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Online Collaborative Information System for Strengthening Tourism Capacities in Local Communities of the Sacred Lake, Puno–Peru, 2025

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ABSTRACT

This research evaluates the impact of the Online Collaborative Information System for strengthening tourism capacities in the local communities of the Sacred Lake, southern Puno–Peru. Using a predictive quantitative research approach, conditional relationships between sociodemographic variables are modeled based on a causality analysis with graphical and probabilistic representation, conditional probability tables, estimation of the Directed Acyclic Graph (DAG) structure, and conditional independence tests and scores of Bayesian Networks (BN). A survey was conducted with 608 residents from the rural communities of Luquina, Titilaca, Socca, and Thunuhuaya regarding the use of an Online Collaborative Information System to strengthen community-based rural tourism. The results show that the design of a probabilistic Bayesian network accurately describes conditional dependency interrelations among sociodemographic variables associated with the Collaborative Information System. The educational level variable directly influences tourism strengthening, with technological interaction—device use, software applications, internet access, and social networks—acting as key elements for supporting service quality and equitable distribution of benefits among community members. The study provides empirical evidence on the role of Information and Communication Technologies (ICT) in Community-Based Rural Tourism (CBRT), generating inputs to guide public policies and intervention plans that promote local self-determination, equity, and cultural-environmental conservation in high Andean contexts.

Keywords: Community tourism; strengthening; collaborative system; Bayesian networks; Puno

INTRODUCTION

The digital transformation presents both challenges and opportunities for rural communities in the Puno region, particularly in the organization and production processes linked to community-based tourism. Online Collaborative Information Systems (OCIS) emerge as valuable tools for systematizing information, improving productivity, and enhancing the visibility of cultural, natural, and ancestral practices in the communities located around Lake Titicaca (Anchundia et al., 2022). Despite the growing adoption of ICT in Community-Based Rural Tourism (CBRT), there remains a need for analytical approaches capable of measuring and predicting the factors that explain the strengthening of these activities and their influence on social, economic, and environmental development. The appropriate use of OCIS constitutes a sustainable alternative for improving living conditions through rural community tourism, a development strategy that also requires equity in the distribution of benefits among community members (Gutierrez de Blume, 2021). Tourism activities in the southern Sacred Lake area of Puno include beaches, viewpoints, handicrafts, gastronomy, agriculture, livestock, kayak fishing, and expressions of living culture such as music and dance. These activities require rethinking collaborative management systems to support community development while reaffirming and revaluing ancestral practices (Aranibar Ramos & Patiño Huayhua, 2022a). Reorienting community-based tourism must represent a genuine commitment from all members, involving the environment, nature, and future generations (ONU, n.d.). From this perspective, local communities identify tourism as a key activity for development, recognizing that its proper implementation can lead to substantial improvements (Kalvelage et al., 2020). Thus, community tourism becomes an important alternative to traditional tourism, as it seeks to empower local populations while valuing their culture and natural environment (Restrepo Rico & Peterek, 2024).

Previous studies highlight the limitations of traditional qualitative approaches for explaining the complexity of community tourism dynamics. In reality, there is a need for Bayesian Networks (BN) and Directed Acyclic Graphs (DAGs) as probabilistic frameworks to identify conditional relationships between sociodemographic and technological variables that support more inclusive and effective decision-making structures. This study seeks to answer the following questions: How does the use of OCIS influence the strengthening of community-based rural tourism in Titilaca, Luquina, Socca, and Thunuhuaya? Which variables significantly contribute to this process? What dependency relationships explain the dynamics of tourism strengthening?

Community tourism in Puno, recognized in the National Tourism Strategic Plan (PENTUR) as a mechanism to diversify tourism offerings and improve the quality of life in historically marginalized areas, still faces structural limitations (Milla Canales, 2024). These include the concentration of benefits among a few actors, dependence on external agents, and limited active participation of the local population. This reality underscores the need for inclusive management models that promote local autonomy, shared decision-making, and the sustainability of rural community tourism (Cayo et al., 2022). Beaches located in Acora, Charcas, and Luquina are among the most frequently visited sites (Aranibar Ramos & Patiño Huayhua, 2022b). In this context, strengthening tourism capacities must be understood not only as an expected outcome but also as a sustained and coordinated effort involving technical training, participation opportunities, and shared decision-making (Gascón, 2022). The incorporation of online collaborative systems allows the articulation of actors, resources, and knowledge, thereby enhancing community ownership of tourism activities along with cultural and environmental conservation (Aragón Navarrete, 2018). Strengthening cultural, mystical, gastronomic, artisanal, and natural attractions—such as beaches and scenic sites—offers an economically viable path for community development based on the foundational principles of community tourism (Cayo-Velásquez et al., 2025). However, most national studies addressing this topic rely on conventional qualitative and quantitative designs, without generating scientific evidence capable of measuring, comparing, and predicting the factors that explain tourism strengthening (Carreón et al., 2019).

This study aims to overcome such limitations by applying Bayesian Networks (BN) and Directed Acyclic Graphs (DAGs) (Scutari, 2010). These probabilistic models allow the identification of conditional relationships among sociodemographic and technological variables, offering a more precise understanding of the factors that influence tourism empowerment. The research seeks to answer key questions: How does the use of collaborative information systems influence the strengthening of rural community tourism in Titilaca, Luquina, Socca, and Thunuhuaya? Which technology-related factors are significant in this process? And what dependency relationships explain the dynamics of tourism strengthening? Addressing these questions not only identifies good practices but also provides useful insights for designing more inclusive and sustainable interventions aligned with the aspirations of local residents (Gascón, 2022). This contribution extends beyond the role of technology in community tourism, offering guidance for public policies that are more equitable and replicable in other Andean regions of Latin America (Gadakh et al., 2025). It also offers evidence regarding the evaluation and implementation of online collaborative information systems (Terán Bustamante et al., 2019), and the use of technology in strengthening tourism (Cayo-Velásquez et al., 2025), supporting public policies that promote justice, equitable benefit distribution (Sun et al., n.d.), and development models grounded in local self-determination (Apaza-Tarqui et al., 2023).

