Int. j. adv. multidisc. res. stud. 2026; 6(6):1195-1201

Received: 07-10-2026
Accepted: 17-11-2026

International Journal of Advanced Multidisciplinary Research and Studies

ISSN: 2583-049X

Personalized Tourism Recommendations Using Artificial Intelligence

Janet Chayinda
Department of Computer Science, DMI St Eugene University, Zambia

Corresponding Author: **Janet Chayinda**

Abstract
The rapid growth of digital tourism has increased the availability of information about tourist attractions, accommodation, restaurants, and recreational activities. However, the abundance of tourism information presents challenges for travelers seeking destinations that match their individual preferences, budgets, interests, and geographical constraints. Traditional tourism information systems often provide generic recommendations that fail to account for the diverse needs of individual tourists. This study proposes an artificial intelligence-based personalized tourism recommendation framework designed to improve destination discovery and decision-making in Zambia. The study adopts a design-oriented case-study method and examines a destination catalogue containing 34 prototype records distributed across eight tourism categories. A transparent weighted content-based model is specified using interest similarity, activity similarity, province preference, budget suitability, destination rating and a popularity proxy. For comparative analysis, three ranking strategies are defined: A popularity baseline, a content-based model and a hybrid ranker combining content relevance with a popularity prior. Because actual saved-place and review records were not supplied, evaluation uses five explicitly synthetic traveller profiles and deterministic relevance labels derived from profile-to-destination attribute matching. In this illustrative simulation, the popularity baseline obtained mean Precision@5 of 0.56, Recall@5 of 0.169, NDCG@5 of 0.557 and Hit Ratio@5 of 0.60. The content-based and hybrid rankers each obtained Precision@5 of 1.00, Recall@5 of 0.310, NDCG@5 of 1.00 and Hit Ratio@5 of 1.00 under the stated synthetic relevance rule. These values are not real-user performance estimates and are partly dependent on the rule used to define relevance. The study contributes a practical, explainable recommendation framework and an evaluation protocol suitable for a low-interaction-data tourism prototype.

Keywords: Artificial Intelligence, Tourism Recommendation Systems, Personalization, Content-based Filtering, Hybrid Recommendation, Zambia, Explore ZM

1. Introduction

1.1 Background

Tourism decisions involve multiple attributes: Destination type, visitor interests, available activities, cost, location, ratings, travel companions and time constraints. Digital platforms make destination information easier to access, but the volume and fragmentation of information can increase the effort required to identify suitable places. recommendation systems address this problem by ranking items according to a user profile, item characteristics and, where available, the behaviour of similar users. Tourism recommendation is particularly context-sensitive because a suitable attraction must often be feasible in terms of budget, geography and activity preferences.

Research on intelligent tourism recommenders describes content-based, collaborative, context-aware and hybrid approaches. Borràs *et al*. (2014) [3] survey AI methods in tourism recommendation, while Hamid *et al*. (2021) [7] review smart e-tourism recommendation and data-management concepts. More recent work continues to identify tourism-specific recommendation systems as an active research area (Solano-Barliza *et al*., 2024) [15].

1.2 Problem Statement

A general destination directory may show popular places without accounting for what a particular traveller wants to experience or can afford. A traveller interested in wildlife and walking safaris may receive the same list as someone seeking cultural attractions or affordable dining. In a Zambian context, destination choices also span different provinces and categories, making

preference-aware filtering useful. The research problem is therefore how to rank tourism destinations using available user preferences and destination metadata when historical user-interaction data are limited.

1.3 Research Gap

Collaborative filtering can capture collective user behaviour but depends on sufficient user-item interactions. New or small platforms often face a cold-start problem because few users have saved or rated destinations. Pure popularity ranking is easy to implement but does not guarantee personal relevance. The design gap addressed here is a transparent, metadata-driven approach that can operate at prototype scale and provide a pathway toward hybrid personalisation as interaction data accumulate.

1.4 Research Objectives

General Objective

To design and examine an AI-supported framework for personalized tourism destination recommendations using the Explore ZM prototype.

