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Destination eWOM: A macro and meso network approach?

Nigel L. Williams [a,*], Alessandro Inversini [b], Nicole Ferdinand [c], Dimitrios Buhalis [d]

[a] *Department of Leadership, Strategy and Organisations, Faculty of Management, Talbot Campus, Bournemouth University, BH12 5BB, UK*
[b] *Henley Business School, Greenlands Campus, University of Reading, Henley-on-Thames RG9 3AU, UK*
[c] *Department of Events and Leisure, Faculty of Management, Talbot Campus, Bournemouth University, BH12 5BB, UK*
[d] *Department of Tourism & Hospitality, Faculty of Management, Talbot Campus, Bournemouth University, BH12 5BB, UK*

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ABSTRACT

The purpose of this paper is to develop a framework that describes the characteristics and the underlying drivers of publically shared electronic word-of-mouth (eWOM) for destinations. Tweets about a destination were collected while the destination hosted a hallmark event over a 5-year period (2011–2015). In each year, interactions on Twitter were analysed using macro and meso-level social network analysis to identify the network structure and hubs of eWOM activity. A K means clustering algorithm was then applied to create clusters of nodes with similar characteristics and eWOM content within each cluster was analysed using automated content analysis. The resulting model indicates that destination and event eWOM maintains a macro network structure in which a small number of accounts or hubs influence information sharing. Hub characteristics evolve over time, whereas eWOM content can fluctuate in response to emergent destination activities.

Introduction

Destinations have been characterised as a combination of spatial elements (e.g. geographic locations, populations and activities) and places (e.g. cultural and social spaces) ((Pearce, 2014). Activities, such as events, can enhance both dimensions by presenting spatial and place characteristics from a new perspective (Ferdinand & Shaw, 2012). They are often used as animators, breathing new life into static attractions within destinations, which would otherwise remain fixed cultural capital (Getz & Page, 2016). Large-scale events can be perceived as part of a destination's offering of products, services and experiences (Getz, 2012), rendering them indistinguishable from the location in which they are staged (Kaplanidou, 2006). Consequently, events can act as a catalyst for online discussions (Deery & Jago, 2010), generating electronic word-of-mouth (eWOM) about the destination while they are being staged (Semrad & Rivera, 2016).

Information sharing platforms on the internet have moved from being relatively static websites, to become dynamic, rapidly updated socio-technical systems, such as social media (O'reilly, 2007, p. 0). In the last five years, social media platforms, such as Twitter, have grown from limited utilisation to widespread usage by a significant proportion of UK users (emarketer, 2014). In addition to the growth in user numbers, technology has increased the number of options for near synchronous distribution of digital data that are mobile and wearable (Katakis, 2015). These technological developments have increased the number of potential participants and the volume of synchronously shared destination eWOM (D. Wang, Xiang, & Fesenmaier, 2014).

A recent strand of research has started to examine social media postings directly in order to understand the topic or relationship context of eWOM (Lu & Stepchenkova, 2015). Social media postings have also been used to identify key influencers

* Corresponding author.
E-mail address: nwilliams@bournemouth.ac.uk (N.L. Williams).

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and topics of discussion in destination eWOM when an event is staged (Williams, Inversini, Buhalis, & Ferdinand, 2015). These previous research studies utilized data collected at a single point in time and may be unable to examine the impact of technological change on destination eWOM (Bronner & de Hoog, 2016).

The aim of this paper is to study changes in information distribution patterns, key users and topics of discussion in public destination eWOM over time. Data from Twitter was used because postings or tweets are publically shared with a low time lag, enabling the examination of synchronously shared destination eWOM. Tweets can also be accessed at a later date, enabling researchers to compare communication activities at different periods (Proferes, 2016).

Data was obtained for 2011 to 2015 and was analysed using social network analysis and text analysis. Findings indicate that while the scale of the destination eWOM network grew over time, the macro structure maintained scale-free characteristics in which a relatively small number of accounts (or hubs) enabled information exchange among users. At the meso level, hub roles evolved from network communication to include network cohesion. This enabled the destination eWOM network to accommodate a range of user discussions, including planned activities such as events and emergent incidents, being reported via media.

Materials and methods: social media and destination ewom

Social media can be defined broadly as socio-technical systems (Zhao, Jiang, Jian, & Qinghua, 2013) that enable the exchange of content (Kaplan & Haenlein, 2010) and opinion (Parent, Plangger, & Bal, 2011). These platforms can create a relational context (Miranda & Saunders, 2003) based on interests and activities (Jacobsen & Munar, 2012). Due to the visibility provided by the scale of social media platforms and the persistence of previous activity by customers, eWOM may not always be a deliberate act (Erkan & Evans, 2016). It can arise intentionally (e.g. posting a comment and/or an experience) or inadvertently (e.g. liking a brand's page on Facebook to obtain updates for personal interest). The latter provides an unintentional highlight for future visitors who may have a relationship with that social media user. In both cases, eWOM hosted on social media can influence visitors' actions and decision-making processes (Hudson & Thal, 2013) each stage of tourism consumption.eWOM has dimensions of perceived and reputed credibility (Tseng & Fogg, 1999). Destination eWOM is viewed as having presumed credibility because sources may be viewed as non-commercial (Dellarocas, 2005) and therefore more authentic than media or destination promotions (Gretzel & Yoo, 2008). It can also have reputed credibility via influencers, such as bloggers or celebrities, to whom potential visitors may pay attention (Hilligoss & Rieh, 2008). These factors can augment the credibility of eWOM, enhancing its ability to encourage tourism purchases (Inversini & Masiero, 2014).

