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Analysis of tourism destination centrality and structural properties of tourism system: Complex network perspective

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Tourism has become a new way of living with the living standard development. This study analyses the tourism destination centrality and spatial patterns of the tourism system using complex network analysis. An analysis of 245 destinations in the South of Thailand has found that the network has a low network density, large average path length and low clustering coefficient. Some a small number of high-degree destinations connect to each other, while most connect to others with a low degree. The network comprises 18 subnetworks that destinations densely connect to others in the same subnetwork but sparsely connect to others in different ones. Destinations play different roles in the network based on which a centrality measure is used, degree, betweenness and closeness centrality. 31 destinations with high hub and authority centrality are the centers playing as hubs of the network. The study's findings draw implications for the sector.

1. Introduction

The tourism industry is a powerful driver of the economic growth of travel destinations and an engine of financial crisis (Peng et al., 2023; Fahimi et al., 2018). Tourism has become a new way of living because of the standard development. Traditional tourism mode does not well meet the needs of today's tourists as the tourism demand has diverse trends. Many tourists pursue an experience and satisfaction during the tour to improve their experience. They need to plan their itinerary before the tour. With the preferences and limits in money and time of tourists, they always search for information about trips from travel blogs or friends to arrange their itineraries. Itinerary planning is a time-consuming task that is difficult to find worthy destinations visiting and schedule tours. Thus, the tour route planning model is used to design a high-quality tour route for tourists. (Wu et al., 2017).

Tourism route planning builds a tourism system (hereinafter called "network"). The tourism network consists of travelling destinations or places (nodes) that are interconnected by travel routes (arcs). The node with the highest connection is the center of the network (Hub) that network connectivity. Nodes in the same area tend to be connected to each other, which reflects the operation of the travel company. Identifying travelling places that are the centrality of tourism is one of the basic management needs in sustainable business strategies. Travelling centrality is determined by the tourism company. Therefore, this research analyses the travelling of the tourism network using the South of Thailand as a case study. It is because more than 40% of tourism revenue in Thailand comes from the South of Thailand (Nonthapot & Srichaiyo, 2017). An analysis is conducted. A hub has a different definition in airports, ports and travelling places. The travelling centrality is determined to pass at least one point between the origin and destination. Due to Thailand's policy of raising the level of being a tourism center of Asia and the Pacific by setting up a tourism network system in the southern region of the country. This will be information to support the planning of transportation and tourism logistics systems in Thailand. Therefore, this study uses the different measures of social networks to analyze the spatial pattern and structural properties of the network. The hub and authority

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centrality measures are used to identify the travel destination centrality. The main innovation of this article is the first analysis of travelling destination centrality in the tourism system, which can explain the dynamics of the tourism industry.

The rest of this paper is structured as follows. Section 2 presents the literature review on the tourism system and tourism network analysis. Section 3 explains the research methodology and data, while Sections 4 and 5 provide the research findings and result discussion. This paper ends with the conclusion and implications for future research directions.

2. Literature review

2.1 Tourism market

2020 was one of the worst years in global economic history and tourism due to the adverse impacts of COVID-19. However, in late 2022, global international travel was expected to be 65% of pre-pandemic. The recovery of tourism worldwide is led by Europe, America and the Middle East, which is boosted by high demand from the regions with pandemic restrictions removed (Labine-Romain et al., 2022). The revenue in the tourism market worldwide was expected to be US$854.80 billion in 2023 with an annual growth rate of 4.41%. This results in a market volume of US$1,016.00 billion by 2027. The largest segment of the market is hotels followed by package holidays, vacation rentals, camping and cruises (Statista, 2023).

In 2018, the tourism market in Asia-Pacific had the fastest growth in the world (Aidjanovich, 2023). The market size of the travel and tourism sector in this region reached $163 billion in 2021. Key travel destinations among tourists in the region include Thailand, Singapore, Vietnam and Hong Kong. Booking Holding Inc, Expedia, China Tourism Duty-Free and Trip.com are the major companies that have a strong presence in the market. The annual growth rate of the market in this region was a negative 18% during 2017-2021 (Globaldata, 2022). However, the market was projected to reach US$280.20 billion in 2023. An expected revenue had an annual growth rate of 7.66%, leading to a projected market volume of US$376.50 billion by 2027. Hotels have the largest market segment followed by package holidays, vacation rentals, camping and cruises (Statista, 2023).

