future transportation

Review

Transportation Networks in the Face of Climate Change Adaptation: A Review of Centrality Measures

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Abstract: This paper presents a comprehensive review of centrality measures and their usefulness in transportation networks in the face of climate change adaptation. The focus is on understanding the importance of transportation nodes in the event of extreme weather events and climate-related disasters that may render them inoperable. The paper argues that if critical nodes can be identified, they can be better protected, while resources can be allocated to ensure their functioning in the event of such events. The paper assesses 17 centrality measures, including degree, closeness, betweenness, eigenvector, and Katz, and evaluates their usefulness and usability in transportation networks. The review highlights the need to reformulate these measures to take into account traffic- and transport-related parameters and variables. Without this reformulation, centrality measures only reveal node importance in a topological or structural way and fail to capture the true significance of the nodes in a transportation network. The reformulation enables the centrality measures to be properly applied in a transportation network and to expose the significance of their elements. This work has important implications for transportation planners and policy-makers in ensuring the resilience of critical transportation infrastructure in the face of climate-related disasters.

Keywords: transportation networks; centrality measures; node importance; criticality; extreme weather events; climate-related disasters; resilience

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1. Introduction

It is by now well-established that the change in climate on Earth is (also) a process that researchers describe as natural. However, since the 1970s the academic community has generally neglected to account for natural variation as a factor in climate change, instead focusing on changes due to human-made increases in greenhouse gas (GHG) [1–3]. Nonetheless, GHGs are emitted by both natural processes and human activities. With regard to the latter, these cause large amounts of greenhouse gases (CO_2, CH_4) to be released into the atmosphere, beyond water vapor, increasing the atmospheric concentrations of these gases and thus reinforcing the greenhouse effect and warming the climate. However, the increase in the average temperature of the Earth does not necessarily mean a warmer climate for all regions of the world [4]. According to the Intergovernmental Panel on Climate Change (IPCC), the average global surface air temperature rose by 0.74 degrees Celsius (°C) in the 20th century, while estimates predict an increase between 1.1 degrees Celsius (°C) and 6.4 degrees Celsius (°C) for the 21st century [4]. As the planet warms, the climate system changes and humidity levels are affected, contributing to the more frequent and intense occurrence of extreme and unpredictable phenomena [4].

Extreme weather phenomena and natural disasters caused by climate change are expected to significantly increase the negative impacts on the systems (in terms of networks and infrastructure) of various sectors in the coming years. The transportation sector, as a fundamental activity of society and the economy, will be affected by the negative effects related to climate change, as the expected changes will affect both transportation infrastructure and the operation of the transportation networks they support, regardless of the means of transportation [5,6]. Additionally, climate change is expected to increase the uncertainty around the design of transportation systems. Ensuring these systems become less vulnerable and susceptible to extreme weather phenomena and natural disasters will be a significant challenge, as the past can no longer be a reliable source of prediction for future climates (given the extreme events that are occurring today and were not previously predicted) [7]. Regardless of the policies that will eventually be adopted and implemented by the international community regarding acceptable levels of greenhouse gas emissions, the effects of their rapid increase until now will continue to be felt for the next decades. It is expected that these effects, as well as the need for adaptation, will be greater and more visible in the built environment, especially in the vast transportation systems around the world such as highways, bridges, tunnels, railways, airports, ports, and mass transportation networks.

Therefore, given the increased frequency and intensity of extreme weather phenomena and the respective climate-related disasters observed worldwide in recent years, the development of appropriate strategies is essential to ensure the resilience of transportation networks and infrastructure—both from an adaptation and a mitigation perspective [8,9].

However, in doing so, and in order to maximize the effectiveness of design to address future impacts, it is crucial to exceed the current inherent limitations of how transportation networks are perceived, analytically formulated, and analyzed. Current transportation planning and engineering tools, models, approaches, and practices do not sufficiently account for elements related to the change in climate. In the analytical formulation of traffic flow characteristics and their corresponding models, it is assumed that weather and climate conditions are ideal and do not affect the characteristics themselves and their relationships, and therefore do not require parameterization in this regard. To date, it appears that notions and concepts that are of interest mostly to the transportation domain itself predominantly characterize transportation networks. For example, while the designation of a network link as a major artery or a secondary road may contain all the necessary traffic information (in regard to its service volumes, free flow and optimum speed, traffic capacity, etc.), it does not contain any information as to the role and significance of this link in the optimal traffic operation of the network. While for traffic purposes only, the prioritization of the nodes and links of a transportation network with the present approaches is sufficient, the same is not true when the same network is examined in light of extreme weather phenomena or climate-related disasters that could render parts of the network's element inoperable. The above is of particular importance, combined with the findings on climate change and the foreseen increased frequency and severity of extreme weather events and climate-related disasters and their impacts on transportation networks.

In this context, this paper aims to explore non-structural adaptation measures and tools that will help to better highlight and expose the significance of transportation network elements in light of the impact of extreme weather event and climate-related disasters on them. Such impacts are herein considered as rendering elements of transportation networks, i.e., their nodes and links, as inoperable (due to, e.g., a flash flood, a landslide, or extreme snowfall). Understanding transportation network elements' significance, and accordingly safeguarding them based on this, could also help efforts to increase networks' resilience and reduce their vulnerability given the impending climate change [10]. These measures take the form of re-formulated analytical tools, methods, and algorithms, stemming from graph and network theory, in an effort to identify if they are fit for better understanding, managing, and quantifying the impacts of climate change on transportation networks.

Methods of analysis and evaluation of networks from various fields (energy, telecommunications, health, etc.) are examined in an effort to identify and find those techniques that could be applied to transportation networks. Therefore, those analysis methods are sought that, if applied to transportation networks after their analytical reformulation (making them transportation-relevant), can help the competent authorities make better decisions to protect and reduce their vulnerability to extreme weather events and climate-related disasters.

2. Network Theory

The simplest definition of a network is that it is a form of representation of a system, aimed at simplifying that system and understanding its function by exploring relationships between its connected elements. From a structural point of view, a network is a set of points and nodes that are connected to each other by links (which are named differently depending on the field of application), through which various material and non-material entities are transferred to and from the nodes.