The credibility of destination eWOM has been challenged as it can be created by a relatively small number of contributors (Hyan Yoo & Gretzel, 2008). Since most users merely consume content, they can be influenced by a relatively small number of individuals or institutions (Nonnecke & Preece, 1999). However, customers may perceive postings on platforms, such as Facebook and Twitter, as more credible because it is possible to evaluate the source and context (place and time) in which the eWOM was generated (Tussyadiah, 2016).

Twitter and destination eWOM

Twitter was used as the data source for this study as it can provide a useful representation of public destination eWOM at the time it was generated. Twitter members use it for public conversations, information-sharing (including eWOM) distributing news and self-promotion (Krishnamurthy, Gill, & Arlitt, 2008). While other social media platforms have significantly larger audiences (for example, Facebook), Twitter postings are public by default, enabling participation without prior social (e.g. Facebook) or professional (e.g. LinkedIn) ties (Zhang, Jansen, & Chowdhury, 2011). Users may also repost eWOM from relatively closed platforms, such as Instagram (A. N. Smith, Fischer, & Yongjian, 2012). Since a significant amount of eWOM may originate outside of Twitter, users are able to draw on a wider range of information sources. While Twitter is only one of several platforms a destination eWOM participant may use, it provides an index of public online activity that can provide empirical illustration of the scale, structure and geographic distribution of information (Takhteyev, Gruzd, & Wellman, 2012).

The Twitter platform has low barriers to participation (e.g. cost and technology), as tweets can be shared via email, dedicated applications (apps) or SMS (Waters & Jamal, 2011). Twitter is also a flexible communications medium since it supports multiple modes of communication from one-to-one and many-to-many (D'heer & Verdegem, 2015).

Twitter also provides insights into the nature of online communications while activities are occurring. It has emerged as a media platform for sharing timely information about politics (Murthy, 2011), natural disasters and social movements (Khondker, 2011), as it has low time lag for updates (D. Zhao & Rosson, 2009). This is particularly relevant for time-sensitive activities, such as events or festivals, as destination related eWOM can be shared while activities are occurring. Unlike some other platforms, Twitter metadata (user profile, location, time and interaction data) are publicly available, which can provide additional detail about the characteristics of users sharing eWOM (Kwak, Lee, Park, & Moon, 2010). Twitter data are also archived by several organizations and can be accessed at a later date (Proferes, 2016). These properties (public posts, low barriers, timely, archiving) support the development of research seeking to examine public communication, such as destination eWOM, generated at different times, which is the focus of this research.

Twitter has limitations in terms of research. Twitter users tend to be younger and located in urban areas (Sloan, Morgan, Burnap, & Williams, 2015). These platform-specific biases may be a challenge for predictive research (e.g. quantifying relationships between variables – (Ruths & Pfeffer, 2014). However, outside of predictive research, Twitter data and metadata have been found valuable for understanding public communication behaviour (Gonçalves, Perra, & Vespignani, 2011). Twitter users exhibit homophily by interest and geography, in a similar manner to real-world interactions (Morales, Borondo, Losada, & Benito, 2014). The information content and language style can also be similar to public speech (Duguay, 2016). Twitter can be useful for research seeking to examine the characteristics and drivers of eWOM, the focus of this paper.

Research context

This research analyses destination eWOM networks over a five-period (2011, 2012, 2013, 2014 and 2015) at a destination while an event was being staged. This period was an ideal time to study destination eWOM because the increase in activity that occurs in the real world can be mirrored online (Gyimóthy & Larson, 2015). Events may also attract new participants to discuss destination elements online and discussions may be more purposeful during the event (Deery & Jago, 2010). Therefore, these periods can provide a useful temporal context in which to examine public destination eWOM.

Research questions

Social network analysis (SNA) supports the development of research insights based on direct examination of relationships between entities rather than relationships between variables (Tran, Jeeva, & Pourabedin, 2016). The origins of SNA are based on an attempt to quantify social structures (Scott, 1988) and it incorporates insights from social science, mathematics and theoretical physics (Kane, Alavi, Labianca, & Borgatti, 2012). For this study's SNA, the entities are Twitter users, which are modelled as nodes, and the relationships between them are regarded as ties. Calculations are performed in order for inferences to be made about the overall structure and individual relationships. A glossary of network metrics is provided below (Table 1).

A growing body of research in the field has examined aggregated relationships in tourism from the macro or structural perspective and the meso or sub-network (community) perspective (Merinero-Rodríguez & Pulido-Fernández, 2016), which will be discussed in the next section.

Macro structure

Macro structure research examines the overall characteristics of tourism systems using SNA (Baggio, 2008), such as communication patterns between organizations, service providers and visitors at a single destination (Del Chiappa & Presenza, 2013) or attraction (Pavlovich, 2003). This research also examines online tourism systems, such as networks formed by websites (Baggio, Corigliano, & Tallinucci, 2007) or interactions between physical and online entities (Del Chiappa & Baggio, 2015). It has also examined spatial phenomena, such as visitor travel patterns (Miguéns & Mendes, 2008) and the global network formed by non-stop flights between airports (Guimerá and Amaral, 2004).

