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METHOD APPROACH TO SOCIAL NETWORK ANALYSIS AS AN ANALYTIC TOOL FOR AGRICULTURAL INFORMATION SHARING AMONG FARMERS IN WESTERN KENYA

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Abstract: Flow of information among farmers is a complex process due to the nature of the unseen interconnected path of communication and actors involved in generation, packaging and dissemination. This complex process hinders adoption of innovations among farmers. To better understand the process of flow and sharing of information, a study was conducted using a Social Network Analysis (SNA) tool to map, measure and analyze social relationships among farmers and their networks that can be utilized in dissemination of agricultural information. Using data from Elwanikha and Ekisumo villages in Western Kenya, the study describes how Social Network Analysis (SNA) can be used as a methodology to map, measure and analyze social relationships and their application to dissemination of agricultural information. The survey data were analyzed using UCINET VI (version 6.624) and Net-draw (version 2.160) software to generate maps and compute relevant network metrics. The results show clear distinctions between villages and for all the SNA measures. SNA offers a valuable approach to information sharing among farmers, extension service providers and researchers to identify opinion leaders, influencers, clusters in the network, and those individuals serving as connectors in the network. SNA can be useful for quantitative analysis of interaction patterns that can facilitate information sharing among farmers.

Keywords: social network analysis; opinion leaders; influencers; network metrics

1.0. INTRODUCTION

Agricultural information among farmers is essential for improved productivity and enhanced economic development. in Kenya, agricultural information is mainly disseminated through the public extension system. However, the success of extension services is affected by a number of factors. First, the insufficient technical staff which was occasioned by the implementation of the Structural Adjustment Programmes (SAPs) in 1980's that resulted in decline of staff and facilitation of public extension (RoK, 2010). Consequently, the ratio of national extension staff to farmers stands at 1:1400 compared to the recommended ratio of (Wanyama, Mathenge, & Mbaka, 2016). Secondly, the government extension system is characterized by low budgetary allocation which hinders effective information sharing. This budgetary constraint affects the mobility of the extension staff to efficiently reach the farmers.

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To overcome the issue of the apparent disconnection between researchers, extension agents and farmers occasioned by deficiencies in the current extension approaches, alternative information sharing approaches from other fields of research are necessary to complement the existing agricultural extension systems. One such methodology is social network analysis (SNA) because it can explore, map and quantify flow of information among farmers. SNA would be valuable to agricultural extension providers, researchers and farmers because it identifies opinion leaders, influencers and individuals acting as bridges in the network by use of metrics such as density, degree, clustering coefficient and centralization.

1.2. Social networks and flow of information

Social network analysis (SNA) is a methodology that can map, measure, and analyze social relationships between persons, groups and institutions (Blanchet & James, 2012). The methodology complements the research with visual and statistical measures that enable researchers to analyze connectedness within a social network (Scott & Carrington, 2011). The method also enables the examination of types and patterns of relationship between actors, where these actors are visually represented in a network map by structural nodes connected by relationships (ties or links) between these nodes.

Actors (nodes) represent persons, groups of persons, or organizations; relationships (ties) can be formal, informal, financial, personal, professional relationship (Davies, 2009). In a directed network, relationships (ties) have two primary directions: in and out. When a tie is sent from an actor and received by another actor, the first actor forms a tie with an out-direction, while the second actor has a tie with an in-direction (Kadushin, 2012). The directions of ties present affects the strength of a network.

Research suggests that information flows most strongly through the interpersonal relationships that make up the underlying social networks of communities (Hardy, 2015). Network structures therefore map out the pathways by which information flows. More frequent exposure to the new information increases the probability that individuals are aware of new innovations earlier and able to gain a more complete picture of the innovation's expected returns to adoption (Aral, 2013).

