COMPARATIVE EVALUATION OF TOURISM ATTRACTIVENESS USING MONTE CARLO SIMULATION AND CROWDSOURCED DATA. CASE STUDY FOR SEVERAL TRANSYLVANIAN CITIES.

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ABSTRACT

Tourism plays a crucial role in regional economic development, yet the extent to which a city transforms its tourism potential into realized visitor attraction remains an area of ongoing research. This study presents a novel methodology for assessing and comparing tourist attraction levels in 16 Romanian cities by integrating Monte Carlo simulation with crowdsourced data. It evaluates both potential and realized tourism attractiveness using five key components: (1) quantification of tourism potential using digital infrastructure data and user-generated content, (2) assessment of tourism infrastructure through accommodations and dining establishments, (3) evaluation of environmental attractiveness via satellite-derived indices such as the Normalized Difference Vegetation Index (NDVI) and the Holiday Climate Index (HCI), (4) probabilistic modeling of tourist behavior using Monte Carlo simulation, and (5) correlation analysis between the modeled results and actual tourism data. Findings reveal that while major cities like Cluj-Napoca and Brașov dominate in absolute attractiveness, smaller towns such as Gheorgheni and Odorheiu Secuiesc show untapped tourism potential when adjusted for population size. The study confirms that crowdsourced data align well with traditional tourism indicators and suggests that integrating computational models enhances tourism assessments. Future research should incorporate pricing factors and test the methodology in other regions. This approach offers valuable insights for policymakers and urban planners, supporting data-driven tourism development strategies.

Key-words: *tourism attractiveness, local development, modeling, destination competitiveness, scenario simulation*

1. INTRODUCTION

Tourism plays an important role in regional development, serving as a catalyst for economic growth, cultural preservation, and social transformation (Scutariu & Ciotir, 2011; Postelnicu & Dabija, 2016; Gamidullaeva et al., 2022). Within this context, Transylvania emerges as a particularly intriguing case study, offering a diverse tapestry of historical heritage, natural landscapes, and cultural traditions (Vegheș & Popescu, 2018). This region, situated in the center and northwestern part of Romania, presents a complex tourism ecosystem where the interplay between existing and vended tourist potential varies significantly across different urban centers (Dulău & Coroș, 2009; Popescu & Corboș, 2010). The disparity in tourism success among Transylvanian cities create an intriguing research opportunity. While cities like Cluj-Napoca and Brașov have successfully transformed their existing tourism potential into vibrant tourist destinations, other smaller towns such as Odorheiu Secuiesc and Miercurea Ciuc, despite possessing considerable tourism assets, have yet to fully realize their potential. This finding challenges the conventional view that tourism success depends solely on the extent of a city's tourism potential or historical heritage. Indeed, some smaller towns have demonstrated remarkable tourism growth without relying on the extensive medieval architectural heritage characteristic of some larger urban centers. In our research, 16 cities were selected (**Fig. 1**) to evaluate their touristic attraction level for 2023, representing different types of destinations based on their significance, with varying numbers of overnight stays taken into account.

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The rapid digitalization of tourism information and the increasing availability of big data sources have created new opportunities for tourism research (Ardito, 2019; Chen et al., 2021). The wealth of user-generated content, satellite imagery, and digital infrastructure data remains largely untapped in the context of systematic tourism attraction assessment. This presents an opportunity to develop more sophisticated, in some cases artificial intelligence based and data-driven approaches to understanding tourism dynamics (Becha et al., 2020; Qin et al., 2022).

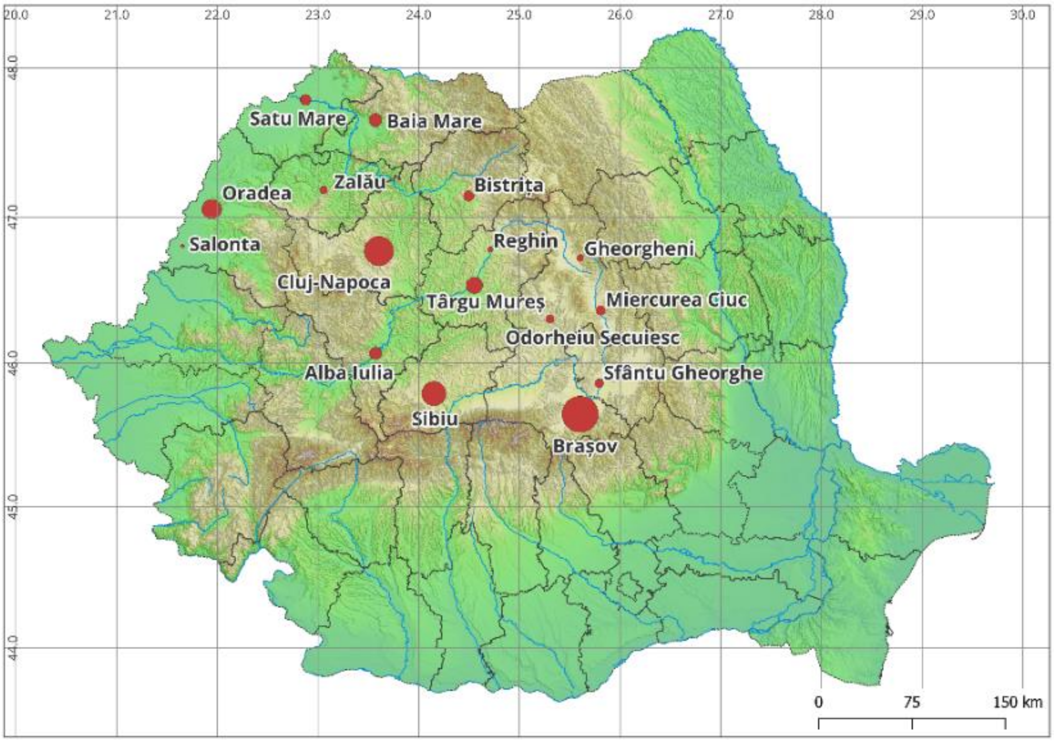

Fig. 1. Evaluated cities in Romania – bubble size is proportional with the overnights stays.