Bayesian Networks encode conditional dependency and independence relationships through graphs in which nodes represent random variables and edges represent dependencies. Each node X has a conditional probability distribution $P(X \mid Pa(X))$, where $Pa(X)$ denotes the parents of X in the network. This approach is widely used for diagnosing, predicting, and assessing risks in complex real-world systems to ensure reliable and credible conclusions (Furlong et al., 2025). The Directed Acyclic Graph (DAG) avoids loops and guarantees the unique factorization of the joint distribution through Conditional Probability Tables (CPTs), allowing probabilistic inference (Scutari, 2017). BN provides a visual representation where vertices correspond to variables, and edges represent direct probabilistic dependencies without elaborating on the statistical assumptions of multivariate models (Scutari, 2010).

Parameters in discrete BN models are estimated using conditional probabilities from local distributions based on empirical frequencies in the dataset:

$$\hat{P}(E|S) = \frac{\hat{P}(E|S)}{\hat{P}(S)} \quad (1)$$

$$\hat{P}(E|S) = \frac{\#\, obvs\ educación\ básica\ y\ mujeres}{\#\, obvs\ mujeres} \quad (2)$$

Where E is the education supervision variable and S is the gender variable. This produces classical frequentist probability and maximum likelihood estimates. In BN, the bn.fit function from the bnlearn package estimates and calculates the parameters of a BN structure using user-specified CPTs or maximum likelihood estimations (method = "mle"). Learning the DAG structure is complex due to the immense space of possible network configurations; typically, only a fraction can be explored efficiently using conditional independence tests and scoring metrics. Conditional independence tests such as the likelihood-ratio test (G2) and Pearson's chi-square (X2) determine whether arcs should be included in the DAG (Peralta Ramírez, 2016).

For the log-likelihood ratio test, the statistic is:

$$G^2(Y, X_3|X_4, X_5) = \sum_{y\in Y} \sum_{x_3\in X_3} \sum_{x\in X_4 * X_5} \frac{n_{yx_3x}}{n} Log \frac{n_{yx_3x} n_{++x}}{n_{y+x} n_{+x_3x}} \quad (3)$$

Where Y is the dependent variable and X_i are the independent variables.

For the Pearson statistic, it is given by:

$$X^2(Y, X_3|X_4, X_5) = \sum_{y\in Y} \sum_{x_3\in X_3} \sum_{x\in X_4 * X_5} \frac{(n_{yx_3x} - m_{yx_3x})^2}{n_{++x}} \quad (4)$$

Where $m_{yx_3x} = \frac{n_{y+x} n_{+x_3x}}{n_{++x}}$

The assumption of conditional independence corresponds to small values for the aforementioned statistics. The ci.test function from bnlearn implements both tests. The G^2 test is obtained when test = "mi", whereas the Pearson X^2 test is obtained when test = "x2". High p-values in these tests indicate that the dependency relationship encoded by X → Y is not significant within a GAD structure. Insignificant arcs are removed based on the unsupported dependency relationship by the data. The significance testing of each arc is automated using the arc.strength function, specifying the test through the criterion argument. This function is designed to measure the strength of the probabilistic dependency associated with each arc by removing that particular arc from the graph and quantifying the change according to a probabilistic criterion (Scutari, 2017).

Network scores focus on the GAD as a whole. They are goodness-of-fit statistics that measure how well the GAD reflects the dependency structure of the data using the Bayesian Information Criterion (BIC). For a BN with the structure A, S, E, C, T_1, T_2, T_3, T_4, T_5, F, it is defined as follows:

$$BIC = log\hat{P}r(A, S, E, C, T_1, T_2, T_3, T_4, T_5, F) - \frac{d}{2}\log n \quad (5)$$

$$BIC = \left[\log \hat{P}r(A) - \frac{d_A}{2}\log n\right] \left[\log \hat{P}r(S) - \frac{d_S}{2}\log n\right] \left[\log \hat{P}r(E) - \frac{d_E}{2}\log n\right] + \left[\log \hat{P}r(E|A) - \frac{d_E}{2}\log n\right] + \left[\log \hat{P}r(C|E) - \frac{d_E}{2}\log n\right] + \left[\log \hat{P}r(F|C, E) - \frac{d_F}{2}\log n\right] \quad (6)$$

Where n is the sample size, d is the total number of parameters in the network, and $d_A, d_S, d_E, d_C, d_{T_1}, d_{T_2}, d_{T_3}, d_{T_4}, d_{T_5}, d_F$, are the numbers of parameters associated with each node.

The decomposition of the global distribution makes it easy to calculate the BIC from the local distributions, assigning higher scores to GADs that better fit the data. Learning the GAD structure from survey data should provide an improved network. Several algorithms address this problem by searching for the GAD that maximizes the score for a given network. One of the simplest is hill-climbing, which, starting from a GAD with no arcs, adds, removes, or reverses one arc at a time, selecting the change that maximally increases the network score. This method is implemented in the hc function, which in its simplest form takes the data as the only argument and uses BIC as the default score. As expected, the removal of any arc from the learned network decreases its BIC score. This is confirmed using arc.strength, which reports the change in score caused by removing an arc (Scutari, 2017).

BNLEARN implements key algorithms that cover all stages of Bayesian network modeling: data preprocessing, structure learning combining data and expert/prior knowledge, parameter learning, inference, and causal inference, providing a comprehensive solution for Bayesian networks in R. It offers tools for working with discrete Bayesian networks, Gaussian Bayesian networks, and conditional linear Gaussian Bayesian networks with real-world data. It also supports incomplete data with missing values. For simulation studies, bnlearn includes constraint-based algorithms, conditional independence tests to learn from data by assuming that conditional independence implies graphical separation so that two independent variables are not connected by an arc; general-purpose score-based optimization algorithms that rank networks according to a goodness-of-fit score; and hybrid algorithms that combine aspects of constraint-based and score-based methods, using conditional independence tests and network scores simultaneously to find the optimal network in a reduced search space.

Inclusive community-based tourism development in times of digital transformation inevitably requires reflection on concepts such as customized online collaborative information systems (Barrientos-Báez et al., 2022) and the strengthening of tourism activities (Aranibar Ramos & Patiño Huayhua, 2022b). The study incorporates organizational identities, including complexity, inclusive openness, and patterns of reciprocal behavior, within digital transformation processes based on collaborative systems that enhance social network competencies (Adco, 2020), such as:

WhatsApp: an instant messaging application for text, voice, video, and file sharing over the Internet using phone numbers, which allows segmentation of users and clients.

