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Research article

Implementation of the Simple Additive Weighting (SAW) Method in a Decision Support System for Tourist Destination Selection in North Bali

I Gede Andi Utama Giri [a*], *Hari Putra Maha Dewa* [b]

[a,b] *Department of Informatics, Institut Bisnis dan Teknologi Indonesia, Denpasar, Indonesia*
email: [a,*] utama.giri@instiki.ac.id, [b] maha.dewa@instiki.ac.id
** Correspondence*

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ABSTRACT

North Bali boasts remarkable natural and cultural attractions, but the process of choosing the best tourist spots is still based on personal opinions and lacks consistency. Without a fair and organized way to evaluate options, visitors and those involved often depend only on trends or individual tastes, which hinders effective promotion and handling of destinations. This research seeks to create a Decision Support System (DSS) that employs the Simple Additive Weighting (SAW) technique to fairly evaluate and rank travel sites using various factors like ease of access, appeal, amenities, hygiene, expenses, fame, security, and crowd levels. The suggested framework combines these prioritized elements to generate an overall rating for each potential location. By examining data from ten well-known spots in North Bali, Pura Ulun Danu Beratan topped the list with a score of (0.8800), showing excellence in most assessed aspects. The findings show that the SAW approach can reliably aid complex choices in tourism oversight, ensuring clear and dependable rankings. This tool offers a flexible and expandable structure suitable for evaluating tourism in other areas. Upcoming efforts will focus on adding live data feeds and visitor input via online or app interfaces to boost the system's precision and ease of use.

1. Introduction

One of the primary industries driving economic progress at both regional and national levels is tourism, particularly in areas rich in natural and cultural assets like Bali. Bali's northern region, often referred to as Bali Utara, holds immense promise for tourism expansion thanks to its stunning landscapes, deep-rooted traditions, and peaceful ambiance that stands in stark contrast to the bustling south [1]. Attractions ranging from pristine shores, cascading waterfalls, serene lakes, and soothing hot springs position this area as a go-to spot for tourists craving genuine and calming adventures. Yet, in spite of these abundant opportunities, tourism in North Bali hasn't reached its full potential regarding marketing, ease of reach, and infrastructure upkeep. Numerous sites suffer from inadequate visibility and the lack of organized tools for decision-making that could benefit travelers and industry players alike. In today's world of digital advancements and eco-friendly travel, relying on impartial, data-informed choices is crucial for elevating tourism standards and fostering balanced growth across different locations [2], [3]. Hence, incorporating smart technologies into tourism administration represents a key breakthrough for enabling choices grounded in evidence.

A major hurdle in the tourism field, specifically when it comes to picking destinations, stems from the absence of a methodical assessment and suggestion process. Travelers frequently base their selections on personal elements like digital feedback, casual recommendations, or individual

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inclinations [4]. Although these reflect social dynamics and viewpoints, they frequently result in erratic and prejudiced outcomes. For officials and tourism bodies, the difficulties intensify with the involvement of numerous interconnected factors including reachability, allure, amenities, hygiene, security, expenses, and fame. The significance of each varies based on what visitors seek and the goals of tourism initiatives [5]. As a result, pinpointing which spots to focus on for enhancement or advertising becomes challenging. This deficiency in organized appraisal causes uneven visitor flows, with certain places becoming overly packed while others get ignored [6]. From a sustainable tourism viewpoint, such disparities can harm ecological conservation, guest contentment, and local financial prosperity. Therefore, a strategy that allows for thorough multi-factor evaluation is essential to aid in crafting decisions backed by data, ultimately boosting the appeal of North Bali's travel hubs [7].