Several studies address various aspects of the current research topic. Numerous publications exist that present research on the subject of tourism attractiveness and touristic potential (Gu et al., 2022; Zhang et al., 2023; Nyulas et al., 2024). Additionally, there are studies aimed at evaluating tourism competitiveness (Ferreira & Sánchez-Martín, 2022; González-Rodríguez et al., 2023; Băbăț et al., 2023). In many cases, tourists' feedback is either absent or limited to questionnaire-based surveys, which may not always provide comprehensive and relevant insights.

Tourism attractiveness is a critical component of a destination or region tourism competitiveness and has a significant impact on its developmental opportunities. The objective of this research is to render the tourism potential and its generated attractiveness measurable and comparable across different tourist destinations.

Attractiveness can be interpreted in two contexts: (1) potential attractiveness, which is generated by the existing tourism potential and infrastructure, and (2) vended attractiveness, which can be measured through tourism demand and tourists' feedback. The aim of my research is to develop a method that integrates these two approaches, enabling the comparison of tourism attractiveness among different settlements using freely accessible data. This method will also facilitate the evaluation of a given settlement's attractiveness as a dynamic indicator across different time periods.

As tourism continues to evolve in response to changing traveler preferences and technological advancement, the need for sophisticated tools to understand and measure tourist attraction level becomes increasingly critical. This research responds to this need by proposing a comprehensive, data-driven approach to tourism attraction assessment. By bridging the gap between potential and vended attraction metrics, it aims to contribute to both the theoretical understanding of tourism development and practical decision-making in destination management.

The evaluation of tourist attraction potential was and remains a complex challenge requiring multi-dimensional approaches (Gearing et al., 1974; Yangzhou & Ritchie, 1993; Bagchi & Uddin, 2021). The field has progressed from relatively simple quantitative measures to more sophisticated multi-dimensional approaches. Early work like Var et al. (1977) focused primarily on measurable attributes, while recent studies incorporate more nuanced elements such as visitor perceptions and cultural value. Modern methodologies increasingly recognize the importance of incorporating multiple stakeholder viewpoints. Ban et al.'s (2019) revised IPA framework exemplifies this trend by combining visitor perceptions with objective measurements. Puerta et al. (2020) made a substantial contribution to the field by developing a specialized Tourist Potential Index focused on historical heritage. Their approach emphasizes the importance of historical authenticity while acknowledging the need for modern tourism infrastructure. The methodology produces a standardized index that allows for comparative analysis between different historical destinations.

Comprehensive models evaluate tourism potential by considering a wide range of factors, including natural resources, cultural heritage, infrastructure, and market demand (Kresic, 2008; Mamun & Mitra, 2012; Krabokoukis & Polyzos, 2021). Ushakova and Tsoy (2020) proposed a method for comprehensive assessment of local tourism opportunities, emphasizing the importance of both quantitative and qualitative evaluations for effective decision-making in regional tourism development.

The point discounting method involves assigning numerical values to attractions based on specific criteria, facilitating a quantitative assessment of tourism potential (Irimuș et al., 2015). Kruczek (2014) discussed this method's application in evaluating tourism values, noting its effectiveness in regional tourism planning. The method's reliance on numerical values allows for straightforward comparisons between different attractions, emphasizing its comprehensive approach to analyzing multiple factors influencing tourism potential.

The Analytical Hierarchy Process (AHP) is a structured technique for organizing and analyzing complex decisions, based on mathematics and psychology. It has been widely applied in tourism studies to evaluate the potential of tourist attractions. Vukoičić et al. (2022) utilized AHP to assess the tourist potential of cultural–historical spatial units in Serbia. They compared AHP with a mathematical model, concluding that both methods yielded similar results, though AHP provided a more nuanced understanding of expert assessments (Stojanov et al., 2013).

Mathematical models offer quantitative assessments of tourism potential by analyzing various indicators (Yan et al., 2017). Comparative analyses of different assessment methods provide insights into their relative effectiveness. Karpycheva et al. (2022) compared various approaches to assess the tourism potential of territories, identifying methodologies best suited for specific regional characteristics. Their research emphasized the need for tailored assessment methods that consider local contexts.

Understanding the factors that determine a city's tourism attractiveness is crucial for effective planning. Calvo-Mora et al. (2023) explored various determinants, including cultural offerings, infrastructure, and visitor perceptions, highlighting the complex interplay of elements that contribute to a destination's appeal. Their study suggests that a multifaceted approach is necessary to accurately assess and enhance tourism attractiveness.

The present research proposes an extent to Calvo-Mora's methodology for measuring and comparing tourist attraction levels across different locations. This approach innovatively combines potential attractiveness – generated by existing tourism assets and infrastructure – with vended attractiveness, as evidenced by tourism demand and visitor feedback based on feedback available on online platforms and the magnitude indicators of realized tourism demand as reported in statistical data. The methodology leverages freely available data sources, making it both practical and replicable.