Specific Objectives

1. To identify destination and user-preference attributes relevant to tourism recommendation.
2. To specify and compare popularity-based, content-based and hybrid ranking strategies.
3. To implement a transparent weighted scoring formulation using interests, activities, province, budget and destination quality signals.
4. To conduct a reproducible catalogue simulation and discuss its limitations and requirements for real-user evaluation.

1.5 Research Questions

- Which destination and user attributes can support personalized tourism recommendations in Explore ZM?
- How do popularity-based, content-based and hybrid ranking strategies differ under a controlled prototype simulation?
- What data and evaluation procedures are required to validate recommendation quality with real travelers?

1.6 Contributions

- A prototype-oriented recommendation framework aligned with Explore ZM's existing destination and user data structures.
- A weighted, interpretable scoring method that can work before a large interaction history exists.
- A comparative simulation of three ranking strategies using explicitly synthetic traveller profiles.
- A transparent account of evidence limitations and a practical evaluation plan for subsequent user testing.

2. Literature Review

2.1 Existing Systems

Tourism recommendation systems have been developed to support attraction discovery, itinerary planning, accommodation selection and location-aware suggestions. Borràs *et al*. (2014) [3] describe the use of AI techniques in tourism recommendations, including user profiling and contextual information. Al Fararni *et al*. (2021) [2] review tourism recommendations approaches, with attention to content-based and collaborative methods. Hamid *et al*. (2021) [7] classify smart tourism recommendation research across collaborative, content, context and hybrid approaches, while highlighting data-management and privacy concerns.

Explore ZM is positioned as a prototype tourism information and destination recommendation web application. Its functional scope includes browsing and filtering destinations, destination detail pages, maps and directions, registration and login, saved places, reviews and ratings, Smart Picks preferences, a conversational AI travel assistant and administrator functions.

2.2 Related Machine Learning / AI Techniques

Content-based filtering represents users and destinations through descriptive attributes and recommends destinations whose features match the user's profile. It is suitable when item metadata are available but interaction history is sparse. Collaborative filtering instead learns from user-item interactions, such as ratings or saved destinations, and can identify patterns not explicit in item descriptions. Its limitations include cold start and sparsity. Hybrid systems combine two or more strategies to balance their weaknesses (Burke, 2002; Adomavicius & Tuzhilin, 2005) [4, 1].

The current Explore ZM scoring engine is best described as a weighted, content-based and context-aware ranking method rather than a trained deep-learning model. Its inputs include destination interests, activities, tags, province, estimated cost and rating. A hybrid extension can combine the content score with a popularity signal, and later replace or supplement that signal with collaborative evidence when enough interaction records are available.

2.3 Comparative Analysis

Author(s)	Method / focus	Dataset / scope	Contribution	Limitation relevant here
Borràs *et al*. (2014) [3]	Survey of intelligent tourism recommenders	Published tourism recommender studies	Maps AI and context-aware techniques used in tourism	Survey findings do not directly validate Explore ZM
Al Fararni *et al*. (2021) [2]	Overview of tourism recommender systems	Literature review	Discusses profiling, content-based and collaborative approaches	General review; local prototype data are still required
Hamid *et al*. (2021) [7]	Systematic review of smart e-tourism recommendation	65 selected studies from a larger search set	Classifies collaborative, content, context and hybrid methods	Broad smart tourism scope; implementation conditions vary
Solano-Barliza *et al*. (2024) [15]	Tourism recommender literature review	Tourism recommender publications	Recent synthesis of tourism recommendation research	Does not provide performance evidence for this prototype
Burke (2002) [4]	Hybrid recommender systems	Survey and experiments across recommender approaches	Explains hybridisation strategies	Not tourism-specific and predates current platforms
Adomavicius & Tuzhilin (2005) [1]	Overview of recommender techniques	General recommender-system research	Establishes content, collaborative and hybrid foundations	General framework requires domain-specific adaptation