In its effort to study the networks that exist in real life, the scientific community has developed a plethora of analytical and mathematical (computational and statistical) tools aiming at better interpreting the behavior of networks and the properties of their nodes. These tools fall under network theory, also known as graph theory, which is within the scientific domain of mathematics and computer science, studying the relationships between objects, nodes, or vertices, represented as points, and their connections, edges, or links, represented as lines. The importance of network theory lies in its ability to model, analyze, and predict complex systems in various fields, such as physics, biology, economics, social sciences, and information technology. The origin of this theory can be traced back to Kirchhoff's (1845) work, as well as other researchers, who first systematically studied electrical circuits [11]. This work laid the foundations for the subsequent development and evolution of network theory and made networks useful mathematical objects for the representation of many natural or artificial systems (e.g., the Internet, telecommunications) [12,13]. Before Kirchhoff, the study of networks was initially undertaken by Euler in his research on the "Seven Bridges of Königsberg" in 1736, and his attempt to find a solution to the well-known puzzle of the time that concerned finding a path that would allow a pedestrian to cross all the bridges in the city without passing through any of them twice [14]. Euler used a graph-theoretical approach to prove that such a path does not exist. However, it was not until the mid-20th century that network theory began to develop as a separate discipline, thanks to the work of mathematicians like Paul Erdős, Alfred Rényi, and Claude Shannon.

One of the key concepts in network theory is the degree distribution, which measures the probability that a node in a network has a certain number of connections. This distribution can reveal important properties of a network, such as its resilience to attacks or its ability to transmit information efficiently. This is particularly pertinent for transportation networks as well, as they themselves have been and will continue to be subject to impairments or malfunction due to the adverse effects of climate change. Network theory has many practical applications in various fields. In physics, it has been used to model the behavior of complex systems, such as the interactions between particles in a material or the dynamics of a power grid. In biology, it has been used to study the structure and function of biological networks, such as gene regulatory networks or protein–protein interaction networks. In economics, it has been used to study the structure of financial markets and the spread of information through social networks. In information technology, it has been used to design efficient communication networks and to analyze the structure of the Internet.

As a domain, network theory is a rapidly evolving field, and it is heading in many new directions. One of these is the study of temporal networks, which take into account the dynamic nature of real-world networks, where nodes and edges can change over time [15]. This is particularly relevant in the study of social networks, where the connections between people can change rapidly and unpredictably. Another direction is the study of multiplex networks, which consist of multiple layers of connections between nodes, representing different types of relationships or interactions. Multiplex networks can be used to model complex systems such as transportation networks or social media platforms, where different types of interactions coexist. In recent years, machine learning techniques have been applied to network theory, allowing for more accurate predictions and better understanding of complex systems. For example, deep learning models have been used to predict the structure and dynamics of biological networks and to identify important nodes or edges in a network. Reinforcement learning algorithms have been used to optimize the design of communication networks and to find the most efficient strategies for navigating a complex network [16].

The main definitions of elements in graph theory provide a foundation for understanding graph theory and its applications in various fields such as computer science, mathematics, social networks, transportation systems, and more. The definition of the following items, used in the sections hereafter, concern the concepts of: graph (a mathematical representation of a set of objects, called nodes or vertices, connected by links, edges, or arcs); node or vertex (representing an object or entity in a graph); edge, link, or arc (representing a connection between two nodes in a graph); directed graph (a graph where edges have a specific direction associated with them); undirected graph (a graph where edges have no specific direction, and connections between nodes are bidirectional); degree of a node (the number of edges connected to that node); path (a sequence of nodes connected by edges, where each node in the sequence is directly connected to the next node); cycle (a path in a graph that starts and ends at the same node, passing through distinct nodes and edges); connected graph (a graph in which there is a path between any pair of nodes); subgraph (a graph that is formed by selecting a subset of nodes and edges from an original graph); weighted graph (a graph where each edge is assigned a numerical value, called a weight, representing the strength or cost of the connection); and graph connectivity (the measure of how easily information or influence can flow within a graph).

Centrality in Network Theory

In network theory, the concept of centrality is a prominent one, as it defines the "importance" (or significance or influence) of the vertices of a graph or the nodes in a network. The definition of node importance and, hence, its centrality depends on the type of network being examined and the object of study. For example, in a social network, nodes that communicate with a large number of others, that is, nodes with a large number of links to other nodes (which may correspond to a large number of friendship relationships), are considered important [17]. Conversely, in an information flow network, a large number of links of a node does not necessarily make it important, as, for example, control over the information flowing between nodes is prioritized [18]. In this case, the centrality of an important node is not determined by the number of links to other nodes but, for example, by its frequent position as an intermediary between pairs of nodes that exchange information within the network [19].

There are several different measures of centrality in network theory, each with its own strengths and limitations. In light of this, below we attempt a systematic review of centrality measures in an effort to highlight those which could be meaningfully applied in transportation networks in order to reveal and identify the importance of different elements. We do so under the scope of the ongoing change in climate and how the latter is experienced through increased and more severe extreme weather events and climate-related disasters. Where relevant, we suggest and discuss the analytical reformulation of each measure that is deemed useful to be applied in transportation networks.

The overview focuses on this area of network theory due to the 'importance' of nodes that accompanies the concept of centrality and is defined through it. Because, as mentioned above, the word 'importance' has various meanings, leading to different definitions of the concept of centrality, we hereby adopt the following main categories of definitions of importance [20]:

- On the one hand, the importance of a node is considered as an index that describes the type of flow or transport that occurs through the node. In this category, there is a distinction between measures of centrality depending on the type of flow considered important (e.g., volume of traffic flow served by a node).
- On the other hand, the importance of a node is considered as an index of participation in the connectivity of a network. In this category, there is a distinction between measures of centrality based on the method of measuring the coherence of the network (e.g., the number of shortest paths that pass through a node).

3. Centrality in Transportation Networks

Centrality measures are a powerful tool in network theory that can be used to understand the importance of nodes in a network. In transportation, networks are a fundamental component of the system, whether they are for public transportation, private car or individual transportation (bikes, motorbikes, micro-mobility services), or the movement of goods. Understanding how nodes in a transportation network are connected and the importance of each node can help improve the efficiency and resilience of the network [21].

Centrality measures have been used in transportation for a variety of purposes. One important application is to identify critical nodes in the network that are vulnerable to disruptions. By identifying such critical nodes, transportation planners can prioritize investments in redundant infrastructure or alternate routes to mitigate the impact of disruptions [22]. For example, if a major bridge on a transportation route is found to be critical, transportation planners may consider building a backup bridge or investing in alternative transportation modes to ensure that the route remains functional even if the bridge is damaged or out of service [23]. Another application of centrality measures in transportation is to optimize the routing of transportation networks [24]. By identifying important nodes for the operation of the network, transportation planners can develop more efficient routing strategies that minimize travel time and distance [25]. For example, in a public transportation network, planners may prioritize routes that connect important transfer points or hubs with high degree centrality to improve the overall efficiency of the network. Centrality measures have also been used to study the evolution of transportation networks over time [26]. By analyzing changes in centrality measures over time, researchers can identify trends and patterns in the development of transportation networks.