Macro-level network scale and structure can influence information flow and, hence, the benefit derived by member nodes (Carrington, Scott, & Wasserman, 2005). Structural properties, such as density and path length, have also been found to influence communication among tourism stakeholders (Strobl & Peters, 2013). Existing research has identified a scale-free structure in tourism communication networks (da Fontoura Costa & Baggio, 2009) with a resulting exponential distribution of metrics, such as betweenness centrality. Travel-related eWOM network structures have similar characteristics with a small number of influential hubs (Faloutsos, Faloutsos, & Faloutsos, 1999) and peripheral nodes (Luo & Zhong, 2015).

Previous research on Twitter networks for events, media and political discussions have identified various macro structures, ranging from the previously discussed scale-free structure (Kimbu & Ngoasong, 2013) to "cluster" networks that do not exhibit these characteristics (Smith, Rainie, Shneiderman, & Himelboim, 2014). Research on examining country-level hashtags has also found similar variations between scale-free and non scale-free structures (Raamkumar, Pang, & Foo, 2016). Since the macro-structural properties of networks can enable and constrain potential benefits to users, the first research question is therefore:

RQ1: How did the structural characteristics of the destination eWOM network change over time?

Table 1
SNA Metrics Description (Adapted from Scott, 1988).

SNA Metric	Description
Nodes	Entity (individual, organization, country, website)
Edges	Relationship between entities (connection or affinity, such as social, information, location or purchase)
Network Size	Number of nodes in network
Density	The ratio of actual network edges to the maximum possible number of edges
Betweenness Centrality	The level of importance of nodes in the overall network
Clustering/Modularity	A collection of edges that are more connected with each other than they are to the overall network. A figure of 0.4 indicates meaningful clusters exist, while 0.6 is a high degree of clustering.
Maximum Nodes in a Connected Component (Giant component)	The largest single sub-graph or cluster
Average Geodesic Distance	The number of edges that lie between any two nodes in the network

Meso structure

Meso-level research examines the characteristics of nodes from a community or sub-network perspective. Research in this area has analysed communities in tourism communication and collaboration networks (Erkuş-Öztürk & Eraydın, 2010). Meso-level work has also examined the configuration of relationships between operators and agencies (Tran et al., 2016) and the relative degree of connectivity of network members (McLeod, Vaughan, & Edwards, 2010).

At the meso level, nodes can be categorised by intra- and inter-community connectivity (Guimera, Mossa, Turtschi, & Amaral, 2005). Using these metrics, eWOM participants can be classified by their sub-network or within-community position, instead of only by their macro or network-wide position. An expansion of this research created directed versions of these metrics (Scripps, Tan, & Esfahanian, 2007) that enabled identification of inward (relationships directed towards node) and outward (relationships directed from node) community hubs. This approach has been used in tourism to examine transportation networks (Guimera et al., 2005; Iñiguez, Plumed, & Martínez, 2014) but has not yet been applied to eWOM research. The second research question is therefore:

RQ2: How did meso-level node characteristics change over the period of study?

eWOM participant characteristics

Social media provides spatial and profile data of users, as well as content unlike earlier online platforms (Wang, Tang, Gao, & Liu, 2010). This information can be used to further classify eWOM hubs and non-hubs by content, user type and location. For example, research about eWOM networks created by commercial organizations has found hubs consisting of employees (Obst, Zinkiewicz, & Smith, 2002) and media organizations (Vilpponen, Winter, & Sundqvist, 2006). However, it is not yet known if destination social media eWOM hubs are necessarily from the host location, with which they are sharing eWOM. Since these hubs help provide network cohesion and connectivity, which is essential for the propagation of eWOM, studying their characteristics and evolution over time is essential for understanding how destination eWOM changes within a given period. The third research question is therefore:

RQ3: How have eWOM participant characteristics changed over time?

Study methods

The research has been designed to investigate the evolution of eWOM while a hallmark event is being staged at a destination. The event, Bournemouth Air Festival, (see bournemouthair.co.uk) was selected due to its importance for Bournemouth as a destination. The Bournemouth Air Festival is staged between Bournemouth and Boscombe beaches (Boscombe is a neighbouring town) and it attracts an average of one million travellers over three days. This event was recently awarded "Tourism Event of The Year 2015" by VisitEngland (bournemouthair.co.uk., 2015).

The scale of the event made it possible to capture a census of social media interactions because, although it is major event for the destination, it does not generate the volume of social media traffic of a mega-event, such as the Olympics. The Bournemouth Air Festival thus facilitated analysis of a complete network that can provide insights into the structure and evolution of eWOM networks (Scott, 1988).

