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Attractiveness Centrality: A new centrality formula for travel planning

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ABSTRACT

This current study aims to establish a new centrality formula for tourism destinations in effective travel planning. Based on network analysis, the results provide several formulas for measuring centrality derived from our basic algorithm, which we call the attractiveness centrality for effective travel planning. Since the attractions at some tourist hup-points have an impact on the centrality scores of each destination, they can be utilized for more effective trip planning based on spatial patterns. With this in mind, several implications for future studies and destination authorities were also discussed.

1. Introduction

Many studies suggest that tourists tend to visit more than one destination in a country or more than one tourist' spot in a given destination (Caldeira & Kastenholz, 2018; Hwang & Fesenmaier, 2003; Hwang et al., 2006; Koo et al., 2012; Santos et al., 2012; Wu et al., 2011). For an industry like tourism, where intangible features are emphasized, it might be challenging to choose from a wide range of possibilities. In other words, even with complete knowledge of all the factors, it is nearly impossible for the tourist to make a completely reasonable decision (Karakuş, 2020). It is important to remember that while analyzing an individual's economic behavior, they may not always act rationally or may only show limited rationality (Sredl et al., 2013). The process by which tourists organize their trips is currently an intriguing subject for research. As a result, many research has focused on multi-destination travel rather than a single destination and has used the graph theory-based network analysis to study tourists' behavior and understand their decision-making processes (Shih, 2006; Lee et al., 2013; Yang et al., 2013; Wu & Carson, 2008). In this regard, network analysis techniques offer quantitative methods for assessing various centrality measures such as degree, betweenness, closeness and eigenvector of a node in a network (Hwang et al., 2006; Pavlovich, 2003; Shih, 2006). Each measure of centrality indicates the centrality of a node from a different point of view. Hence, the node's role in the network- whether it is a start, end, or hub (transit) node- can be determined upon its measures of centrality (Jeon et al., 2019). In this context, employing the network analysis techniques, some researchers examined the trip patterns of tourists in their studies (e.g., Shih, 2006), while some of them focused on tourists' behavioral differences according to the actual travel data (Šauer & Bobkova, 2018).

On the other hand, several technological developments, such as the growth of the internet and mobile device usage, affect tourists' behaviors substantially (Law et al., 2018). Nowadays, most people find much information about a destination without visiting it through internet technologies (Chung et al., 2017; Xiang et al., 2015). Thanks to map applications, people can plan their itinerary in detail. Almost all map applications label the point of interest (POI) in their maps and allow their users to share their reviews/experiences about that POI with others. Additionally, many sites on the internet, such as map applications, including hotel-booking sites, rate the POIs according to the users' scores. Consequently, many scholars (e.g., Bizirgianni & Dionysopoulou,, 2013; Fotis et al., 2012; Gretzel & Yoo, 2008; Sparks & Browning, 2011; Vermeulen & Seegers, 2009) previously suggested some substantial pieces of evidence that this kind of online

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Theoretical Article

reviews affects tourists' behaviors and their decision-making process.

However, despite great endeavors to build tourism networks through tourist mobility (e.g., Asero et al., 2016), it is still a challenging problem for an ordinary tourist to make an optimal travel plan, which maximize his/her satisfaction in a restricted time and with a restricted budget. From this perspective, the fact that individuals with limited rationality make these decisions may cause obstacles in the formation of a sense of satisfaction towards the tourism product, which has an integrated structure. Additionally, the intention of tourists to visit many destinations in one trip complicates optimal travel planning (Jeuring & Haartsen, 2017; Park et al., 2019). Numerous studies (e.g., Han et al., 2018; Kang et al., 2018; Šauer & Bobkova,, 2018) have attempted to better understand the tourists' multi-attraction travel network patterns by simply comparing the centrality, and density scores and interpreting the structural characteristics of the existing travel networks, but have wholly failed to come up with an attractiveness centrality (AC) based applicable formula. Therefore, in our study, to fill this omitted gap by suggesting a new centrality measure entitled "attractiveness centrality" that denotes the proximity of a node to other nodes in the network in terms of travel time. Compared to Ho and McKercher's (2014) and Park et al.'s (2019) studies, we focused on travel time rather than distance because time constraint in a touristic trip is one of the essential constraints and affects the other constraints as budget substantially. Thence, the AC of a node is an average of the node scores (e.i., the attractiveness score of a touristic point), weighted according to travel time from that node to all others. Here, it is assumed that a node score denotes the attractiveness of that node. So, it is purposed to obtain a new criterion representing the gathered scores per unit travel time for a node. This new criterion will reduce the complexity of the trip planning problem and help develop new ones of trip planner algorithms whose number has been rapidly increasing recently. Also, it could be utilized for creating attractiveness maps of a city or a destination, etc.