Facebook: a social network that interconnects friends and communities through photo and video posts, messages, groups, and pages, with profiles linked to email accounts or phone numbers, enabling privacy configuration (Adco, 2020).

TikTok: a platform for creating and consuming short videos with high-quality editing tools, music, and effects (Nuzuli, 2022). Through content recommendation algorithms, it enables massive interaction, user preferences, digital applications with privacy, content security, authentication, and permissions (Yuliana, 2022). Engagement refers to user interaction with content through likes, comments, and shares, achieving natural reach compared to advertising and promotional campaigns on social media (Mier Uribe & Rojo Gutiérrez, 2023). Information content at the metadata level, including dates, locations, and devices, is presented on dashboards to support decision-making as a result of electronic processes (Adco, 2020). This requires infrastructure such as personal computers (PCs), laptops, smartphones, or other devices (processors, memory, storage, GPU, motherboard, sensors) for automated processing. It also requires user-customized software applications to perform daily tasks efficiently, supporting programmable devices with compatibility, interoperability, and security features, such as updates, patches, antivirus, firewalls, and encryption (González, 2018; Mier Uribe & Rojo Gutiérrez, 2023).

The Internet, as a global public network, interconnects computers and devices using TCP/IP protocols, providing unique addresses to identify devices on a network and ensuring reliable data delivery over a connectivity infrastructure to guarantee transfer speed and response time (Mier Uribe & Rojo Gutiérrez, 2023).

Internet applications, such as web hosting, email, browsers, cloud storage, and streaming, rely on mobile operators or companies providing voice and data services over mobile networks (4G/LTE, 5G, 6G, and 7G) and VoIP technology, along with alternatives such as data, minutes, messages, international roaming, mobile banking, and tethering (hotspots) (Mihret et al., 2021).

Strengthening community-based tourism mediated by technology drives activity in an objective and participatory manner, identifying resources, capabilities, and stakeholders, and generating projects and programs that improve community quality of life (Fasanando, 2021).

Empowerment in tourism has multiple dimensions: how individuals feel about themselves, understand their environment, participate in training, and make leadership decisions within their community, creating a model where residents organize and manage their own cultural and natural resources (Dangi & Jamal, 2016)(Dangi & Jamal, 2016).

Active community participation in tourism requires training and collective socialization to provide security and unity in defending their interests, ensuring that benefits are distributed fairly among all stakeholders (Pahrudin et al., 2022)

Sustainability is not only about protecting nature but also empowering community members to make effective decisions, where choices are not solely made by authorities or companies, but collectively, respecting and listening to the living culture of each place (Santos-Roldán et al., 2020).

Strengthening should not only be viewed as an expected outcome but as a deliberate, sustained, and coordinated process that originates from local communities and projects towards structural transformations (Restrepo Rico & Peterek, 2024).

Social networks allow sharing community stories, local production processes, hiking routes, craft workshops, traditional festivals, and mystical tourism, attracting travelers seeking authentic experiences. This approach is particularly relevant in rural and peripheral contexts, such as communities in the Peruvian highlands Ara(Aranibar Ramos & Patiño Huayhua, 2022a), where historically communities have been excluded from decision-making processes and development benefits (Milla Canales, 2024). In these territories, collaborative information systems must serve as tools to activate effective strengthening processes for the local population, recognizing their knowledge and forms of solidarity in benefit distribution (Barrientos-Báez et al., 2022).

Consequently, studying the influence of online collaborative information systems on tourism strengthening helps understand tourism practices as appropriated by local actors, based on their cultural identity and natural resources, and supports the development of community-based tourism alternatives that are fairer, more inclusive, and sustainable.

In this sense, tourism strengthening is not only a theoretical goal but an inclusive practice for all community members to improve quality of life and serve as a lever for sustained development. In areas like the highlands, where deep cultural roots coexist with structural challenges, such approaches are especially valuable, connecting local transformation with broader institutional and territorial processes.

METHODOLOGY

A non-experimental, cross-sectional research design with a quantitative approach was used. The study population consisted of individuals over 18 years of age residing in rural population centers with consolidated tourism activities: Luquina, Titilaca, Socca, and Thunuhuaya. A structured survey was administered to 608 individuals selected through simple random sampling. The causal analysis employed graphical, probabilistic, and parametric representations of conditional probability tables, as well as the estimation of a Directed Acyclic Graph (DAG) structure using conditional independence tests and Bayesian Network (BN) scoring criteria.

The variables used in the study are as follows:

Age (A) (Young, Adult, Elderly) refers to the age groups of the population: Young from 18 to 30 years, Adult from 31 to 60 years, and Elderly 60 years and above.

Sex (S) (M, F) indicates the gender of the population: M for male individuals and F for female individuals engaged in gastronomy and crafts.

Education (E) (Illiterate, Basic, Higher) refers to the educational level attained by the population: Illiterate for those without formal education, Basic for those with primary and secondary education, and Higher for those pursuing higher or professional studies.

Interest (C) (No, Yes, Leads) refers to the population of residents interested in community-based rural tourism entrepreneurship. No indicates those who do not express interest, Yes refers to those who support TRC initiatives, and Leads refers to individuals who guide the community toward TRC activities.

Strengthening (F) (None, Regular, Strengthens) is the supervision variable that evaluates the impact of TRC-related activities in empowering improvements to the minimum conditions of quality of life.

Phone (T1) (Movistar, Claro, Bitel, Don't know) refers to the mobile phone service operator providing telecommunications coverage and acting as Internet Service Providers (ISP).

Devices (T2) (PCs, Laptop, Smartphone, Don't know) constitute the hardware infrastructure available to the population to support online collaborative systems.

Internet (T3) (Wi-Fi, Cellular, Don't know) refers to Internet access mechanisms, including data Mbps provided by the mobile phone service.

Collaborative System (T4) (School, Agency, Don't know) refers to software systems implemented as applications in some state institutions (educational or health) as well as by private companies, promoting custom TRC software systems.