To tackle these challenges, the research introduces the creation of a Decision Support System (DSS) that applies the Simple Additive Weighting (SAW) technique for choosing and ordering tourist spots in Bali Utara. The aim is to deliver a clear, quantifiable, and logical structure to assist tourists and stakeholders in reaching more precise conclusions. The rationale behind opting for SAW rests in its straightforwardness and effectiveness, making it a popular choice in Multi-Criteria Decision Making (MCDM) [8], [9]. SAW functions by standardizing and combining weighted factors, facilitating impartial comparisons among options. Here, eight core criteria were employed—Accessibility, Attractiveness, Facilities, Cleanliness, Cost, Popularity, Safety, and Visitor Density—each capturing key elements that shape tourist choices. Weights were allocated to each based on their relevance, drawn from scholarly reviews and expert insights [10]. This ensures SAW offers a unified evaluation method that cuts down on bias while keeping calculations uncomplicated. Consequently, it serves as a robust tool for handling complex tourism information and producing trustworthy destination hierarchies [11].

The study's outcomes reveal that Pura Ulun Danu Beratan secured the top ranking with a score of (0.8800), trailed by Pantai Pemuteran and Danau Buyan, underscoring the SAW method's reliability in delivering unbiased assessments [12]. The system not only streamlines decision processes but also promotes balanced tourism growth in Bali Utara by spotlighting sites needing greater focus. By transforming subjective qualities into numerical data, the proposed DSS enhances openness and simplifies result interpretation for public and private tourism strategists [13]. Furthermore, its straightforward computational nature allows seamless incorporation into smartphone or online apps for instant user guidance. The results also suggest that adding dynamic information from sources like Google Maps, TripAdvisor, or official databases could further refine the system's precision and applicability. Subsequent investigations should explore merging SAW with advanced methods such as fuzzy logic, AHP, or TOPSIS to develop a combined DSS capable of managing unpredictability and evolving data more adeptly [14], [15]. In summary, this work advances smart decision aids in tourism, encouraging management based on facts and strategies for sustainable progress that resonate with the digital age. This approach not only addresses immediate gaps in North Bali's tourism but also sets a precedent for broader applications, potentially influencing how other regions evaluate and promote their attractions. By prioritizing objectivity, it helps mitigate issues like overcrowding and underutilization, ensuring that natural and cultural treasures are preserved for future generations. Moreover, the integration of user feedback loops could make the system more adaptive, allowing for continuous improvements based on real-world experiences. Overall, the DSS represents a step toward more equitable and efficient tourism ecosystems, where data drives innovation and inclusivity.

2. Related Work

Decision Support Systems (DSS) have undergone extensive development to aid in fields that demand intricate multi-criteria evaluations. At their heart, DSS combine information, analytical frameworks, and intuitive interfaces to facilitate decisions that are partially structured or entirely unstructured [16]. In the last ten years, DSS research has broadened to incorporate artificial intelligence and multi-criteria optimization, enhancing precision and flexibility in choices. Numerous investigations have proven the value of merging Multi-Criteria Decision-Making (MCDM) techniques like the Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Weighted Product (WP), and Simple Additive Weighting (SAW) to bolster decision processes in various sectors [17]. Of these, SAW stands out for its ease of calculation, clarity, and

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ability to manage both qualitative and quantitative inputs efficiently. Within tourism research, DSS frameworks are commonly used to assess and order destinations using diverse factors, including appeal, ease of access, security, and expenses. As noted in [18], employing MCDM-driven DSS yields more uniform and logical outcomes than conventional approaches that depend exclusively on expert opinions or basic statistical hierarchies. Furthermore, linking DSS with online platforms has fostered adaptive choices, incorporating feedback from users and live updates into the assessment framework [19].

Prior research has tested the SAW technique in assorted decision scenarios to confirm its durability and precision. For example, in [20], SAW was utilized to identify the top supplier in a production setup, proving its adeptness at managing numerous criteria with differing significance. The research indicated that SAW delivered steadier rankings than AHP for datasets of modest to average size. In the realm of education, [21] adopted SAW to build a DSS for awarding student grants, factoring in academic achievements, household finances, and non-academic activities as prioritized elements. The outcomes verified that SAW can generate equitable and precise appraisals by blending positive and negative attributes. Likewise, [22] applied SAW to assess housing options, stressing that its normalization and weighting steps streamline calculations while upholding quality in decisions. Collectively, these explorations underscore SAW's versatility, applicable in scenarios needing ranking and choice across varied domains. Its triumphs in such areas bolster its promise for tourism, especially in destination picking where several elements must be weighed concurrently.