Thailand's tourism is one of the most popular vacation destinations in the world. The tourism industry is a core pillar of Thailand's economy, contributing 20 % of the gross domestic product (GDP) in 2019 (NESDC, 2020). This makes Thailand rank in the top 3 in the Asia-Pacific region. Thailand has strong price competitiveness and abundant natural and cultural resources, leading to it having a high ability to attract foreign tourists every year. Thailand's international tourism income increased to US$60,521 million in 2019, ranking as the highest tourism earner in this region. Although Thailand does not have a high-income economy, it stands out in the sector worldwide (Ferry et al., 2023). This indicates that Thailand should get more attention for conducting academic research.

2.2 Tourism network analysis

A network can be analysed from the network (global) level to a vertex (local) level. At the global level, an analysis is conducted to explore the structural properties of a network, and subgroups and groups based on different measures and methods. Local analysis describes vertices by various measures to identify the most relevant ones based on the measure. Based on the network theory, an analysis of the tourism network is carried out to the collective features of organisational behavior, coordination and constraints (Pavlovich, 2003; Seok et al., 2021). Tourism is a networked and geographically dispersed industry that comprises a set of personal relationships and businesses. The network's concepts can analyse, conceptualize and visualize the relationships. Thus, network analysis is an appropriate approach for tourism network analysis (Gonzalez-Diaz et al., 2015).

The most popular method used to analyse tourism networks in recent years is social network analysis (SNA). SNA is a diagnostic method for analysing data about collaboration patterns that is relationships among vertices or actors within the social structure connecting actors in different groups (Hu & Racherla, 2008). SNA is used to investigate tourism information networks, destination marketing and tourism management (Wang & Xiang, 2007; Bhat & Milne, 2008; Feng et al., 2013).

In recent years, there have been many studies analysing tourism networks using social network analysis (SNA). Leung et al. (2012) analysed the overseas tourist movement patterns in Beijing during the Olympics in 2008. Wäsche (2015) analysed cooperative relations among organizations in an informal sports tourism network in a German community and its surrounding area. Tran et al. (2016) analysed relationships between entities in Hanoi tourism services distribution channels. Zeng (2018) identified the characteristics and network patterns of Chinese tourist flows in Japan at inter destination level. Lozano and Gutiérrez (2018) analysed the flows of the global tourism network (GTN) to investigate the structure and integration between source and destination markets. Kc et al. (2019b) and KC et al. (2019a) investigated the effects of social influence, network characteristics, and entrepreneurial motivations of wildlife tourism microentrepreneur network.

In the last few years, Chung et al. (2020) analysed the global tourism networks' structure and found that the networks are highly consolidated over time. Reducing transaction costs is important to attract international tourists more than cultural and natural attractions. Seok et al. (2021) investigated the changes and characteristics of the structure and international tourism network. Valeri and Baggio (2021) analysed the relationships among tourist enterprises that affect the organizational assets of the Italian travel system. Gan et al. (2021) examined the characteristics associated with the spatial network structure of the tourism economy in the Urban Agglomeration in the middle reaches of the Yangtze River. Ledesma González et al. (2021) analysed the structural properties of the networks of three tourist destinations, focusing on the degree centrality indicator for socio-centric networks and asymmetrical relationships to obtain the indegree (prestige) and outdegree (influence). Yang et al. (2022) analysed the spatial network structure of tourism efficiency in China.

In the Thai tourism industry, it can be considered that there is continuous expansion of the sample. Moreover, under the promotion of the Thai government to increase the number of foreign tourists in Thailand to more than 40 million by 2023. For this reason, the determination of the network and geographic distribution of tourists that represent the relationship between personnel and businesses is still limited in the Thai tourism area. And there is still no relationship study with the tourism network of southern Thailand. Moreover, the above studies focus mainly on the structural properties of tourism networks, which is an analysis of the global level. Only a few studies analyse at local level by considering individual tourism destinations. Moreover, limited research identifies the roles that tourism destinations play in the networks and the lack of research analyses the centrality of the destinations. These will be addressed in the present study.

3. Methodology

This section the research mythology of an analysis of the tourism network using complex network analysis. The tourism network studied is considered as a binary directed graph, *G* (*V, E*), consisting of the set of nodes (tourism destinations), $V; V=\{v_i=1,\ 2,\ldots n\}$, and the set of edges or links (tourism routes), $E; E=\{e_i=1,\ 2,\ldots m\}$. The network consists of 245 destinations connected by 401 routes. The packages will be served to people in 2023. Various measures of complex network analysis used to analyse the structural properties and spatial pattern of the network as well as the role of the tourism destinations (Table 1). The hub and authority centrality measures are used to analyse the tourism destination centrality.

Table 1
The measures of complex network analysis are used to analyse the tourism network studied.