Social Network Analysis will examine groups of heterogeneous actors who interact in the generation, exchange, and use of agricultural innovations. It will also examine the institutional factors that condition their actions and interactions. In effect, the approach moves knowledge dissemination away from a linear, input-output model to a model of innovation that mirrors a web of related individuals that learn, change and innovate through iterative and complex processes. (Borgatti, Everett, & Freeman., 2002)

Using network data, one can generate different types of information and insights from the resulting network metrics and maps. Firstly, the general structure of a network, in terms of its cohesion and shape, are two properties that can be informative. Cohesion refers to the number of connections within a network; the more connections, the higher the density of the network. The network shape relates to overall distribution of ties in the network, and can be useful to differentiate the core actors (those that are highly connected and prominent) in a network from those on the periphery (those with loose or few links) (Borgatti, Everett, & Johnson, 2013)

Researchers have used SNA to determine social interactions, diffusion of innovations, social influence, belief systems, efficacy of interventions, small-group dynamics and small-world and scale-free networks ((Carolan, 2013). For instance, using SNA methodologies, (Hoppe & Reinelt, 2010), evaluated a leadership network, (N.Kapucu, F.Yuldashev, F.Demiroz, & T.Arslan, 2010) determined the change of students' friendship networks in a collaborative learning class, (Prell, Hubacek, & Reed, 2009) assessed stakeholders' connections with natural resources conservation initiatives; and (Bartholomay, Chazdon, Marczak, & Walker, 2011) examined the University of Minnesota Extension's outreach to other external organizations. The literature has clearly laid out the functionality of SNA and provided guidance for the present study.

2. Materials and Methods

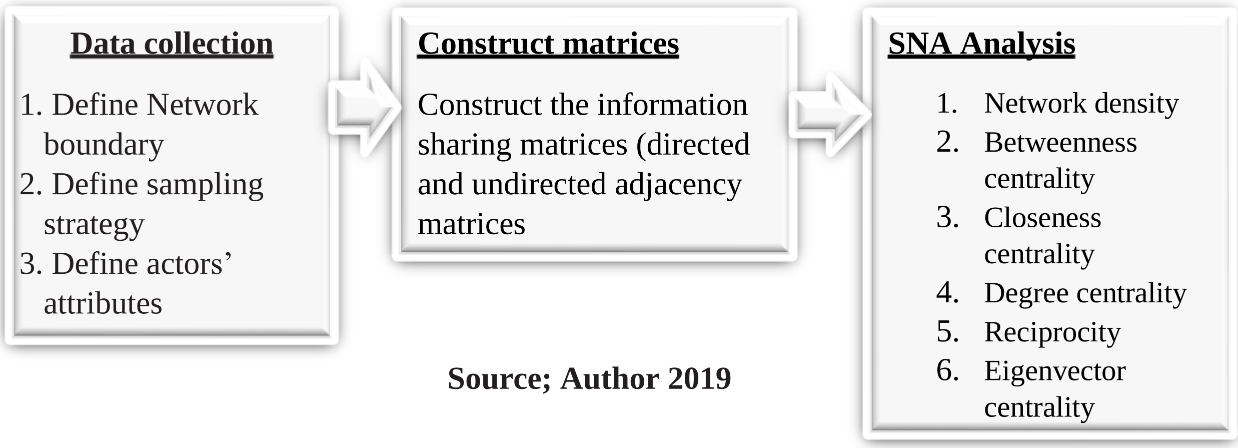
2.1. Context

This study was conducted in in two villages of Nambale Sub-county namely Elwanikha and Ekisumo Nambale Sub-county in Busia County. The villages are fairly similar to each other in terms of agro-ecological and socio-economic situation. Farming in this area, is characterized by low input and low output. Repeated use of land has led to overexploitation of land resulting in nutrient poor soils. To improve agricultural productivity, the study area has had interventions from NGOs and National and County government programs. Despite all these efforts, agricultural productivity still remains low. This has led to increased poverty levels which is estimated at 64.2% compared to national poverty level of 45.9. (KNBS, 2015)

2.2. Participants

Participants for the study were farmers. The study examined the farmers in Nambale sub-county of Western Kenya. The rationale of choosing farmers is because they are the producers and are the beneficiaries of agricultural information from extension workers. It is anticipated that the network will facilitate sharing of information.

Figure 2. Step by step approach to application of SNA to information flow



Source; Author 2019

2.3. Network Boundary

Identification of network boundaries is the first step in SNA. According to (Scott J. , 2017), definition of study area and population is important because in network analysis, exclusion of important actors can result in erroneous conclusions. Identify the geographical area. For this study Nambale sub-county was chosen as the study area. A census of key actors involved in the process was conducted. The identified actors then identify other actors that they are connected to.