2. METHODS AND DATA

The applied methodology consists of five interconnected analytical components. This multi-faceted approach ensures a comprehensive evaluation (**Fig. 2**).

The first methodological component focuses on quantifying the tourism potential inherent to each location. This assessment involves the development of two distinct indices: an absolute tourism potential index and a population-adjusted index. The absolute index aggregates data on cultural institutions, tourist attractions, and recreational opportunities, sourced primarily from Google Maps by using its APIs. The population-adjusted index normalizes these values against the city's population size (values obtained from the Romanian National Statistical Institute), providing a relative measure of the indices. User ratings for individual attractions are integrated into both indices through a weighted scoring system, incorporating visitor perspectives into the potential assessment.

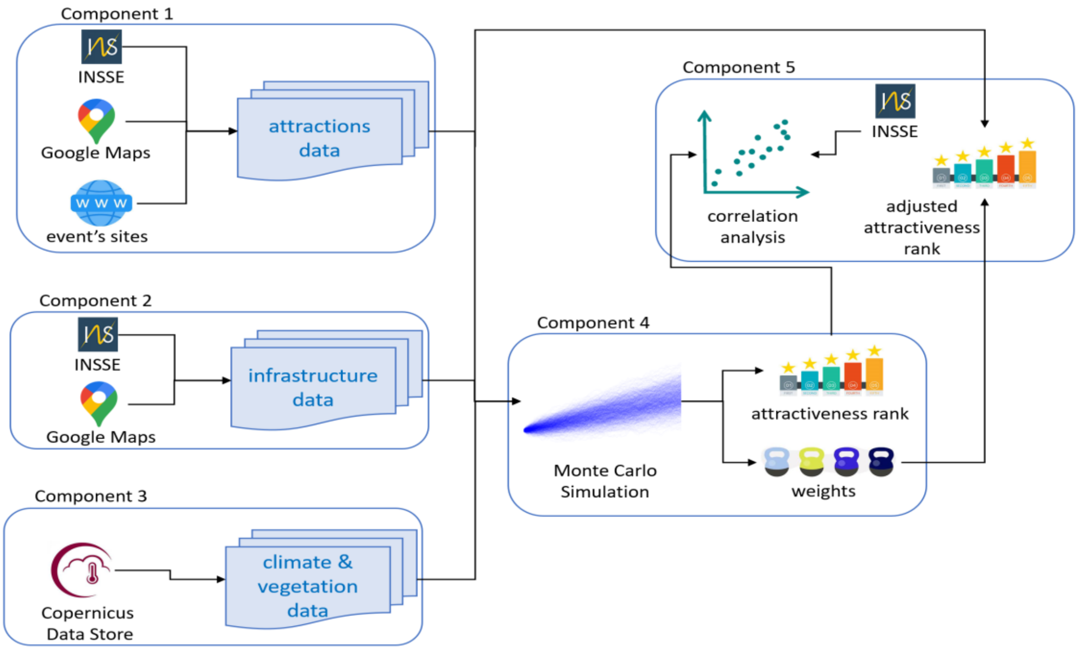

Fig. 2. Analysis workflow.

A Python script in a Jupyter Notebook collected, merged and saves the necessary data. The following Google Maps categories were considered as attractions: amusement parks, art galleries, casinos, movies and theatres, parks, spas, tourist attractions, churches and zoos.

Based on the saved JSON files applying another Python script we calculated the following indicators considering both as absolute values (**Table 1**) and relative to local population:

- *Number of attractions and their ratio relative to the population size (ATTS_no, ATTS_rel_no).* The number of attractions serves as a primary indicator of a destination's tourism appeal. However, when adjusted for population size, this measure highlights cases where a smaller settlement possesses significant tourism potential. A high number of attractions can also contribute to an increased number of overnight stays, thereby enhancing the location's overall touristic potential.
- *Number of attractions with at least one review and their ratio relative to the population size (ATTS_rev, ATTS_rel_rev).* For an attraction to function as a true draw, it must be both recognized and visited. To assess this, we examined how many attractions had received at least one review. We consider this approach effective in minimizing the impact of less significant attractions (e.g., public statues) on the overall evaluation.

- *Number of total reviews for attractions and their ratio relative to the population size (ATTS_revs, ATTS_rel_revs).* Once an attraction has received reviews, its level of recognition and significance can also be reflected in the total number of reviews it has accumulated. The population-adjusted version of this metric allows for a more accurate representation of the tourism appeal of smaller settlements.
- *Average rating for attractions (ATTS_avg_rev).* This indicator represents the overall perception of the tourism attraction in the given settlement. Whether expressed by local residents, day-trippers, or tourists, these ratings contribute to assessing the tourism potential of the destination.
- *Weighted average rating based on the number of reviewers (ATTS_wavg_rev).* The average rating of attractions cannot be considered in isolation from the number of reviewers. A higher number of reviews generally enhances reliability. This metric accounts for that aspect, ensuring a more balanced evaluation.

Since we do not have information on how long the given attraction has been in operation, we did not take the year of each review into account. However, we believe that considering all reviews, regardless of their date, is a valid approach when assessing the overall attractiveness of the destination.

Related to events and festivals the data was collected from the Internet from mizu.ro and romaniantouris.ro sites. The considered statistical indices were: *the number of events (ATTD_no)* and the *mean length of events (ATTD_len)* expressed in days. Both indicators were also calculated relative to the local population number (*ATTD_rel_no* and *ATTD_rel_len*).