A repeated approach (2011–2015) was taken to analyse tweets about the destination generated while the event was being staged. Similar approaches have been used to examine the impact of an event on a destination (Litvin & Fetter, 2006) and effect of weather on events' sales (Clarke & Hoaas, 2007). Fig. 1 illustrates the seven methodological steps:

1) *Obtain Archived Tweets:* Tweets were obtained from Discovertext using the Sifter system, which enables access to both current and historical twitter data, before being archived using the term 'Bournemouth'. This term was selected because it captured destination-related tweets, along with terms related to the festival, such as 'Bournemouth Air Festival' and 'Bournemouth Air Show'. Tweets were archived for a 17-day period, 7 days before the event, the three days on which the event was staged and 7 days following it.
2) *Isolate Destination eWOM:* The archived tweets were analysed to identify eWOM in the form of twitter retweets, replies or mentions. This approach has previously been deployed to isolate twitter conversations from archived content (Yardi & Boyd, 2010).
3) *Analysis of Metadata:* eWOM metadata was analysed to identify and categorize the sources from which updates originated.
4) *Social Network Analysis (Structure):* SNA was used to model the interactions identified earlier as nodes (Twitter users) and edges (retweets, replies and mentions) (Latour, 2007). The network for each year was modelled as a directed graph using the Gephi software. This approach is appropriate for information relationships, as there is an inherent direction for the interaction, unlike social relationships, such as families, where linkages are mutual (Carrington et al., 2005).
5) *Social Network Analysis (Community Roles):* Steps 5) and 6) were performed using the programming language R with the code available from https://github.com/CompNet/Orleans (accessed August 23rd 2016). Community structure detection was conducted using the R implementation of the Louvain method as it can process large networks efficiently (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). Directed community node metrics, based on an extension

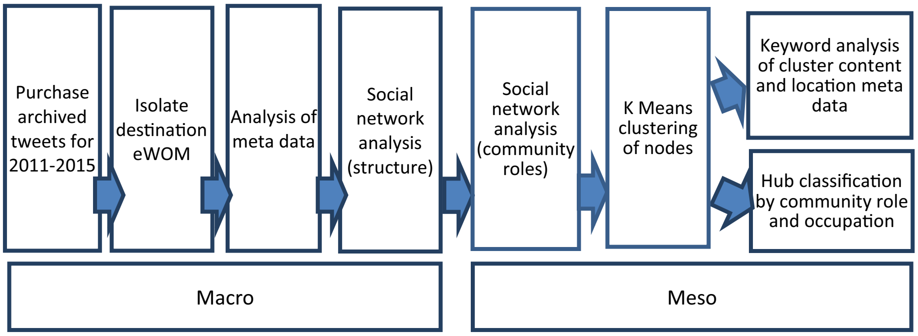

Fig. 1. Research Process.

Table 2
Directed Community Roles Metrics.

Participation (Ratio In)	The inward connectivity of a given node outside its community, as compared to other nodes. For Twitter, this indicates that eWOM from the node is visible across the network.
Participation (Ratio Out)	The outward connectivity of a given node outside its community, as compared to other nodes. For Twitter, this indicates that the node shares eWOM from other users outside of its home community
Internal (Intensity In)	The inward connectivity of a given node within its community, as compared to other nodes.
Internal (Intensity Out)	The outward connectivity of a given node within its community, as compared to other nodes.

of Guimera and Amaral (2005), were then computed using the community structure revealed in the previous stage of the research (Table 2) using R. Since eWOM networks can exhibit scale-free properties, like other large-scale tourism networks, community sizes may be power-law distributed. Therefore, community role measures were expressed as z scores (Table 2) to enable comparability.

6) *K Means Clustering:* To identify hub and non-hub characteristics, a cluster analysis approach was then applied to the output for stage 5. An unsupervised K Means clustering algorithm was applied and the optimal result was selected based on the Davies-Bouldin index (Dugué & Perez, 2014). The K Means algorithm partitions objects (nodes in the network) into a fixed number of clusters with the nearest mean (community node metrics) in this particular case. This approach enables identification of eWOM participants with similar roles that may be embedded in different communities across the network. The range K 2–15 was selected as it was previously used for a corpus of 5 million tweets (Dugué & Perez, 2014) and is much larger than any of the datasets in this study. The resulting clusters were classified into different roles using a directed version of the categorization created by Guimera and Amaral (2005). Hubs (z score > 2.5) were identified by analysing the inward or outward intensity of nodes, following which the hubs and non-hubs were further classified based on directed participation coefficients (Table 3).
7) *Keywords Analysis of Cluster Content and Metadata:* The content and location data of Twitter posts were analysed using the Antconc text analysis software to identify topics of conversation in each cluster and the geographic origin of Twitter content. While Twitter provides the option to include GPS location data, this was not available in 2011; furthermore, less than 0.5% of tweets in the remaining years afforded this information. Previous research suggests that user-supplied location data in profiles and tweets can provide sufficient detail to enable classification at a city or regional level (Xu, Wong, & Yang, 2013), an appropriate level for this study.
8) *Categorization of hub profiles:* The public profile data of hub members was reviewed inductively using a modified version of the categorization created by Wu, Hofman, Mason, and Watts (2011) for the Twitter profiles relating to organization, celebrity, music celebrity, media, online only media and ordinary user (see Appendix 1). Once completed, the findings from each year were compared to understand the evolution of the network, characteristics of key users and the topics discussed.

Table 3
Community Role Classification.