Network boundaries are of particular importance due to the interactive nature of relational systems. Undefined network boundary may include or exclude not only some set of relevant or irrelevant entities, but also all relationships between those entities and others in the population (not to mention all relationships internal to the included/excluded entities). Furthermore, many structural properties of interest (e.g. connectivity) can be affected by the presence or absence of small numbers of relationships in key locations (e.g. bridging between two cohesive subgroups). Thus, the inappropriate inclusion or exclusion of a small number of entities can have implications which extend well beyond those entities themselves, and which are of far greater importance than the types of misspecification which occur in most non-relational settings. As such, it is vital to define the network boundary in a substantively appropriate manner, and to ensure that subsequent analyses reflect that choice of boundary (and not, for example, a boundary which simply happens to be methodologically convenient).

2.4. Sampling strategy-

After the identification of the boundary of the initial geographic area and the population of interest, the unit of analysis at which the variable has to be measured is identified. There are two methods of collecting relational data

a. Non-probability sampling such as respondent driven sampling ((Gile & Handcock, 2010).

b. Probability sampling such as link tracing sampling or centric sampling. A census gathering information form the entire population not only about individual characteristics but also about the relations linking each unit with the other.

The study adopted respondent driven sampling design. The design applies to situations where the size and boundaries of the sample are unknown and no standard sampling frame exists (Gile & Handcock, 2010). The technique starts with selection of focal actors within the process either randomly or purposively which provides names of some focal actors within the process either randomly or purposively. In turn, these actors are asked to provide names of other actors. The process goes on until a comprehensive coverage of relevant population is reached. Respondents can either recall the names of their contacts i.e. in free recall survey or select them from a provided list. This process is preferred because it reduces the possibility of missing data. Once a representative sample of these individual networks is obtained from the population, ego-networks can be compared to one another to obtain a regular pattern.

2.5. Data collection and procedure

SNA data for this study was collected using interviews or surveys. The farmers were asked to name the people who live outside their household, with whom they felt very close and somewhat close. Farmers were also asked to respond to questions addressing the frequency of their contact and collaboration with other members of the network, as well as their sources of formal or informal support within the network. To establish who are the most influential farmers or opinion leaders in the village, respondents were asked “which two farmers do you talk to most frequently?” and “Who do you consult to for new ideas or better ways of farming?” By asking these kinds of relational questions, both methods generate data which shows not only directions of communication flow, but also communication structures of social systems.

Survey responses are then tabulated and entered in an adjacency matrix as described below. For each column in the row, the entry of a 1 or 0 indicated the presence or absence of a relationship by the person represented on the row. This resulted in a directed as opposed to an undirected matrix, meaning in this case that connections between members were not necessarily reciprocal. Reciprocal connections would occur only if 2 members consulted each other when making decisions. The resulting matrices were then imported into UCINET *version* 6 software to compute quantitative measures of network structure.

2.6. Construction of SNA Matrices and Network Graphs

SNA analyzes patterns of connections (ties) among information-processing agents (nodes). Data are recorded in the form of an adjacency matrix, where each node is assigned both a column and a row in the matrix. A matrix constructed in this way will have two cells representing the intersection of any 2 nodes, 1 above and 1 below the diagonal. If a connection or tie exists between 2 nodes, then a 1 (or another positive number representing the strength of the tie) is entered in the matrix cell representing the intersection of these 2 nodes. If no tie exists, then a 0 is entered. It is not necessary that the 2 cells for each pair of notes have the same value. For example, in Figure 2.1, A consults B when making a decision, but B does not consult A. In this case, the cell at the intersection of row A and column B would contain a 1, but the intersection of row B and column A would contain a 0. A matrix that has this property is called a directed matrix. If the tie being studied is not directional (ie, if A talks to B, then B must also talk to A), then the matrix cells below the diagonal are identical to those above the diagonal and are ignored in the SNA calculations (Figure 2.2.).