	Measure	Description	Equation
Global level	*Density*	*Fraction of the number of links that a network has and to the maximum possible number of links.*	$\rho(G)=\frac{m(G)}{n(n-1)}$
	Clustering coefficient	*Proportion of the number of links between the nodes within its neighbourhood to the possible number of links that exist between them.*	$C=\sum_{i=1}^{n}\frac{2E_i}{k_i(k_i-1)}$
	Average path length	*The average number of links along the shortest path for all possible pairs of nodes.*	$L=\frac{1}{n(n-1)}\sum_{i\neq j}^{n} d_{ij}$
	Assortativity	*The proportion of the number of links between nodes with the same degree*	$r=\frac{\sum_{jk} jk\left(e_{ik}-q_j q_k\right)}{\sigma_q^2}$
	Modularity	*Partitioning links within the groups relative to the expected proportion of all links placed randomly.*	$Q=\frac{\sum_{i,j}\left[A_{ij}-P_{ij}\right]\cdot\delta\left(g_i,g_j\right)}{2m}$
Local level	*Degree centrality*	*A sum of the number of links that a node has.*	$C_D(i)=\sum_{j=1}^{n} a_{ij}$
	Betweenness centrality	*Sum of the fraction of the total number of shortest paths from node s to node t passing through node i. to the total number of shortest paths from node s to node t.*	$C_B(i)=\sum_{s\neq i\neq t}\frac{\sigma_{st}(i)}{\sigma_{st}}$
	Closeness centrality	*Inverse of the shortest paths from a node to all other nodes.*	$C_C(i)=\sum_{i\neq j}^{n}\frac{1}{d_{ij}}$

where:

n = number of nodes,

m = number of links,
k = degree of a node,
d_{ij} = the number of links from nodes i to j
$\sigma_{st}(i)$ = fraction of the total number of shortest paths from node s to node t passing through node i,
σ_{st} = total number of shortest paths from node s to node t.
a_{ij} = a binary, is one if node i and node j are linked, zero otherwise.

3.2 Hubs and authority centrality

Hubs and authorities are a natural generalization of eigenvector centrality analysing the node's effect in a network and allocating relative scores to all nodes (Jeon et al., 2019). Each node must have both a hub and an authority score. A high node has many good authorities, and a node with high authority receives from many good hubs. Therefore, the hub score is proportional to the authority scores of the nodes on the outgoing links, and the authority score of a node is proportional to the sum of the hub scores of the nodes on the incoming links. Calculating hubs and authorities utilises an iterative algorithm. For each node p, a non-negative *authority weight* (x^p) and a non-negative *hub weight* (y^p), are collectively defined where the set of weights x^p as a vector x, and the set of weights y^p as a vector y. The weights of hubs and authorities are normalised as to maintain $\sum_{p\in S_\sigma}\left(x^p\right)^2=1$ and $\sum_{p\in S_\sigma}\left(y^p\right)^2=1$. A better authority has a larger x^p, and A better hub has a larger y^p (Jeon et al., 2019).

Hubs and authorities have reciprocal reinforcement relations as follows. If node p connects to many nodes having large x values, it receives a large y value. This signifies that the definition of the two equations on the weights is denoted by operations Ψ and Φ. If x^p and y^p are calculated from the above equation, Ψ operation updates the x-weights as:

$$x^p \leftarrow \sum_{q:(q,p)\in E} y^q \tag{1}$$

The Φ operation updates the y-weights as:

$$y^p \leftarrow \sum_{q:(q,p)\in E} x^q \tag{2}$$

Thus, Ψ and Φ are primary tools that reinforce hubs and authorities. This study uses the hub and authority centrality to analyse the centrality of tourism destinations. The above measures are applied to the tourism network studied. Network density is used to analyse network work connectivity level. A network with low density is a sparsely connected network. A high-density network is a compact network (Ducruet, 2020). The clustering coefficient is used to analyse the intra-connection among nodes within the network. The average path length is applied to analyse the efficiency of tourism information or mass tourist transport in the network. Modularity is used to analyse the strength of the network divided into the communities of subnetworks, reflecting the community structure of the network. Assortativity is used to analyse the tendency of nodes with the same degree to connect to each other. Local analysis is analysed using degree centrality, betweenness centrality and closeness centrality in order to identify the roles that nodes play in the network. Degree centrality is used to identify the importance of nodes controlling network connectivity. Betweenness centrality is used to identify the node with considerable influence over the network as it plays the bridging role. Closeness centrality is used to analyse a node that can spread the tourism information the quickest since it is the closest to all others in the network, implying a node has high reachability.

Analysis of this study uses the secondary data collected from the websites of tourism agencies and companies, consisting of 100 tourism packages covering 245 tourism destinations in the South of Thailand. The packages are operated and serviced by many companies, which are planned to service tourists in 2023. Note that the data set was collected in early 2023, and any cancellations and schedules are not updated and considered. This study defines tourism destinations as stops on trips, such as bays, beaches, islands and places. An analysis is conducted using R statistical software.