Table 1.

Attraction indicators as absolute values.

City	ATTS_no	ATTS_rev	ATTS_revs	ATTS_avg_rev	ATTS_wavg_rev	ATTD_no	ATTD_len
Alba Iulia	125	99	51169	4.581	4.734	4	14
Brașov	388	311	125565	4.528	4.580	29	109
Sfântu Gheorghe	70	49	7097	4.406	4.585	19	77
Odorheiu Secuiesc	51	40	7042	4.613	4.756	11	55
Miercurea Ciuc	52	45	11103	4.616	4.679	8	32
Gheorgheni	33	29	3021	4.648	4.399	5	26
Salonta	27	19	1169	4.340	4.549	0	0
Oradea	358	288	97440	4.511	4.541	18	83
Zalău	70	51	4184	4.580	4.439	1	1
Târgu Mureș	199	156	54710	4.559	4.532	3	12
Sibiu	334	239	95245	4.453	4.636	33	121
Reghin	56	33	2820	4.576	4.279	0	0
Bistrița	108	94	11220	4.402	4.528	1	3
Satu Mare	106	86	9489	4.480	4.314	10	43
Cluj-Napoca	612	483	137649	4.505	4.595	15	67
Baia Mare	176	140	27918	4.543	4.569	10	25

The second component examines tourism infrastructure through a systematic evaluation of accommodation facilities and dining establishments. This analysis employs both absolute and relative metrics, with the latter adjusted for local population size to enable meaningful comparisons between destinations of varying scales. Data collection relies primarily on Google Maps APIs, while the evaluation incorporates visitor feedback through a weighted analysis of user reviews. This approach ensures that both the quantity and perceived quality of infrastructure contribute to the final assessment.

Similar to the categorization of tourist attractions, the collection of various elements of tourism infrastructure was conducted using Google Maps data and a Python script written in a Jupyter Notebook. The gathered data was stored in JSON files, followed by an additional script that computed the relevant aggregate statistical indicators. The following Google Maps categories were considered as part of the tourism infrastructure: lodgings, bakeries, bars, cafés, and restaurants.

Based on the collected data, we established the following indicators to characterize each destination in their absolute (**Table 2**) and relative to local population:

- *Number of locations and their ratio relative to the population size (SERV_no, SERV_rel_no)*. A higher number of locations indicates a greater presence of businesses engaged in tourism, suggesting a more developed tourism infrastructure. The population-adjusted value of this metric serves as a comparable indicator of tourism potential between differently sized settlements.

- *Number of reviewed locations and their ratio relative to the population size (SERV_rev, SERV_rel_rev).* The number of reviewed locations reflects public awareness of these establishments, regardless of whether the feedback is positive or negative. This indicator goes beyond merely assessing existing tourism infrastructure; it also provides insight into its level of utilization and recognition. The population-adjusted version of this metric allows for comparisons across settlements of different sizes, thereby offering a measure of relative tourism potential.
- *Total number of reviews and their ratio relative to the population size (SERV_revs, SERV_rel_revs).* This indicator expands on the previous one by measuring the degree of recognition. A higher number of reviews generally suggests greater popularity or awareness of a given location. Its population-adjusted variant serves as another useful measure of relative tourism potential.
- *Average rating of reviewed locations (SERV_avg_rev).* This indicator represents the overall perception of the tourism infrastructure in the given settlement. Whether expressed by local residents, day-trippers, or tourists, these ratings contribute to assessing the tourism potential of the destination.
- *Weighted average rating based on the number of reviewers (SERV_wavg_rev).* The average rating of tourism-related establishments cannot be considered in isolation from the number of reviewers. A higher number of reviews generally enhances reliability. This metric accounts for that aspect, ensuring a more balanced evaluation.

Additionally, data concerning the number of *maximum overnight capacity (ACC_abs, ACC_rel)* was obtained from the TEMPO database of the Romanian National Statistical Institute (http://statistici.insse.ro:8077/tempo-online/).

Table 2.

Service and infrastructure indicator as absolute values.

City	SERV_no	SERV_rev	SERV_revs	SERV_avg_rev	SERV_wavg_rev	ACC_abs
Alba Iulia	356	312	79087	4.385	4.376	486823
Brașov	1198	1044	380876	4.427	4.355	3794792
Sfântu Gheorghe	168	141	30815	4.304	4.318	215408
Odorheiu Secuiesc	169	150	28160	4.479	4.416	177153
Miercurea Ciuc	148	127	34912	4.396	4.333	206949
Gheorgheni	74	65	11619	4.500	4.410	186904
Salonta	60	47	13980	4.470	4.451	15532
Oradea	980	813	199253	4.466	4.403	984690
Zalău	144	116	25055	4.296	4.216	243275
Târgu Mureș	561	485	135057	4.360	4.299	718724
Sibiu	829	730	239541	4.400	4.327	1894373
Reghin	125	106	18970	4.341	4.299	70277
Bistrița	267	240	59296	4.369	4.279	407681
Satu Mare	315	279	66033	4.349	4.257	355332
Cluj-Napoca	1292	1141	439018	4.353	4.323	2620942
Baia Mare	412	360	104056	4.393	4.320	746970

The third methodological component addresses environmental influences on tourism attraction. This analysis utilizes remote sensing data to derive two key environmental metrics: the Normalized Difference Vegetation Index (NDVI) and the Holiday Climate Index (HCI). Both indices were extracted from Copernicus database satellite imagery, providing standardized measures of environmental attractiveness. The NDVI quantifies vegetation coverage and health, while the HCI evaluates climatic conditions conducive to tourism activities.

