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# Application of Social Media Analytics in Assessing Decision Insights of Tourists under Disruption

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## Abstract

Decision making is a critical challenge under disruptive conditions. Information flow as critical component to decision making may exacerbate or mitigate the impact of disruptive conditions. Such highly complex and unpredictable conditions produce a high demand for information. Extant literature was found to be critical of unidirectional and sender-oriented models in crisis communication which essentially blocks the feedback loop and paralyzes the crisis managers to roll-out responses. However, the pervasive social media has created new patterns of dynamic information exchange to empower the individuals to be engaged in a more evidence-based participatory form of crisis communication to frame decisions. This study used social media analytics to identify the decision clusters arising out of information exchange over social media under disruptive uncertainties. The Theory of Complexity by Edgar Morin was used as the epistemological foundation of the study. Crawled data was used from the Tourism Tribe Facebook fan page. Normalized degree and betweenness centrality measures were used to analyse the semantic networks. Tourism Tribe exhibited the highest degree centralities for both before and during the pandemic-driven disruptions. Four individuals (names changed for anonymity) were identified to be the most influential in decision making based on information shared. The causality between uncertainty and decision revealed a wide array of decision parameters - health precautions to alternative leisure engagement. The study provided practical implications for a number of stakeholders. The tourism service providers and product designers are likely to get deeper insights into the choice and priorities of the tourists confronting disruptive conditions and may re-strategise tourism offers. The alternative leisure and recreational platforms (OTT, gaming platforms etc.) may introduce new products and/or re-design their schemes.

**Key words:** disruption, social media, analytics, semantic networks, influential

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## 1. Introduction

Tourism industry is one of the most vulnerable industries to pandemics and other crises (Gössling et al.,2020; Yu et al., 2020). The COVID-19 pandemic has had serious ramifications with countries closing their borders to prevent the coronavirus from spreading (Albattat et al., 2020; Connor, 2020; UNWTO, 2020).During the height of the crisis, the tourist industry was impacted hard, with 56 percent fewer international arrivals until May, 2020 (UNWTO, 2020). As several publications speculated on what the second wave of Covid-19 would look like (Kleczkowski, 2020), the destinations seek to revive tourism in order to stay afloat economically (Valeri & Baggio, 2020a, 2020b).Tourism recovery after a crisis is linked to the management of public perception (Beirman, 2003). Public knowledge of crises is critical for delivering accurate evaluations of potential hazards while avoiding stress and anxiety (Boin & McConnell, 2007). The pandemic driven disruptions made a deep-rooted cognitive impact on millions of travellers and decision making was challenging.

The decision-making process for the tourism sector has altered dramatically since the introduction of social media. Consumers frequently use social media to get information regarding their next trip (Dabija et al., 2018; Lin and Huang, 2006); moreover, social media is a valuable platform for sharing their experiences both during and after the trip (Dabija et al., 2018; Lin and Huang, 2006). Social media arose as a result of the explosive proliferation of internet networking sites (Cox et al., 2009). They can increase the influence of knowledge passed on to others by being recognised as opinion leaders (Jalilvand, 2017).A study carried out by Rakuten Marketing (2019) among 3,600 tourists spreaded across five countries suggested that 88% of respondents framed their decisions about destination choice under the influence of anonymous referrals. However, social media and social media influencers could engage tourists in repulsive behaviour with negative contents (Varkaris and Neuhofer, 2017) which serves as an exclusion criterion in decision-making. Studies on crisis communication have criticized the unidirectional sender-driven model which doesn't trigger a feedback loop and are now focusing on a community who can self-organize information and communicate as a network to provide deeper insights into disruptive conditions. New patterns of information exchange are evolving as the actors in the networked community seek more evidence-based participatory form of crisis communication (Wendling et al., 2013). A theoretical model, namely Social-Mediated Crisis Communication (SMCC) (Park, Kim and Choi, 2018; Jin, Liu and Austin, 2014; Freberg, 2012) was introduced to address the theoretical gap in comprehending the viral dissemination of information and to provide guidelines to effectively meet expectations of socially networked members. The model identified three stakeholders on social media platforms – influential generators, followers and inactives who are likely to be engaged in a complex regime of information production and consumption.

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The virtual community has also witnessed the evolution of geographically and temporally traceable data (Park et. al, 2018), using social sensing techniques, to share more equitable information on crisis and disruptions (eg. COVID-19 pandemic condition).Researches have been undertaken to understand the utilization of 'big social data' (Wang and Ye, 2018). The emerging use of social media analytics intend to assess the objective methodology and models to trace, mine, and analyse big social data from four perspectives, namely, space, time, content and network for decision making and forecasting (Stieglitz, Dang-Xuan, Bruns, & Neuberger, 2014).

## 2. Literature Review

### 2.1 Evolution of Social Media Analytics (SMAs)

Social media, defined as "a series of Internet-based apps that build on the ideological and technological underpinnings of Web 2.0 and allow the production and exchange of user-generated content" (Kaplan and Haenlein, 2010), has grown pervasive in consumers' daily lives. Consumers leave 'digital traces' on social media while engaging with information search and sharing behaviours. Enabled by social media analytics (SMAs) these digital traces or footprints become available and form massive and abundant databases from which researchers and marketers can extract meaningful marketing and business intelligence, such as demand forecasting (Moon and Kamakura, 2017) and consumer preference (Abrahams et al., 2013), which has become increasingly important for developing and implementing successful marketing strategies such as resource allocation and product innovation. SMAs have evolved to extract patterns and intelligence by analyzing voluminous unstructured data churned out by social media transactions, thereby, assisting stakeholders (eg. tourists) in decision making (Gandomi and Haider, 2015).. These datasets, termed as 'big data' are characterised by its *Volume* (much bigger than traditional data sets), *Velocity* (the speed with which it is produced and available), *Variety* (of formats in particular), *Variability* (over time and diversity of sources), and *Volatility* (inconsistent levels of production) (Power, 2015).