4. Empirical analysis results and discussion

Using complex network analysis, this study investigates the structural properties of the tourism network both at the network and destination levels. The study also analyses the centrality of the destinations.

4.1 Network properties

Fig. 1 shows the graph of the tourism network with 245 destinations connected by 401 links (tourism routes). The network is directed, with destinations are connected by links in a direct way. The network consists of many clusters (subnetworks). Some subnetworks are not connected to the other subnetworks. This is because tourism companies may design a short-duration tour (1-day trip) with a few destinations. This mostly is a tour visiting islands without mainland activity. Destinations in the two big subnetworks comprise destinations in the land and islands. Four links connect the two subnetworks through Ko Klang (KKL), including the routes Pakbara Pier (PAP)-KKL, Ko Lipe (KOP)-KKL, KKL- Mahathat Laem Sak Temple (MLS) and KKL- Khao Khanab Nam (KKN). This indicates that KKL is an intermediary destination of a connection between the two biggest subnetworks.

The network has a density of 0.0067 which is relatively low, a typical aspect of an observed network. This reflects that about 0.67% of links that the network has, connect destinations to the network work. The low density also indicates that destinations are not connected to all others in the network, signifying that the network is sparse. Destinations in the network do not have tight relationships.

The network has a clustering coefficient of approximately 0.192 which is relatively low, indicating that the network has a low intra-connection among tourism destinations. This reflects that there are not many destinations that have first-order neighbours that are well-connected with one another (Viljoen & Joubert, 2016). A low clustering coefficient of the network is also caused by tourism companies not opening direct services to relatively close destinations or on the already-existing tourism routes to reduce costs and maximize profit (Guo et al., 2017). In addition, the companies would not go to operate new tourism routes. They usually use the common routes.

The average path length of the overall tourism network is 6.770 relatively high, reflecting that the tourism services needed are achieved in at least six or seven connection steps (links). A high average path length of the network also indicates that the network has a low efficiency of connection between destinations, leading to a high tourism transit cost.

Assortativity reflects the tendency of destinations with the same property to connect to each other, reflecting the preferential attachment The overall assortativity of the network is positive, reflecting that destinations with similar degrees tend to be connected to each other but less connect to destinations with a different degree. The network has an assortativity of approximately 0.118, indicating that only 11.80% of destinations with similar degrees connect to each other. The rest tend to be connected to others with different degrees.