The Normalized Difference Vegetation Index (NDVI) data were downloaded from the Copernicus Data Store database, available since 2020. This dataset features a 10-day temporal resolution and a 300-meter spatial resolution. Based on this, three data files are available per month in NetCDF format. Data extraction was carried out using a custom-developed R script, which calculated both the average NDVI for the year 2023 and the monthly average values for each analyzed municipality individually. The statistical characterization for each location included the *average monthly NDVI value (NDVI_avg)*, the *minimum (NDVI_min) and maximum (NDVI_max) values of NDVI*.

To extract data for the Holiday Climate Index, datasets calculated and projected for Europe between 1970 and 2100 by the Copernicus data provider were utilized. The data are accessible through the EUR-11 rotated grid model applied to Europe within the CORDEX regional climate model framework, provided in NetCDF format. Prior to data extraction, it was necessary to reproject the rotated grid model into a traditional geographic coordinate system. This transformation was performed using the Climate Data Operator (CDO) software package, applying bilinear interpolation onto a 3600 x 1800 grid. The resulting raster data layer achieves a spatial resolution that closely approximates the native 0.11-degree original resolution.

Subsequently, a script created in R was employed to calculate the average value of the 2023 Holiday Climate Index for each municipality. This calculation was performed for the entire year, utilizing daily data available from the original data source. The statistical characterization for each location included *the average monthly HCI value (HCI_avg)*, the *minimum (HCI_min) and maximum (HCI_max) values of HCI* (**Table 3**).

Table 3.

Holiday Climate Index and NDVI statistics for each location.

City	HCI_avg	HCI_max	HCI_min	NDVI_avg	NDVI_max	NDVI_min
Alba Iulia	73.32545	91.68282	61.16089	0.378505	0.494139	0.265070
Brașov	68.99290	87.46114	57.56995	0.381743	0.524544	0.161424
Sfântu Gheorghe	67.54476	87.00309	55.65424	0.435560	0.578291	0.198200
Odorheiu Secuiesc	68.39466	87.19347	54.18711	0.492800	0.648510	0.215986
Miercurea Ciuc	68.08367	85.45272	55.30385	0.419099	0.593931	0.086718
Gheorgheni	64.71073	79.13382	55.00216	0.477821	0.664523	0.091206
Salonta	72.12359	90.50865	57.66345	0.485219	0.598030	0.359515
Oradea	70.49587	88.55828	55.30675	0.421988	0.523878	0.291887
Zalău	68.38098	84.71291	57.27938	0.514304	0.666952	0.353521
Târgu Mureș	70.91531	89.51012	57.58782	0.452826	0.592889	0.258299
Sibiu	71.82399	88.42288	61.80397	0.405267	0.534836	0.222812
Reghin	69.87018	88.91307	54.65160	0.470451	0.603915	0.294610
Bistrița	69.66804	88.19640	52.10381	0.519850	0.678667	0.214526
Satu Mare	70.71367	87.72084	54.87198	0.428589	0.549981	0.310082
Cluj-Napoca	69.68483	86.66595	59.68284	0.420495	0.565557	0.243994
Baia Mare	67.02193	87.56602	47.73801	0.446839	0.570960	0.277705

To address the inherent variability in tourism behavior, the fourth component implements a Monte Carlo simulation framework. The generated values represent the weights that indicate the relative importance of various location attributes in a tourist's decision-making process. These attributes may include factors such as the rating of a specific attraction, the significance of favourable weather conditions, and other site-specific characteristics. Essentially, these weights quantify how much each factor influences a tourist’s choice of destination. This probabilistic approach generates multiple scenarios of tourist behavior patterns, allowing for the dynamic weighting of different attraction components in the final attraction index calculation. The simulation incorporates random variations in tourist preferences and behavioral patterns, providing a more robust assessment of potential tourism outcomes.

The final methodological component involves a correlation analysis between the derived indices and actual tourism demand data. The correlation analysis serves two primary purposes: validation of the developed indices and identification of potential discrepancies between predicted and actual tourism patterns. This component provides feedback for refining the overall assessment methodology and understanding the practical applicability of the developed indices.