The sheer amount and rich data variety that characterises the domain, as well as the data management necessary given the growing expansion of datasets and user-produced material, are beyond the capabilities of most existing support technologies. Databases, rules, models, and other conventionally applicable technologies and methodologies used in decision support systems were not meant to function with social media data in the majority of scenarios (Demirkan and Delen, 2013; Tsai, Lai, Chao and Vasilakos, 2015). Instead, they perform best with highly organised data. 95 percent of big data, on the other hand, is unstructured, necessitating the creation of new analytic tools and methodologies tailored to the characteristics of huge data sets (Gandomi and Haider, 2015). To drive future choices, big data analytics use various datasets from diverse array of related media and information and use predictive analytics for decoding the behavioural and decision-making patterns. Most analytics in tourism have focused on travel recommender systems (TRS), while early systems seldom utilised social media and were not intended for use by DMOs.

Kurashima et al. (2013) used the sequence of locations in geotagged photographs provided by visitors to find and recommend trip itineraries that may be tailored to preferences and time restrictions. Shi, Sherdyukov, Hanjalic, and Larson (2011) used geotagged Flickr images to find destinations that are suited to individual users' interests and are not usually the most popular landmarks. Similarly, Khotimah et al. (2014) proposed a TRS that harvested data from multiple social media platforms in Indonesia to provide a user-related recommendation, which may overcome the scarcity problem caused by users who rarely post, as well as the static nature of information in traditional systems Bao et al. (2015) did a comprehensive review of TRS in social networks that employ location-based data, but none of these are connected to DMO strategic decision-making. Cheng and Edwards (2015) used visual analytics on Sina Weibo (the "Chinese Twitter") data to provide destination managers with insights into the influence of travel news on potential Chinese customers' sentiments. Marine-Roig and Clavé (2015) proposed a five-step technique for collecting and analysing massive volumes of social data and photographs, which include the following steps: destination selection, web-hosting selection, data collection, pre-processing, and content analysis. Despite the fact that their research did not result in the development of a new analytics tool, their findings are immensely significant in the context of smart tourist design.

### 2.2 Role of Social Media in Tourist Decision Making

Given the intangible nature of travel services and the perceived risk throughout the decision-making process related to the trip, the influence of social media on customer behaviour has been extensively studied in the tourism and travel sector (Minazzi, 2015). Ayeh et al., 2013; Casaló et al., 2011; Filieri and McLeay, 2014; Parra-López et al., 2011). The use and impact of social media on travel information searches (Jacobsen and Munar, 2012; Xiang and Gretzel, 2010), attitudes and purchase intentions (Sparks et al., 2013; Vermeulen and Seegers, 2009), and travel decisions (Arsal et al., 2008; Sidali et al, 2008) also received empirical attention. Because of the widespread use of social media in different elements of tourist decision-making, a comprehensive study of the role that social media in visitors' information search and decision-making processes is required (Cox et al., 2009; Zeng and Gerritsen, 2014).

The research by Cox et al. (2009) was the first to address social media's involvement in trip planning and examining the function of user-generated content (UGC) sites in comparison to other information sources. According to the findings of this study, social media is primarily utilised after a location has been picked, particularly for information searches related to lodging and where to go inside the destination. UGC is regarded to be akin to offline recommendations or word-of-mouth (Buttle, 1998) and provides more authentic, up-to-date and believable information than other marketer-controlled sources or marketer-generated material (Liang et al., 2020; Zeng and Gerritsen, 2014). In comparison to more conventional sources, such as official and governmental tourist websites, information gained via social media is not always considered as trustworthy and dependable (Cox et al., 2009). This shows that social media should be used in conjunction with traditional sources of travel information rather than as a replacement. Tourists are increasingly gathering and combining information from a range of channels and sources in order to make an informed decision about travel components (Xiang et al., 2015). Tse (2013) used a case study approach to investigate the marketing function of social media in the hotel business, focusing on online communication and dissemination based on marketer-generated content. Schroeder and Pennington-Gray (2015) looked at crisis management alternatives and the influence of social media on foreign visitors' decision-making when a crisis occurs while they are travelling. Their research discovered that foreign travellers' willingness to use social media to look for crisis-related information is linked to their previous travel experience and risk perceptions. Chen et al. (2015) investigated the role of electronic word-of-mouth (eWOM) in the phases of information search, assessment, and purchase in consumers' decision-making related to online vacation purchasing.

Study conducted by Xiang and Gretzel (2010) revealed that social media plays a crucial role in the online tourism platform as a ubiquitous information source for travellers looking for destination-related information. Sparks and Browning (2011) investigated the influence of social media in hotel booking intent and perceptions of hotel trust. The findings demonstrated that social media information has complex framing impacts, such as valence and ratings that target consumers' booking intents and trust in an accepted hotel. Consumers utilise review intensity and valence, as well as message substance and style, to judge the reliability of the UGC (Filieri, 2016). Song and Yoo (2016) found that social media has a significant impact on visitors' purchasing decisions and pre-purchase selections.