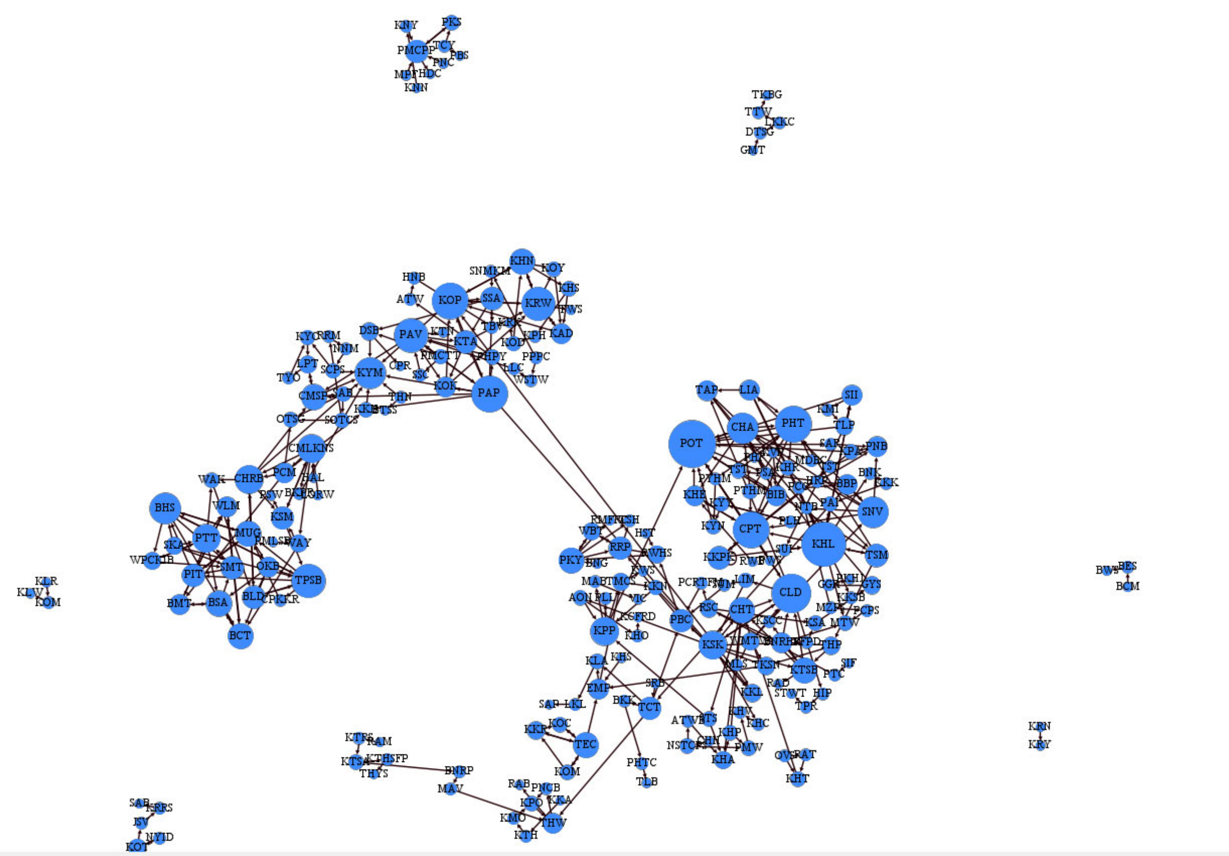


Fig. 1. Graph of the tourism network in the South of Thailand

Modularity clusters the tourism destinations in the network into different clusters (groups or subnetworks). The measure clusters destinations into the subnetworks randomly, leading to the network having 18 subnetworks. Modularity measures the strength of the tourism network divided into clusters (subnetworks). High modularity indicates there are dense connections between tourism destinations. The network has a modularity of 0.792, indicating that destinations densely connect to others within subnetworks but sparsely connect to destinations in other subnetworks. Fig. 2 shows that the network is divided into 18 subnetworks with different sizes.

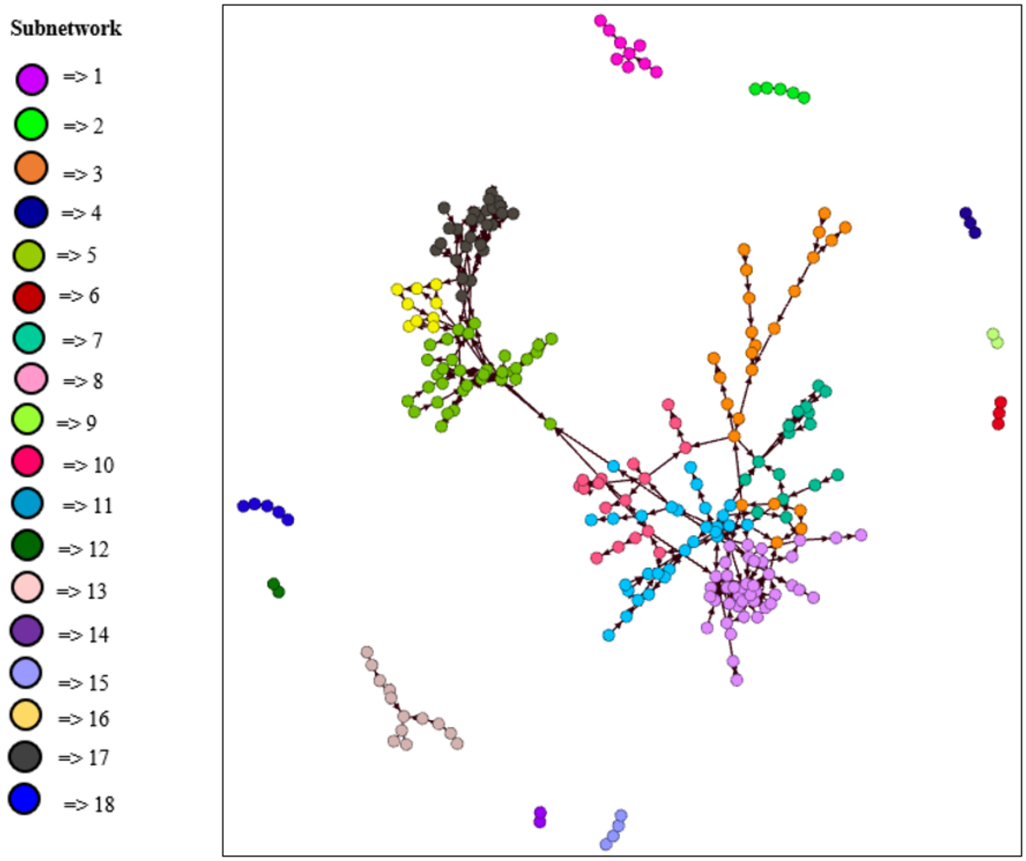


Fig. 2. Modularity graph of the tourism network.