To determine the tourism attraction potential of each settlement based on the collected data and defined indicators using Monte Carlo simulation, we employed the following data processing algorithm (**Fig. 3**) which was implemented in RStudio.

```
PHASE 1. - Preparation
     Step 1. Selection and possible categorization of the indicators necessary
              for the analysis.
     Step 2. Normalization of the values of each indicator.
     Step 3. Determination of the relative weight of different indicators for
              each settlement based on the normalized values.
PHASE 2. - Simulation and Validation
     Step 1. Application of Monte Carlo simulation to model different tourist
              behaviors, following these steps:
                 -     generating random values representing the weights of
                 indicators deemed important by a given tourist (e.g., how
                 significant favorable weather conditions are in choosing a
                 destination).
                 -     assigning an evaluation score to each settlement based on
                 the randomly generated weights and the importance of the
                 individual indicators.
                 -     identifying the preferred settlement for a given tourist
                 based on three evaluation methods derived from the research by
                 Mazurek & Strzałka (2022):
                    M1: The settlement with the highest total score receives a
                    point, while others do not.
                    M2: Points are assigned based on the ranking of a settlement's
                    score relative to others.
                    M3: Each settlement receives a score reflecting its
                    suitability based on the given tourist's preferences.
     Step 2. Correlation analysis between the results of the three evaluation
              methods and the actual number of overnight stays recorded in each
              settlement.
PHASE 3. - Evaluation
     Step 1. Transferring the averaged weights used in the simulation to
              population-adjusted indicators, enabling the ranking of settlements
              based on their inner (population based) tourism potential.
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Fig. 3. Algorithm of tourism attractiveness assessment.

3. RESULTS AND DISCUSSION

During the preparatory phase, we categorized the indices listed in the previous section into six groups based on the factors a tourist might prioritize when selecting a destination. As a result, the following groups were established: climatic indicators, indicators reflecting the presence of green spaces, the existence of tourist attractions, the evaluation of these attractions, the presence of tourism infrastructure, and the evaluation of tourism infrastructure (**Table 4**).

Table 4.

Group of factors that tourists might prioritize when selecting a destination.

CLIMATE	VEGETATION	ATTRACTION PRESENCE	ATTRACTION EVALUATION	INFRASTRUCTURE PRESENCE	INFRASTRUCTURE EVALUATION
HCI_avg	NDVI_avg	ATTS_no	ATTS_rev	SERV_no	SERV_rev
HCI_min	NDVI_min	ATTD_no	ATTS_revs	ACC_abs	SERV_revs
HCI_max	NDVI_max	ATTD_len	ATTS_avg_rev		SERV_avg_rev

The indices values were normalized across locations, and after that expressed as relative to the total for each city, allowing to determine the relative importance of each index. The Monte Carlo modeling was conducted using 1,000,000 simulations, with randomly generated values for indices groups representing tourist behavior, drawn from a uniform distribution.