In the sphere of tourism administration, scholars have investigated DSS tools to pinpoint ideal travel spots, create suggestion engines, and gauge tourism effectiveness. Research in [23] suggested an AHP-driven system to rank coastal tourism growth, effectively pinpointing reachability and ecological viability as key influences on visitor choices. Meanwhile, [24] contrasted AHP and SAW for ordering tourism sites, finding that while both delivered similar results, SAW offered easier computations and clearer insights for lay users. Another work by [25] presented a blended model merging SAW and TOPSIS for tourism aid, boosting ranking steadiness and resilience to variable weights. Moreover, [26] crafted a DSS with fuzzy SAW to tackle vague and personal criteria, revealing that the fuzzy method boosts adaptability in reflecting human judgments during evaluations. In Indonesia, various projects have deployed MCDM strategies in tourism DSS, covering hotel picks, food suggestions, and eco-tourism focus [27]. These efforts affirm the rising significance of MCDM in fostering eco-friendly tourism and enriching experiences for travelers and officials.

Focusing on the Simple Additive Weighting (SAW) technique in Indonesian tourism decision tools, its popularity has surged owing to the nation's varied terrains and traditions, posing challenges in harmonizing access, charm, and eco-friendliness. For instance, [28] employed SAW to formulate a DSS for choosing sites in Yogyakarta, incorporating elements like proximity, amenities, entry fees, and renown. The investigation showed that SAW rankings matched real visitor tastes, affirming the model's trustworthiness. Similarly, [29] used SAW to appraise eco-tourism spots in West Java, adding environmental purity and heritage as extra metrics. Findings indicated SAW's strength in quantifying subjective aspects, promoting clear, evidence-based choices. Another project in [30] built an online DSS with SAW for village tourism selection, featuring an accessible portal for users to enter likes and get tailored advice. Beyond site choices, SAW has aided other tourism tasks, such as rating hotel services [31] and refining travel paths [32]. These uses validate SAW's ideal mix of straightforwardness, flexibility, and exactness, fitting for settings with scarce computing power but needing openness..

Regarding this investigation, it sets itself apart by deploying SAW on a full suite of eight criteria mirroring the multifaceted nature of tourism excellence in Bali Utara: reachability, allure, infrastructure, hygiene, pricing, fame, protection, and crowd levels. Unlike prior works like [28]–[30] that concentrated on narrower or targeted criteria, this offers a broader model encompassing both advantages and drawbacks. Plus, weaving in regional tourism traits for weight assignment boosts the model's pertinence, matching North Bali's realities and growth aims. The appraisal here also uses comparative checks to ensure the system's precision and uniformity in site rankings. The resultant DSS not only aids impartial destination picks but also fuels local progress by supplying factual bases for tourism strategies. Echoing earlier results [24], [26], [27], SAW's use here proves potent in

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demystifying tough choices without losing depth. Thus, this research expands on past efforts, broadening their uses for eco-conscious regional tourism oversight. In doing so, it reinforces the notion that MCDM-powered DSS, especially with SAW, provide a reliable, expandable, and clear path for decisions in real-life situations [33]. This approach could inspire similar integrations elsewhere, potentially revolutionizing how tourism boards worldwide handle complex evaluations. By emphasizing data over intuition, it helps prevent biases that might overlook hidden gems or overburden popular spots. Furthermore, the adaptability of SAW allows for easy updates as new criteria emerge, such as climate impact or digital accessibility, ensuring the system evolves with tourism trends. Overall, this work not only validates SAW's role in Bali Utara but also paves the way for more innovative, user-centric tools in the industry, fostering a more inclusive and sustainable future for global travel.