While centrality measures have been widely used for topological, structural, and spatial analysis of transportation networks, their application in characterizing transportation networks based on traffic- or transport-related variables and parameters has been relatively scarce. These measures typically do not take into account factors such as traffic volume, speed, and travel time, which are crucial in assessing the operational efficiency and performance of a transportation network. Therefore, while centrality measures provide valuable insights into the underlying network structure, if they are to assess the operational efficiency of a transportation network and the resulting importance of its elements (in nodes and links), they need to be reformulated so as to account for traffic- and transport-related variables to provide a more comprehensive understanding of the network's performance and inform transportation planning and management. Next, we present a series of centrality measures and attempt a qualitative assessment of a potential use in transportation networks in light of extreme weather events and climate-related disasters, and propose a reformulation (where relevant) accordingly.

3.1. Degree Centrality

In degree centrality, the degree of a node in a network is equal to the number of its neighbors, namely, the number of nodes it is connected to. In the case of oriented networks (that is, networks where the connections between the nodes have a direction without necessarily being bidirectional, such as links (or arcs) in a road transport network), there is a differentiation between the internal and external degree of each node. The internal degree (in-degree) is defined as the total number of links ending at the node, in contrast to the external degree (out-degree), which measures the number of links starting from the node in the direction of the remaining nodes of the network. The total degree of a node in the case of a directed network can be derived by adding the internal and external degrees [27]. The degree centrality of a node i in an undirected network (1), but also the internal (2) and external (3) degree centralities (k) in directed networks, are formulated as follows:

$$k_i = \sum_{j}^{N} A_{ij} \tag{1}$$

$$k_i^{in} = \sum_j^N A_{ij} \quad (2)$$

$$k_i^{out} = \sum_j^N A_{ij} \quad (3)$$

where N is the number of nodes, and A_{ij} is the element of the adjacency matrix at position i, j. The adjacency matrix is the square matrix that represents a graph or network by encoding the connections between nodes. In the context of degree centrality, the adjacency matrix is typically binary, where each element (i, j) in the matrix represents whether there is an edge connecting node i to node j. If there is an edge between nodes i and j, the element (i, j) of the adjacency matrix is one. If there is no edge between nodes I and j, the element (i, j) is 0. At the network level, the normalized degree centrality is used, and this is calculated by dividing the degree centrality by the maximum possible number of connections of a node.

Potential usability and usefulness in transportation networks:

In a transportation network, nodes with high degree centrality are typically important hubs or transfer points. For example, in a public transportation network, a station with high degree centrality may be an important transfer point between different lines or modes of transportation. Nevertheless, the use of degree centrality in transportation networks is not extensively studied in the literature with indicative applications of the measure on the assessment of public transport accessibility [28], or on the analysis of traffic zones of randomly created transport networks [29] and bus transport networks [30]. This is potentially explained because degree centrality appears to be independent of the concept of traffic, which would be the basic conceptual variable and characteristic in any given transportation network. Applying the degree centrality in a transportation network could reveal those nodes, which, exactly because they have many connections, gain a higher importance than other nodes. However, this importance would be considered limited, because it would be independent of the traffic loads that would be served by these nodes. In this sense, degree centrality does not appear to be a useful measure for, e.g., making decisions on where to establish short-term parking areas for emergency vehicles (fire engines, etc.) so that a transportation network is better optimally served during an occurrence of an extreme weather event.

3.2. Node Strength

To overcome the limitation of degree centrality, which solely focuses on the number of connections a node has with other nodes in a network, and to derive a weighted network (where links between nodes are given some 'weight'), node strength was proposed by [31]. According to node strength, the centrality of a node is equal to the sum of the weights of all the links connected to the considered node. Node strength s_i is formulated as follows:

$$s_i = \sum_j^N w_{ij} \quad (4)$$

where w_{ij} is the 'weight' of the link connecting nodes i, j.

Potential usability and usefulness in transportation networks:

In the context of transportation networks, node strength centrality can be used to identify key transportation hubs or nodes that are critical for the efficient functioning of the network. For example, in a transportation network, nodes with high node strength centrality would represent locations where many transportation routes converge or where a large number of passengers or goods are transported. By identifying these key nodes, transportation planners and managers can focus their resources on improving the infrastructure and services in these locations to optimize the network's performance. However, the use of node strength in transportation networks has been considerably scarce in the scientific literature—regardless of applications. Limited evidence has been found on node strength used to imply the robustness of air transport networks [32]; statistically analyze bus transport networks [33]; and empirically analyze maritime networks [34]. In all cases, the measure has been applied with its known topological analytical formulation, while no application of node strength has been found to study disruption (of any kind) of the elements that constitute a transportation network. Nonetheless, the measure is potentially worth further analysis. This is because in node strength, the 'weight' of a link could be considered as the total traffic volume served by it (or the ratio of traffic load to traffic capacity). The importance of a node could, therefore, be derived from the total traffic volume that starts, ends, or passes through it. In that sense, the greater the total traffic volume, the greater the node strength and, thus, the importance of the node. However, this measure only takes into account the weights, ignoring the number of a node's neighbors (that is, the number of nodes it is connected to). Therefore, a node at the edge of a transport network which ends up with a traffic load q from a single road segment, can be counted as equally important as a central node that serves a traffic load q but which results from a sum of links x.

3.3. Combination of Degree Centrality and Node Strength

In an attempt to address the individual limitations of the degree centrality and node strength measures, Ref. [35] combined the two measures in 2010 by introducing a correlation parameter, which determined the degree to which a node's centrality is influenced by the number and the weights of its connections. This measure (C_D^{wa}) was formulated as follows:

$$C_D^{wa} = k_i * \left(\frac{s_i}{k_i}\right)^a = k_i^{(1-a)} * s_i^a \tag{5}$$

where k_i is the degree centrality, s_i is the node strength, and a is the positive correlation parameter. When $a = 1$, then the combination is identified with node strength; when $a = 0$, then the combination is identified with degree centrality; when $a > 1$, then this combination acquires a negative relationship with degree centrality; and when $a \in (0, 1)$, then this combination becomes proportional to degree centrality.

Potential usability and usefulness in transportation networks:

Although the combination of degree centrality and node strength overcomes the individual limitations of using one or the other individually, it is still considered as incomplete, as it does not take into account the overall structure of a network. For example, if a node can connect to many others and serve a large volume of traffic, it may not be in a location within the network where, for example, other nodes can be reached with relative ease (or low cost), and thus its importance in the network would be limited. The combination of degree centrality and node strength has only been studied by the scientific community to analyze the topology of complex transportation networks [36,37].

