1. **Identified Groups and Clusters and their Main Characteristics**

Group	Number of Users	Role	Group Characteristics
1	131	Tight crowd/ broadcast network	"Alulamoments" was the hub in this cluster and played the role of broadcasting.
2	107	Tight crowd/ broadcast network	"ludovic_pouille" and "rcu_sa" were the hubs in this cluster and played the role of broadcasting.
3	70	Community clusters/ring crowd	There were many isolated individuals, indicating that the topic was public, and discussed by an individual who tweeted to their network on a narrow scale. There were also very few connections across the divide.
4	20	Broadcast network /hub crowd	"alhamrani77," a photographer, acted as a hub and played the role of broadcasting by sharing his photographs of #Alula.
5	19	Broadcast network /hub crowd	"visitsaudi" acted as a hub in this cluster and played the role of broadcasting.
6	18	Broadcast	"bandar0k1" and "_3ssm"

		network /hub crowd	are a photographer and personal account, respectively. They played the role of broadcasting to their network on a narrow scale. "Bandar0k1 acted as a hub, playing the role of broadcasting by sharing his photographs of #Alula, mentions, and replies.
7	14	Broadcast network/hub crowd	Broadcast network on a narrow-scale business account.
8	13	Broadcast network /hub crowd	Broadcast network on a narrow-scale individual level.

Source: own elaboration

Table 2. **Top Hashtags in the Social Graph**

Top Hashtags	Count
alula	892
alulamoments	262
tantoracelebration	77
franceksa	77
winterattantora	63
experiencealula	47
saudiarabia	37
idverde	35

Source: own elaboration

5.2 Influencer Characteristics

Table 3 lists the network influencers, based on the calculated betweenness centralities. Betweenness centrality is defined as "The number of shortest paths connecting other nodes in the network that pass through that node" (Kane et al., 2014). This measure shows which nodes are "bridges" between nodes in a network. A high betweenness indicate fast access and control over network flows (Kane et al., 2014). We observed that network influencers were scattered throughout the network, and belonged to different groups or clusters. All the influencers were involved in four types of social activities: tweets, retweets, mentions, and replies. We observed that the main roles were broadcasting, network sharing, #Alula events, and collaboration. Our investigation revealed that the two large groups identified (Groups 1 and 2) resulted from the involvement of more powerful influencers.

We aimed to identify patterns in the network structures, and the roles and types of contributors in the social network of #Alula. As the power of influencers decreased, because of a decrease in their influence (followers), the network size correspondingly decreased. As evidenced in Groups 4, 6, and 8, less influential power (fewer followers) resulted in a smaller network. This was because the influencers in these groups were individuals and photographers with a small number of followers. This resulted in a narrow-scale reach for the social messages. An exception was observed in Group 5, as it had a small network with a narrow-scale reach for the social message despite the powerful influencer (user account of "visitsaudi") in this group. "Visitsaudi" is a powerful influencer with a large number of followers, yet its in-degree was low (23).

The present analysis revealed that larger groups and clusters resulted from the involvement of powerful influencers with high in-degrees. Table 4 summarizes the in- and out-degrees of the "Top Ten Users Ranked by Betweenness Centrality."

Figure 2 and Table 4 show how the network influencers were distributed across the network.

Table 3. **Top Ten Users Ranked by Betweenness Centrality**

NAME	Rank	Type	Followers	User Handle	Betweenness	Group
alulamoments	1	Official account of Alula Events	106,046	alulamoments	61178.078605	1
ludovic_pouille	2	Personal account of the Ambassador of France	61,283	ludovic_pouille	34226.634098	2
rcu_sa	3	Official account of Alula Commission	161,155	rcu_sa	24401.609349	2
amralmadani	4	CEO of Alula Commission	21,042	amralmadani	18971.398175	1
experiencealula	5	Official account of AlUla Tourism	106,356	experiencealula	11437.211939	1
alhamrani77	6	Personal account of photographer	16,207	alhamrani77	11249.433436	4
visitsaudi	7	Official account of Saudi Tourism	69,100	visitsaudi	9883.985309	5
bandar0k1	8	Personal account of photographer	2,977	bandar0k1	6806.766188	6
mybeautifulksa	9	Personal account	2,236	mybeautifulksa	5928.251212	8
_3ssm	10	Personal account	1,103	_3ssm	4284.271735	6