4.2 Destination properties

Phuket Old Town (POT) is the destination that has the highest degree of centrality since it is connected by 15 other destinations in the network. Khao Lak (KHL) ranks second with a degree centrality of 14, followed by Cheow Lan Dam (CLD) with 12 degrees. KOP, Pakbara Pier (PAP), Cape Phrom Thep (CPT) and Phra Thong Temple (PHT) rank fourth. The fifth destinations with a high degree of centrality are Tae Pu Su Bridge (TPSB), Pakbara Viewpoint (PAV) and Ko Ra Wi (KRW). These indicate that They are important in the network in terms of having high connectivity. The network has an average degree of 3.27, reflecting that each destination can be connected to at least 3 destinations on average. POT has a 4.59 times better chance of being connected to other destinations than others on average. KHL has 4.28 times, and CLD has 3.67 times higher than average. Destinations rank fourth and fifth having a degree centrality of 3.36 and 3.05 times higher than average. This may signify that these destinations are the main competitor destinations of the network (Tran et al., 2016).

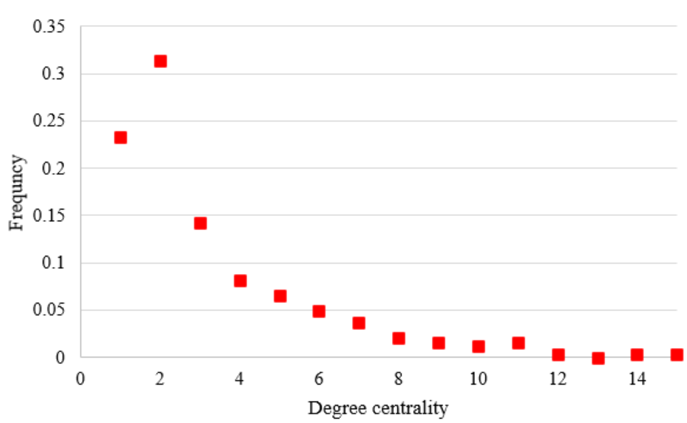


Fig. 3. Degree distribution of tourism destination

Degree distribution presents how links (tourism services) are distributed among all tourism destinations in the network. Fig. 4 illustrates that the tourism network is highly skewed with a large fraction (more than 80%) of destinations having low connectivity of 1-5 links. Among these, 57 destinations have one degree, 77 destinations have two degrees, 35 destinations have three degrees, 20 destinations have four degrees and 16 destinations have five degrees. There is a small proportion (less than 20%) of destinations with high connectivity of more than 5 links. In terms of betweenness centrality, POT has the highest betweenness centrality of 10, followed by Kim Yong Market (KYM) and KHL with betweenness centrality of 9 and 8 respectively. CLD and CPT rank third of the destinations with a high betweenness centrality of 6, followed by KOP with a betweenness centrality of 6. This indicates that they are an intermediary destination that allows information to pass from one destination to the other. This may reflect that most tourists will stop at these destinations while travelling between other destinations (Shih, 2006). Table 2 shows many destinations have betweenness centrality values between 1-5. Among these, more than 50% of destinations have a betweenness centrality of 1, 15.10% have a value of 2, 11.84% have a value of 4 and 2.04 have a value of 5. This reflects that these destinations play less of an intermediary role. Interestingly, 13.47% are peripheral destinations with a betweenness centrality of zero.

Table 2
Betweenness centrality distribution of tourism destinations

Betweenness centrality	Number of destinations	Share of total (%)	Betweenness	Number of	Share of total (%)
0	33	13.47	6	1	0.41
1	124	50.61	7	2	0.82
2	37	15.10	8	1	0.41
3	29	11.84	9	1	0.41
4	11	4.49	10	1	0.41
5	5	2.04	6	1	0.41

In terms of closeness centrality, 19 destinations have the highest closeness centrality of one, including Ton Tae Waterfall (TTW), Ko Mattra (KOM), Leekpai Bridge (LEB), Ta Pi River (TPR), Ban Khun Pitak Raya (BKPR), Betong Stadium (BES), Ko Mat Sum (KMS), Wat Phra Yai (WPY), Ko Hong (KHO), Phra Mahathat Woramahawihan Temple (PMW), Phangnga City Pillar Shrine (PCPS), Lighthouse Koh Lanta (LKL), Pee Hua Toe Cave (PHTC), Khamin Cave (KHC), Hin Ngam Bay (HNB), Trang Church (TRC), King Rama V Rock and Statue (KRRS), Maya Bay (MAB) and Kan Tang Hot Spring Forest Park (KTHSFP). This is because they are in very peripheral locations. Interestingly, these destinations have high closeness centrality but their degree and betweenness centrality value is very low. This confirms that these destinations have a high number of connections that they need to take to connect to distant others in the networks. Therefore, they have low reachability to others. There 69.8% of destinations have a low closeness centrality of 0.00-0.02 (Table 3), indicating that they are directly connected or a hop way from most others in the network. Thus, they are destinations with high reachability (Hansen et al., 2020, Smith et al., 2020). This is because they are closer apart in distance from these reachable destinations, so it is more central and closer to all of the other destinations (Shih, 2006).