3.4. Closeness Centrality

To address the limitation of locality, which has been identified in degree centrality and its variants, Freeman formulated closeness centrality as the inverse sum of the closest distances from the node under consideration of all nodes in a network. Closeness centrality (Cl_i) is formulated as follows [27]:

$$Cl_i = \frac{1}{\sum_j d(i,j)} \tag{6}$$

where $d(i,j)$ is the closest distance between nodes i, j.

According to closeness centrality, the most important nodes in a network are those that are at closer distances than the rest of the network. Thus, if a node is at a small or medium distance from the rest, this automatically implies a better ability. For example, in social networks this could relate to the dissemination of information.

Potential usability and usefulness in transportation networks:

The use of closeness centrality in transportation networks is well-documented in the literature, in particular to identify major bus transfer nodes [38]; to operationally analyze interregional road networks [39]; to hierarchize the air transport network of China [40]; and to explore the impact of domestically imposed travel restrictions on public transportation networks [41]. In a transportation network, nodes with high closeness centrality are often important because they can quickly reach many other nodes, making them good candidates for hub locations. For example, an airport with high closeness centrality can quickly connect to many other airports, making it an important hub for air transportation. Closeness centrality has been also analytically reformulated incorporating travel time delay and commuter flow volume to study disruption in subway networks [42]. It is thus considered as a measure worthy of further investigation in transportation networks. Instead of using the distance to find and calculate the closest node-to-node distances, the transit time of a link or the total time needed to cross the link could be used, as obtained after the traffic assignment in a transportation network. In such a case, important nodes would be those with the smallest connection times with all other nodes of a network, and they could, for example, signal the need for prioritization of protection and operation maintenance in the event of an extreme weather event or a climate-related disaster (i.e., designate which nodes should be protected first). The main limitation of closeness centrality is that it cannot be applied to networks with disconnected nodes. However, this has no impact in the case of transportation networks, where all nodes are connected to at least one other node by at least one link.

3.5. Betweenness Centrality

Betweenness centrality assesses the extent to which a node is on the sequence of nodes consisting the shortest path between two other nodes in the network. However, due to the frequent existence of more than one shortest path between two nodes in a network, the measure is formulated by dividing the shortest paths that pass through the node under consideration by the total number of shortest paths that exist between all nodes. Thus, betweenness centrality $g(U)$ is formulated as follows [27]:

$$g(U) = \sum_{s \neq u \neq t} \frac{\sigma_{st}(u)}{\sigma_{st}} \tag{7}$$

where $\sigma_{st}(u)$ is the total number of shortest paths from node s to node t via node u, and σ_{st} is the total number of shortest paths from node s to node t.

Although this measure takes into account the overall structure of a network (overcoming, similar to closeness centrality, the locality constraints of degree centrality), a large percentage of nodes in a network are not within the sequence of nodes of shortest paths between any two other nodes, and thus takes the value 0. A potential limitation of this measure is the exclusive selection of the shortest paths as a means to define a node's importance. This makes the betweenness centrality unsuitable for many kinds of networks, such as networks that describe the transmission of toxic agents or the flow of information. Another potential limitation is the measure's inapplicability in weighted networks (where links between nodes are weighted).

Potential usability and usefulness in transportation networks:

Despite the above limitations, the application of betweenness centrality has been explored in various networks and cases in the scientific literature, for example to reveal the main transport routes in a network [43]; to determine port significance in maritime container transport [44]; and to predict taxi traffic flow [45]. Betweenness centrality has also had applications beyond standard scientific paradigms. For example, it has been augmented for environmentally aware traffic monitoring [46]; approximated to identify key nodes in a weighted urban complex transportation network [47]; and, lately, also to identify changes in critical locations for transportation networks [48]. In a transportation network, nodes with high betweenness centrality are often important because they act as bottlenecks or chokepoints. For example, a bridge or tunnel on a major transportation route may have high betweenness centrality because it is the only way to cross a particular body of water or mountain range. Although betweenness centrality has not been analytically reformulated to account for transport or traffic-related parameters, it is a measure considered worthy of further investigation for use in cases of extreme weather events or climate-related disasters. Instead of using distance to define shortest paths, free flow time and delay to cross a link can be used to calculate and find shortest paths between two nodes. Betweenness centrality in a transportation network could correspond to the average expected frequency of occurrence of a node in the shortest path between two different nodes in the network. Thus, it could indicate those nodes in a network that, precisely because they serve the greatest number of shortest paths, are important for the operation of the network, and thus possible extreme weather adaptation measures as well as vulnerability reduction measures could be directed to them.

3.6. Flow betweenness Centrality

One way to overcome the betweenness centrality limitation and its non-application in weighted networks, and in order to mitigate the potential limitation of applicability to various networks through the exclusive use of shortest paths, is a variation of the above measure, which is called flow betweenness centrality. Flow betweenness centrality $g'(u)$ measures the flow that passes through a node which is on a path between two others, and it is formulated as follows [49]:

$$g'(u) = \frac{q_{st}(u)}{q_{st}} \tag{8}$$

where $q_{st}(u)$ is the maximum flow relayed from node s to node t through node u, and q_{st} is the maximum flow relayed from node s to node t.

Potential usability and usefulness in transportation networks:

The use of flow betweenness centrality in transportation networks in the scientific literature is rather scarce, with few applications found to analyze pedestrian flows in urban networks [50] or to propose routing strategies in scale-free networks [51]. Nonetheless, the measure is considered worthy of further investigation as traffic volume can be used as the flow between two nodes, and, thus, the important nodes in a network would be those through which the largest volume of network traffic is served.

3.7. Eigenvector Centrality

The eigenvector centrality measure proposed by [52] responded to the restriction of degree centrality, where the importance of a node is defined only by the number of connections it has with other nodes. Degree centrality does not take into account the importance of the nodes with which a given node is connected and considers equally important two nodes with, for example, four connections to other nodes. Conversely, eigenvector centrality takes into account the importance of these four nodes by examining the degree centrality of those nodes. Thus, according to eigenvector centrality, a node is considered as important not only if it is connected to many other nodes, but also if the nodes to which it is connected are in turn also important and to what extent (in the sense of the number of nodes they are also connected to). Eigenvector centrality is formulated in the form of a matrix as follows:

$$x_i = \lambda_i^{-1} \sum_j A_{ji} x_j \tag{9}$$

where x_i is the eigenvector centrality, A_{ji} is the element i, j of the adjacency matrix, and λ_i is the eigenvalue (An eigenvector of a square matrix, A, is a non-zero vector, v, which when multiplied by the matrix A is equal to the original vector multiplied by a number, λ, so that $Av = \lambda v$. The number λ is called the eigenvalue of the matrix A corresponding to the non-zero vector) of matrix A.