Source: own elaboration

Table 4. **Impact of the Number of Followers and In-Degree on Network Size**

Network Size	Group		Influencer Ranks by Betweenness Centrality	Number of Followers	In-Degree	Out-Degree
Large network	*Group 1* ***Size 131***	alulamoments	1	106,046	114	3
		amralmadani	4	21,042	6	10
		experiencealula	5	106,356	32	2
Large network	Group 2 ***Size 107***	ludovic_pouille	2	61,283	68	15
		rcu_sa	3	161,155	76	3
Small network	Group 4 ***Size 20***	alhamrani77	6	16,207	20	1
Small network	Group 5 ***Size 19***	visitsaudi	7	69,100	23	1
Small network	Group 6 ***Size 18***	bandar0k1	8	2,977	9	6
		_3ssm	10	1,103	0	5
Small network	Group 8 ***Size 13***	mybeautifulksa	9	2,236	15	1

Source: own elaboration

6 Discussion

This study aimed to investigate the transverse and reach of tourism messages on Twitter(X), and their impact on achieving the goals of promoting tourism and contributing to the local economy.

These findings can help examine the effectiveness of Twitter(X) in reviving the tourism sector, by disseminating tourism messages and connecting individuals with tourist destinations. By tracking the spread and reach of the social network of #Alula through December 2022, we achieved better visibility of the network growth, by capturing the number of vertices and connections among them, and the changes in the network diameter throughout the month. We investigated the social network of #Alula and identified and examined its subnetworks/clusters. We identified the main clusters, along with the powerful influencers that played a role in cultivating the network. Serman and Sims (2020) found that bloggers can influence blog readers' purchase habits through their recommendations. They identified factors that influence consumer intentions to adopt recommendations which are trust, credibility, prior experience, perceived usefulness, sponsorship, social attractiveness, and subjective norms. Thus, influencers can affect the intention and attitude of individuals. We identified the importance of the combination of the in-degree and number of followers, which played important roles in cultivating the network of #Alula. We observed that the network shape and structure of #Alula was that of a community network, that is, #Alula was discussed among clusters at a large scale, and among small isolated clusters and individuals at a small scale. This indicates that the topic was publicly discussed on social media; however, the network size must be cultivated to actively promote this tourism destination. Li and Pan (2021) found that overall marketing processes that involve multiple stakeholders in the tourism sector, and active participation on social platforms by reposting and sharing campaign videos and high quality content generators, can attract new followers and make impact. Influencers play important roles in disseminating social content; their role is like a hub that generates a snowball effect by passing messages to their networks (Barbagallo et al., 2012). Thus, it is crucial to have some "influencers" rather than "regular users." In addition, the reach and sentiments of social content influence the image of tourism destinations (Scharl et al., 2008). Influencers can be divided based on their scale of followers including mega-influencers, macro-influencers, micro-influencers, and nano-influencers (Borges-Tiago et al., 2023). Specifically, they identified mega-influencers as those who have over one million followers, macro-influencers as having between 40,000 and 1 million followers, micro-influencers who having between 1,000 and 40,000 followers, and nano-influencers who having fewer than 1,000 followers. Liu et al. (2021) investigated the impact of micro-influencers on followers' purchase intention on social media, and found that despite the size of their networks they can play an important role to influence their followers through credibility and transparency. We found that various hashtags are used which result in dispersion, rather than focusing on the tourism destination image on social media presence. Nautiyal et al. (2023) found that there is differences between how individuals and tourism organizations use hashtags. They found that while residents and international individuals used similar hashtags focusing on natural landscape, tourism organizations used different hashtags that focused on adventure-related concepts. Based on these findings, they developed a hashtag strategy for destination promotion which suggest the use of a minimum of four hashtags by tourism organizations, with both experiential and interpersonal hashtags for promoting destination images. Arslan and Trier (2022) developed an integrated process model for social media marketing (SMM) that compromise of eight steps, and can be used to guide strategic management endeavors for using social media.