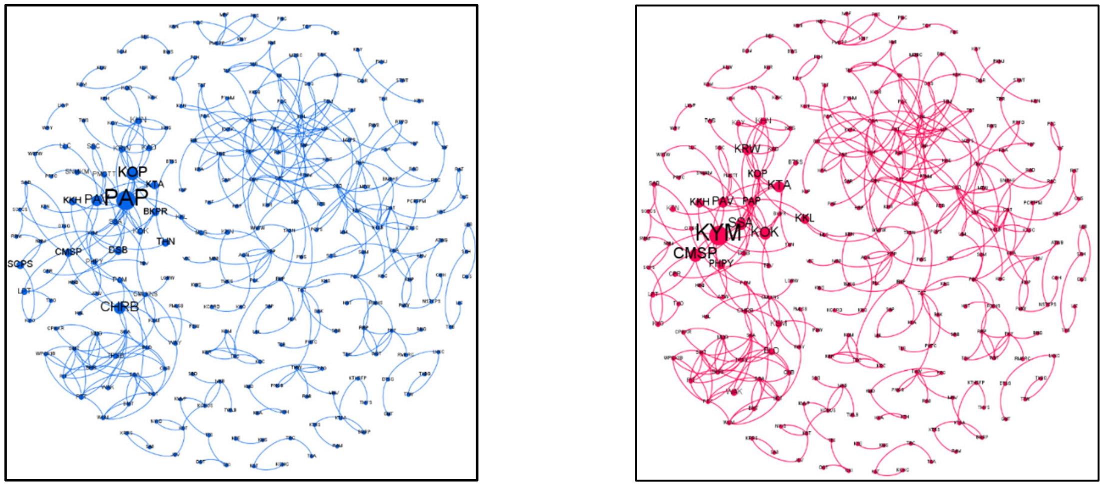
Table 3
Closeness centrality distributions of tourism destinations

Closeness centrality	Number of destinations	Share of total (%)
0.0000-0.0200	171	69.8
0.02100-0.0400	6	2.45
0.0410-0.0600	7	2.86
0.0610-0.0800	3	1.23
0.0810-0.1000	4	1.63
0.1100-0.2000	17	6.94
0.2100-0.3000	1	0.41
0.3100-0.4000	11	4.50
0.4100-0.5000	6	2.45
1.00	19	7.76

To sum up, KHL, CLD, KOP and CPT are the most important tourism destinations as they have high values of degree and centrality. Some destinations have only the highest value of one centrality measure. This indicates that different centrality measures reveal different properties of destinations (Kanrak & Nguyen, 2022).

5. Destination centrality analysis results

The tourism network is directed that collaborative relationships occur between tourism destinations. For instance, a trip offered to tourists comprises four different destinations. Most tourists want to visit attractive destinations and do not want to visit less attractive ones. That is if a destination is connected to high-impact destinations (attractive tourism destinations), the attractiveness of destinations will gradually increase. Thus, destination centrality is analysed in terms of the influence (attractiveness) of connected destinations A high hub centrality shows destinations have tourism services to high-impact destinations. A high authority centrality presents that the destination receives tourism services from high-impact destinations (Hörlesberger and Schiebel, 2006). Figure 4 illustrates destinations with different hub and authority centrality values. Bigger dots are destinations with higher values, whereas smaller dots are destinations with smaller values.



a. Hub centrality **b.** Authority centrality

Fig. 4. Hub and authority centrality of destinations.

The hub score average of 245 destinations in the South of Thailand is 0.0092. Table 4 presents the five destinations with centrality and authority centrality values larger than average.