3. Methodology

3.1. Data Collection

The information employed in this investigation originates from an inventory of 10 renowned tourist sites in North Bali, as detailed in the document: Pantai Lovina (A1), Air Terjun Gitgit (A2), Danau Buyan (A3), Danau Tamblingan (A4), Air Terjun Sekumpul (A5), Pura Ulun Danu Beratan (A6), Desa Munduk (A7), Air Panas Banjar (A8), Pantai Pemuteran (A9), and Pulau Menjangan (A10). For each option, assessment scores were gathered across eight factors: accessibility (C1), tourist appeal (C2), amenities (C3), cleanliness (C4), expenses (C5, cost), fame (C6), security (C7), and visitor congestion (C8, cost). Data sources encompassed secondary observations (public records, digital reviews), evaluations from local experts, and aggregated ratings on a 1–5 ordinal scale, as outlined in the document's assessment matrix. Weight assignments for each factor (e.g., C2 = 0.20, C6 = 0.16, etc.) were established based on the relative significance of these elements in destination decision-making, as explained in the document. The data gathering process aimed to create an evaluation matrix of alternatives by criteria, serving as the primary input for the SAW technique.

3.2. Data Preprocessing

The preprocessing phase requires uniformity in scales and handling of benefit or cost-type criteria. All attributes were encoded on a numerical scale from 1 to 5 (1 = very poor, 5 = excellent) according to the document's notes; expense (C5) and congestion (C8) were classified as cost factors, meaning lower values are preferable. Preprocessing involved checking for completeness (handling missing values), adjusting outliers if present, and verifying consistency among assessors. For SAW, normalization follows next—for benefit criteria, division by the maximum value per column, and for cost criteria, the ratio of the minimum divided by the candidate value—as per the normalization formulas in the document: $r_{ij} = x_{ij} / \max_j x_{ij}$ (benefit) and $r_{ij} = \min_j x_{ij} / x_{ij}$ (cost). The normalized results are stored as matrix R (values 0–1) and rounded (the document uses 3 decimals) before proceeding to subsequent steps.

3.3. SAW Implementation (Simple Additive Weighting)

The application of SAW adheres to the standard steps listed in the document. The initial step involves constructing the evaluation matrix X (dimensions m×n, with m alternatives and n criteria). The second step performs normalization into R based on criterion type (benefit or cost). The third step multiplies each R column by the assigned weight w_j to obtain the weighted normalized matrix $W = R \cdot w$. Finally, the ultimate score S_i for each alternative is calculated as the sum of the W row: $S_i = \Sigma j\ w_j \cdot r\{ij\}$. Alternatives are then sorted by descending S_i to derive destination rankings. In this document, the process yielded rankings with Pura Ulun Danu Beratan (A6) at the top (score 0.8800), followed by Pantai Pemuteran and Danau Buyan. Practical execution can be carried out using spreadsheets (Excel) or basic scripts (Python/Matlab) to ensure calculation reproducibility.

3.4. System Integration & Decision Support System Design

Drawing from the SAW calculations, the decision support system (DSS) is crafted to present rankings and visualize outcomes for users (stakeholders or tourists). The DSS architecture includes an input layer (forms for entering criterion values or importing review data), a processing module (preprocessing, normalization, SAW computation), and an output interface (ranking tables, suggestions, comparison charts). The system is designed for easy updates: weights can be adjusted,

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alternative data can be added, and cost/benefit rules can be configured. Given SAW's lightweight computation, integration into web or mobile apps is straightforward, enabling transparent destination recommendations for end-users.

3.5. (Extension) Deep Learning Application — Optional Integration

The original document does not incorporate deep learning; here, I outline detailed steps for optionally integrating it as a DSS enhancement. Deep learning can extract features from unstructured data sources: (1) image processing: CNN models (e.g., ResNet, MobileNet) to evaluate visual quality of destinations from photos (estimating visual appeal), (2) sentiment analysis: NLP models (e.g., lightweight BERT) to derive sentiments from online travel reviews and compute scores for popularity, cleanliness, or services, (3) demand forecasting: RNN/LSTM to model visitation patterns (congestion) from historical data. Workflow: collect image and review datasets, perform labeling/annotation if needed (e.g., 1–5 scores), train DL models with augmentation and cross-validation, then map outputs (e.g., probabilities/scores) to a 1–5 scale for integration as criterion inputs into SAW. This addition boosts objectivity when secondary data is largely unstructured and enriches the evaluation matrix with automatically extracted features.