Examples of Adjacency Matrices

Figure 2.1. Directed Adjacency Matrices

	A	**B**	**C**
A	-	1	0
B	0	-	1
C	1	1	0

Figure 2.2. Undirected Adjacency Matrices

	A	**B**	**C**
A	-	1	0
B	0	-	1
C	1	1	-

2.5. SNA analysis

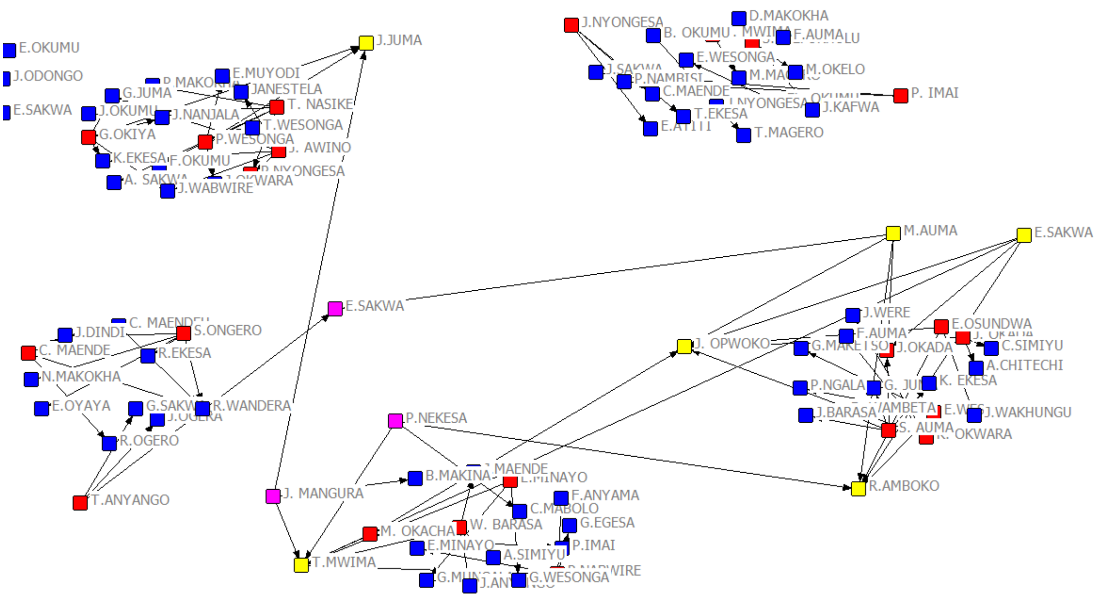
Survey data were analyzed using UCINET (version 6. *6.624*) (Borgatti, Everett, & Freeman., 2002) and Net-draw (version 2. *160*) (Borgatti, Everett, & Freeman., 2002), software to generate network maps and to compute relevant network metrics (Wasserman & Katherine Faust, 1994). Using UCINET, the social network data enabled the generation of a network map and computed network metrics, including centrality, centralization and density.