Conclusion

In this study, we captured and analyzed the social graph of tourism destination networks and investigated the transverse and reach of Twitter(X) content in the context of Alula, a Saudi tourism destination promoted by the Ministry of Tourism of Saudi Arabia. Based on our SNA analysis, we classified the social network of #Alula as a community cluster. In this community cluster, the network is composed of multiple smaller clusters/groups with their own centers, audiences, influencers, and information sources. Therefore, many hubs exist, each with its own crowd. Based on the network visualization, we identified eight main clusters/groups with various shapes and sizes, revealing the variations in groups and roles that each individual plays in the network. The presence of multiple clusters indicated that Alula's tourism destination was public and discussed among these clusters at varying scales, depending on the cluster size. We found few connections across clusters that functioned as bridges between various clusters and groups. Furthermore, we identified the most frequent uses of hashtags in the entire #Alula network. We found variations in using hashtags and the frequency of using specific hashtags among clusters/groups; we also found common and unique hashtags used by groups. Thus, the results showed fragmentation in traverse and reach and illuminated the importance of unified hashtags for tourism destinations to promote content reach and to facilitate continuous social connection with actual and potential visitors. Furthermore, weak link-sharing behavior in the network was found. We observed that broadcasting networks of both large and small scales were dominant in the #Alula social network on Twitter(X). The generalizability of these findings can be in terms of their rich insights into the destination for social networks and manipulating important network metrics that can help cultivate a network to promote tourist destinations.

Our findings can be of interest to practitioners and academics. Academics can pursue further research focusing on the cultivation of social networks and identify influential factors on network size and traverse. Practitioners can focus on incorporating SNA in a planned manner for tourism planning, management, and marketing strategies. Networks on social media platforms comprise various structures. The mapping of social media networks enables a better understanding of the involvement and contribution of people on social networks and highlights their roles and the content they share, along with their reach. Such findings help us to use social networks better to disseminate tourism content. Leveraging social media in the tourism industry can be successful. SNA can be incorporated into the design and management of social media presence and promotion strategies for tourism destinations by focusing on cultivating the social network to actively promote the tourism destination and identify key players in the social networks as they assume important roles in disseminating social content. These results also help to track and gauge the effectiveness of promoting endeavors for tourism destinations.

The primary limitation of this study is that it only used one social media platform, Twitter(X), for data collection. The Twitter(X) users and data (tweets) investigated cannot be considered representative samples. The dataset was limited to Twitter(X) data, with 18,000 tweets per day. We tracked the changes in the social network of #Alula through December 2022 to examine the network cultivation over time. However, the detailed analysis was based on data from December 31, 2022. There were variations in the characteristics and usage patterns of various social media platforms. The analysis of such data can be expanded to other networks, destinations, or industries. These findings can help tourism stakeholders to better harness social media to promote tourism destinations for improved branding.

Nevertheless, the study findings have valuable theoretical implications for future research. Theoretically, this study contributes to social network research by illuminating the importance of influencers, in degrees, and the content of messages on social networks. Future research should empirically examine this relationship to develop a mathematical formula for calculating network growth.

Recommendations

The small size of the social network of #Alula, along with its weak network density, involvement, and reach, may be due to the integration, alignment, and strategic fit between the interests of the targeted crowd and the social content being shared, as well as its alignment with the target culture. Promoting Alula as a tourism destination should be customized to local interests and culture to attract both locals and local and interested global crowds. Using social media to disseminate tourism content should be part of a strategic plan with clearly identified goals. The social content should be tailored and customized for target groups, as variations exist in group characteristics, interests, cultures, and languages. Variations also exist in global and local target groups. They must be considered for the successful use of social media to promote tourism. There are many promising opportunities for cultivating the #Alula network. At the local level, the local community and surrounding area should be engaged around the year by activating social and community activities for schools, universities, and families, while competitions in various sports and hobbies should be organized for all ages. At the global level, social messages in different languages can be tailored to meet different cultural and individual demands. The concept of fulfilling needs plays an important role in growing networks and increasing their density and involvement.

A strategic plan that places the user and their involvement at the center should be devised, as it can play an important role in the creation and transmission of tourism images (Hernández et al., 2016). The overall reach can be enhanced by focusing on word-of-mouth diffusion on social media, using social technologies and platforms. Furthermore, simultaneously using various hashtags may cause distractions and scatter the tourism content, reducing its accessibility and reach. Top management must leverage their social media presence to increase returns on investment, convert crowds to actual visitors/tourists, enhance the experience by providing adequate content, and build and maintain communities. Sharing knowledge is different from sharing experiences; thus, encouraging tourists and visitors to share the cognitive, affective, and conative components of their experience of a tourism destination can cultivate its social network.

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