Community Role				External Connectivity
Within-Module Degree (In or Out)		Participation Coefficient (Inward or Outward)		
Hub (Inward or Outward)	$Z \geq 2.5$	Provincial	$P \leq 0.30$	Low
		Connector	$0.3 \leq P \leq 0.75$	Strong
		Kinless	$P > 0.75$	Very Strong
Non-Hub (Inward or Outward)	$Z < 2.5$	Ultra Peripheral	$P \leq 0.05$	Very Low
		Peripheral	$0.3 \leq P \leq 0.62$	Low
		Connector	$0.62 \leq P \leq 0.80$	Strong
		Kinless	$P > 0.80$	Very Strong

Results

Sections '*Macro: Destination eWOM Network Size*', '*Macro: Destination eWOM Network Structure*', '*eWOM Participant Characteristics*' describe the structure, key member characteristics and topic content of the eWOM network.

Macro: destination eWOM network size

The period 2011 to 2013 showed a growth rate of 60% in the number of network edges, slower than Twitter's usage growth rate in the UK for the same period (74.7%) (emarketer, 2014) but greater than the UK's growth rate for smartphone usage (just over 30%) (Kakihara, 2014). The period 2014 to 2015 shows an increase (76.5%) in the number of interactions about Bournemouth (i.e. the hosting destination), which is higher than both the smartphone and Twitter usage growth rates for 2014–2015 (9% and 8.8% respectively).

Fig. 2 shows that the destination's eWOM network is becoming increasingly dominated by mobile users, most likely sharing data synchronously. It also shows the relative proportion and absolute numbers of web users have been falling, with the exception of 2015.

Macro: destination eWOM network structure

The number of nodes (Twitter users) has also grown rapidly, which might suggest potential visitors may gain more value from the network (Chen, Tang, Wu, & Jheng, 2014). The number of users engaged increased from 15,500 to 66,000, a faster growth rate than for smartphones or Twitter in the UK (Table 2). Modularity for all networks exceeded 0.6, indicating high-level clustering and suggesting communication within communities is higher than their communication with the rest of the network (Table 4). Network metrics, such as betweenness centrality, are also exponentially distributed.

In this case, Twitter eWOM has maintained its distinctiveness over the period of study; furthermore, the Geodesic distance has decreased over time, indicating members of the network require fewer information connections to contact a given node. This is also another surprising finding, as it can be the opposite of what typically happens when a network is increasing in size (Rowley, 1997) (Fig. 3).

Larger random networks can fragment into ever-smaller components, increasing geodesic distance and reducing the relative proportion of the giant component, i.e. the connected component (created by multiple-nodes with shared connections) that contains a significant fraction of all the nodes (Himelboim, Smith, & Shneiderman, 2013). These findings indicate public destination eWOM exhibits properties of scale-free networks (Himelboim et al., 2013). The former exist where a degree of preferential attachment occurs and nodes agglomerate to create patterns where a few nodes are highly influential over the entire network, in a similar manner to commercially-driven networks (Obst et al., 2002).

eWOM participant characteristics

The numbers of clusters identified by K means clustering vary from eight in 2011 and 2014 to a maximum of fifteen in 2015. Most nodes in the network are peripheral, with low directed inter- and intra-community z scores. A relatively small group of users can be classified as hubs (González-Bailón, Wang, & Borge-Holthoefer, 2014), having a within-community Z Score of $\geq$2.5. Table 5 shows the classification of these hubs in the network.

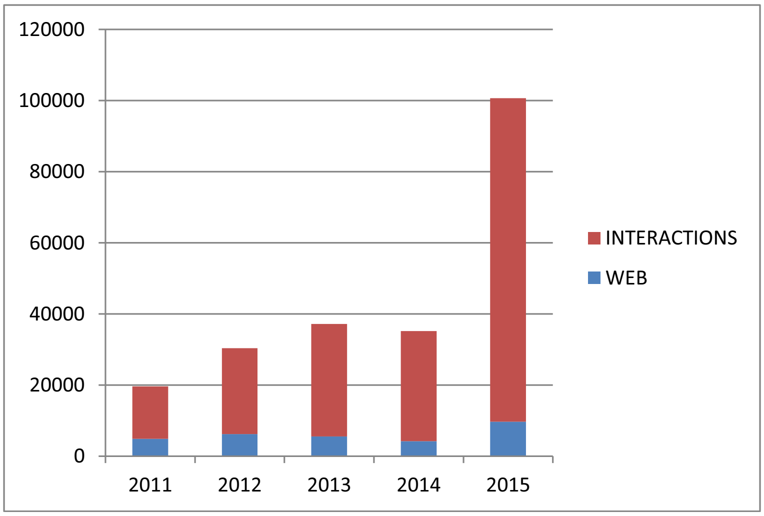

Fig. 2. Number of Bournemouth Interactions (http://www.airshows.org.uk). Please note that the event in 2014 was staged during bad weather.

Table 4
Comparison of Network Statistics.