3. RESULTS

3.1. Social networks maps

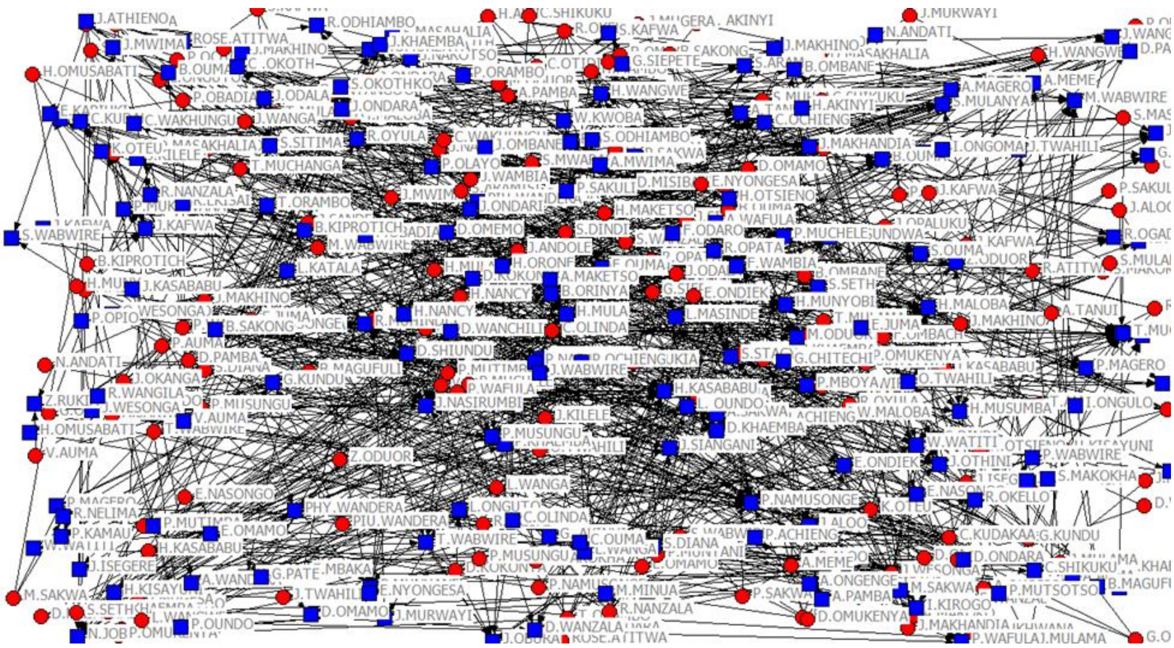
Using Net Draw *version 2.160*, a program within the UCINET suite, visual representation of the networks was generated to illustrate the web of information sharing of the entire network in two villages (Ekisumo and Elwanikha). The network diagrams from the study are shown in Figure 3.1 and Figure 3.2. An arrow leading from one member to another indicates that the first member consults the second member for information. A double-headed arrow between 2 members indicates that both members consult each other for information. It is clear from inspection of these 2 diagrams that decision-making consultation patterns are different in these two networks. Elwanikha village (Figure 3.1) shows the existence of many sub-groups within the network which are loosely connected to each other. Loosely connected groups indicates that social networks are less cohesive. The network also illustrates a mix of weak and strong ties

Figure 3.1. Social Map Elwanikha Village



Ekisumo village (Figure 2) has a more collaborative information sharing process. The network diagram is fairly dense and cohesive.

Figure 3.2: Ekisumo social networks



The visually apparent differences in the 2 diagrams can be quantified, as described below.

3.2. SNA Quantitative Measures

The quantitative measures provide information about how the network as a whole is functioning. The measures communicate information about the entire network, its structure and degree of cohesion. The quantitative measures developed for use in SNA include density, clustering coefficient and centralization and degree.

3.2.1. Network density.

The density of a network is the number of actual connections between members divided by the number of possible connections. In social networks, higher density indicates a greater degree of interaction among the members in the process of making decisions. In this study, Ekisumo Village (Figure 3.2) has a density of 0.1038 which indicates an extremely cohesive network. This is also supported by the average distance score of 1.362 which indicates great proximity between people.

The Network density of Elwanikha village is 0.030. The low density indicates that network farmers do not interact with each other frequently. There are many sub-groups within the Elwanikha village that are loosely connected to each other. Loosely connected groups indicates that social networks in the village are less cohesive.

3.2.2. Clustering coefficient

The average clustering coefficient for Elwanikha village was 0.030 while the maximum clustering co-efficient is 0.50. This illustrates a wide variation in the measure of how individual actors are connected to each other (Figure 3.1).

3.2.3. Centralization

Centralization measure provides an overall indicator of how clustered ties are to one or a few individuals in the network, where scores closer to 1 indicate a highly centralized network, and figures closer to 0 indicate a decentralized network. A decentralized network may be more resilient, as the network is not dependent on only a few individuals, and instead social influence and ties are more evenly distributed, and tend to be less hierarchical (West, Barron, Dowsett, & Newton, 1999). Therefore, if one or two central individuals were removed or left the network, it would not leave a major gap in support for individuals, i.e., the decentralized nature of relationships can act as a protective factor, and ensure continuing support is available for most in the network. The impact is likely to be more significant if one or two central individuals were removed from a highly centralized and hierarchical network.

3.2.4. Degree

Degree represents the number of links to a person (*in-degree*) and from a person (*out-degree*). Degree metrics are often used as a way to identify visible people or opinion leaders in a network. Elwanikha village has an average in-degree and out-degree of 1.46 and a maximum in-degree of 4. This implies that majority of farmers in the village have at least two interpersonal source of information and also acts as a source of information for two farmers. The popular farmer (in-degree) receives information from four interpersonal connections in the village. In-degree centrality is an indicator of popularity and potential for influence and leadership while out-degree centrality is an indicator of the capacity for sociability and extent of dependency.