The study of human behavior within the scope of behavioral economics theory is very important for the tourism and hospitality industries, as well as many other industries. When we consider destinations as an integrated tourism product (Middleton, 1989), it becomes difficult to ensure the satisfaction of tourists towards this product. The fact that tourists tend to visit as many locations as possible while making travel plans (Caldeira & Kastenholz, 2018; Hwang & Fesenmaier, 2003; Hwang et al., 2006; Koo et al., 2012; Santos et al., 2012; Wu et al., 2011) makes it difficult to create optimum product designs (Bramwell, 1998). At the same time, although tourists want to use their values such as time and money in the most appropriate way, the lack of information about potential tourism attractions and their translation into a tour plan may reduce the rationality of the individual's purchasing behavior (Asero & Patti, 2009; Mosalev, 2020). This may lead to low consumer satisfaction and may harm the success of tourism activities in the long run. The concept of attraction centrality developed in this current research and the possibility of creating optimal tour itineraries may facilitate tourists' decision-making actions. According to the theory, also called the cognitive principle of least resistance or the principle of least effort, people are predisposed to choose the course of action that involves the least amount of work on their part (Önder et al., 2020). The principle of least effort implies that people frequently choose the option that is simplest or most convenient for them when making decisions. At this point, a reliable tool that can be most suitable for the tourism industry and can save time and money for tourists can be very valuable.

2. Calculation Model for Attractiveness Centrality

A node's attractiveness centrality measure (ACM) is calculated using the node scores in this study. However, even though the node scores themselves take an essential role in the calculation, the measure does not depend on how they are computed. We assume that all node scores denote the individual attractiveness measure for each node. Therefore, a node score can count website users' " like " votes or obtained from different quantitative methods such as surveys and like scoring from travel platforms.

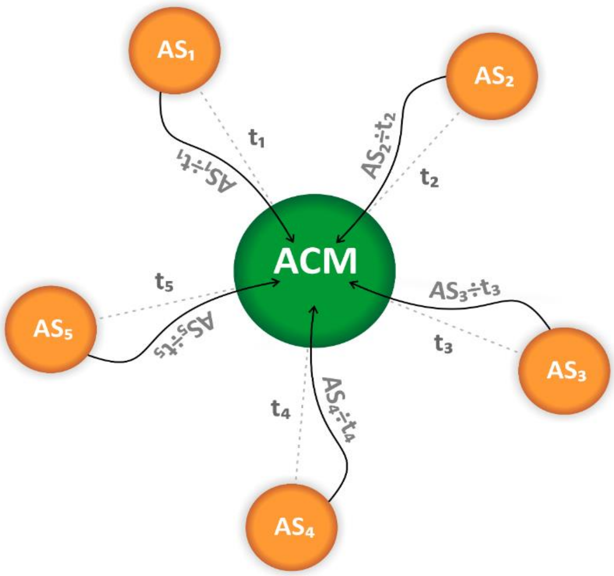

Figure 1. The illustration of ACM calculation
Source: Elaborated by Authors

After node scores (attractiveness scores) are obtained or calculated using any one of the methods mentioned above, attractiveness centrality would be computed using the following formula:

$$AC_i = \frac{n}{\sum_{j=1}^{n} \frac{TC(N_i, N_j)}{AS_j}}$$

F1 – Formula of the global AC

where TC is the travel cost function between i-th and j-th nodes (touristic point), and n is the number of nodes in the network.