Year	No of Users	Maximum Vertices in a Connected Component	Diameter	Density	Average Geodesic Distance	Modularity	Average Clustering Coefficient
2011	15,505	7074	21	5.56264E−05	6.311869	0.831648	0.002995
2012	24,773	10,341	27	3.37621E−05	6.246006	0.789903	0.003513
2013	29,100	11,788	24	3.17922E−05	6.972382	0.75327	0.011196
2014	26,934	14,053	21	3.48519E−05	6.659259	0.772607	0.010204
2015	66,649	49,754	20	1.66771E−05	5.390428	0.84755	0.0081736

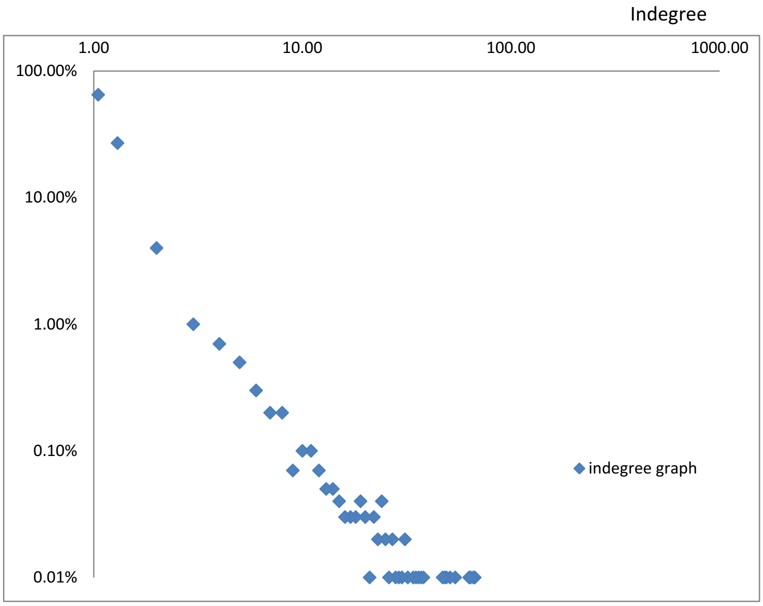

Fig. 3. Log in degree Distribution for the 2014 Network.

These findings share some similarities with extant work that examines large-scale Twitter networks (Borge-Holthoefer & Gonzalez-Bailon, 2015). Inward Kinless hubs were accounts whose content was shared across the network. They are, perhaps, to be expected in large networks, such as the Bournemouth eWOM network, and were present in all years. Outward Provincial and Outward Connector Hubs had outgoing metrics higher than incoming metrics. These hubs share content from other people within their host community. Inward Connector Hubs (2012) were more prominent within their community than across the network. Finally, Outward Kinless Hubs present in 2013, 2014 and 2015 share content from other people across the entire network.

In 2012, a "cluster" was identified consisting of a single node that was a highly mentioned hub in the network. In 2013, a hub also exhibited high-request characteristics, which suggests that it mentioned a large number of users outside its host community. These hubs may be necessary for network cohesion as they share others' information, both within and outside their host community. Since they are present in the latter three years when the network became mobile driven, they may have evolved as a response to the growth in synchronous eWOM.

Cluster characteristics

Text analysis of content was used to classify each cluster by keyword frequency, an example of which is provided in Appendix 1. The keyword analysis reveals that, while the air show is a topic of conversation, twitter users also discussed football, local events and UK-wide issues. Interestingly, despite the large scale of the air show (one million visitors attending over a few days each year), it was not the dominant topic of conversation on social media every year. In 2011, 2012, 2014 and 2015, the Air Festival was not the lead topic of discussion in clusters, possibly due to specific happenings, such as an aircraft accident in 2011. In 2012, there was a visit from a famous pop group, One Direction. In 2014, a political march took place that attracted national media coverage. Finally, in 2015, a high volume of football-related discussions occurred as Bournemouth joined the Premier League.

In 2011, 2013 and 2014, the network was created by interactions between UK- and Dorset-based users; notable exceptions are 2012 and 2015 when there was an influx of international Twitter users. The findings suggest that international

Table 5
Hub Types.

	Inward	Outward
Within Community	Inward Connector Hub (2012)	Outward Provincial Hub Outward Connector Hub (2011, 2012, 2014)
Across Network	Inward Kinless Hub (all years)	Outward Kinless Hub (2013, 2014, 2015)

users occupy a significant position in the Bournemouth network only when there is an unusual occurrence that brings the destination to the attention of previously existing networks, such as news providers (e.g. aircraft crash in 2011) or fan communities (e.g. AFC Bournemouth in 2015).

An examination of hub profiles revealed them as mostly celebrities and organizations. Despite Twitter's open nature, individuals already prominent in the network shared the content considered most valuable. These findings are similar to previous work on websites that indicate a shift towards organization-owned pages (Bronner & de Hoog, 2016). This reliance on familiar sources may reflect the need for customers to reduce risk by consulting sources viewed as credible or reliable (Lu, Gursoy, & Lu, 2016).

Discussion: destination eWOM characteristics and drivers

Previous macro-level work on destination eWOM has identified a scale-free structure dominated by a giant component (Luo & Zhong, 2015). The repeated observational approach deployed in this paper's approach confirms this scale-free structure exists in public destination eWOM and persists over time. Further, the meso- and cluster-level analysis was able to identify changes in hub types and destination discussions over time.

Macro-Level structural rigidity and scale growth

Earlier research on pre-social media eWOM indicates that most destination networks failed to grow to a sustainable size (Chan & Guillet, 2011), as most members did not produce useful primary eWOM (Ip, Law, Lee, 2011). Destination eWOM networks, like other real-world networks, exhibit scale-free properties when users tend to engage with a small number of hubs (Newman, 2005). Luo and Zhong (2015) also identified scale-free eWOM structures with distinct hubs in a destination's communication network.