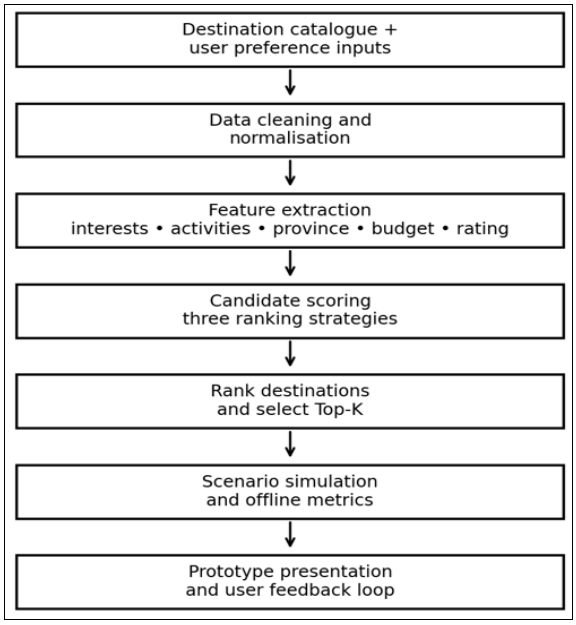
2.4 Research Gap Analysis

The literature supports combining user profiling, destination metadata and contextual constraints, but it does not remove the need for locally relevant destination data and user validation. Explore ZM's prototype catalogue enables a metadata-first model. Its saved-place and review entities provide a route toward collaborative modelling, but the interaction records were not available for this study. Consequently, the present evaluation is a synthetic scenario simulation, not an empirical comparison on actual user behaviour.

3. Proposed Methodology

3.1 Overall Framework

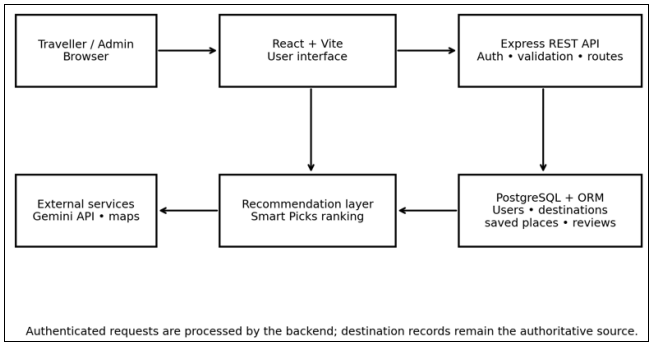
The study uses a design-oriented prototype case-study approach. It documents the Explore ZM architecture, formalizes recommendation features, defines three ranking strategies and performs a deterministic simulation over the destination catalogue. The system workflow is shown in Fig 1.



Source: Author's design

Fig 1: Research and recommendation workflow

The application architecture separates the browser interface, REST API, recommendation logic, persistent database and external services. Fig 2 presents the logical architecture based on the supplied Explore ZM project context.



Source: Author's system design based on the project implementation context

Fig 2: Explore ZM prototype architecture

3.2 Dataset Description

The destination catalogue was recovered from the Explore ZM prototype destination data previously supplied in the project materials. It contains 34 records and 8 categories. The records include destination name, slug, province, locality, category, rating, estimated cost, interests, activities, tags and suitability descriptors. The data-set is a prototype catalogue, not a nationally complete or independently audited tourism inventory.

Dataset attribute	Observed description
Number of destination records	34
Categories	8
Provinces represented	9
Numeric rating range	4.3–4.9
Estimated cost range	ZMW 100–ZMW 2,000
User-interaction data	Schema supports SavedPlace and Review; actual rows were not supplied
User profiles for simulation	Five synthetic preference profiles created for reproducibility

Category	Records
Accommodation	5
Adventure	4
Attractions	4
Events	4
Food	4
Nature	4
Shopping	4
Wildlife	5