3.6. (Extension) Utilizing Optimization Models to Enhance Outcomes

Although SAW relies on expert-determined weights, optimizing these weights can boost precision and system acceptance. Applicable strategies include: (1) Data-driven optimization—employing algorithms (e.g., Genetic Algorithm, Particle Swarm Optimization) to find weights w that maximize ranking consistency with ground truth (e.g., user preferences or historical data), (2) Weight learning—framing as a learning-to-rank problem: use supervised methods (e.g., RankNet, LambdaMART) to learn weights/feature combinations that mirror real preferences, (3) Hybrid MCDM + Optimization—combine SAW with AHP for initial weight validation, then refine weights via numerical optimization to minimize ranking prediction errors. Optimization procedure: define an objective function (e.g., minimize Spearman distance between SAW rankings and reference rankings), set weight constraints ($w_j \geqslant 0$, $\Sigma\ w_j = 1$), run the optimizer, and validate through cross-validation. This enables more adaptive weights aligned with actual preferences and dynamic data.

3.7. Validation & Evaluation

Methodological assessment in the document involved comparing SAW rankings with field indicators (popularity/online ratings) and internal consistency (sensitivity to weight changes). For extensions involving deep learning and optimization, evaluation should include quantitative metrics: accuracy/MAE for score predictions, AUC for sentiment classification models, and ranking correlation coefficients (Spearman/Pearson) between model rankings and ground truth. Sensitivity tests (e.g., what-if analyses on weight alterations) assess ranking stability. Qualitative validation can use user studies (surveys of stakeholders/tourists) to gauge recommendation reasonableness. The final implementation is recommended to be tested on larger, more diverse datasets for generalizable results.

3.8. Limitations & Practical Considerations

The SAW approach offers a clear and straightforward solution, but it heavily depends on input quality and weights. The document's primary constraints include reliance on ordinal assessments and potentially biased secondary data sources. Incorporating deep learning or optimization enriches the model but demands data labeling, computational power, and rigorous validation protocols. In real-world application to North Bali, maintaining local stakeholder involvement during weight calibration and result interpretation is crucial to ensure policy decisions reflect the region's socio-cultural realities.

4. Results and Discussion

4.1 Results

The application of the Simple Additive Weighting (SAW) technique within the constructed Decision Support System (DSS) for picking travel spots in North Bali delivered quantifiable and understandable outcomes. Employing eight assessment factors—reachability (C1), allure (C2), amenities (C3), hygiene (C4), pricing (C5), renown (C6), protection (C7), and crowd levels (C8)—along with assigned weights (C1 = 0.14, C2 = 0.20, C3 = 0.12, C4 = 0.10, C5 = 0.08, C6 = 0.16, C7 = 0.10, C8 = 0.10), the SAW framework computed a conclusive ranking score (Si) for ten vacation locales [34].

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Following standardization and weight application, the resultant matrix facilitated the derivation of a combined score for each potential site. The ultimate findings reveal that Pura Ulun Danu Beratan (A6) secured the top position with a score of 0.8800, trailed by Pantai Pemuteran (A9) at 0.7827, and Danau Buyan (A3) and Danau Tamblingan (A4) each attaining 0.7520. These leading spots exhibit shared traits like superior access, compelling charm, pristine upkeep, and robust services.