According to Hudson and Thal (2013), social media is influential and valuable at all stages of the travel process (pre-trip, during-trip, and post-trip), as well as throughout the entire consumer decision-making journey (consideration, evaluation, purchase, and post-purchase stages) (Hudson and Thal, 2013; 2015). According to the researchers, tourist organisations have focused a large amount of emphasis on the contemplation and purchase stages. Consumers, on the other hand, might be heavily impacted by social media throughout the assessment and post-purchase stages. Previous research has highlighted the importance of social media in tourists' attitudes and behaviour intentions in the context of travel planning; however, little is currently known about the impact and role of social media throughout the entire decision-making process in a real and live experienced travel context rather than a hypothetical (what-if) travel context.

Furthermore, the majority of previous social media studies have focused on a specific aspect of travel, such as restaurants (Jeong and Jang, 2011; Mkono, 2012; Zhang et al., 2010), hotels (Lu et al., 2018; Varkaris and Neuhofer, 2017) and destination choices (Di Pietro et al., 2012; Tham et al., 2013). Information searches for some travel components (e.g. nightlife activities and restaurants) are more directly tied to social media than other components (e.g. cuisine attractions) (Xiang and Gretzel, 2010).

Cox et al. (2009) discovered that social networking sites are often utilised to aid in destination, lodging, and attraction selections throughout the information search and alternative evaluation phases of trip planning. These materials, on the other hand, are rarely utilised during the trip to learn about certain sites. Consumers tend to have diverse information search patterns based on the important travel components as well as the stages of the holiday decision-making process, according to Chen et al. (2015). Social media, in particular, plays a significant role in the pre-decision stage of the decision-making process. Fotis et al. (2011), on the other hand, discovered that social media is mostly utilised for reflecting and sharing travel experiences during the post-trip period. Furthermore, the study discovered that social media was seen as having the greatest influence on destination and lodging selections. The data also revealed that there are disparities in social media adoption and usage trends across national marketplaces, with cultural factors perhaps playing a role (Fotis et al., 2011; Gretzel et al., 2008).

The epistemological foundation of the study has been laid by using the Theory of Complexity by Edgar Morin(1990), which elucidates that uncertainty, randomness, indeterminacy and contradictions appear in complex networks not as residues to be eliminated but as signals to see the whole. The information exchange in social media is dynamic and random which poses challenges for the users to identify the causalities for framing decisions. The complexity lies in the notion of auto-causality which demands an external or recursive causality whereby the organizing process explains the actions and effects. The complexity in the present study evokes from the perils of pandemic and explosion of asymmetrical information over the social media. Therefore, the study would like to examine the nature of causality that exist between the information shared and the decision parameters in pre COVID-19 and post Wave-IICOVID-19 phases.

### 2.3 Research Questions

This study originated from the precarious condition confronting people all across the world in an unprecedented breakout of COVID-19 pandemic and the intense nationwide lockdowns and logistic embargos that escalated uncertainties in cross-globe mobility. Given the nature of disruption the researchers posited that tourists would access social media with more intensity to collate information and frame decisions. The COVID crisis grew exponentially while uncertainty and randomness governing Government decisions and healthcare service providers loomed large. The crisis-driven disruptions intensified as people were stagnated for a prolonged period of time outside their home nation. These were times to access genuine information from credible sources and sharing of the same. Studies focussing examination of information sharing to causally relate the nature of disruption and decision parameters under such intensified global disruption are scarce. The researchers questioned whether social media data could fill up this knowledge gap. Most of the tourism literature viewed social media as a marketing and branding platform without assessing how tourists interact, share information and frame decisions (Wang and Ye, 2018). Understanding the structure of information flow and locating influential information sources within the structure would strategically determine the components of decision making. The Tourism Tribe Facebook page (https://www.facebook.com/TourismTribe) was considered for this quasi-longitudinal study (pre COVID-19 and post Wave-II COVID-19 phase). Accordingly, the research questions were formulated as:

(1) Who were the most influential members in the Facebook page of Tourism Tribe in the pre COVID-19 and post Wave-II COVID-19 phases?

(2) What were the most influential words of information within the Tourism Tribe semantic network which evoked decisions during the pre-COVID-19 and post Wave-II COVID-19 phases?

## 3. Research Design

The process of how an individual's thoughts and decisions are moulded cannot be conceived by a logic-driven scientific technique, given the complexity of life, human acts, and experiences in reality. In contrast to a deductive technique, which is typically quite organised, an inductive approach that embraces the richness and depth of qualitative interpretative approaches allows the researcher to uncover unexpected results or information (Ryan, 2006). Hence, qualitative research method was used for the study. We used digital and visual ethnography to capture the sensory experience of tourists facing uncertainty and disruptions in decision framing. Growing number of ethnographic studies are addressing the embodied sensory experience related to new devices, media and content. Studies on haptic technologies (Pink et al., 2010) using kinaesthetic communication through smart devices on web-enabled platforms (Pink and Hjorth, 2012) have demonstrated the significance of sensory interpretation of reflexive knowledge. Visual Ethnography was chosen as it essentially addresses two

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paradigms: first, ‘a scientific and realist’ framework based on observational approaches to sociological inquiry (Collier and Collier 1986; Prosser 1998). This paradigm uses the visual materials as data and the epistemological structure demands objectivity and scientific validation. Second, ‘a phenomenological, sensory and non-representational approach’ which is concerned with the reflexivity and ways of knowing rather than with data collection (Pink 2013). Thus, visual ethnography as a reflexive, situated and collaborative practice necessitates critical and multisensory approaches and synchs with digital ethnography (Cox, Irving, and Wright 2015).