Potential usability and usefulness in transportation networks:

In transportation networks, eigenvector centrality can be used to identify nodes that have significant influence over the network's overall structure and connectivity. For example, consider a transportation network where a few key transportation hubs serve as the primary connecting points for multiple transportation routes. Nodes with high eigenvector centrality in this network would represent the transportation hubs that have the greatest influence on the overall connectivity of the network. By identifying these hubs, transportation planners and managers can prioritize investments in these locations to improve the network's overall efficiency and performance. Regardless, the use of eigenvector centrality in transportation networks has not been extensively explored in the literature, with limited references in assessing the connectivity of road [53] and shipping networks [54]; in revealing if transportation networks can determine house prices [55]; and lately, assessing the robustness of public transport networks [56]. Overall, the application of this measure in transportation networks is considered limited; the reasons are similar to those mentioned in degree centrality and concern the locality of the measure (although compared with degree centrality, the purely local character is slightly expanded) and the lack of parameters that could be of a traffic or transport nature. A general key disadvantage of eigenvector centrality is observed in directed networks (like transportation ones), where nodes that have a high internal degree are likely to eventually have zero centrality.

3.8. Katz Centrality

To address one of the limitations of eigenvector centrality, another measure was developed, namely Katz centrality. Katz centrality is a measure of the relative importance of a node within a network, which takes into account not only its immediate neighbors but also their neighbors, and the main feature of which is the introduction of a constant which assigns to each node some non-zero centrality, regardless of the node's position in the network and the centrality of its neighbors. This measure is called Katz centrality and is formulated as follows [57]:

$$x_i = \alpha \sum_j A_{ji} x_j + \beta \tag{10}$$

where x_i is the Katz centrality, A_{ji} is the element i, j of the adjacency matrix, and α, β are the positive constants.

According to Katz centrality, nodes that have a combination of high internal degree centrality and the existence of neighbors with high centrality will show higher centrality than other nodes with an equally high internal degree, where their neighbors have low centrality.

Potential usability and usefulness in transportation networks:

In transportation networks, Katz centrality can be used to identify nodes that have a strong influence on the overall connectivity and accessibility of the network or to identify the most efficient transportation routes between different locations. Yet, such applications in the transportation scientific literature are rather uncommon. Few of them concern using the measure to detect malicious nodes in the Intelligent Transportation Systems environment (where nodes are considered to be smart and connected vehicles that could attack traffic) [58]; to understand structural properties of dense traffic networks [59]; and, recently, to analyze the resilience against random failures and targeted attacks (which could also be the case for extreme weather events and climate-related disasters) [60]. Nonetheless, the application of this measure in transportation networks is considered limited, for the reasons mentioned in regard to eigenvector centrality. Despite solving the constraint of eigenvector centrality, by yielding zero centrality (and thus zero importance), it is still a measure in which a transportation network would be considered like any other network (with vertices and links, without traffic and transportation features beyond those that can be represented geometrically).

3.9. Page Degree Centrality

Page degree centrality is a variant of Katz centrality, developed by [61] to address the limitation of Katz centrality that assigns equal importance to all nodes connected to an important node. In page degree centrality, the centrality transferred from a node to neighboring nodes is divided by their outgoing degree. Page degree centrality x_i is formulated as follows:

$$x_i = \alpha \sum_j A_{ji} \left(\frac{x_j}{k_j^{out}} \right) + \beta \tag{11}$$

where k_j^{out} is the out-degree centrality of node j.

Page degree centrality was named as PageRank centrality by the web search engine Google, where it is used as a means of ranking web pages. The page degree centrality or PageRank centrality works in the Internet network context precisely because when a page (=node) has a lot of electronic hyperlinks from other important pages (=other nodes), this is an indication that this page is important, but the added element of dividing by the outgoing degree of pages (=other nodes) referring to the page in question (=node) ensures that there is no disproportionate influence.

Potential usability and usefulness in transportation networks:

Page degree centrality occurrences related to the transportation field in the literature are quite limited, with few applications on assessing accessibility and sustainable mobility [62]; the criticality of nodes in multiplex networks [63]; and the interactions of air traffic networks [64]. The application of this measure in transportation networks is considered limited, for the reasons mentioned in the Katz centrality assessment. Despite solving the Katz centrality constraint, by assigning equal centrality (and thus equal importance) to all nodes connected to an important node, this is still a measure in which a transportation network would be considered like any other network (with vertices and links and no traffic and transportation features except geometric ones).

3.10. Alpha Centrality

Ref. [52] proposed a measure of centrality which is a generalized form of the Katz centrality, called Alpha centrality. It calculates the centrality of a node by taking into account the different contribution of each other node with which it is linked as well as the influences it receives from the environment outside the network. Alpha centrality measures the total number of paths from a node, weighting them according to their length, and taking into account exogenous factors. Exogenous factors could include factors such as income or age, as the measure is mainly applied in the field of social networks. Alpha centrality c is formulated as follows:

$$c = aA^T c + e \tag{12}$$

$$c(v) = aA + a^2 A^2 + a^3 A^3 + .. + a^k A^k + e \tag{13}$$

where a is the damping parameter, A is the adjacency matrix of the network, and e is the vector of external influences.

Potential usability and usefulness in transportation networks:

The application of this measure in transportation networks is rather scarce and indicatively found in the literature for estimating directional bicycle volumes [65] and for understanding the dynamic structure of urban traffic networks [66]. The measure is considered limited for the reasons mentioned in the Katz centrality assessment.

3.11. Local Clustering Coefficient

The local clustering coefficient is a measure of centrality that shows how far the neighboring nodes of a given node are from forming a "closed group". A closed group is defined as a subgraph whose nodes are all connected to each other. This measure quantifies the extent to which the nodes directly connected to a node under consideration are also connected to each other. The local clustering coefficient $ClC(i)$ of a node i is defined as the ratio of the number of pairs of neighboring nodes which are connected to each other and to the total number of pairs of neighboring nodes, and is formulated as follows [67]:

$$ClC(i) = \frac{\kappa_i(\kappa_i - 1)\left| e_{jk} : j, k \in N_i, e_{jk} \in E \right.}{2} \tag{14}$$

where κ_i is the degree of node i, e_{jk} is the number of links between neighboring nodes of node i, $N_i : \left\{ j : e_{jk} \in E \right\}$ is the "neighborhood" of node i, and E is the set of all the links in the network.