The hierarchy suggests that locations blending natural and cultural elements typically excel in various aspects. Conversely, Air Terjun Gitgit (A2) placed at the bottom with a score of 0.6907, primarily because of poorer reachability and scarce amenities, even with its impressive scenery [35]. This observation matches the idea that visitors often favor convenient entry and supportive setups when selecting spots. The weighted standardization guarantees that elevated expenses and high visitor numbers—as cost-oriented factors—detract from the total score, fostering equilibrium between fame and eco-friendliness. Additionally, the SAW outcomes' reliability was affirmed through sensitivity checks, where slight adjustments (±5%) in factor weights caused negligible ranking shifts, affirming the model's resilience [36].

For validation of clarity, the ranking outcomes were compared with genuine online fame metrics (such as Google Maps and TripAdvisor reviews). Pura Ulun Danu Beratan truly boasts the greatest exposure and visitor feedback among the ten sites, with strong approval for hygiene and service standards. Pantai Pemuteran, despite its isolation, earned high marks for its eco-tourism focus and manageable crowds, showcasing SAW's capacity to handle subtle balances between advantages and drawbacks [37]. These outcomes verify that the system mirrors authentic traveler decision patterns while preserving ease of computation.

4.2 Discussion

The outcomes illustrate the suitability of the SAW-driven DSS as an open, versatile, and potent instrument for aiding choices in travel oversight. In comparison to traditional decision processes that depend on gut feelings or isolated factors, the SAW framework merges multi-faceted elements, producing an impartial hierarchy that matches specialist opinions [38]. This impartiality is vital for travel strategists and officials aiming to harmonize growth goals across varied locations. The framework delivers practical knowledge—pinpointing which spots excel holistically and which need enhancements in particular domains. For example, although Air Terjun Sekumpul (A5) excelled in appeal, it suffered penalties for average access and steeper costs, indicating that infrastructure upgrades should be a priority.

Methodologically, SAW's cumulative design permits straightforward comprehension of each factor's role in the overall hierarchy. Each factor's weight mirrors its comparative significance, enabling users to explore different situations by tweaking weights. For instance, if eco-viability or crowd control takes precedence, the weight for "crowd levels" can be boosted, instantly altering ranking results. This adaptability renders SAW ideal for fluctuating settings like travel planning, where tastes and regulations shift [39].

Furthermore, the standardized scoring approach guarantees comparability among varied factors with distinct scales, outperforming unstandardized methods like basic weighted totals. The outcomes also affirm that benefit and cost categories are properly differentiated via fitting standardization equations, preventing favoritism toward sites with extreme values in certain areas [40]. This equity through standardization is especially pertinent in travel, where renowned places (elevated C6) might also face overcrowding (elevated C8), necessitating fair assessment to avoid unsustainable suggestions.

Additionally, SAW showcases computational thriftiness. Its linear combination structure enables instant ranking computations, even with extra sites or factors. This expandability implies the framework can seamlessly blend into online or handheld DSS tools for widespread adoption [41]. Consequently, the discoveries not only endorse the model's conceptual integrity but also its feasibility for real-world use on regional or broader scales.

4. Conclusion

This investigation showcased the use of the Simple Additive Weighting (SAW) technique in crafting a Decision Support System (DSS) aimed at identifying top travel spots in North Bali. The framework was built to tackle the shortage of organized, impartial, and evidence-based approaches in

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site selection and travel organization. By merging eight assessment factors—reachability, charm, amenities, hygiene, expenses, fame, security, and crowd levels—the SAW framework effectively transformed both subjective and objective elements of travel appraisal into a cohesive structure. Information gathered from ten typical locations underwent standardization and treatment via a weighted summation process, enabling the derivation of conclusive ranking scores for each option.

The outcomes revealed that Pura Ulun Danu Beratan secured the leading position overall (score 0.8800), with Pantai Pemuteran (0.7827) and Danau Buyan (0.7520) following closely. These discoveries affirm that sites blending scenic wonders, historical significance, and convenience typically excel in comprehensive reviews. The SAW framework demonstrated clarity, computational speed, and the ability to uphold consistent hierarchies despite minor weight adjustments. Moreover, cross-verification with digital feedback data verified that the system's rankings matched genuine visitor choices and contentment rates, bolstering its trustworthiness for practical travel decisions. When pitted against alternative multi-factor techniques like AHP and TOPSIS, SAW exhibited strengths in ease, flexibility, and rapidity while preserving outcome precision [49].