Social Networks (T5) (WhatsApp, Facebook, TikTok, Don't know) refers to social media systems that have expanded their use among the population under study.

RESULTS

The analysis of the data collected through a structured survey applied to registered residents of the communities of Titilaca, Luquina, Socca, and Thunuhuaya allowed the identification of significant factors associated with the strengthening of community-based rural tourism capacities in the Puno region. Please take note of the following items when proofreading spelling and grammar:

Graphical Representation

The relationships among variables in a Bayesian Network are represented through a Directed Acyclic Graph (DAG), where each node corresponds to one of the study variables. The resulting graph contains ten nodes: Age (A), Sex (S), Education (E), Interest (C), Devices (T_1), Mobile Operator (T_2), Internet Access (T_3), Collaborative Systems (T_4), Social Networks (T_5), and Strengthening (F), coded as A, S, E, C, T_1, T_2, T_3, T_4, T_5, and F, respectively.

Direct dependency relationships are represented by arcs between pairs of variables (e.g., $S \rightarrow E$ indicates that Education depends on Sex). The node from which the arc originates is considered the parent, and the node receiving the arc is the child. Indirect dependencies appear as sequences of arcs connecting two variables through one or more mediators (e.g., $S \rightarrow E \rightarrow T_1$ implies that Devices depend on Sex through Education). Such sequences form a path, enabling the interpretation of both direct and indirect dependencies.

Although arcs may visually suggest causality (e.g., $E \rightarrow T_1$ might appear to imply that Education causes Devices), this interpretation is rarely justified empirically. Therefore, the term dependency is preferred over causal effect.

To create and manipulate DAGs in the context of Bayesian Networks, the bnlearn library is used:

```
library(bnlearn)
```

A DAG with no arcs and one node per variable is created as the initial structure:

```
Gad<-empty.graph(nodes=c("A","S","E","C","T1","T2","T3","T4","T5","F"))> Gad

  Random/Generated Bayesian network

  model:
   [A][S][E][C][T1][T2][T3][T4][T5][F]
  nodes:                               10
  arcs:                                0
    undirected arcs:                   0
    directed arcs:                     0
  average markov blanket size:         0.00
  average neighbourhood size:          0.00
  average branching factor:            0.00

  generation algorithm:                Empty
```

The arcs that encode the direct dependencies between the variables Age and Sex do not result in statistically significant influences. Therefore, there are no arcs pointing toward these variables. On the other hand, the variables within the education dimension have a direct influence on the variable Fortalece (Strengthening).

```
> Gad <-set.arc(gad,from="A", to="E")
> Gad<-set.arc(Gad, from="A", to="E")
> Gad<-set.arc(Gad, from="S", to="E")
> Gad<-set.arc(Gad, from="E", to="C")
> Gad<-set.arc(Gad, from="E", to="T1")
> Gad<-set.arc(Gad, from="E", to="T2")
> Gad<-set.arc(Gad, from="E", to="T3")
> Gad<-set.arc(Gad, from="E", to="T4")
> Gad<-set.arc(Gad, from="E", to="T5")
> Gad<-set.arc(Gad, from="C", to="F")
> Gad<-set.arc(Gad, from="T1", to="F")
> Gad<-set.arc(Gad, from="T2", to="F")
> Gad<-set.arc(Gad, from="T3", to="F")
> Gad<-set.arc(Gad, from="T4", to="F")
> Gad<-set.arc(Gad, from="T5", to="F")
> Gad
Random/Generated Bayesian network
  model:
  [A][S][E|A:S][C|E][T1|E][T2|E][T3|E][T4|E][T5|E][F|C:T1:T2:T3:T4:T5]
  nodes:                               10
  arcs:                                14
    undirected arcs:                   0
    directed arcs:                     14
  average markov blanket size:         6.00
  average neighbourhood size:          2.80
  average branching factor:            1.40
  generation algorithm:                Empty

 > plot(Gad)
```

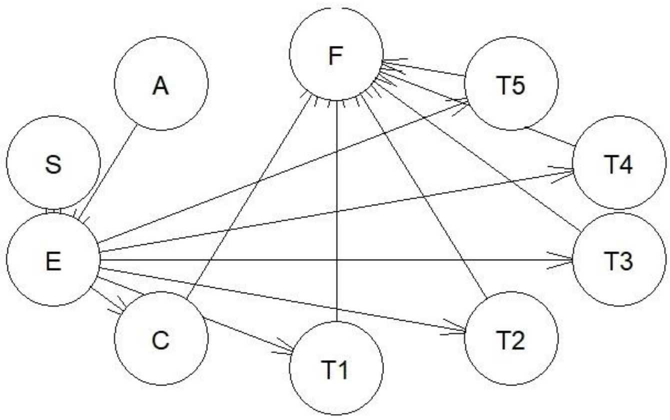

Figure 1

The bnlearn library provides many additional functions for analyzing and manipulating bn objects such as nodes and arcs.

```
nodes(gad)
## [1] "A" "S" "E" "C" "T1" "T2" "T3" "T4" "T5" "F"
arcs(gad)
```

I. Probabilistic Representation

Once the relationships among the variables are represented, a DAG is used to complete the Bayesian Network modeling by specifying a joint probability distribution over these variables. All of them are defined within a set of unordered states, referred to as levels in R.

```
> A.lv<-c("Joven","Adulto","Mayor")
> S.lv<-c("M","F")
> E.lv<-c("Iletrado","Básica","Superior")
> C.lv<-c("No","Si","Líder")
> T1.lv<-c("Movistar","Claro","Bitel","No sabe")
> T2.lv<-c("PC","Laptop","Smartphone","No sabe")
> T3.lv<-c("Wi fi","Celular","No sabe")
> T4.lv<-c("Colegio","Agencia","No sabe")
> T5.lv<-c("WhatsApp","Facebook","Tik Tok","No sabe")
> F.lv<-c("Nada","Regular","Fortalece")
> F.lv<-c("Nada","Regular","Fortalece")
```