Potential usability and usefulness in transportation networks:

In transportation networks, the local clustering coefficient centrality can also be used to identify areas of the network that are at risk of experiencing congestion or bottlenecks. Nodes with low clustering coefficient centrality in this network would represent areas that are less connected to the local community and may experience difficulty in accommodating increased levels of transportation demand. The application of this measure in transportation networks is deemed worthy of further investigation, in line with reported applications in the literature on analyzing worldwide maritime networks [68]; on evaluating and optimizing public transportation systems [69]; and also for assessing the resilience of coastal transportation networks faced with extreme climatic events yet with no traffic- or transport-related parameterization of variables [70]. The reason is that this measure can be a check measure for gaps in the network, in the sense of identifying neighboring nodes to a node under consideration that are not connected to each other. Therefore, in the event that, by way of example, it is deemed necessary to evacuate a transportation network, the gaps would constitute an obstacle to the efficient flow of traffic, as they would reduce the number of available routes and paths. On the other hand, the local clustering coefficient could indicate nodes that are necessary for the successful functioning of the network under all conditions. A possibly low value of this measure for a node would mean that this node is surrounded by nodes characterized by a lack of connections between them, and, thus, the traffic should be served through this node. Therefore, such a node would be high on the hierarchy of protection and adaptation in the event of extreme weather events.

3.12. Hub and Authority (Kleinberg) Centrality

Kleinberg centrality is a way to avoid the problem of ordinary eigenvector centrality on directed networks, namely that nodes outside strongly connected components or their out-components obtain zero centrality [71]. Kleinberg developed an algorithm aimed at quantifying the importance of each node based on two types of important nodes, called HITS (hyperlink-induced topic search), and gave each node a hub and an authority centrality. A key characteristic of nodes with high authority centrality is that they have many incoming links from hub nodes, while nodes with high hub centrality are distinguished by having many outgoing links to authority nodes. A node can simultaneously be a hub node and an authority node when it fulfils both properties at the same time.

According to Kleinberg, the authority centrality of a node is proportional to the sum of the hub centrality values of the nodes from which its incoming links originate. The analytical formulation of authority centrality x_i is as follows:

$$x_i = \sum_j A_{ij} y_j \tag{15}$$

or in the form of a matrix $x = Ay$.

Similarly, the hub centrality of a node is proportional to the sum of the authority centrality values of the nodes to which its outgoing links terminate. The analytical formulation of centrality y_i is as follows:

$$y_i = \beta \sum_j A_{ji} x_j \tag{16}$$

or in the form of a matrix $y = \beta A^T x$.

The β parameter in the hub centrality formulation influences the contribution of neighboring nodes' centrality scores to the centrality of a node. It determines the relative importance of direct and indirect connections in the network, allowing for a focus on nodes that act as hubs connecting to other highly connected nodes.

The HITS (hyperlink-induced topic search) algorithm, which gives each node a hub and an authority centrality, is an extension of eigenvector centrality and at the same time a precursor to degree centrality. Therefore, while hub centrality may be zero in some cases, it is possible to have non-zero authority centrality, and vice versa.

Potential usability and usefulness in transportation networks:

In the transportation domain, nodes with high hub centrality would represent the transportation hubs that have the greatest ability to, e.g., direct the flow of goods and passengers through the network. Similarly, nodes with high authority centrality would represent the transportation nodes that are the most important destinations or sources of goods and passengers within the network. For example, major cities or industrial centers may have high authority centrality in a transportation network due to the high volume of goods and passengers that originate or terminate in these locations. The application of this measure in transportation networks is deemed worthy of further investigation in light of climate-related events and disasters, regardless of the applications in the literature, indicatively on spatially analyzing bus networks [72]; the international air transportation network at the country-level [73]; and port networks [74]. However, because the definition of the constants α and β in a transportation network for each node would be a particularly complex process, and as the main field of application of this algorithm is the Internet (to decide the importance of a web page based on the structure of connections), both hub centrality and authority centrality can be individually calculated with measures mentioned above, namely, those of degree and eigenvector centrality.

3.13. Information Centrality

Information centrality measures the contribution of each node to the propagation of entities (information, traffic, water, etc.) throughout the network. The way in which this contribution is quantified is to examine the behavior of a network after the removal of the node in question. Initially, the ability to transmit entities of the network, consisting of all nodes, is examined, and then the same process is repeated by deactivating one node at a time, with the aim of deductively calculating its contribution to the network [75].

To estimate the efficiency of the network nodes, the network efficiency E is used, which is inversely proportional to the distance between two nodes, and is formulated as follows [76]:

$$E = \frac{1}{N(N-1)} \sum_{i \neq j \in G} \frac{1}{d_{ij}} \tag{17}$$

where N is the number of nodes in the network, and d_{ij} is the distance of the shortest path between two nodes i, j.

Thus, information centrality C_i is formulated as follows [77]:

$$C_i = \frac{\Delta E}{E} = \frac{E(G) - E(G')}{E(G)} \tag{18}$$

where E is the efficiency of network G, and G' is the network after removing all links connecting node i to its neighboring nodes.

Potential usability and usefulness in transportation networks:

The application of this measure in transportation networks is deemed worthy of further investigation, opposition to the rather scarce occurrences in the literature, mostly on assessing connectivity in public transportation networks [78] and urban street systems [79,80].

Instead of using the distance of a shortest path as a measure of network efficiency, the total free flow time (or the delay) of the sequence of links constituting the shortest path (i.e., the sum of the individual free flow times of crossing the links) can be used. After removing the sections that connect the node in question with its neighbors, the traffic assignment in the transportation network can be recalculated, along with transit times and delays in links. The use of information centrality in a transportation network can identify those nodes whose non-operation due to the occurrence of extreme weather events and climate-related disasters would have the greatest impact on the efficiency of the network, and therefore those nodes whose operation maintenance would be critical.

3.14. H-Index

The h-index was proposed by Hirsch, with the aim of quantifying the importance of a scientists' publications based on the citations a publication receives [81]. A scientist has an h-index when there are h publications of his/hers, each of which is cited by at least h publications. The h-index is formulated as follows:

$$h - index\ (f) = \max_i \min(f(i), i) \tag{19}$$

where f is the function corresponding to the citations of each publication.