Table 4

Destinations with high a hub and authority centrality higher than average

Rank	Destination	Hub centrality	Destination	Authority centrality
1	KOP	1.00000	KHN	1.0000
2	KOK	0.31009	KOP	0.3748
3	KHN	0.20003	KRW	0.3458
4	KRW	0.18850	PAP	0.2963
5	KAD	0.12453	KYM	0.1219
6	KTA	0.09750	SSA	0.1035
7	KOD	0.08541	KAD	0.0766
8	PAP	0.05415	KOY	0.0756
9	PAV	0.04378	KOK	0.0717
10	KKL	0.03175	KTA	0.0331
11	CHRB	0.02467	KHS	0.0195
12	KKH	0.02064	TWS	0.0183
13	KOY	0.01297	CMSP	0.0120
14	SCPS	0.01116		
15	CMSP	0.01077		
16	THN	0.01041		
17	DSB	0.01041		
18	BKPR	0.01032		

18 destinations have a hub centrality higher than average. KOP ranks the first in hubs (1.00), followed by Ko Khai (KOK), Ko Hin Ngam (KHN), Ko Ra Wi (KRW), Ko Adang (KAD), Ko Tarutao (KTA), Ko Dong (KOD), PAP, PAV, KKL, Chang Hai Rat Buranaram (CHRB), Khao Kho Hong (KKH), Ko Yang (KOY), Songkhla City Pillar Shrine (SCPS), Central Mosque of Songkhla Province (CMSP), Thale Noi (THN), Dragon Spine Beach (DSB) and BKPR, respectively. This means that these destinations connect to many destinations with high hub centrality. That is, they provide tourism services to high-impact destinations. Thus, the destinations with a high hub centrality are classified as outgoing hubs (centers) of the network.

The average authority centrality value is 0.0107. 13 destinations have an authority centrality higher than average, including KHN, KOP, KRW, PAP, KYM, Satun Street Art (SSA), KAD, KOK, KTA, Ko Hin Son (KHS) and Trang Walking Street (TWS). That is, they receive services from high-impact destinations. In other words, they are connected to other influential destinations. That is these destinations are connected by many destinations with high hub centrality. So, they receive tourism services from high-impact destinations. In other words, they receive many incoming links. Therefore, the destinations with a high authority centrality are classified as incoming hubs of the network.

6. Conclusion

This study analysed the structural properties of the tourism network and destination centrality in the south of Thailand, using the data of 245 destinations connected by 401 tourism links. Analysis was conducted using complex network analysis. The analysis results show that the network is a sparse network, in which destinations have a low probability of being connected to other destinations. This indicates that destinations do not have tight relationships. There is an intra-connectivity among destinations with a low clustering coefficient and a low connection efficiency with a high average path length. Some destinations tend to be connected to others with similar degrees, reflected by a positive assortativity. The network is divided into 18 subnetworks. Destinations densely connect to others in the same subnetworks value but sparsely connect to others in different subnetworks. A small number of destinations play crucial roles in the network based on centrality measures. Destinations that play the central role in connecting others are POT, KHL, CLD, KOP, PAP, CPT, PHT, TPSB, PAV and KRW. Intermediary destinations with a high betweenness centrality are POT, KYM, KHL, CLD, CPT and KOP. This reflects that they are more accessible to one another. TTW, KOM, LEB, TPR, BKPR, BES, KMS, WPY, KHO, PMW, PCPS, LKL, PHTC, KHC, HNB, TRC, KRRS, MAB and KTHSFP are destinations with the largest closeness centrality. Therefore, they have a high reachability to all others in the network. 18 tourism destinations are outgoing hubs or centers of the network with high hub centrality, while 13 destinations are incoming hubs with high authority. So, they influence destinations in the network, controlling tourism services and network connectivity.

An analysis result can draw implications for the tourism sector to improve operations, provide attractive promotions and design the service network. The tourism network in the South of Thailand is sparse with a low network density. This can be improved by designing tourism trips visiting destinations with low centrality scores, leading to the network becoming tighter. A tourism company can design a central tourism route consisting of destinations with a high degree as these destinations have a large number of connections (popular). This route may become a popular tourism route. Destinations that have a low degree, betweenness and closeness centrality, indicate that they have low connections with adjacent destinations, acting as an intermediary between others and low reachability to others. Authorities should promote their destinations becoming popular by providing attractive activities and promotions to attract more tourists. This leads to the destinations having more connections, bringing the network high connectivity. These destinations should also get a competitive advantage from the government in allocating tourism resources.

Although this study analyses many properties of the tourism network and destinations, it is subjected to some limitations that should be considered in future research. First, this study analyses only a binary network in which the frequency of services (weights of links) was not considered. Future research should take into account an analysis of the weighted tourism network. Second, this study analysed the tourism network based on the secondary. Future research should interview the tourism companies to get insight into a comprehensive analysis and result. These can reflect the operations of the companies. Third, this study analyses only assortative that reflects the tendency of connections between destinations with the same degree. Future research should consider the connections between destinations which might be affected by other attributes and factors.

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