AC is calculated on attractiveness scores (AS) of points other than a touristic point (TP) itself; the attractiveness score of the point whose center of gravity is calculated is not included in the calculation (Figure - 1). Therefore, our formula does not involve a prior gravity model that has its root in Newton's gravity theory and uses the concept of gravitational force as a comparison to illustrate the level of trade, financial flows, and migration between countries (Roy & Thill, 2004). While AC is being calculated, the AS of each TP included in the calculation is divided by the travel cost (time or distance) of the calculated point to this point. Thus, the total AS (as a unit benefit) to be obtained in return per unit cost in a visit from one TP to another TP is calculated. Finally, the average of unit benefits from a node to all others is constituted the AC of that node. (Figure - 1).

Since the unit benefits are proportional (rate) values, it has been deemed appropriate to use the harmonic mean to calculate the average. However, when calculating the ACM, there may be situations where it would be appropriate to use different average types according to the characteristics of the attractiveness scores of the TPs. For example, suppose that visitors vote for each TP on a portal where TPs are listed with one of the options "like" or "dislike". Suppose the AS is measured by the difference between the number of "likes" and "dislike" votes; negative and positive AS values may arise. It may be preferable to use the mean square instead of the harmonic mean to calculate AC scores. In another scenario, the median can be used instead of the mean so that AC scores are not affected by extreme values or an average calculated over quartiles as in the formula F2 may also be preferred.

$$\bar{X} = \frac{Q_1 + 2Q_2 + Q_3}{4}$$

F2 – An alternative formula that could be used instead of the mean

Conditional Attractiveness Centrality

In model F1, it is clear that the more nodes would need, the more calculations for travel cost between the node pairs. Thus, it would be necessary to restrict the number of connections between the nodes in large networks to keep the calculation time in a permissible range. The entire network could be confined to nodes in a single city or connections between the nodes to reduce the number of nodes used in the calculation. Only the node pairs whose travel cost is under a pre-defined value could be taken into account. Therefore, model F1 is the unconditional or global form of AC, and various conditional models can be derived from F1 due to multiple conditions. The following models demonstrate some examples of conditional attractiveness centrality (CAC). The difficulty of unconstrained calculating the AC scores of all APs in an extensive network such as a country was mentioned above. Furthermore, it is not possible to think that a TP at a destination will affect the attractiveness of a TP located far away, and it is evident that this effect will be close to zero mathematically due to the considerable distance. Therefore, it would not be very meaningful to include a parameter whose effect can be considered as zero in the calculation. For this reason, it is easier and more meaningful to do the calculation under various constraints.

Time-Restricted Conditional Attractiveness Centrality (TRCAC)

An ACM of a TP can be calculated using time-constrained AC by considering only the TSs whose distances from it are less than a predefined maximum travel time. The restriction on the ultimate travel time can be determined by considering the full travel time in the literature that a tourist can afford to visit a tourist spot.

$$TRCAC_i = \frac{|TD(t, N_i)|}{\sum_{j=1}^{|TD(t,N_i)|} \frac{TT(N_i, N_j)}{NS_j}}, N_j \in TD(t, N_i)$$

F3 – The formula of TRCAC

where TD is a subset of the nodes, consisting of the nodes whose travel time from N_i is less than the pre-defined constant value of t.

Distance Restricted Conditional Attractiveness Centrality (DRCAC)

The distance-constrained ACM is calculated by considering the ASs of the TPs located less than a maximum distance from the relevant TP. Thus, ACMs suitable for different travel scenarios can be calculated based on distances such as walking distance or scooter/bike driving distance.

$$DRCAC_i = , N_j \in DD(d, N_i)$$

F4 – The formula of DRCAC

where DD is a subset of the nodes, consisting of nodes whose distance from N_i is less than the pre-defined constant value of d.