The results obtained from the three ranking methods applied in the algorithm (**Fig. 4**) were compared with the actual number of overnight stays recorded in 2023 (**Fig. 5**). Since we cannot assume a linear relationship between the actual number of overnight stays and the computed indicators – although we can assume a monotonically increasing trend – we used Spearman's rank correlation to validate the relationship.

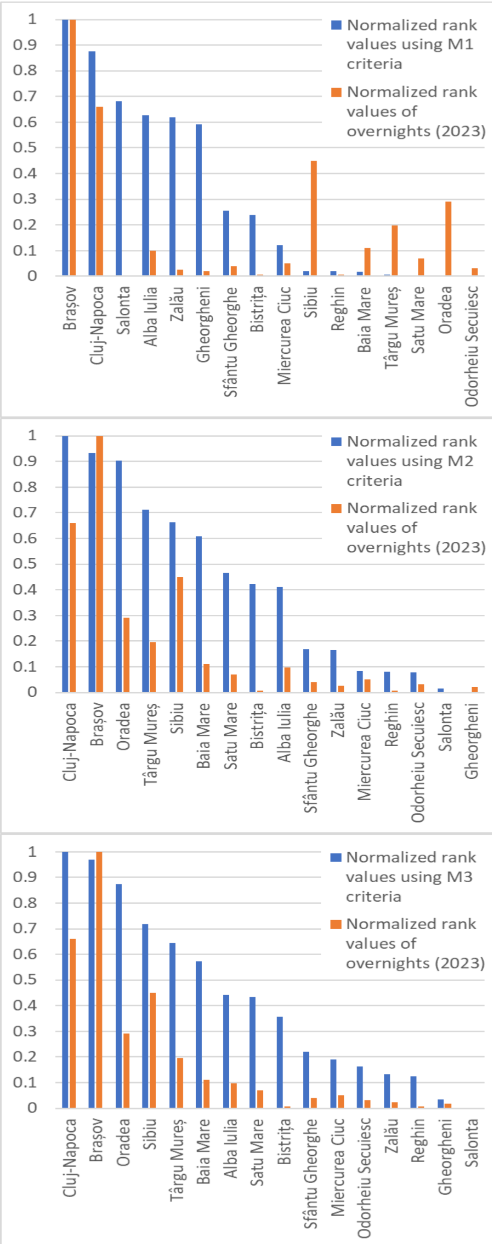

Fig. 4. Comparative charts of the simulated normalized rank values based on M1, M2 and M3 evaluation methods and normalized rank of overnights stays.

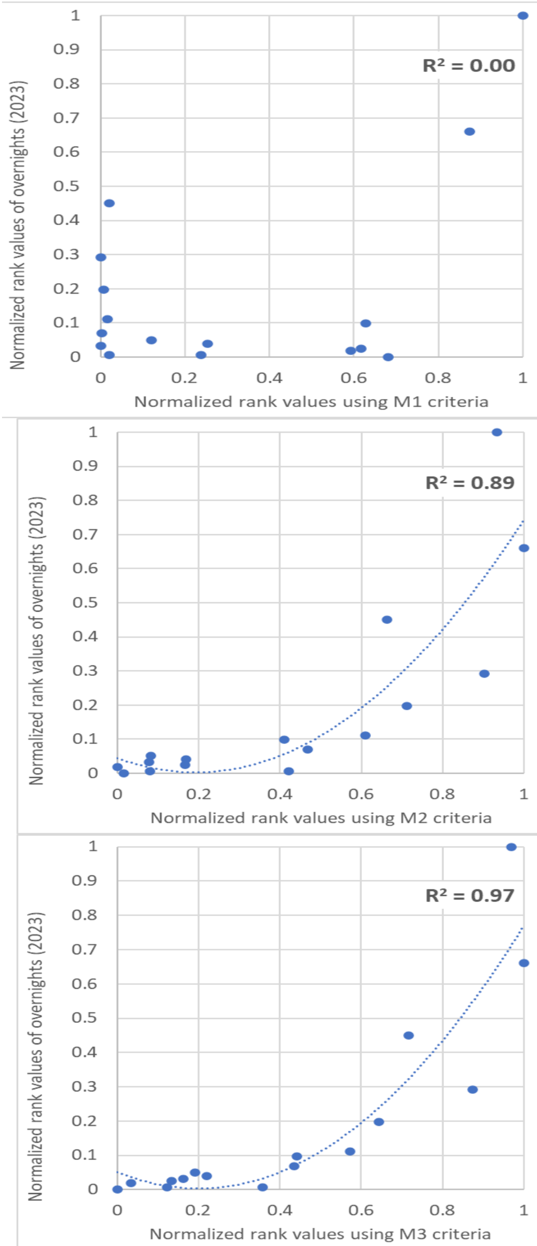

Fig. 5. Best fitting polynomial regression curve and Spearman correlation strength between the simulated normalized rank values based on M1, M2. and M3 evaluation methods and normalized rank of overnights stays.

Our findings indicate that the M1 method, which relies on exclusivity, shows a very weak correlation between the ranking of destinations chosen by simulated tourists and the actual number of overnight stays. In contrast, the M2 method, where destinations received scores based on their ranking position, yielded a much stronger correlation of 0.89. The M3 evaluation method, which assigned scores based on the absolute values of the indicators, demonstrated an even stronger correlation of 0.97, suggesting a highly robust relationship between the simulated tourist preferences and actual tourism activity. Although the M1 evaluation method does not show a strong correlation, **figure 4** highlights its effectiveness in identifying the top two destinations. Therefore, if the objective is not to establish a ranking but rather to determine the destinations with the highest potential, using this method would be appropriate.

Building on the previously validated correlation, we used the average weight values obtained from the Monte Carlo simulations for each indicator to assess the tourism attractiveness of each settlement, incorporating population-adjusted indicators where applicable (**Table 5**). This approach allows for a more nuanced evaluation of tourist potential's relative significance in proportion to the local population.

Table 5

Group of factors considered to assess population adjusted tourism attractiveness.

CLIMATE	VEGETATION	ATTRACTION PRESENCE	ATTRACTION EVALUATION	INFRASTRUCTURE PRESENCE	INFRASTRUCTURE EVALUATION
HCI_avg	NDVI_avg	ATTS_rel_no	ATTS_rel_rev	SERV_rel_no	SERV_rel_rev
HCI_min	NDVI_min	ATTD_rel_no	ATTS_rel_revs	ACC_rel	SERV_rel_revs
HCI_max	NDVI_max	ATTD_rel_len	ATTS_wavg_rev		SERV_wavg_rev

The obtained results were compared with the values modeled using Monte Carlo simulation, which included each indicator in absolute terms rather than adjusted for population size (**Fig. 6**). Based on the values derived from the Monte Carlo modeling, Cluj-Napoca, Brașov, and Oradea emerged as the most attractive destinations for tourists, while Gheorgheni and Salonta ranked the lowest. Using indicators adjusted for population size – weighted according to the previous Monte Carlo simulation – the leading destinations were identified as Alba Iulia, Oradea, Brașov, and Sibiu, while Zalău ranked last.

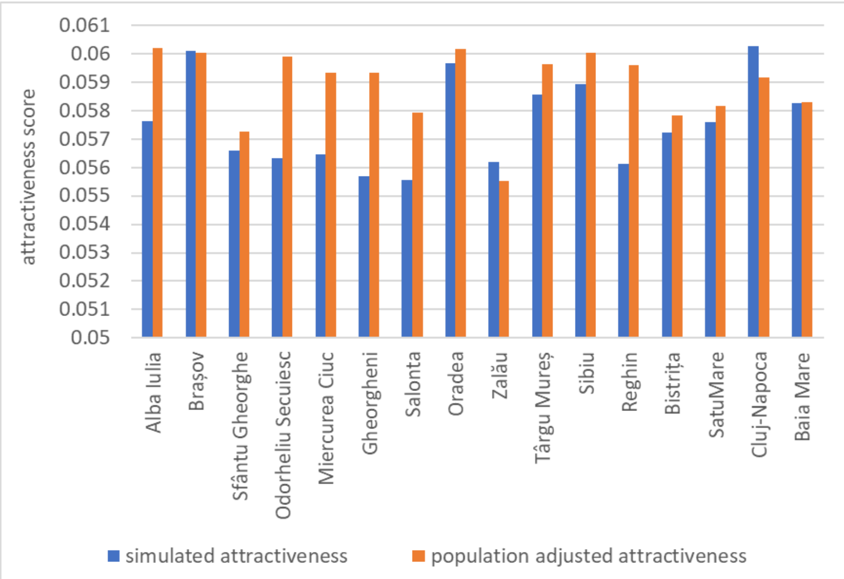

Fig. 6. Comparative charts of the simulated and population adjusted attractiveness.

Comparing these two sets of results, it can be observed that, in relative terms, Alba Iulia, Odorheiu Secuiesc, Gheorgheni, Miercurea Ciuc, and Reghin possess significant tourist appeal and untapped potential. These settlements thus have considerable resources to leverage in developing their tourism sector, allowing them to enhance their tourism-related revenues in proportion to their population size. Brașov and Baia Mare appear to be the most balanced locations, as their population-dependent and population-independent attractiveness scores are closely aligned. Meanwhile, Cluj-Napoca and, somewhat unexpectedly, Zalău received a simulated attractiveness score that exceeds the value calculated based on population-adjusted indicators. This suggests that these cities already have strong vended potential for generating tourism-related revenue, which plays a crucial role in their local economies.