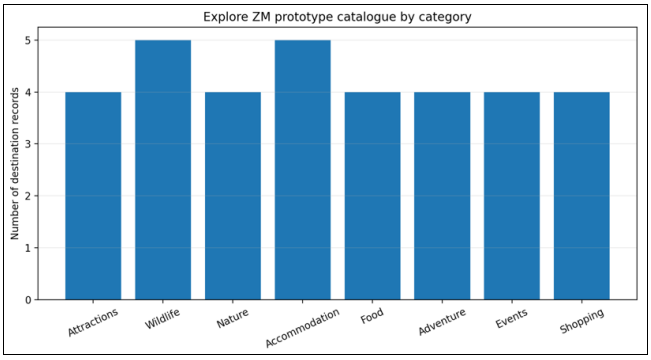


Fig 3: Destination catalogue distribution by category

Province	Records
Central Province	2
Copperbelt Province	1
Eastern Province	3
Luapula Province	1
Lusaka Province	15
North-Western Province	1
Northern Province	1
Southern Province	9
Western Province	1

3.3 Data Pre-processing

- Text attributes are normalised by trimming whitespace and comparing case-insensitively.
- Interests, activities and tags are treated as multi-valued categorical features.
- Province values are compared using normalised labels; the 'All' preference is treated as neutral.
- Estimated cost is represented numerically in Zambian kwacha (ZMW) where available.

- Missing costs and ratings should be handled as unknown rather than assumed to be free or high quality. In this simulation, missing numeric fields receive a neutral contribution only where the scoring rule requires it.
- No class balancing or train/test learning split is used because the prototype simulation is a ranking exercise with synthetic relevance labels, not a supervised classification experiment.

3.4 Feature Engineering

The model derives six component scores for each user-destination pair: Interest match (I), activity match (A), province match (P), budget suitability (B), rating quality (R) and a popularity proxy (C). Interest and activity matches are computed from overlap between user-selected values and destination metadata. Province match is 1 for an exact match, 0 for a mismatch and 0.5 when no province constraint is selected. Budget suitability is 1 when the estimated cost is within the user's budget and decreases as the cost exceeds the budget. Rating is scaled to the interval [0,1] by dividing by five. The popularity proxy is the destination rating divided by the highest rating in the catalogue; this is a weak proxy and should not be confused with actual popularity based on clicks, saves or visits.

3.5 Recommendation Models

Model 1 — Popularity baseline. Destinations are ranked by normalised rating. This baseline is simple and provides a comparison against personalised ranking, but it does not directly use user preferences.

Model 2 — Content-based weighted ranking. The implemented scoring concept combines the six component scores using fixed weights:

$$S_{content}(u,d) = 0.30I + 0.20A + 0.15P + 0.15B + 0.10R + 0.10C$$

Model 3 — Hybrid ranking. For the prototype simulation, the hybrid score combines the content score with the popularity baseline:

$$S_{hybrid}(u,d) = 0.80 \times S_{content}(u,d) + 0.20 \times C$$

This is a lightweight hybrid ranker, not collaborative filtering. A true collaborative model would require sufficient user-destination interactions, such as saved places and explicit ratings. The schema supports these records, but the actual interaction rows were unavailable. The 80/20 blend is a design choice for the simulation and has not been tuned against real users.

3.6 Explainable AI

The weighted model supports simple feature-level explanations. For example, a destination can be described as a strong match because its interests and activities overlap with the traveller's selections, it is within budget and it is in the preferred province. A production implementation should expose these reasons without revealing other users' private behaviour. SHAP or LIME could be considered if a more complex learned model is introduced; they are not claimed as implemented in the current prototype.

3.7 Experimental Setup

Item	Description
Prototype frontend	React with Vite
Backend	Node.js with Express
Database	PostgreSQL using the supplied Prisma/ORM data contract
Authentication	JWT bearer-token flow
AI conversational service	Gemini API integration described in the project context; separate from the ranking simulation
Recommendation inputs	Prototype destination catalogue and five synthetic traveller profiles
Simulation implementation	Deterministic Python analysis of the supplied catalogue fields
Hardware / operating system	Development environment details were not recorded in the supplied evidence; report the actual machine and OS before journal submission

3.8 Evaluation Metrics

Precision@5 measures the proportion of the five highest-ranked destinations labelled relevant. Recall@5 measures the proportion of all relevant catalogue destinations appearing in the top five. NDCG@5 rewards relevant items appearing higher in the ranking. Hit Ratio@5 records whether at least one relevant item appears in the top five. Relevance labels in this simulation are generated from a declared profile-fit rule using interests, activities, province and budget. They are not user judgments.