The study used the crawled data which came from the Tourism Tribe Facebook fan page. The raw crawled data was transcribed into a network matrix following the data filtration protocol. The study adopted normalized degree and betweenness centrality measures to analyse the Tourism Tribe Facebook network data. Text mining and visual analysis were deployed to extract words and images/ videos from members’ posts and constructed the semantic network matrices. Semantic network analysis is a method for determining the interrelationships between coded segments in the posts. Words that appear in several communications reveal generally shared concepts and patterns (Schnegg & Bernard, 1996) and are axially coded to fit the context. Each word is handled as a node in a semantic network, and the co-occurrence connection between words is represented as a link. The frequency with which two or more codes appear together determines the degree of connection between them (Jang & Barnett, 1994). A co-occurrence distribution for each code-pair link is utilised as an input for producing matrix data. The semantic networks were analyzed via a normalized degree centrality measure and visualized. Images and videos posted by the members during the study period were also mined out for analysis. To execute the social media analytics the study used a number of application tools. Rapidminer Studio 9.10 was used to stream in data from Facebook. Qualitative assessment and semantic network analysis of the data was done using MaxQda 2020. This study collected data from the member comments section of the Tourism Tribe Facebook fan page during the 1st July to 31st July, 2019(before the onset of COVID-19 pandemic) and then 1st July to 31st July, 2021 (post-Wave-II COVID-19).

The study was based on a proposition that social media analytics might be useful in assessing decision making under disruptive turbulence and uncertainty. The population for the study is the social media users of the Tourism Tribe Facebook Fan Page. The population has high volatility in terms of their digital footprint and hence cannot be clearly defined (finite) at a given point of time. Therefore, the sampling plan for the study used the Lemeshow formula:

$$n = \frac{Z\alpha^2 \ x \ P \ x \ Q}{L^2}$$

where,
n = sample size required
Zα = standard distribution with α at 5% = 1.96
P = Prevalence of Outcome, 50% for unknown population
Q = 1 – P
L = Level of accuracy, 10%
Therefore, the required sample size for the study was computed as:

$$n = \frac{(1.96)^2 \ x \ (0.5) \ x \ (0.5)}{(0.1)^2} = 96.4$$

The minimum sample size required from each population was 97. The study decided to fix the sample size to 100 from each population (Tourism Tribe Facebook Fan Page)

## 4. Data Analysis

The dataset for Tourism Tribe Facebook page has been represented in Table-1 (both pre and during COVID-19 phases as fixed). The number of participants involved in the conversation within the Tourism Tribe Facebook community before and during COVID-19 were 4987 and 5812, while the total number of comments before and during COVID-19 were 6734 and 5643 respectively, which is equivalent to approximately 250,000 words. The data were purified (removal of non-English comments, emoticons and other stop-words) and 2109 and 2893 comments (pre and during COVID-19 phase respectively) were retained in the analytical framework. The visuals shared in the form of images and videos were also used for analysis. A total of 197 graphical images and 28 videos showcasing the mood of pre COVID-19 phase were streamed in, while for the post Wave-II COVID-19 phase the study could manage 76 graphical images and 29 videos. The study used 100 samples each for the two phases of the study. Members with most number of posts followed by comments, like and share were included in the sampling frame.

**Table-1: Tourism Tribe Facebook Fan Page Dataset in Pre and During COVID-19 Phases**

| Period of Data Collection | Pre-COVID-19 1st July to 31st July, 2019 | post-Wave-II COVID-19 wave 1stJuly to 31stJuly, 2021 |
|---|---|---|
| Number of Facebook Page member | 4987 | 5812 |
| Number of comments | 2109 | 2893 |

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Insights to the decision making could be identified based on the speed of information dissemination triggered by the most influential actors of a virtual community with respect to a target phenomenon (Yoo, Rand, Eftekhar, and Rabinovich, 2016). Table-2 compares normalized degree centralities of the Tourism Tribe Facebook Page members in pre and during COVID-19 periods (as specified in the study). This study summarized the top five members (accounts) with high degree centrality. The Facebook account of the Tourism Tribe exhibited the highest degree centralities for both in pre-COVID-19 and post Wave-II COVID-19 phases followed by four individual members. while the next four leading Facebook accounts are individual Facebook users. Karatzias ranked highest among the individuals in degree centrality followed by Zenda, Vilas and Itama during the pre-COVID-19 information sharing. Karatzias shared a lot of information on ethno-cultural and heritage tourism and advocated spiritual alignment with travel decisions. He endorsed himself as a lone-traveller. Itama and Vilas exhibited keen interest on leisure and recreational opportunities. Zenda searched for information about destinations with festivals and carnivals and shared her experience of Rio Festival through exotic visuals and video clips. During COVID-19 phase of the study, Cassius, from Spain, was ranked highest in individual normalized degree centrality and shared information on destinations recovering from the trauma of the pandemic. Liam endorsed the concept of 'responsible tourism' in post-pandemic phase and shared her predictions on the possible choice of new destinations for the tourists. Karatzias, ranked fourth in degree centrality, explored the Government policies to balance out visit intensity and health issues and shared information on vaccination status and entry & exit parameters across the destinations in Europe. Sekharan, located in Indianapolis, shared his first trip experience in about one year as he flew to the Bahamas. Karatzias exhibited the strongest diffusion power in the Tourism Tribe network providing actionable insights in decision making both in the pre and post Wave-II of COVID-19 pandemic. The findings in Table 2 disclosed that the magnitude of the normalized degree centrality value of Tourism Tribe network as much stronger during the post-Wave-II of the pandemic compared to the pre-pandemic period. This result is indicative of Tourism Tribe's intent to communicate with its Facebook members with accelerated information on resurgence of tourism activities targeted to support decisions.