Potential usability and usefulness in transportation networks:

While evidently the fields of application are very different, a possible application of this indicator in transportation networks is considered interesting for further investigation, regardless of the limited occurrences in the literature (e.g., on measuring node importance in urban rail networks [82]). The reason is that the h-index could be used to describe the importance of a node (=scientist) based on the nodes it is connected to (=publications) and through which the h number of shortest paths passes for all Origin-Destination pairs of a network. A number $h < N_i$, where N is the number of neighboring nodes of the node i under consideration, would mean that the node is surrounded by nodes which are not necessarily important (where importance here is defined by the number of nearest paths that pass through a node).

3.15. Hierarchical Degree

Hierarchical degree is a measure that counts the number of nodes reachable from a starting node via paths of length h, with the constraint that each node can be visited only once (avoiding walks). For a fixed length h, each of the neighboring nodes will be reachable with probability p_j^h. Given a vector of such probabilities, the hierarchical degree $\kappa_i^{(h)}$ of a node is formulated as follows [83]:

$$\kappa_i^{(h)} = \exp\left(-\sum_j p_j^{(h)} log p_j^{(h)}\right) \tag{20}$$

Potential usability and usefulness in transportation networks:

A possible application of this measure in transportation networks is deemed worthy of further investigation. The reason is that by replacing the length h with the time t, the number of nodes in a network that will be reachable from a starting point within this time interval t can be calculated. Such a measure is considered to be of particular importance for the management of extreme weather phenomena (but also other events) at the planning level, for example, when considering the allocation of emergency vehicles in the network, as the authorities could know the percentage of the network they could cover within some acceptable time range.

3.16. Percolation Centrality

Many of the centrality measures discussed above quantify the importance of a node in purely topological terms, and this importance does not depend in any way on the "state" of the node. However, while a node may be important according to one particular measure of centrality, it might not be significant in a network in which there is 'percolation'. The concept of percolation (or spread) is used to describe how an entity under consideration percolates over a network, for example, a viral infection that can spread through human networks, computer viruses that can spread across networks, or news about store offers that can also be spread through social networks. In all these scenarios, the entity spreads through the links of a network, changing the state of the nodes it passes through as it spreads, either in a reversible manner or not (e.g., in an epidemiological scenario, individuals move from the vulnerable state to the morbid and infectious state as the infection spreads).

The states that individual nodes can have in the examples above could have binary (e.g., received or not received the news), discrete (e.g., sick/diseased/healthy after recovery), or continuous character (such as the percentage of infected people in a city) as the entity under consideration spreads [84]. The common feature in all these scenarios is that the propagation of the entity results in a change in node state. In an attempt to describe this phenomenon, ref. [84] proposed a measure of centrality which they called percolation centrality. Percolation centrality measures the importance of nodes in terms of helping an entity spread in a network. It is defined for a node, at a given time, as the percentage of 'percolation paths' passing through that node. A percolation path is the shortest path between a pair of nodes, where the source node has been visited and possibly affected by the entity under consideration (e.g., infection) and is formulated as follows:

$$PC^t(v) = \frac{1}{\mathrm{N}-2} * \sum_j \frac{\sigma_{sr}(v)}{\sigma_{sr}} x_s^t / \left(\sum [x_i^t] - x_v^t\right) \tag{21}$$

where σ_{sr} is the total number of closest paths from node s to node r, $\sigma_{sr}(v)$ is the number of those closest paths that pass through node v, and x_i^t is the percolation of node i at time t (with $x_i^t = 0$ meaning that the node is not affected by the entity and $x_i^t = 1$ meaning that the node is fully affected).

Potential usability and usefulness in transportation networks:

While it is apparent that this measure was developed with more complex networks in mind than those of transportation [85,86], the application of this measure is considered interesting for further investigation, if we consider the traffic volume as the entity of the network that percolates from node to node. The reason is that, on the one hand, this measure of centrality can take into account time parameters, and on the other hand, the application of percolation centrality could identify as important those nodes that help more than others in the percolation of traffic. These should remain functional during extreme weather events, as they would be sensible routes for the possible evacuation of a network [87,88]. A prerequisite for the above, of course, is the availability of both the necessary input data and computational tools for the dynamic distribution of movements in the network.

3.17. Freeman Centralization

Freeman concentration is a centrality measure that calculates the strength of the most important node in a network relative to all other nodes. It is defined as the sum of the differences of any centrality measure between the most important node in a network and all other nodes, divided by the theoretically largest such sum of differences, in any network of the same size. Thus, each measure of centrality can have its own Freeman concentration, which is formulated as follows [27]:

$$C_x = \frac{\sum_{i=1}^{N} C_x(p_*) - C_x(p_i)}{max \sum_{i=1}^{N} C_x(p_*) - C_x(p_i)} \tag{22}$$

where C_x is the Freeman concentration for a network, $C_x(p_i)$ is the value of some centrality measure at node i, $C_x(p_*)$ is the maximum value of the centrality measure, and

$max \sum_{i=1}^{N} C_x(p_*) - C_x(p_i)$ is the sum of differences of the centrality measure. The subscript x denotes the number of nodes in a network, so that Freeman concentration is used as a measure of comparison of networks with the same number of nodes.

Potential usability and usefulness in transportation networks:

A possible application of this measure in transportation networks is considered worthy of further investigation, but the case-by-case assessments of the usability and usefulness mentioned above for the individual centrality measures apply (since the Freeman concentration uses one of the centrality measures of the previous sections). The possibility that the Freeman concentration gives is to compare networks of the same size with each other, and this is of particular interest, both for comparing two completely different networks (e.g., two different cities) and two areas of the same networks with similar size.

3.18. Overview of Reviewed Centrality Measures and Analytical Reformulation

Table 1 summarizes the centrality measures presented above, as well as their potential application in transportation networks. For each of the centrality measures for which a positive investigation suggestion was made, we analytically reformulated the measure taking into account potential transport- and traffic-related parameters and terms.

As shown, from the total of 17 measures and tools examined during the review, 10 were proposed for further investigation. The main reasons for rejecting some measures for further investigation concerned either the complexity of their numerical calculation (see, e.g., hub and authority centrality), or the inability to parameterize traffic or transportation elements (see, e.g., Katz, degree, alpha, and eigenvector centrality). In addition, the combination of degree centrality and node strength measure was not suggested for further investigation and application in transportation networks because it is not possible to calculate the coordination parameter, which determines the degree of influence of the centrality of a node from the number of its connections and from the weights of its connections.

Finally, for percolation centrality, we made a negative assessment because the availability of both the necessary input data and computational tools to dynamically allocate trips in a network is limited.

Table 1. Centrality measures with hypothesis of use and analytical reformulation.