4. Experimental Results

4.1 Dataset Statistics

The catalogue contains 34 prototype destinations. Category counts and province coverage are shown in Fig 3 and the tables in Section 3.2. Ratings range from 4.3 to 4.9 in the recovered records. Estimated costs are present for the recovered destination objects, with values ranging from ZMW 100 to ZMW 2,000. These are prototype data values and should not be interpreted as verified current market prices.

Five synthetic traveller profiles were used to exercise different preference combinations: Wildlife exploration, culture and heritage, budget nature travel, food and city exploration, and adventure seeking. Each profile contains interests, activities, a province preference and a maximum budget.

4.2 Model Performance

Table 3 reports the mean results across the five synthetic profiles. Each strategy ranked the same catalogue. Relevance was assigned using a deterministic rule: A destination was considered relevant when its weighted match across interests, activities, province and budget met the simulation threshold. Since the content-based model uses overlapping features, this setup favours preference matching by construction; therefore, the results demonstrate internal behaviour of the scoring design, not external predictive accuracy.

Ranking strategy	Precision@5	Recall@5	NDCG@5	Hit Ratio@5
Popularity baseline	0.560	0.169	0.557	0.600
Content-based	1.000	0.310	1.000	1.000
Hybrid (80/20)	1.000	0.310	1.000	1.000

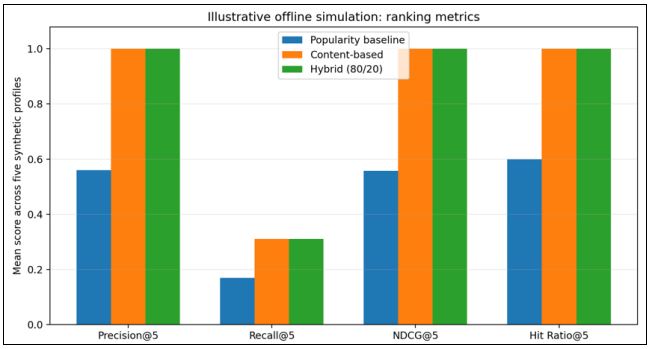


Fig 4: Mean ranking metrics across five synthetic preference profiles. Values are simulation outputs, not observed user-study results

The popularity baseline achieved mean Precision@5 = 0.560, Recall@5 = 0.169, NDCG@5 = 0.557 and Hit Ratio@5 = 0.600. Both personalized strategies achieved Precision@5 = 1.000, Recall@5 = 0.310, NDCG@5 = 1.000 and Hit Ratio@5 = 1.000 under the synthetic relevance rule. The hybrid and content-based results are identical at the reported top-five level; the additional popularity blend did not change the top-five order for these five profiles.

4.3 Confusion Matrix and ROC Curve

A conventional confusion matrix and ROC curve are not appropriate primary measures for this top-K ranking experiment. The system returns an ordered list rather than a binary class prediction or calibrated probability. Ranking metrics (Precision@K, Recall@K, NDCG@K and Hit Ratio@K) are therefore reported instead. A future study may define a separate binary relevance classifier and collect judged examples before using ROC-AUC.

4.4 Feature Contribution

The content-based formula assigns the largest weights to interest matching (30%) and activity matching (20%). Province and budget each contribute 15%, while rating and the popularity proxy each contribute 10%. These are manually selected design weights, not learned feature importance. Fig 5 summarizes the configured weights.