**Table-2: Comparing the Normalized Degree Centralities of Tourism Tribe Facebook Page Members in the Pre and Post Wave-II of COVID-19 Pandemic.**

| Rank | Pre-COVID-19 | | post-Wave-II COVID-19 wave | |
|---|---|---|---|---|
| | Facebook Member | Normalized Degree Centrality | Facebook Member | Normalized Degree Centrality |
| 1 | Tourism Tribe Facebook Network | 2.628 | Tourism Tribe Facebook Network | 7.982 |
| 2 | Karatzias | 0.174 | Cassius | 0.721 |

| | | | | |
|---|---|---|---|---|
| 3 | Zenda | 0.092 | Liam | 0.672 |
| 4 | Vilas | 0.079 | Karatzias | 0.601 |
| 5 | Itama | 0.054 | Sekharan | 0.495 |

The boundary spanner is a special actor with a high betweenness centrality score who may be thought of as a controller of information between other actors (Newman, 2005). A boundary spanner may broaden social connections by dispersing information from multiple communities(Hagen et al., 2017; Snijders and Borgatti, 1999) and may be thought of as a regulator for information transmission and a controller for information flow between distinct people and/or organisations.

Table 3 compares the normalized betweenness centralities of Tourism Tribe Facebook network members in the pre and post Wave-II COVID-19 periods. It was Karatzias who shared the maximum normalized betweenness centrality measure in both the pre and post Wave-II COVID-19 periods and has emerged as the most influential member in decision framing.

**Table-3: Comparing the Normalized Betweenness Centralities of Tourism Tribe Facebook Page Members in the Pre and Post Wave-II of COVID-19 Pandemic**

| Rank | Pre-COVID-19 | | Post-Wave-II COVID-19 | |
|---|---|---|---|---|
| | Facebook Member | Normalized Degree Centrality | Facebook Member | Normalized Degree Centrality |
| 1 | Karatzias | 18.732 | Karatzias | 14.291 |
| 2 | Ravi | 9.817 | Mathews | 8.093 |
| 3 | Lynda | 7.187 | Scot | 5.443 |
| 4 | Bhumika | 5.091 | Ken | 2.992 |
| 5 | Erica | 3.116 | Piramani | 1.087 |

The semantic networks for the pre COVID-19 and post WAVE-II COVID-19 phases were constructed using the MAXMaps (MAXQda). The posts from the most influential members of the Tourism Tribe(based on normalized degree centralities and betweenness centralities), for both the periods under study, were axially coded for categorisation and clustering. The study adopted the coding models prescribed by Hallahan (2008), Park & Reber (2008) and Edman (2010) which emphasized on organization-public relationships. The code classification and clustering were grounded on the dialogic communication theory (Kent and Taylor, 1998, 2003).

A Facebook page (in this case the Facebook Page of the Tourism Tribe) is considered as a living organisation with in-built health and vitality, and, can change and sustain itself through altering circumstances, even disruptions. Imposed changes are not required because of the organic adaptability. The coding focused on member participation,

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coherence and awareness. The semantic networks were drawn on code-proximity and co-occurrences. Fig. 1 and Fig. 2 represented the semantic networks for the pre COVID and post Wave-II Covid-19 phase respectively.

**Fig.1: Semantic Network of Travel Decision Components in Pre-COVID-19 Phase**

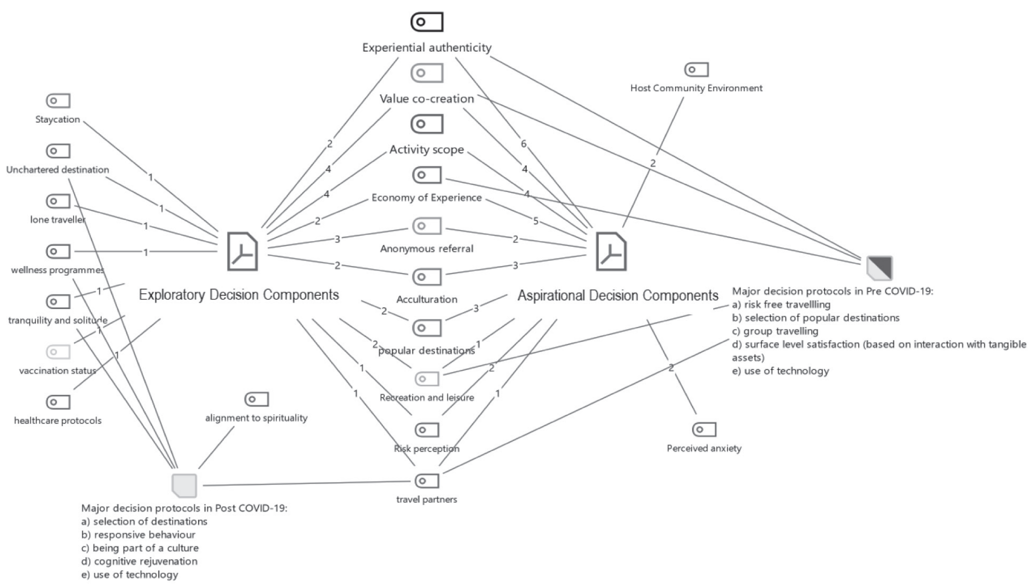
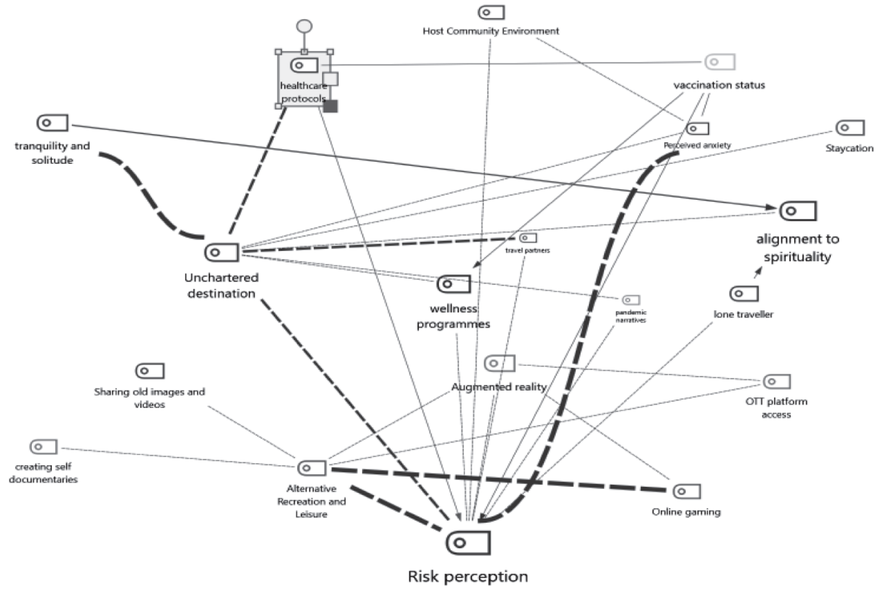