The network scores focus on the GAD as a whole; they are goodness-of-fit statistics that measure how well the GAD reflects the dependency structure of the data using the Bayesian Information Criterion (BIC), which for the BN with the structure $A, S, E, C, T_1, T_2, T_3, T_4, T_5, F$ is defined as follows:

$$BIC = log\hat{P}r(A, S, E, C, T_1, T_2, T_3, T_4, T_5, F) - \frac{d}{2}\log n \qquad (5)$$

$$BIC = \left[\log\hat{P}r(A) - \frac{d_A}{2}\log n\right]\left[\log\hat{P}r(S) - \frac{d_S}{2}\log n\right]\left[\log\hat{P}r(E) - \frac{d_E}{2}\log n\right] + \left[\log\hat{P}r(E|A) - \frac{d_E}{2}\log n\right] + \left[\log\hat{P}r(C|E) - \frac{d_E}{2}\log n\right] + \left[\log\hat{P}r(F|C,E) - \frac{d_F}{2}\log n\right] \qquad (6)$$

Where n is the sample size, d is the number of parameters of the entire network, and $d_A, d_S, d_E, d_C, d_{T_1}, d_{T_2}, d_{T_3}, d_{T_4}, d_{T_5}, d_F$, are the numbers of parameters associated with each node.

The decomposition of the global distribution makes it easy to compute the BIC from the local distributions, assigning higher scores to GADs that fit the data better. Learning the GAD structure from the survey should provide an improved network. There are several algorithms that address this problem by searching for the GAD that maximizes the score of a given network. One of the simplest is hill-climbing, which, starting from an arc-less GAD, adds, deletes, or reverses one arc at a time, and chooses the change that increases the network score the most. This algorithm is implemented in the function *hc*, which in its simplest form takes the dataset as its only argument and uses the BIC score by default. As expected, the removal of any arc from the learned network decreases its BIC score. This is confirmed using *arc.strength*, which reports the change in the score caused by the deletion of an arc (Scutari, 2010).

The natural choice for the joint probability distribution is a **multinomial distribution** that assigns a probability to each combination of states of the study variables, known as the global distribution. This is complex because it defines a very large number of parameters; in this case, the set of parameters exceeds 143 probabilities corresponding to all combinations of variable levels. Therefore, the information encoded in the GAD is used to decompose the global distribution into a set of smaller local distributions, one for each variable. The arcs represent direct dependencies—if there is an arc from one variable to another, the latter depends on the former. In other words, variables that are not connected by an arc are conditionally independent.

As a result, the global distribution is factorized as follows:

$$\Pr(A,S,E,C,T_1,T_2,T_3,T_4,T_5,F)=\Pr(A)\Pr(S)\Pr(E|A,S)\Pr(C|E)\Pr(X_5|E)\Pr(Y|X_4,X_5)\Pr(A,S,E,C,T_1,T_2,T_3,T_4,T_5,F)=\Pr(X_1)\Pr(X_2)\Pr(X_3|X_1,X_3)\Pr(X_4|X_3)\Pr(X_5|X_3)\Pr(Y|X_4,X_5)$$

The absence of cycles in the DAG ensures that the factorization is well defined. Each variable depends only on its parents; its distribution is univariate and has, comparatively, a small number of parameters.

Even the set of all local distributions generally has fewer parameters than the global distribution, since the latter represents a more general model, as it makes no assumptions about the dependencies among the variables.

In other words, the above factorization defines a nested model, or a submodel, of the global distribution.