Regional Attractiveness Centrality (RAC)

$$RAC_{i,R_k} = \frac{|RD(R_k)|}{\sum_{j=1}^{|RD(R_k)|} \frac{TT(N_i, N_j)}{NS_j}}, N_i \in RD(R_k), N_j \in RD(R_k)$$

F5 – The formula of RAC

$$EnAC_{R_k} = \frac{\sum_{i=1}^{|RD(R_k)|} RAC_{i,R_k}}{|RD(R_k)|} = \frac{\sum_{i=1}^{|RD(R_k)|} \frac{|RD(R_k)|}{\sum_{j=1}^{|RD(R_k)|} \frac{TT(N_i,N_j)}{NS_j}}}{|RD(R_k)|} = \sum_{i=1}^{|RD(R_k)|} \frac{1}{\sum_{j=1}^{|RD(R_k)|} \frac{TT(N_i,N_j)}{NS_j}}$$

F6 – The formula of the EnAC

where RD is a subset of the nodes in a certain geographically restricted region k (e.g., city, destination, etc.) and R_k denotes k-th region.

Endogenous and Exogenous Attractiveness Centrality

Endogenous attractiveness centrality (EnAC) is TPs' average attractiveness centrality score in a geographically limited region (country, province, county, etc.). Although this value alone does not make much sense, it is an important parameter that can be used to calculate a region's exogenous attractiveness.

Let the set of the nodes in a network split into none-intersected m subsets, and R_k denotes the k-th subset. An endogenous attractiveness centrality has been defined as average attractiveness centrality of the nodes in a subset that can be computed using F6 for each subset.

The formula above assumes that the subsets are geographically restricted regions like RAC.

Exogenous attractiveness centrality (ExAC) can be defined as an ACM of cities in a country. When calculating the attractiveness centrality of a city, the EnAC measures of other cities (the average AC scores of the TPs in these cities) are used as the attractiveness scores. The F2 formula is calculated over these values for each city.

Let $M(R_i)$ denotes the node whose AC is highest in the Ri region, and TT is a function that returns travel time between the nodes with the highest AC in two areas. An exogenous attractiveness centrality represents the AC score of a region according to its endogenous AC score and would be computed as in formula F7.

$$ExAC_{R_k} = \frac{n}{\sum_{i=1}^{n} \frac{TT(M(R_i), M(R_k))}{EnAC_{R_i}}}$$

F7 – The formula of ExAC

where n denotes regions count.

ExAC can be calculated for cities or generalized for different geographical regions (province, country, etc.). It is also possible to calculate the AC scores of countries in a hierarchical way using ExACs. For example, if you take the average of the AC scores of the TPs in a district, you can calculate its EnAC score. Then the ExAC scores of the districts are calculated over these scores. These scores give the AC score of each district. The average of these scores can be considered the EnAC score of the province. The provincial ExAC scores are thus calculated using these scores. As a result, the AC scores of all provinces are calculated in this way. This process is continued hierarchically; it is possible to calculate the AC scores of the countries.

Categorical Attractiveness Centrality (CAC)

Depending on their characteristics, TP (node) can have various properties that attract tourists' interests and travelling aims. Therefore, labelling touristic places categorically is trending in most internet and mobile applications. So, users can be informed about a touristic area whether it is in a category that he/she is interested in. For that reason, representing a categorical attractiveness centrality of a touristic place would be appropriate for this study's purpose.

Let C_k is a set of nodes that belong to a specific category and $N_i \in C_k$. Categorical attractiveness centrality represents the AC score of a node among all nodes in the same category and would be computed similar to conditional attractiveness centrality as in Formula F8.

$$CAC_k = \frac{n}{\sum_{i=1}^{n} \frac{TT(N_i, N_k)}{NS_i}}$$

F8 – The formula of the categorical AC

where n is the nodes count that belongs k-th category.