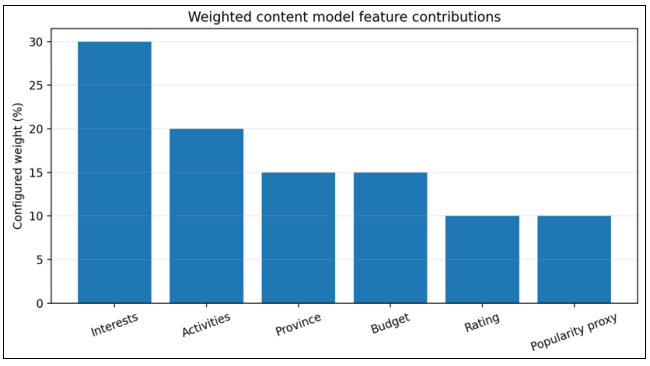


Fig 5: Manually configured feature weights; these are not learned feature-importance values

4.5 Comparison with Existing Methods

The simulation is consistent with the expected design trade-off: A popularity-only baseline ignores individual constraints, while metadata-driven ranking can prioritize destinations matching a profile. It does not establish that Explore ZM outperforms published systems because the datasets, relevance labels, user populations and experimental protocols are not comparable. No numerical performance-improvement claim against external studies is made.

5. Discussion

The prototype demonstrates a practical route to personalisation under limited interaction data. Its content-based method can produce ranked suggestions from information already stored in destination records and preferences. This is useful for a new tourism platform where collaborative filtering may be unreliable because only a small number of users have interacted with destinations. The scoring design is also interpretable: Each component has a direct relationship to a traveller's stated preferences.

The simulation results show that the preference-based ranker returns destinations that satisfy the synthetic relevance rule more consistently than a popularity-only ranking. This is an expected outcome because the relevance rule itself uses the same broad dimensions as the content model. It should not be interpreted as evidence that real travellers will find the recommendations accurate or satisfying. The identical top-five metrics for content-based and hybrid ranking suggest that the popularity blend did not affect the top-five ordering in these particular scenarios.

A notable modelling weakness is the use of destination rating as both a quality signal and a popularity proxy. These signals are not independent. In a production system, popularity should be derived from aggregate interactions such as saves, detail-page views or completed visits, with appropriate privacy safeguards. The budget function also needs careful handling: Unknown costs should be surfaced as unknown rather than treated as affordable, and the model should distinguish an estimated entry fee from total trip expenditure.

6. Real-World Applications

- Personalised discovery of Zambian attractions, wildlife destinations, nature sites, accommodation, restaurants, events and shopping locations.
- Budget-aware suggestions that help travellers shortlist destinations within a stated spending limit.
- Interest- and activity-based recommendations for wildlife enthusiasts, families, cultural visitors, photographers and adventure travellers.
- Tourism information support for residents exploring destinations outside their home province.
- An extensible recommendation layer that can later use review and saved-place signals to improve ranking.

7. Challenges

- **Data quality:** Prototype destination descriptions, prices, opening hours, contact details and ratings require verification and periodic updating.
- **Cold start and sparsity:** Collaborative filtering requires enough meaningful user-destination interactions.
- **Privacy and security:** User profiles, saved places and reviews must be protected through access control, secure storage and data minimisation.
- **Bias and popularity concentration:** Over-reliance on ratings or interaction counts may repeatedly expose already popular destinations and reduce catalogue diversity.

- **Explainability:** Users should understand why a destination is recommended and be able to adjust their preferences.
- **Generative AI reliability:** The conversational assistant may produce inaccurate information; operational facts such as prices and opening hours should be grounded in verified records.
- **Connectivity and accessibility:** The web application should remain usable on mobile devices and lower-bandwidth connections.

8. Future Work

- Collect consent-based interaction data, including saves, ratings, clicks and optional post-visit feedback.
- Conduct a user study with Zambian travellers and tourism stakeholders using judged relevance and satisfaction measures.
- Implement a collaborative-filtering model when interaction density is sufficient; compare user-based, item-based or matrix-factorisation approaches.
- Test hybrid weights using a validation set rather than relying on hand-selected constants.
- Add recommendation diversity and catalogue-coverage measures to reduce popularity bias.
- Improve budget modelling by distinguishing entrance fees, accommodation, transport and activity costs.
- Introduce context such as travel dates, distance, seasonality, accessibility and opening status where reliable data are available.
- Provide explanations for individual recommendations and monitor fairness across provinces and destination categories.