A careful observation of network map (Figure 3.1) for the degree centrality that is the number of ties a household has with respect to information sharing reveals that most of the household have a good number of ties with other households. There are however a few households who stand out boldly and these are the focal points who are the source of information for the others i.e. ***J. Maroko and P. Namusonge.***

Closeness centrality measures how quickly an actor can access more actors more actors. Farmers with low closeness measure are able to have quick access to other farmers in the network. These farmers have shorter paths to reach other households and they are knowledgeable about what is happening in this network. They have high visibility. Interviews reveal that these households are not only able to have quick access to information from relationships with other households in their cluster but also enjoy the benefits with households belonging to their clusters.

3.3. Importance of bridging actors

Elwanikha socio-grams show the importance of bridging actors in a network. ***Figure 3.1*** shows farmers who act as connectors/bridges (yellow color) to other farmers or other sub-groups. On further analysis, the bridging farmers have high betweenness centrality. These farmers play important role in connecting the other farmers or sub-network. The farmers act as a link in disseminating information in the network given their positional advantage (Scott J. , 2017). They are positioned on a shorter geodesic path and central in the network. They play the role of information brokers or gate keepers. However, such farmers can also hoard information and therefore starve many farmers within the network key information. It is not a good indicator of the sustainability of the network. Even if this farmer is important in the network, displacement may lead to problems in the network and ultimately the collapse of the network.

Based on these centrality measures, the farmers occupying the central position in the network are identified as farmers ***J. Opwoko, T. Mwima, R. Amboko, J.Juma, J.Mangura, E. Sakwa*** and P.Sakwa. these farmers are either nodal or bridging farmers in the network. for example, farmer J. Mangura connects two central farmers (T. ***Mwima and T. Mwima)*** in two sub-networks. Similarly, farmer ***P. Nekesa*** is the connecting farmer between ***T. Mwima and R. Amboko*** who are central in two sub-networks.

4. Discussions

This paper has described the value of social network analysis as a methodology to explore, depict, and understand the operation of networks and systems. This case study, investigating the information flow among farmers in Elwanikha and Ekisumo villages, demonstrates the value of social maps and metrics under the social networks. The methodology offers a valuable approach to information sharing in agriculture because it offers a means of depicting activity relevant to network questions of interest to identify opinion leaders, influencers, or clusters in the network, and those individuals serving as bridges in the network.

At the individual level, this method identified central actors in the network; in this case, those who were contacted most for information in the network. Using metrics such as betweenness and in-degree, it is possible to identify those that occupied strategic positions in the network, and those that were most visible and influential. Importantly, SNA can account for different kinds of centrality; actors in a network may be influential, but the approach enables understanding of the type of role they play in their central position. For example, betweenness is an especially useful metric for leadership studies, as it measures the degree to which a node occupies a strategic position in a network (Valente, 2010), and has been described as a strong predictor of perceived leadership (Martin Kilduff, 2003). Similarly, degree can identify opinion leaders in a network, or act as a measure of social integration in the network. SNA also allows for the identification of those acting as bonders or bridges in a network, serving to connect parts of the network that may otherwise be isolated. These individuals, acting as gatekeepers, play an important role in diffusion across the network. Knowledge of the links and bridges in the network can be employed strategically to addresses gaps in the network and build on strengths.

In sum, we find that respondents turn first to family and friends within close geographic proximity whose opinions matter most to them, whether or not they have the best agricultural information. Those considered “experts” are disassociated from social groups, which prevents information from circulating throughout the networks; instead, whatever attitudes and information individuals in respondents’ inner circles hold—good or bad—is diffused. In order to improve the quality of information flowing through the networks, it will be important for service providers to identify the most influential farmers and connectors in the villages.

Conclusions

This case study described the results of a study investigating flow of information among farmers. The study highlights the value of their methodology to map, identify and analyze information networks and can be effectively applied to evaluate interventions to improve the network. The of this method in agricultural extension is significant, yet its use is still limited. We hope this study highlights the benefits and strengths of this approach in facilitating information flow among farmers. A broad range of potential applications of this tool is possible, including using it to help design interventions to promote adoption of agricultural innovations.

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