Based on **Figure 7**, we can conclude that the population-adjusted tourism attractiveness potential does not exhibit significant variation across the different settlements. Only one location, Zalău, has an exceptionally low value, while five settlements – Salonta, Bistrița, Satu Mare, Baia Mare and Sfântu Gheorghe – fall into the moderately low category. The remaining settlements possess considerable and comparable tourism appeal, meaning that, in population relative terms, Gheorgheni could benefit from tourism to the same extent as Cluj-Napoca or Târgu Mureș. However, Bistrița's population-adjusted tourism attractiveness has not yet reached the level of, for example, Odorheiu Secuiesc.

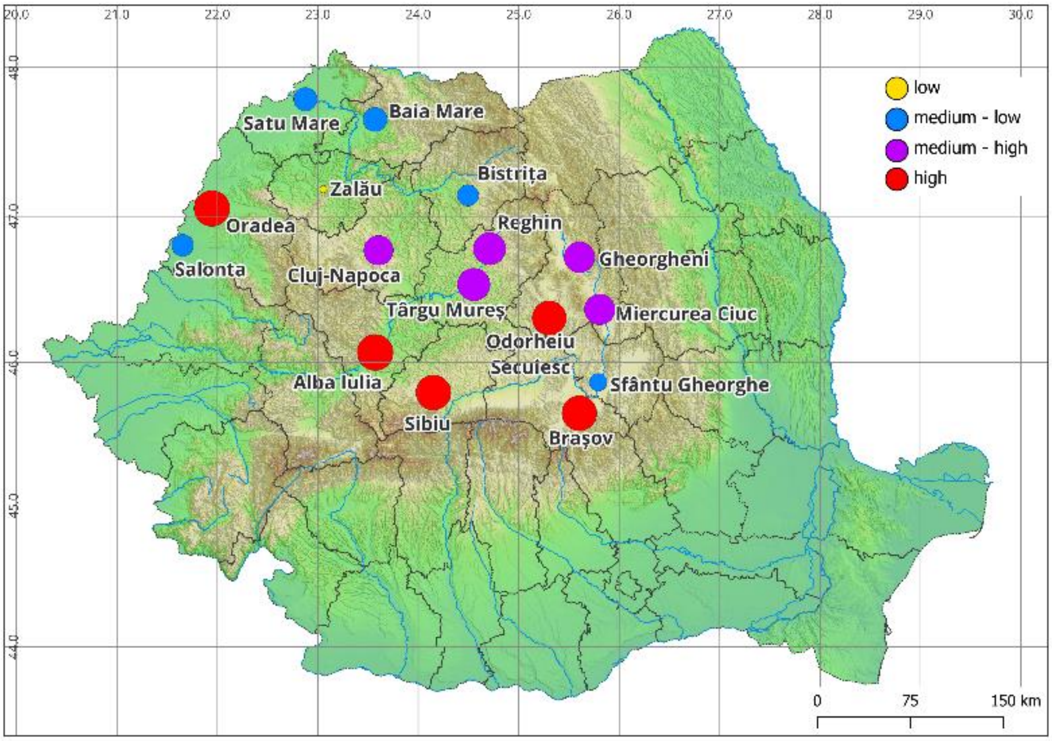

Fig. 7. Simulated population adjusted values of touristic attractiveness (higher radius represents higher values).

4. CONCLUSIONS

The obtained results are partly as expected and partly exploratory in nature. Crowdsourced data inherently poses some limitations. The number of touristic objectives doesn't have linear relationship with their attractiveness, even if it may be compensated by the number of reviews. Because it is not possible to filter reviews by date, our analysis may include outdated evaluations, which is a concern given that the quality of attractions can evolve over time. The inability to separate reviews by local residents raises potential bias issues, as their assessments might be influenced by emotional attachment, even though they are familiar with the local context.

Despite all these limitations crowdsourced data could be used in the determination and evaluation of attractiveness, the modelled results align well with the actual number of overnight stays. This indicates that crowdsourced data can be effectively utilized in assessing tourism attractiveness.

In future analyses of a similar nature, it would be valuable to consider the pricing of tourism services, as this factor can significantly influence the realized attractiveness of a given destination. Additionally, it would be worthwhile to test the developed methodology in different geographical locations to assess its applicability and robustness across various contexts.

This research is significant for several reasons. From a theoretical perspective, it contributes to our understanding of the relationship between tourism attractiveness and overnight stays, potentially challenging or refining existing models of tourism development. From a methodological standpoint, it introduces a novel approach to tourism attraction assessment that combines traditional metrics with big data sources and advanced statistical techniques. Practically, the findings can inform tourism development strategies and investment decisions in Transylvanian cities.

The potential applications of this research extend beyond its immediate geographical focus. The methodology can be adapted to assess tourism attractiveness in other regions, contributing to comparative studies of tourism development. Furthermore, the automated analysis system developed through this research could evolve into a web-based geospatial application, serving both market practitioners and academic researchers.

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