The economic variables are modeled using simple one-dimensional probability tables, since they have no parents.

```
> A.prob<-array(c(0.5,0.3,0.2), dim=3, dimnames=list(A=A.lv))
> A.prob
A
 Joven Adulto  Mayor
   0.5    0.3    0.2
> S.prob<-array(c(0.45,0.55), dim=2, dimnames=list(S=S.lv))
> S.prob
S
   M    F
0.45 0.55
> C.prob<-array(c(0.4,0.3,0.3,0.3,0.6,0.1,0.3,0.5,0.2), dim=c(3,3), dimna
mes=list(C=C.lv,E=E.lv))
> C.prob
       E
C       Iletrado Básica Superior
  No         0.4    0.3      0.3
  Si         0.3    0.6      0.5
  Líder      0.3    0.1      0.2
> T1.prob<-array(c(0.2,0.2,0.2,0.4,0.1,0.3,0.3,0.3,0.2,0.3,0.3,0.2), dim=
c(4,3), dimnames=list(T1=T1.lv,E=E.lv))
> T1.prob
         E
T1         Iletrado Básica Superior
  Movistar      0.2    0.1      0.2
  Claro         0.2    0.3      0.3
  Bitel         0.2    0.3      0.3
  No sabe       0.4    0.3      0.2
> T2.prob<-array(c(0.1,0.1,0.2,0.6,0.3,0.3,0.3,0.1,0.2,0.3,0.5,0), dim=c(
4,3), dimnames=list(T2=T2.lv,E=E.lv))
> T2.prob
            E
T2           Iletrado Básica Superior
  PC              0.1    0.3      0.2
  Laptop          0.1    0.3      0.3
  Smartphone      0.2    0.3      0.5
  No sabe         0.6    0.1      0.0
```



```
> T3.prob<-array(c(0.1,0.1,0.8,0.4,0.5,0.1,0.5,0.5,0), dim=c(3,3), dimnam
es=list(T3=T3.lv,E=E.lv))
> T3.prob
          E
T3        Iletrado Básica Superior
  Wi fi        0.1    0.4      0.5
  Celular      0.1    0.5      0.5
  No sabe      0.8    0.1      0.0
> T4.prob<-array(c(0,0.1,0.9,0.3,0.4,0.3,0.45,0.55,0), dim=c(3,3), dimnam
es=list(T4=T4.lv,E=E.lv))
> T4.prob
          E
T4        Iletrado Básica Superior
  Colegio      0.0    0.3     0.45
  Agencia      0.1    0.4     0.55
  No sabe      0.9    0.3     0.00
> T5.prob<-array(c(0.1,0.1,0,0.8,0.3,0.4,0.3,0,0.3,0.2,0.5,0), dim=c(4,3)
, dimnames=list(T5=T5.lv,E=E.lv))
> T5.prob
           E
T5         Iletrado Básica Superior
  WhatsApp      0.1    0.3      0.3
  Facebook      0.1    0.4      0.2
  Tik Tok       0.0    0.3      0.5
  No sabe       0.8    0.0      0.0
> F.prob<-array(c(0.7,0.2,0.1,0.1,0.3,0.6,0.2,0.4,0.4,0.8,0.1,0.1,0.1,0.2
,0.7,0.2,0.3,0.4,0.7,0.2,0.1,0.1,0.1,0.8,0.1,0.3,0.6,0.8,0.1,0.1,0.6,0.3,
0.1,0.6,0.2,0.2), dim=c(3,4,3), dimnames=list(F=F.lv,C=C.lv,T2=T2.lv))
Error en array(c(0.7, 0.2, 0.1, 0.1, 0.3, 0.6, 0.2, 0.4, 0.4, 0.8, 0.1, :

  la longitud de 'dimnames' [2] no es igual a la extensión del arreglo
Tabla de probabilidades condicionales
> F.prob<-array(c(0.7,0.3,0.0,0.2,0.8,0.0,0.1,0.2,0.7,0.4,0.6,0.0,0.2,0.5
,0.3,0.3,0.5,0.2,0.5,0.5,0.0,0.1,0.5,0.4,0.1,0.3,0.6,0.6,0.4,0.0,0.2,0.5,
0.2,0.3,0.5,0.2), dim=c(3,3,3), dimnames=list(F=F.lv,C=C.lv,E=E.lv))
> F.prob
, , E = Iletrado

           C
F            No  Si Líder
  Nada      0.7 0.2   0.1
  Regular   0.3 0.8   0.2
  Fortalece 0.0 0.0   0.7

, , E = Básica

           C
F            No  Si Líder
  Nada      0.4 0.2   0.3
  Regular   0.6 0.5   0.5
  Fortalece 0.0 0.3   0.2

, , E = Superior

           C
F            No  Si Líder
```

```
  Nada       0.5 0.1   0.1
  Regular    0.5 0.5   0.3
  Fortalece 0.0 0.4   0.6

> F.prob<-array(c(1.0,0.0,0.0,0.2,0.5,0.3,0.2,0.5,0.2,1.0,0.0,0.0,0.2,0.6
,0.2,0.3,0.6,0.2,1.0,0.0,0.0,0.1,0.6,0.3,0.2,0.5,0.3,1.0,0.0,0.0,0.1,0.6,
0.3,0.2,0.5,0.3,0.6,0.4,0.0,0.2,0.5,0.2,0.3,0.5,0.2), dim=c(3,4,3), dimna
mes=list(F=F.lv,T1=T1.lv,E=E.lv))
> F.prob
, , E = Iletrado

           T1
F           Movistar Claro Bitel No sabe
  Nada             1   0.2   0.2       1
  Regular          0   0.5   0.5       0
  Fortalece        0   0.3   0.2       0

, , E = Básica

           T1
F           Movistar Claro Bitel No sabe
  Nada           0.2   0.3     1     0.1
  Regular        0.6   0.6     0     0.6
  Fortalece      0.2   0.2     0     0.3

, , E = Superior

           T1
F           Movistar Claro Bitel No sabe
  Nada           0.2     1   0.1     0.2
  Regular        0.5     0   0.6     0.5
  Fortalece      0.3     0   0.3     0.3

> F.prob<-array(c(0.7,0.3,0.0,0.2,0.8,0.0,0.1,0.2,0.7,0.4,0.6,0.0,0.2,0.5
,0.3,0.3,0.5,0.2,0.5,0.5,0.0,0.1,0.5,0.4,0.1,0.3,0.6,0.6,0.4,0.0,0.2,0.5,
0.2,0.3,0.5,0.2), dim=c(3,4,3), dimnames=list(F=F.lv,T2=T2.lv,E=E.lv))
> F.prob
, , E = Iletrado

           T2
F             PC Laptop Smartphone No sabe
  Nada       0.7    0.2        0.1     0.4
  Regular    0.3    0.8        0.2     0.6
  Fortalece 0.0    0.0        0.7     0.0

, , E = Básica

           T2
F             PC Laptop Smartphone No sabe
  Nada       0.2    0.3        0.5     0.1
  Regular    0.5    0.5        0.5     0.5
  Fortalece 0.3    0.2        0.0     0.4

, , E = Superior

           T2
F             PC Laptop Smartphone No sabe
```



```
  Nada      0.1    0.6         0.2     0.3
  Regular   0.3    0.4         0.5     0.5
  Fortalece 0.6    0.0         0.2     0.2

> F.prob<-array(c(0.7,0.3,0.0,0.2,0.8,0.0,0.1,0.2,0.7,0.4,0.6,0.0,0.2,0.5
,0.3,0.3,0.5,0.2,0.5,0.5,0.0,0.1,0.5,0.4,0.1,0.3,0.6,0.6,0.4,0.0,0.2,0.5,
0.2,0.3,0.5,0.2), dim=c(3,3,3), dimnames=list(F=F.lv,T3=T3.lv,E=E.lv))
> F.prob
, , E = Iletrado

           T3
F           Wi fi Celular No sabe
  Nada        0.7     0.2     0.1
  Regular     0.3     0.8     0.2
  Fortalece   0.0     0.0     0.7

, , E = Básica

           T3
F           Wi fi Celular No sabe
  Nada        0.4     0.2     0.3
  Regular     0.6     0.5     0.5
  Fortalece   0.0     0.3     0.2

, , E = Superior

           T3
F           Wi fi Celular No sabe
  Nada        0.5     0.1     0.1
  Regular     0.5     0.5     0.3
  Fortalece   0.0     0.4     0.6

> F.prob<-array(c(0.7,0.3,0.0,0.2,0.8,0.0,0.1,0.2,0.7,0.4,0.6,0.0,0.2,0.5
,0.3,0.3,0.5,0.2,0.5,0.5,0.0,0.1,0.5,0.4,0.1,0.3,0.6,0.6,0.4,0.0,0.2,0.5,
0.2,0.3,0.5,0.2), dim=c(3,3,3), dimnames=list(F=F.lv,T4=T4.lv,E=E.lv))
> F.prob
, , E = Iletrado

           T4
F           Colegio Agencia No sabe
  Nada          0.7     0.2     0.1
  Regular       0.3     0.8     0.2
  Fortalece     0.0     0.0     0.7

, , E = Básica

           T4
F           Colegio Agencia No sabe
  Nada          0.4     0.2     0.3
  Regular       0.6     0.5     0.5
  Fortalece     0.0     0.3     0.2

, , E = Superior

           T4
F           Colegio Agencia No sabe
  Nada          0.5     0.1     0.1
```

```
  Regular       0.5     0.5     0.3
  Fortalece     0.0     0.4     0.6

> F.prob<-array(c(0.7,0.3,0.0,0.2,0.8,0.0,0.1,0.2,0.7,0.4,0.6,0.0,0.2,0.5
,0.3,0.3,0.5,0.2,0.5,0.5,0.0,0.1,0.5,0.4,0.1,0.3,0.6,0.6,0.4,0.0,0.2,0.5,
0.2,0.3,0.5,0.2), dim=c(3,4,3), dimnames=list(F=F.lv,T5=T5.lv,E=E.lv))
> F.prob
, , E = Iletrado

           T5
F       WhatsApp Facebook Tik Tok No sabe
  Nada       0.7      0.2     0.1     0.4
  Regular    0.3      0.8     0.2     0.6
  Fortalece  0.0      0.0     0.7     0.0

, , E = Básica

           T5
F       WhatsApp Facebook Tik Tok No sabe
  Nada       0.2      0.3     0.5     0.1
  Regular    0.5      0.5     0.5     0.5
  Fortalece  0.3      0.2     0.0     0.4

, , E = Superior

           T5
F       WhatsApp Facebook Tik Tok No sabe
  Nada       0.1      0.6     0.2     0.3
  Regular    0.3      0.4     0.5     0.5
  Fortalece  0.6      0.0     0.2     0.2
```