This research posits that this structure is maintained even while the network grows in size over the years, a finding not identified in previous work (e.g. Morales et al., 2014). Over the period analysed, the destination eWOM network has maintained its modularity, indicating the presence of 'echo chamber' behaviour identified in previously studied networks, in domains such as politics (Himelboim et al., 2013). While research on eWOM assumes a wide range of participants are able to engage in online discussions, eWOM occurred in the destination's network within coherent groups and with a few dominant members.

Meso-level hub evolution

Within the stable macro structure that increased in scale, the meso-level hub roles expanded beyond providing local and global prominence for information shared with them. This echoes previous research which suggests social media communication platforms can illustrate the co-evolution of technology and social behaviour (Croft, 2013). In this case, locally prominent hubs provided cohesion within clusters and content from their shared topics visible to members, whereas globally prominent hubs provided cohesion across clusters from their shared content visible across the network. This paper also identified another type of global hub in destination eWOM that acted as both sender and recipient of information from a range of communities. This indicates a change in the role of hubs from being solely prominent sources of information to include the role of being prominent requesters of information from across the network. As technology has matured and an increasing number of users engage in destination eWOM, hubs provide the crucial role of maintaining and growing the network. Without hub evolution, the highly modular nature of the network may result in fragmentation of the network into incoherence.

Public destination eWOM discussion topics

Twitter acts as the host for both planned and emergent online destination topics of discussion, which include events, breaking news and entertainment. Clusters' content reflected activities at the local level and the effect of external shocks or one-off occurrences. Over the period examined in this study, emergent activities overshadowed planned initiatives and dominated destination eWOM discussions. While the hallmark event was an important topic of discussion, other occurrences, such as the aircraft crash (2011), celebrity visits (2012) and AFC Bournemouth's ascendance to the Premier League (2015), attracted significant attention during the period immediately preceding, during and just after the Bournemouth Air Festival, despite the scale and reputation of the event.

Since most users posted information using Bournemouth or the UK as locations, it supports the perspective of Twitter as a virtual public space (Kim, 2016). While events can attract new interest in destination space and place features, occurrences

Table 6
Summary of Findings.

Research question	Findings
RQ1: How did the structural characteristics of the destination eWOM network change over time?	Destination eWOM networks are characterised by macro structural rigidity. A destination's eWOM network structure remains unchanged despite changes in size and information distribution sources.
RQ2: How did meso-level node characteristics change over the period of study?	Hubs within eWOM destination networks can evolve with the passage of time from high-mention to include high-request hubs that may provide network cohesion
RQ3: How have eWOM participant characteristics (content and hub profiles) evolved over time?	The hallmark event was not the dominant generator of destination eWOM in all of the years studied. Network participants are predominantly UK-based and hubs are media and celebrities. International members only have a significant presence when there is an external incident or shock. This suggests that role of events as an online animator of destinations needs further critical examination.

reported via Twitter can perform a similar role. Since the volume of synchronous destination eWOM may grow in future, the role of events as online animators of destination features may need additional critical examination.

Table 6 summarizes the key findings of this research, based on the questions presented in section two.

Conclusion

The growth and current volume of destination eWOM may cause confusion, as it may not be possible to make sense of this growing volume of data. Mobile applications may also increase the proportion of updates shared synchronously with a limited amount of information processing. Mobile applications may also encourage particular interactions, such as retweeting, and prevent users from seeing all but the most popular content.

In the absence of formal filtering mechanisms, such as those on Facebook, Twitter eWOM sharers may adopt simple heuristics (i.e. mental rules) that focus attention on updates shared from the point of the experience (Aladhadh, Zhang, & Sanderson, 2014). In this scenario, hubs play a critical role in the cohesion of local and global destination eWOM networks. Due to their high visibility, they reduce the confusion community participants may face in their search for useful information.

Inward-oriented hubs can share information from a host community across the entire network. While they provide global cohesion, they may also limit the diversity of perspectives to which a non-hub user is exposed. However, outward-oriented hubs may do the opposite. These hubs may engage in a process of context collusion (Davis & Jurgenson, 2014), bringing varying interests together by sharing content from a wide range of interests within their host community. The interplay between these two hub types enables the network to accommodate a varying volume and variety of destination eWOM that includes planned (hallmark event) and emergent (breaking news) activities.

In this study, hubs are established accounts from celebrities, media or institutions, whose identity is independently verifiable and therefore have source credibility. EWOM participants are more likely to believe the content shared by them and share it in turn. Emerging technological platforms, such as wearable devices, have the potential to increase the volume of destination eWOM even further. Since a scale-free macro structure was maintained over the 5-year period of destination eWOM growth, it suggests the proportion of users who hold influence in these networks will remain small. The role of source credibility may be of similar or greater importance in these future networks.

Implications and recommendations

Findings highlight a relatively small number of hubs exist within the studied networks. This suggests that network activity can be approximated by identifying a subset of individuals. This enables future research to focus on the evolution of interactions among these individuals in greater depth. To understand hubs' changing roles, future research can also examine the longitudinal evolution of hubs during the period of Twitter's emergence as an eWOM platform to its ubiquity, as well as the hubs' evolution in other social network platforms, such as Snapchat, Facebook and Instagram.