**Fig.2: Semantic Network of Travel Decision Components in Post Wave-II COVID-19 Phase**




Two clusters, based on the code co-occurrence and code proximity, could be identified and named as 'aspirational decision components' (primarily having focus on pre COVID-19 phase) and 'exploratory decision components' (combination of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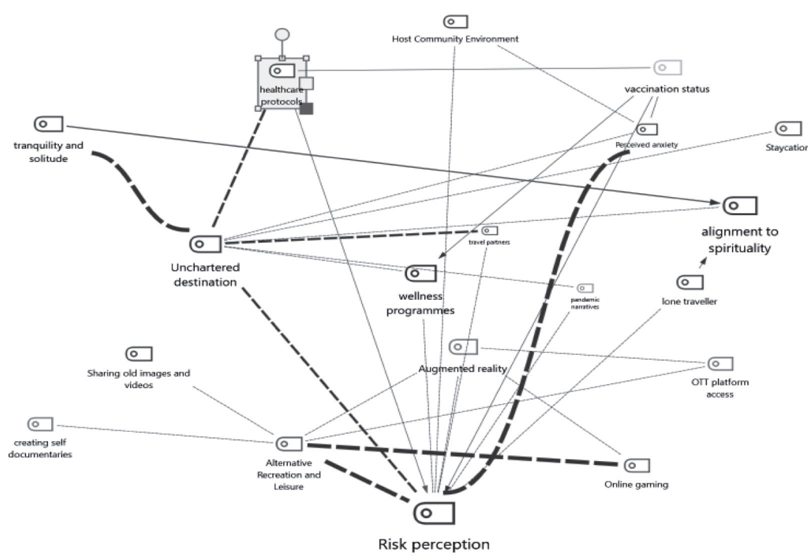
pre COVID-19 and COVID-19 phases). Each identified cluster was considered as an individual case. A Two-cases model was used to visualize the extent to which the codes, related to the discussions on the Tourism Tribe Facebook members' platform, occur in two cases or only in one case. Fig.1 represents the Two-Case model. The frequencies of the codes per case and their memos were integrated. The model clearly revealed a set of unique decision components in post Wave-II COVID-19 phase, namely, 'vaccination status', 'healthcare protocols', 'wellness programme', 'lone traveller', 'staycation' and 'unchartered destinations'. These decision components are apprehensive in nature and intentionally exploratory. The other set of decision components derived from the posts of the members during the pre COVID-19 phase of the study demonstrated a relationship with the codes derived from the posts during post Wave-II COVID-19 phase. Major decision components revolved around 'experiential authenticity', 'value co-creation', 'acculturation', and 'activity scope'; while 'travel partners', 'recreation and leisure', 'popular destination' and 'anonymous refer al' were considered significant too. There were few posts hinting towards 'economy of experience' as decision instrument.

**Fig.3: The Two-Case Code-Cluster Model**




Next, we used the images and videos for analysis. We used Orange 3.31; a Python wrapped C++ software application that helps in qualitative data visualization based on machine-learning embedding. We have two separate collections (based on the timeline of the study) of Facebook images and videos posted and shared in the Tourism Tribe Facebook page by the members and the organization itself. The Image Analytics function was used which allowed to embed the images from both still and video graphics. The objective was to transform the raw images into their

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vector representations using deep neural network which has been trained on millions of real-life images and embed the images and videos into a multi-dimensional feature space. The embedding allowed to assign image descriptors or numeric indicators that describe the content of the images and videos. For clustering purpose, we used the cosine distance parameter. Fig.4 represented the sequence of widget-linkages in Orange to perform clustering. Fig. 5 and Fig. 6 represented the clusters. For the pre COVID phase of the study we could identify 3 clusters which captured 'the activity scope', 'the landscape and eco-interaction' and 'acculturation and value-co-creation'. In contrast, the post Wave-II Covid phase identified 2 distinct clusters. The first cluster represented the 'inherent urge for tourists and the industry to bounce back' while the second cluster embedded the 'apprehensive perception of tourists'. However, the inherent urge for the tourists to re-initiate their ventures reflected a big part of their mentality in the pre COVID stage.