Parameter Estimation: Conditional Probability Tables

The dataset containing the data collected through the survey, in accordance with the DAG design, defines the parameters of the local distributions that make up the Bayesian Network. In this scenario, these are used as systems that formalize the knowledge of one or more experts in community-based rural tourism activities, in order to estimate the parameters of the local distributions from the information observed in the dataset, stored in a text file named *Lago_s.txt*, which is imported using `read.table`.

```
> Lago_S.data<-read.table("D:/Lago_s.txt", header=TRUE, stringsAsFactors
= TRUE)
> head(Lago_S.data)
      A S        E  C      T1      T2      T3      T4      T5    F
1 Mayor F Iletrado No No sabe No sabe No sabe No sabe No sabe Nada
2 Mayor F Iletrado No No sabe No sabe No sabe No sabe No sabe Nada
3 Mayor M Iletrado No No sabe No sabe No sabe No sabe No sabe Nada
4 Mayor M Iletrado No No sabe No sabe No sabe No sabe No sabe Nada
5 Mayor M Iletrado No No sabe No sabe No sabe No sabe No sabe Nada
6 Mayor M Iletrado No No sabe No sabe No sabe No sabe No sabe Nada
```

The discrete BNs, whose parameters are estimated using the conditional probabilities in the local distributions, along with the corresponding empirical frequencies in the dataset:

$$\widehat{Pr}(C = Si|E = Superior = \frac{\widehat{\Pr}\,(C = Si, E = superior)}{\widehat{\Pr}\,(E = educación)}$$
$$= \frac{\#obsv\ con\ C = Si\ y\ E = Superior}{\#Obsv\ con\ E = Supeior}$$

The classical frequentist and maximum likelihood probability estimates. In **bnlearn**, these are computed with the **bn.fit** function, which allows building a BN using a set of user-specified custom parameters, while the estimates are obtained from the survey data, producing the classical frequentist and maximum likelihood probability estimates, which are presented below:

```
> bn.mle<-bn.fit(Gad, data=Lago_S.data, method="mle")
> prop.table(table(Lago_S.data[,c("C","E")]),margin=2)
       E
C           Básica   Iletrado   Superior
  Lïder 0.04316547 0.01869159 0.15476190
  No    0.13908873 0.57009346 0.05952381
  Si    0.81774580 0.41121495 0.78571429
```

Conditional Independence Tests

This produces the classical frequentist and maximum likelihood probability estimates. In bnlearn, these estimates can be computed using the bn.fit function, which allows constructing a Bayesian Network using a set of user-specified custom parameters, while the estimated values are obtained directly from the data:

```
> ci.test("F","E",c("C"),test="x2", data=Lago_S.data)

       Pearson's X^2

data:  F ~ E | C
x2 = 70.024, df = 12, p-value = 3.171e-10
alternative hypothesis: true value is greater than 0

> ci.test("F","E",c("T1"),test="x2", data=Lago_S.data)

       Pearson's X^2

data:  F ~ E | T1
x2 = 44.891, df = 16, p-value = 0.0001442
alternative hypothesis: true value is greater than 0

> ci.test("F","E","T2",test="x2", data=Lago_S.data)

       Pearson's X^2

data:  F ~ E | T2
x2 = 64.206, df = 16, p-value = 1.009e-07
alternative hypothesis: true value is greater than 0

> ci.test("F","E",c("T3"),test="x2", data=Lago_S.data)

       Pearson's X^2

data:  F ~ E | T3
x2 = 66.238, df = 12, p-value = 1.608e-09
alternative hypothesis: true value is greater than 0

> ci.test("F","E",c("T4"),test="x2", data=Lago_S.data)

       Pearson's X^2

data:  F ~ E | T4
x2 = 68.926, df = 12, p-value = 5.085e-10
alternative hypothesis: true value is greater than 0

> ci.test("F","E",c("T5"),test="x2", data=Lago_S.data)
```



```
        Pearson's X^2

data:  F ~ E | T5
x2 = 57.533, df = 16, p-value = 1.355e-06
alternative hypothesis: true value is greater than 0
```