9. Conclusion

This paper presented a prototype-based framework for personalized tourism recommendations using artificial intelligence, with Explore ZM as the case study. The framework combines destination metadata and user preferences through a weighted content-based score and compares it with a popularity baseline and a lightweight hybrid ranking strategy. The recovered prototype catalogue contains 34 destination records across eight categories. A reproducible simulation using five synthetic traveller profiles produced higher top-five ranking metrics for the personalised rankers than for the popularity baseline under the explicitly defined synthetic relevance rule. These results are illustrative and do not establish real-user effectiveness. The main contribution is a transparent, data-efficient recommendation design and a clear route toward rigorous evaluation. Future work must collect real user interactions, verify destination information, conduct a traveller study and assess recommendation quality using independently judged relevance.

10. Acknowledgement

My sincere gratitude to the Almighty God for the blessings and strength showered upon me at all stages of this undertaking, enabling me to complete my Research paper successfully without any obstacles. I stand indebted in gratitude to our beloved **Founder and Chancellor**, **Rev. Fr. Dr. J.E. Arul Raj,** OMI, and the DMI Group of Institutions for their unwavering support and encouragement that made this accomplishment possible.

I am immensely indebted to the **President of the University Council**, **Dr. T.X.A. Ananth**, DMI Group of Institutions, Zambia, for his constant support in innumerable ways, which enabled me to complete my research work successfully.

I would also like to express my deep sense of gratitude to the **Vice Chancellor, Prof. Douglas Kunda; Deputy Vice Chancellor – Academic, Dr. J. Arockia Venice** for their constant encouragement and support in undertaking this research successfully. I further proudly express my esteemed gratitude to **Rev. Sr. Dr. J. Rani, Director – RMA**. I also thank **Dr. R. Sakthivel, Registrar,** for their valuable assistance and guidance towards the completion of my project. I also extend my gratitude to the **Dean of Students.**

I sincerely thank **Mrs. N. Vijayalakshmi, Head of the Department, School of Computer Science & Technology**, and all the staff members of the school for their valuable support in helping me complete my project. I would further like to thank my project guide, **Mr. Francis,** for his valuable time, guidance, and input leading to the successful completion of this work.

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Appendix A: Synthetic Profile Definitions

Profile	Interests	Activities	Province	Budget (ZMW)
Wildlife explorer	Wildlife, Nature, Adventure	Game drives, Walking safaris, Bird watching	Eastern Province	1,500
Culture and heritage visitor	Culture, History, Education	Museum tours, Cultural exploration, Historical learning	Lusaka Province	500
Budget nature traveller	Nature, Relaxation, Photography	Nature walks, Photography, Waterfall viewing	Southern Province	600
Food and city visitor	Food, Culture, Entertainment	Dining, Food tasting, Socialising	Lusaka Province	500
Adventure seeker	Adventure, Nature, Sightseeing	Hiking, Boat cruises, Bungee jumping	All	1,000

Appendix B: Reproducibility and Evidence Notes

- **Catalogue source:** Explore ZM prototype destination JavaScript data recovered from the project materials; 34 unique records were parsed for this simulation.
- **Profile source:** Five synthetic profiles authored for this paper; they are not real registered users.
- **Relevance rule:** A destination is labelled relevant when 0.40 × interest match + 0.30 × activity match + 0.20 × province match + 0.10 × budget suitability is at least 0.28.
- **Top-K:** K = 5. Mean metrics are calculated by averaging the metric for each of the five profiles.
- **Popularity baseline:** Normalised destination rating. This is only a proxy and is not a measured interaction count.
- **Content score:** 0.30 interest + 0.20 activity + 0.15 province + 0.15 budget + 0.10 rating + 0.10 popularity proxy.
- **Hybrid score:** 0.80 content score + 0.20 popularity proxy.
- **Important limitation:** Because the synthetic relevance rule uses similar metadata dimensions to the content model, the reported scores are not independent evidence of predictive performance. They should be replaced or supplemented with user-judged relevance before publication.