**Fig. 4: The Orange Widget Sequence for Hierarchical Clustering of Images and Videos**

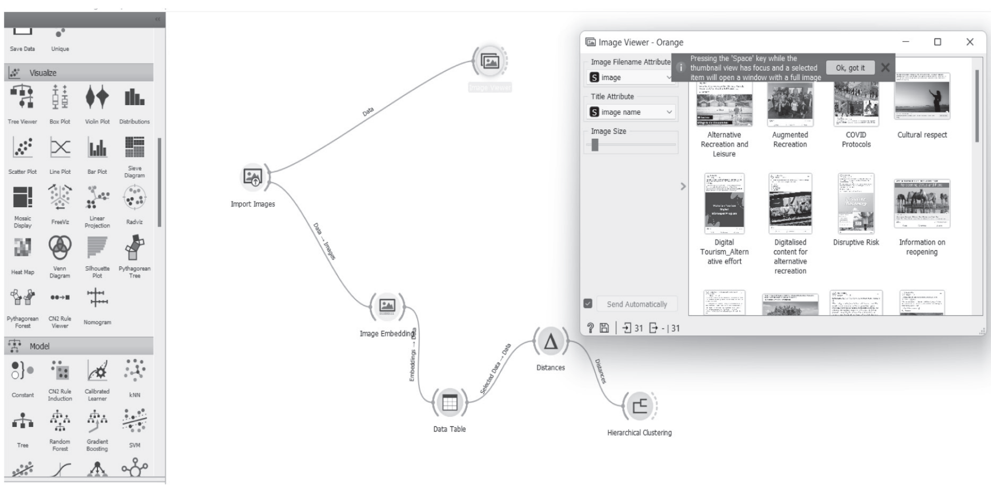


**Fig.5: The Pre COVID Phase Clustering of Images and Videos**

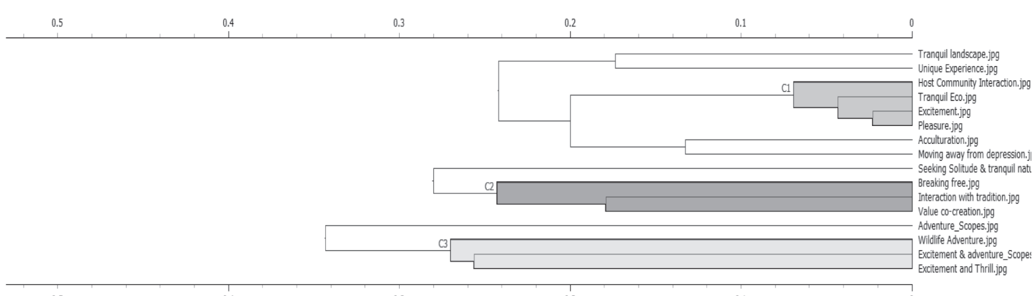



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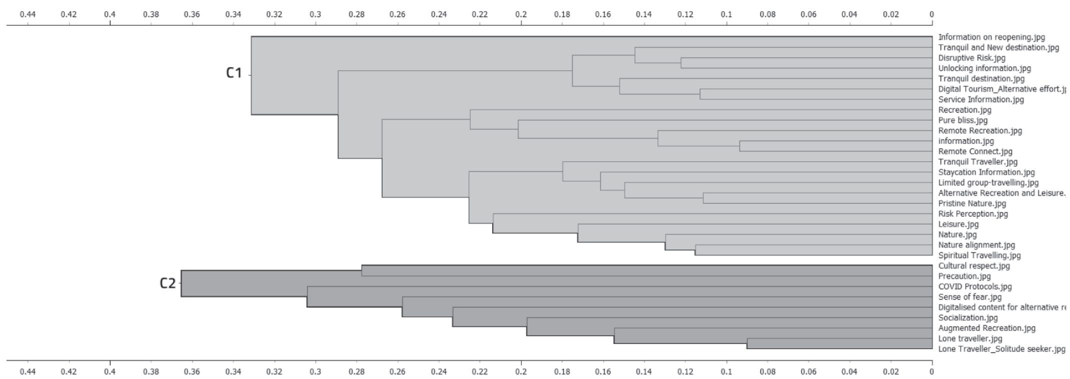
**Fig.6: The Post Wave-II COVID Phase Clustering of Images and Videos**




The last part of the analysis deployed the image classification and predictive analysis to check the accuracy of prediction of decision components. We used Orange 3.31 for the purpose. The Logistic Regression results were represented in Table-4. The results confirmed a better classification of decision components in post Wave-II phase of study compared to the pre COVID phase of the study. The AUC value (0.711) is significant for prediction purpose. The precision (0.670) confirmed the robustness of the model and the recall value (0.677) established the models ability to predict positive classes. The Silhouette analysis reinforced the quality of classification of decision components in the post Wave-II phase of the study.