The project advances both conceptual and applied aspects of decision aid and travel administration, delivering a replicable, expandable, and user-focused blueprint for policy creation and strategic design. It also champions eco-friendly travel ideals by encouraging balanced visitor flows and spotlighting enhancement chances for lesser-performing sites.

Looking ahead, multiple avenues could bolster the system's features and reach. Incorporating advanced learning algorithms for emotion and visual scrutiny might automate the retrieval of appeal and renown metrics from raw data, whereas refinement techniques such as Genetic Algorithm or Particle Swarm Optimization could adaptively tune weighting to align more closely with actual user tastes [50]. Moreover, blended strategies—like uniting uncertain reasoning or AHP–SAW frameworks—might elevate clarity amid ambiguity. Constructing an online or portable DSS interface that embeds live information, participant input, and location tracking will evolve this work into a responsive suggestion tool for cutting-edge travel uses. Via these improvements, the suggested structure can mature into a clever, enduring decision-aid platform poised to drive wider travel advancements across Indonesia and further afield.

5. Suggestion

Although the application of the Simple Additive Weighting (SAW) technique in this research has shown solid results for prioritizing and choosing in the travel industry, numerous avenues exist for additional progress and academic inquiry. Upcoming investigations should emphasize boosting the model's flexibility, expandability, and cleverness to overcome drawbacks in fixed and rule-dependent decision frameworks. The subsequent paths are proposed for future endeavors.

Initially, subsequent works ought to examine the incorporation of artificial intelligence and advanced learning methods to streamline data gathering and trait identification. Present assessments mostly depend on manually set scores and auxiliary information. Advanced learning frameworks like Convolutional Neural Networks (CNNs) might be applied to scrutinize visual content—such as vacationer images or site pictures—to impartially evaluate charm and hygiene standards [51]. Similarly, Natural Language Processing (NLP) tools like BERT or GPT-driven emotion detectors could be used to pull out emotion and fame ratings from user comments on sites like Google Maps or TripAdvisor. The derived information would enrich and refine the decision dataset, minimizing human prejudice and allowing instant refreshes.

Next, additional inquiry can delve into blended multi-criteria decision-making (MCDM) structures that merge SAW with supportive methods including AHP, TOPSIS, or uncertain reasoning [52]. These combined setups can manage ambiguities and descriptive terms—like "excellent," "spotless," or "reasonable"—that frequently emerge in personal judgments. Adding fuzzy collections or chance-based logic could aid in depicting specialist opinions more organically and produce tougher ranking results amid unclear or partial information scenarios [53].

Thirdly, refinement strategies might be added to autonomously adjust the weighting of factors. Employing metaheuristic refinement algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), or Ant Colony Optimization (ACO) can interactively find ideal weights that boost alignment between system-created hierarchies and actual visitor likes [54]. This strategy would

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enable the DSS to evolve with shifting user habits and administrative aims without needing manual rebalancing.

Fourthly, the creation of a cloud-hosted or online-linked DSS interface should be advanced to facilitate ongoing data gathering, examination, and participant engagement. By linking Internet of Things (IoT) devices—like crowd trackers or ecological sensors—with the SAW framework, upcoming systems could offer instant decision advice grounded in current crowd numbers or ecological states [55]. Such linkage would improve reactivity and back intelligent travel oversight aligned with eco-friendly progress objectives.

Lastly, extended studies should evaluate the social and economic effects of DSS uptake on travel administration and nearby populations. Gauging how evidence-based suggestions affect visitor spread, asset use, and stakeholder choices will yield crucial knowledge for policy crafting and travel regulation. Via these investigation paths, future experts can broaden the existing SAW-driven structure into a completely flexible, smart, and eco-conscious travel decision network able to handle the intricate and fluctuating characteristics of contemporary travel setups.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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