Destination marketers need to therefore develop social media strategies that meet the requirements of both current and potential visitors. For current visitors to the destination, the scale-free macro structure would allow information to reach them rapidly via a small number of hubs. This can support the development of real-time destination management strategies, in which visitors can engage with planned activities, including attractions and spontaneous activities, such as pop-up events. Recruiting opinion leaders with broad knowledge of the destination may increase the influence of these hubs, as their eWOM may be seen as more credible (Bao & Chang, 2014).

The challenge of such an approach is that potential visitors observing the destination via social media may be confused by the dizzying array of updates. Peripheral Twitter or other social media users may use manual and computer-supported filtering techniques that reduce the effectiveness of social media marketing. Therefore, to reduce this confusion, destination marketers may need to provide structured data via hubs for these visitors. To increase the reach of these promotions, marketers may need to recruit hubs from target markets with interests that intersect with those of potential visitors. Finally, the dependence on hubs suggests a greater need for verifying and checking the credibility of eWOM. Destination marketers can provide meta data or other verification tools to users to support checking of eWOM sources and content.

Appendix 1

Year	Cluster no of Hub	Hub Cluster Size (Number of participant)	Average Participation ratio –in (Z score)	Average Participation ratio –out (Z score)	Average Community Node z-in	Average Community Node z-out	Hub Description	Hub Classification	Topic	Account classification
2011	3	37	5.016391	0.681874	12.39827	−0.39126	Hub, High inward external community connections	Inward Kinless Hub	National news coverage about crash Local news about event	Media Music Celebrity Organization Online Media
2011	5	46	0.69965	2.731258	0.711635	8.065841	Hub, high outward internal and external community connections	Outward Connector hub	Football	Media Celebrity Ordinary Users
2011	7	389	−0.07747	−0.08524	0.119485	2.502697	Hubs, all metrics low	Outward Provincial Hub	Local news and issues	Media Online Media Ordinary Users
2012	0	46	0.173833	0.705981	0.346633	10.44295	Hub, high outward internal and external community connections	Outward connector hub	Air show	Media Organizations Ordinary Users
2012	1	130	0.47584	−0.09565	3.80799	−1.72175	Hub, all metrics low	Inward Connector hub	Air show	Music Celebrity Celebrity Organization Online media
2012	4	1	0.70519	−0.09565	72.11297	−11.5173	Hub	Inward Connector hub	Drummer from one direction	Music Celebrity
2012	8	25	4.987624	1.688744	13.88335	−0.052	Hub , high inward external community connections	Inward Kinless hub	Bournemouth media coverage about festival	Media Music Celebrity Clelebrity Organization Online Media

2013	2	32	6.29768	4.178934	3.12335	11.34326	Hub all metrics high	Outward Kinless hub	Local Air festival coverage	Organization Ordinary Users Media Online Media Celebrity
2013	3	97	2.42738	0.111101	6.763761	−0.54763	Hub, high inward external community connection	Inward Kinless hub	Air festival performances	Organizations Music Celebrity Celebrity Media
2013	4	136	−0.00271	0.934632	0.291722	5.28149	Non Hubs, high community outward connection	Outward Kinless hub	Local events (not festival)	Ordinary User Celebrity Organization
2013	6	19	4.12988	1.828761	19.95149	−0.25531	Non hub, high diversity and heterogeneity	Inward Kinless hub	Football	Celebrities Organization Music Celebrities
2014	3	59	0.159493	1.797141	0.550504	9.25795	Hubs, high community outward connection	Outward Kinless hub	Nightlife including clubs	Celebrity Organizations
2014	4	58	2.988866	0.866272	13.55165	−0.77999	Hub, high inward external community connection	Inward Kinless hub	football	Celebrity Organization Media Online Media
2014	5	524	−0.04864	−0.04838	0.363031	2.666869	Non Hubs, high community outward connection	Outward Provincial hub	Air festival performers	Celebrity Organization Media Online Media
2015	1	579	−0.0855	3.54638	−0.01252	2.63772	Hubs, external community outward connection	Outward Kinless hub	Football, some air show	Ordinary User Organization Media
2015	3	16	5.197118	1.297156	39.64095	1.311386	Hub high external community inward connections	Inward Kinless hub	Football	Celebrity Organization Media Online Media
2015	7	245	0.213812	1.065693	0.085652	7.329991	hub, high internal community outward connection	Outward Kinless hub	Football	Ordinary User Organization Media

(*continued on next page*)

Appendix 1 (*continued*)

Year	Cluster no of Hub	Hub Cluster Size (Number of participant)	Average Participation ratio –in (Z score)	Average Participation ratio –out (Z score)	Average Community Node z-in	Average Community Node z-out	Hub Description	Hub Classification	Topic	Account classification
2015	8	18	3.07807	2.263278	1.789338	24.44344	hub high outward internal and inward external community connections	Outward Kinless hub	Football	Media Online Media Organization
2015	12	56	3.693889	0.686244	17.1995	0.033042	Hub, high inward connection from external communities	Inward Kinless hub	Football	Organization Media Online Media Celebrity
2015	13	163	1.877365	0.147443	5.96309	−1.02216	Hub, high inward connection from external communities	Inward Kinless hub	Football	Organization Media Online Media Celebrity

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Dr Nigel L. Williams is a Senior Academic in Project Management at Bournemouth University. His research examines online stakeholder communications and implications for organisations in a variety of contexts including NGOs, Festivals locations and Mega Projects.