Personalised Attractive Centrality Measure

It is also possible to calculate AC measures weighted based on category prioritization, rather than AC scores calculated for one category only. For example, when it is known how much priority the different tourist profiles give to which category - and this can be determined with different scales - a weighted AC can be calculated according to the identified priorities instead of calculating the AC measure according to a category. Thus, an AC, which is adjusted to the preferences of the respective profile, provides a more meaningful measure of attractiveness. In another scenario, the AC, calculated based on personal priorities, provides a more specific measure of personal attractiveness than a profile pattern.

The weighted averages of the categorical AC scores can easily be used to calculate personalized AC measures. This problem fits very well with the issues of multi-criteria decision making (MCDM). Therefore, using one of the

MCDM methods may be preferred in the personalized AC calculation.

3. Discussions and Conclusions

Recently, many researchers (e.g., Han *et al.*, 2018; Kang *et al.*, 2018; Šauer & Bobkova, 2018) have focused on examining tourist flows utilizing centrality measures in network analysis techniques. Unlike prior research, we suggest a new measure of centrality named *Attractiveness Centrality* to address the issue based on an applicable formula.

AC indicates the centrality of a tourist spot relative to the surrounding attractions around it. For most tourist trips, the answer to "Where do I start?" is not easy for visitors. A TP with a high AC value indicates many other APs with high appeal near that point. Therefore, it is a valuable and straightforward solution for visitors to start their visit at a point with a high AC score and follow the same route in the next step when selecting possible visit points.

AC measurements also offer an easy and efficient way to create AC maps of a city or country. The easy dimensions' calculation also allows these maps to be created digitally and in real-time. Even for a professional travel company, planning an itinerary takes many years of experience. Furthermore, even if the destinations to be visited are known, planning the best route between the destinations remains complicated. Calculating the absolute optimal solution to these problems, called as combinational problems in the literature, is impossible for most cases. This situation highlights using heuristic methods and artificial intelligence algorithms to solve such problems. As in many other fields, artificial intelligence has recently become widespread in tourism, and intelligent systems based on artificial intelligence algorithms have been developed to solve the problem of travel planning and many other tourism issues. Therefore, this current study suggests that ACMs can be used in travel planning or that new artificial intelligence algorithms can be developed based on ACMs. Moreover, it seems possible to create auxiliary algorithms to accelerate the convergence of heuristic methods to the absolute optimum using ACMs.

Nodal attractiveness metrics can be used to plan a trip more effectively and be more manageable for an ordinary tourist. Therefore, it is suggested that local or central authorities include the attractiveness metrics of the tourist attractions in their informative publications or advertisements, such as brochures and other promotional materials. In addition, the attractiveness centrality measures can be used to speed up the techniques of travel planning algorithms to find optimal solutions more quickly. It is thought that attractiveness centrality would increase tourists' satisfaction and meet their expectations in their limited holiday time. ACs, which can be designed as a highly reliable and customizable tool for individuals who tend to prefer easy by nature and have asymmetric information in order to act rationally, and the ability to set effective and efficient tour routes have the chance to be quickly accepted and adopted by the society. In this way, a very important, useful and efficient source of information can be obtained for the decision-making mechanisms of tourism providers as well as tourism travelers.

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Abstract

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Keywords: *Formula, Attractiveness centrality, Travel planning, Destinations.*

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Full Name	Author contribution roles	Contribution rate
Eren Erkılıç:	*Conceptualism, Methodology, Resources, Writing - Original Draft, Writing - Review & Editing*	*40%*
Ali Akay:	*Conceptualism, Methodology, Resources, Writing - Original Draft, Writing - Review & Editing*	*40%*
İbrahim Cifci:	*Writing - Original Draft, Writing - Review & Editing*	*20%*

Author statement: *Author(s) declare(s) that All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.* ***Declaration of Conflicting Interests:*** *The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article*

This paper does not required ethics committee report

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