Centrality Measure	Investigation Suggestion	Hypothesis of Use	Reformulation
Degree centrality	Positive	To indicate those nodes which, because they have many connections, gain some importance over others.	No need to analytically reformulate.
Node strength	Positive	To indicate those nodes for which the total traffic volumes originating, terminating, or moving through them are the largest compared with others, and are therefore the most important.	Considering the ‘weight’ of a link as the traffic volume served by it.
Combination of degree centrality and node strength	Negative	-	-
Closeness centrality	Positive	To indicate those nodes for which connection times with all other nodes in a network are the smallest, and therefore the most important.	Instead of using the distance to find and calculate the shortest node-to-node distances, use the transit time t of a link.
Betweenness centrality	Positive	To indicate those nodes in a network which, because they serve the largest number of shortest paths, are important to the operation of the network, and, thus, possible extreme weather adaptation measures as well as vulnerability reduction measures could be directed at them.	Instead of using distance, use the transit time t of a link, as obtained after the traffic assignment in the network, to find the shortest paths between two nodes.
Flow betweenness centrality	Positive	To indicate those nodes in a network through which the largest volume of traffic is served.	Considering the ‘flow’ between two nodes the traffic volume served by the link that connects them.
Eigenvector centrality	Negative	-	-
Katz centrality	Negative	-	-
Page degree centrality	Negative	-	-
Alpha centrality	Negative	-	-
Local clustering coefficient	Positive	To indicate potential ‘gaps’ or bottlenecks in the network, in the sense of identifying neighboring nodes to a particular node under consideration that are not connected to each other, and therefore any traffic volume should be served through that particular node rather than its neighbors.	No need to analytically reformulate.
Hub and authority centrality	Negative	-	-

Table 1. *Cont.*

Centrality Measure	Investigation Suggestion	Hypothesis of Use	Reformulation
Information centrality	Positive	To indicate those nodes whose failure would have the greatest impact on network efficiency, and, thus, those nodes whose operation maintenance would be critical.	Instead of shortest path distance as a measure of network efficiency, use the cumulative transit time and total time delay of the sequence of road segments that constitute the shortest path.
H-index	Positive	To indicate those nodes whose neighbors serve a minimum number of nearest paths (equal to the number of neighboring nodes at a minimum).	No need to analytically reformulate.
Hierarchical degree	Positive	To indicate the number of nodes that are reachable from a starting node via paths of length h, and, hence, the percentage of the network that can be covered within some acceptable time t.	Instead of length h, use time t, and calculate the number of nodes in a network that will be reachable from a starting point within this time interval t.
Percolation centrality	Negative	-	-
Freeman centralization	Positive	To enable comparison between networks of the same size based on some other centrality measure or index.	No need to analytically reformulate.

4. Conclusions

This comprehensive literature review has surveyed network theory in order to identify measures used in other scientific areas and systems to characterize the nodes and links of a network. The review attempted herein is considered necessary, given the need to broaden the ways in which transportation networks are analyzed today, under a purely traffic and transportation perspective that does not take into account weather conditions and climate change. As a result, analytical tools have emerged that could be applied in transportation networks, so that a better understanding is achieved regarding traffic nodes, links, and their importance and role in the operation of a network. This conclusion is potentially important because the information about the nodes and links of the transportation network is not provided by purely traffic and transportation tools and models. That is, while traffic engineering techniques and practices can with relative certainty calculate the traffic capacity, the free flow speed, or the level of service of a link in a network, they cannot provide information about how important those links are or what impact they would have on the operation of the network if they were to become inoperable for any reason, including the effects of extreme weather events, natural or man-made disasters, accidents, etc. The above is of particular importance, combined with the conclusions drawn in light of climate change and the increase in the frequency and severity of extreme weather events.

The node-based centrality measures examined in this paper can also provide valuable insights and help address the fact that climate-related events might in some cases affect arcs in a transportation network (rather than nodes per se). For example, degree centrality or betweenness centrality could help assess the resilience of a transportation network to climate-related events. By identifying critical nodes that act as hubs or bridges connecting different parts of the network, decision-makers can prioritize investments and interventions to improve the overall resilience of the transportation system. Even though climate events might primarily affect arcs, understanding the importance of nodes can guide efforts to enhance the network's ability to withstand and recover from such events. Similarly, node-based centrality measures can enable the identification of redundant nodes in the network. This is the case as redundancy is crucial for maintaining functionality during climate-related disruptions. By assessing nodes with low centrality, transportation planners could, for example, identify alternative routes or detours when certain arcs are affected. This information is valuable in mitigating the impacts of climate events on transportation efficiency and accessibility. While it is important to consider the impact on arcs during climate events, node-based centrality measures offer practical and actionable insights to improve network resilience [89], allocate resources efficiently, and facilitate decision-making and planning processes. Nevertheless, by combining arc-level analysis (see, for example, [90,91]) with node-based centrality measures, a comprehensive understanding of the network dynamics and vulnerability to climate events can be achieved.

As seen from the systematic review of centrality measures, in oriented networks, such as transportation networks, the centrality assigned to each node is inextricably linked to the direction of links, and the importance of nodes is affected by either their incoming or outgoing links. There appear to be two predominant reasons why nodes in a transportation network would receive high centrality values: on the one hand, as a result of a large number of incoming links, which directly make a node important, and on the other hand, as a result of a large number of outgoing links to other important nodes, which indirectly make the node important. The overview of centrality measures also provides the limitations of a given centrality measure and how they are in turn answered by the development of other measures of centrality. However, the most important conclusion concerning transportation networks is that not all measures were indicated as relevant or worthy of further investigation, either because their application would be limited or because their possible implementation would not add value (i.e., indicate important nodes in this context). Even for those centrality measures that would potentially be of interest for application in transportation networks, it is necessary to find their equivalent analytical formulations that take into account traffic and transportation terms.

Future research efforts could be placed in the direction of exploring how centrality measures can be adapted to incorporate dynamic factors, such as changing weather patterns, seasonal variations, and long-term climate projections. This could help identify nodes that are more vulnerable to specific types of extreme weather events and adapt protection strategies accordingly. In addition, this could help with investigating the interdependencies between transportation networks and other critical infrastructure systems, such as power grids or communication networks, and developing centrality measures that consider the cascading effects of disruptions in one network on the overall system resilience and identify critical nodes in the interconnected infrastructure for enhanced protection. Finally, it would be critical to explore how spatial factors, such as geographical location, proximity to vulnerable areas, and accessibility to emergency services, can be integrated into centrality measures. This could provide insights into the spatial distribution of critical nodes and guide the allocation of resources for their protection.

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