**Table-4: Predictive Analysis Based on Image and Video Classification**

| **Model** – Logistic Regression | **Pre COVID phase** | **Post Wave-II Covid phase** |
|---|---|---|
| AUC | 0.421 | 0.711 |
| CA | 0.398 | 0.677 |
| F1 | 0373 | 0.671 |
| Precision | 0.335 | 0.670 |
| Recall | 0.377 | 0.677 |

**Fig.7: Silhouette Analysis (Post Wave-II COVID Phase** **Fig.8: Silhouette Analysis (Pre COVID Phase**

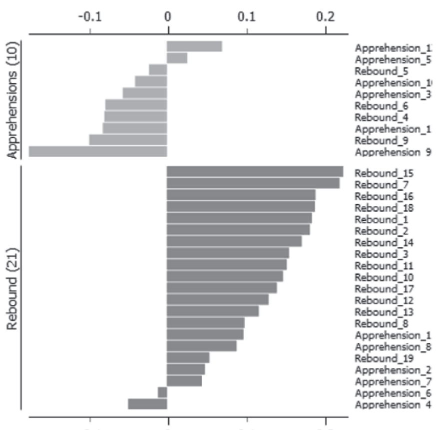



Fig.7: Silhouette analysis (post Wave-II COVID Phase

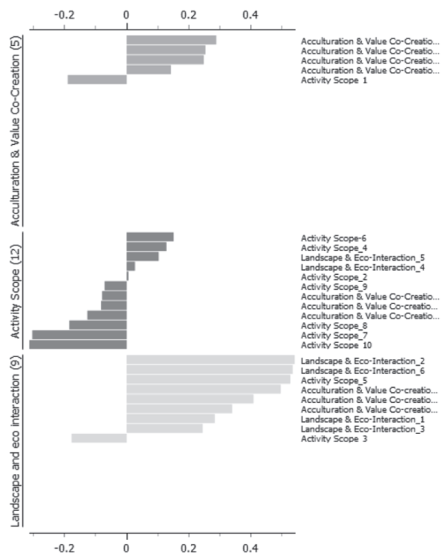



Fig.8: Silhouette analysis (pre COVID Phase

## 5. Conclusion and Discussion

Information exchange during tourism crisis is of paramount importance as the impact of the crisis may be disproportionate to the actual disruptive impacts. Social media, by virtue of its ubiquitous nature, generates voluminous data. This tends to escalate during disruption and crisis situation as network members try to mine out accurate information that facilitates decision making. This has given rise to a host of applications, known as social media analytics, which can stream-in traceable social media data irrespective of geo-location. Social media analytics help users to identify the communication patterns in the context of the disruption and digs out the causality that exists between the disruptive phenomenon, information exchange and decision outcomes.

## 6. Academic Implications

Information exchange and assimilation over social media is a complex phenomenon. The complexity multiplies under conditions of uncontrolled disruptions. The has been an growing academic interest involving social media and use of social media analytics in tourism crisis, however, the majority of the work includes post-hoc anecdotal cases barring a few empirical attempts (Ketter,2016). A few studies were conducted in tourism disruption context by streaming data from Twitter network and Instagram posts (Park, Jang and Ok, 2016; Park, Kim, and Ok, 2017; Park, Ok, and Chae,

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2016). Facebook has different implications for information exchange compared to Twitter and Instagarm. While Twitter emancipates sentiments and Instagram captures visual emotions, Facebook allows more intensive member engagement in the form of content sharing. This study utilized data (text, visuals and videos) generated from the membership posts of Tourism Tribe Facebook page from two separate periods out of which one period was identified as disruptive. The data was streamed and processed by following the application protocol of the social media analytics. The study identified the most influential members (boundary spanners) in the network in both phases of the study and established the semantic networks of axial codes. The codes represented the decision components derived out of the conversational and visual exchanges between members of the Tourism Tribe Facebook page. This part of the study reinforced the notion of SMCC theory of identifying the most influential members in a network organization who could effectively generate disruptive response to manage recovery phases (Austin et al., 2012; Jin et al., 2014). The study used Edgar Morin's Theory of Complexity to understand the uncertainty, randomness, indeterminacy and contradictions arising out of complex exchange of information in the Tourism Tribe network, particularly during the post Wave-II COVID-19 phase of study. The Two-Case model revealed the complicacy in decision making as exploratory and aspirational decision components converged. COVID-19 inflicted disruption was the eco-auto-causality factor that did trigger the organizing process of the information which was based on asymmetrical information. The convergence of the decision components in the semantic network confirmed the uncertainty, indeterminacy and randomness in decision making under disruptive conditions. The image and video analysis provided in-depth understanding about the decision components. The image and video data in the pre COVID phase churned out three distinctive clusters, namely, 'the activity scope', 'the landscape and eco-interaction' and 'acculturation and value-co-creation', however, the classification model used for predictive analysis did not provide enough conviction. The post Wave-II COVID phase of the study presented a binary classification of decision components, namely, 'inherent urge for tourists and the industry to bounce back' and 'apprehensive perception of tourists'. The classification model supported an acceptable predictive quality.

## 7. Practical implications

The study provides implications for the industry, particularly, in the context of managing the adverse impact of information flow in disruptive environment. The findings have identified the most influential members in the Tourism Tribe Facebook network based on normalized degree and betweenness centralities which depicted their preferences, interests and predictions. The set of preferences, interests and predictions of the most influential members in the network forms the decision components. It offers the service designers and marketing campaigners with rich insights into the perceptual space of tourists and their anticipated travel behaviour. The marketers can specifically target the influencers or the opinion leaders to break through the uncertainties and indeterminacy of tourists during period of disruptions. They can apprehend the alternative form of recreation that could engage the tourists during periods of stagnancy and immobility.

The semantic network analysis reveals the code-clusters that represent the major issues in decision making, particularly in the post Wave-II COVID-19 phase as compared to the pre COVID-19 phase. For instance, post Wave-II COVID phase evoked 'risk perception' as the major decision element which was found to be associated with 'perceived anxiety' presumably spinning out of risk and uncertainty. The search for information about alternative means of recreation and alternative travel destinations was also in stark contrast to the pre COVID phase which exchanged information about 'value co-creation', 'excitement' and 'souvenir shopping'. Disruption period must be closely monitored by digital platforms, like Tourism Tribe, and provide authenticate information to its members that support decision making.

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