Network Scores Headings,

The scores focus on the DAG as a whole; they are goodness-of-fit statistics that measure how well the DAG reflects the dependency structure of the data using the Bayesian Information Criterion (BIC). For the Bayesian Network with the structure defined by the variables $A, S, E, C, T_1, T_2, T_3, T_4, T_5, F$ and F, it is defined as follows:

$$BIC = log\hat{P}r(A, S, E, C, T_1, T_2, T_3, T_4, T_5, F) - \frac{d}{2}\log n \quad (5)$$

$$BIC = \left[\log\hat{P}r(A) - \frac{d_A}{2}\log n\right]\left[\log\hat{P}r(S) - \frac{d_S}{2}\log n\right]\left[\log\hat{P}r(E) - \frac{d_E}{2}\log n\right] + \left[\log\hat{P}r(E|A) - \frac{d_E}{2}\log n\right] + \left[\log\hat{P}r(C|E) - \frac{d_E}{2}\log n\right] + \left[\log\hat{P}r(F|C,E) - \frac{d_F}{2}\log n\right] \quad (6)$$

where n is the sample size, d is the total number of parameters in the entire network, $d_A, d_S, d_E, d_C, d_{T_1}, d_{T_2}, d_{T_3}, d_{T_4}, d_{T_5}, d_F$, are the numbers of parameters associated with each node, obtained as follows:

```
> arc.strength(Gad,data=Lago_S.data,criterion="x2")
   from to      strength
1     A  E 6.715942e-113
2     S  E  9.280302e-06
3     E  C  6.287544e-22
4     E T1  2.275942e-35
5     E T2  3.031208e-54
6     E T3  4.192132e-28
7     E T4  2.657087e-16
8     E T5  2.059956e-45
9     C  F  3.171e-10
10   T1  F  0.0001442
11   T2  F  1.009e-07
12   T3  F  1.608e-09
13   T4  F  9.414e-12
14   T5  F  3.577e-11
Aviso:
In check.unused.args(extra.args, test.extra.args[[test]]) :
   unused argument(s): 'criterion'.
```

In general, the network scores indicate that the DAG as a whole is significant for all arcs; that is, the Bayesian Network modeling system is fully interrelated among the variables. Age (A) and Sex (S) have a probabilistic influence on Education Level (E), while Interest (C) and the variables derived from Devices (T_1), Phone Operator (T_2), Internet (T_3), Software Programs (T_4), and Social Networks (T_5) depend on the educational level. Furthermore, all of these contribute to the Strengthening (F) of tourism activities.

The modeling of conditional relationships between sociodemographic variables and the characteristics of the Online Collaborative Information System (OCIS) using Bayesian Networks (BN) and Directed Acyclic Graphs (DAGs) is adequately represented. These models are supported by a survey of 608 residents from the communities of Luquina, Titilaca, Socca, and Thunuhuaya, both in the estimation of the DAG structure and its Conditional Probability Tables (CPTs).

The results show that the Education variable influences the OCIS-related variables (devices, software applications, Internet access, and social network usage), where the organizational context affects service quality and benefit distribution.

Overall, the findings summarize that the adoption of OCIS, coupled with training and inclusive governance, promotes a more equitable and sustainable community-based tourism development in the high-Andean communities of Peru.

DISCUSSION

The results show that the strengthening of community-based rural tourism is a complex process that involves the participation of the entire community in organization and decision-making. This participation must be guided by knowledge of best practices, which subsequently allows access to the economic, cultural, social, and environmental benefits derived from these activities, with each member contributing to decision-making (Aranibar Ramos & Patiño Huayhua, 2022a). This aligns with (Santos-Roldán et al., 2020), who indicate that tourism strengthening impacts economic, social, political, and emotional dimensions, focusing on empowering local communities to self-manage and sustainably benefit from their natural and cultural resources. This is achieved through project management training, infrastructure improvement, the design of viable tourism packages, and destination promotion (Barrientos-Báez et al., 2022). Therefore, it is imperative to adopt a participatory approach that includes all groups—women, youth, collectives, peasant patrols, farmers, artisans, and fishermen (Gascón, 2022)—whose success depends on the educational level of community members to ensure service quality and tourist satisfaction (Aragón Navarrete, 2018).

In the context of digital transformation, training in the appropriate use of Online Collaborative Information Systems (OCIS) for digital marketing can expand the tourism offer and increase the visibility of sustainable cultural practices. Specifically, leveraging social media platforms such as Facebook, TikTok, and Instagram, which are available within the communities (Adco, 2020), allows services and resources to reach a global tourism audience (Pahrudin et al., 2022). However, strengthening tourism in rural communities is also associated with the proper management of cultural, economic, and environmental resources, as well as fostering joint action and building active citizenship for community-based tourism (Dubuc-Piña, 2022). In this sense, the educational level of community members is key, both to ensure service quality and to take advantage of automated global systems for presenting tourist attractions, while fostering leadership in sustainable and autonomous development (Barrientos-Báez et al., 2022). Social networks and collaborative information platforms tend to strengthen tourism resources and widely disseminate projects that improve quality of life and reinforce local identity, provided there is inclusive governance and adequate education (Alcocer-Sánchez et al., 2023). Intensive training in OCIS and digital marketing is also required to expand the tourism offer and the visibility of sustainable cultural practices (Geneteau, 2021). Thus, the results confirm that tourism, when responsibly managed, becomes a concrete tool for improving life in the communities, as long as there is a willingness for continuous learning and a fair distribution of benefits. Nevertheless, the achieved tourism strengthening may remain fragile if it is not built on solid foundations, supported by institutions that listen to and endorse the diversity of proposals for constant improvement.

CONCLUSIONS

Bayesian Networks are effective techniques for verifying the relationships, and particularly the interrelationships, among variables. In this study, the Education Level variable depends largely on Age Group and Sex, while the OCIS-related variables depend on the educational level. Finally, the Strengthening of the OCIS variables is not only significant but highly significant.

The strengthening of community-based rural tourism in the digital context is a complex process that requires the equitable participation of community members, whose organizational capacities and educational level ensure service quality and fair distribution of benefits. Social networks and collaborative information platforms promote the marketing and visibility of resources, capacities, and actors, fostering projects that improve quality of life and reinforce local identity. However, sustainability depends on the institutionalization of co-management processes, continuous training, and accountability mechanisms that prevent benefit concentration among a few.

Tourism strengthening emerges when there is active participation, equitable benefit distribution, organization, and education. Each community follows its own path, where tourism must be built locally, with community leadership and respect for cultural diversity.

The adoption of OCIS, accompanied by training and inclusive governance, can contribute to a fairer, more sustainable, and resilient tourism development in the Sacred Lake region and similar high-Andean contexts.

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