Smart Destination Digital Marketing Dashboard: Architecture and Empirical Validation for Bukhara Region Heritage Tourism

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Abstract: This paper proposes and evaluates a Smart Destination Digital Marketing Dashboard (SD-DMD) - a five-layer web-based analytical platform designed to consolidate tourism data streams and deliver analytics-assisted marketing intelligence for heritage destinations. The system architecture integrates a data ingestion layer (RESTful APIs, web scraping agents), a processing layer (ETL pipeline with Python/Apache Kafka), an analytics layer (CAGR computation module, Pearson correlation engine, SWOT scoring algorithm), a visualisation layer (React.js dashboard), and a recommendation layer (content-based filtering for personalized itineraries). Empirical validation employs longitudinal secondary data from Bukhara Regional Tourism Department (2017–2024) across 14 KPIs. Results confirm substantial sectoral growth: aggregate tourist volumes expanded 4.5-fold (CAGR = 24.1%), international arrivals grew 10.3-fold (CAGR = 39.4%), and tourism revenues amplified 11.7-fold (CAGR = 42.1%). Digital infrastructure correlation with tourist flows yielded $r = 0.89$ ($p < 0.01$). Dashboard prototype evaluation using System Usability Scale (SUS) produced a mean score of 81.3 (Grade B, 'Good'indicating prototype-level usability and readiness for limited pilot evaluation. The proposed architecture addresses an identified gap in open-source smart-destination tooling for Central Asian UNESCO heritage sites and aligns with UNWTO smart destination criteria and Uzbekistan's 2030 national tourism target.

1 INTRODUCTION

Digitalization of international tourism has changed the structure of international tourism significantly and rapidly. UNWTO statistics reveal that in 2024, 1.5 billion international arrivals were registered and about 70 percent of the decisions to plan a trip were mediated by digital channels [1]. The dilemma facing heritage destinations is to use digital platforms to compete in the global arena and preserve Outstanding Universal Value. However, there is still a tooling gap to be overcome, as the majority of open-source smart-destination analytics platforms will be available to the cities of Western Europe; there is yet to be a tested, deployable dashboard that will address Central Asian UNESCO sites [2].

Uzbekistan Bukhara region features a UNESCO World Heritage historic center (inscribed 1993, >150 medieval monuments), and was designated the ICESCO Capital of Islamic Culture (2020), which gives it a perfect validation context. According to the official statistics, there is recorded unprecedented growth of tourism (2017-2024) alongside the growth of digital infrastructure, but the destination managers are currently operating on a fragmented spreadsheet report, instead of utilizing built in analytical tools [3].

The present study makes four distinct contributions to the smart tourism literature. First, it proposes a five-layer SD-DMD architecture integrating tourism KPI analytics, SWOT scoring, and content-based recommendation within a single prototype-level open-source framework - a configuration absent from prior Central Asian tourism information systems. Second, unlike existing dashboards designed for Western European city-tourism contexts, the architecture is explicitly adapted to UNESCO heritage-conservation constraints, incorporating monument-sensitive visitor routing and multilingual SEO generation. Third, the system is empirically validated on an eight-year longitudinal dataset (14 KPIs, 2017-2024) using a triangulated methodology combining CAGR computation, Pearson correlation analysis, architecture specification, and SUS usability evaluation. Fourth, the architecture is designed as a prototype for future pilot adoption by regional destination management organizations with minimal infrastructure requirements, directly supporting Uzbekistan's national target of 20 million international visitors by 2030.

2 LITERATURE REVIEW

2.1 Related Work

The conceptualization of smart tourism destinations (STD) views the introduction of technology as a component of ideas of pre-visit, during-visit and post-visit in dimensions of smart economy, governance, mobility, environment and living [4]. The empirical analysis of the STD literature supports the fact that data analytics and AI-driven customization are the areas of core competencies deficit in the environment of emerging markets with heritage [5].

Online tourism marketing analytics tools have been discussed in a number of implementation settings. Digital marketing has become particularly important for tourism businesses seeking to strengthen market visibility, customer engagement, and competitiveness in changing tourism environments [6]. More recent smart-tourism research further highlights the growing role of artificial intelligence in transforming destination management, tourism services, and strategic decision-making [7]. The destination management organizations usually have the dashboard systems which combine the web analytics, social media monitoring, and booking information, but published architectures usually pertain to the European city-tourism environments, but not to the heritage-conservation environments [8]. Tourism recommender systems based on AI have been found to rely heavily on destination selection behavior [9], and AR/VR applications at UNESCO sites have shown an effect of visitor satisfaction and conservation awareness improvement [10].

A study of digital marketing preparedness in emerging economies reveals that infrastructure, human capital, and policy congruency are the predictors of an effective adoption [11]. Studies specific to Uzbekistan have shown positive relations between digital infrastructure indicators and inflow of tourists [12], yet no previous research suggests an integrated deployable platform that could be used in this relation. This gap is directly answered in the current research.

Subsequent scholarship has validated and extended these models across various tourism sectors, confirming that digital marketing effectiveness is contingent upon strategic integration rather than isolated tactical implementation [13].

2.2 SD-DMD System Architecture

Smart Destination Digital Marketing Dashboard (SD-DMD) is a web-based application of five layers (Table 1) which can be piloted by regional destination management organizations. All the layers are explained below with the technical specification.

2.3 Data Ingestion Layer (L1)

L1 integrates four data-source categories: (1) official regional and national tourism statistics accessed through structured CSV/API exports; (2) accommodation-related platform indicators obtained from publicly available or partner-accessible online booking sources; (3) digital infrastructure indicators, including payment-terminal and accommodation-connectivity records; and (4) web-derived destination-content signals collected through Scrapy-based agents. Data are ingested in JSON/CSV formats and buffered through Apache Kafka with a 7-day retention window to support both scheduled batch processing and near-real-time updates.

2.4 ETL Pipeline (L2)

Apache Airflow coordinates the nightly DAG (Directed Acyclic Graph) executions that run: outlier detection (IQR method, threshold 1.5); missing - value imputation (linear interpolation of time-series gaps 3 periods); currency normalization (USD at annual average exchange rate); indicator categorization into four analytically relevant categories (tourist flows, digital infrastructure, payment infrastructure, economic indicators). Year and indicator category partitions of a PostgreSQL 15 relational store hold processed data.

2.5 Analytics Engine (L3)

The analytics engine is an implementation of three fundamental algorithmic modules. The CAGR Computation Module implements the formula:

$$\mathrm{CAGR} = \left(\frac{\mathrm{EndValue}}{\mathrm{StartValue}}\right)^{\frac{1}{n}} - 1,$$

where *n* is the number of years (n=7 for 2017–2024);

The Pearson Correlation Engine calculates pairwise correlation matrix between infrastructure indicators and the outcomes variable of the tourists and returns r coefficients with two tailed p-value. The SWOT Scoring Algorithm measures the internal (strengths/weaknesses) and external (opportunities/threats) factors as composite SWOT scores through the application of a weighted scoring matrix (5-point Likert rating by domain experts) which are updated every quarter.

2.6 Visualization Layer (L4)

The React.js frontend provides five dashboard panels, (1) KPI Overview - scorecard tiles with YoY delta indicators; (2) Growth Trends - D3.js multi-line charts with pandemic annotation overlays; (3) Digital Infrastructure Map - Mapbox GL choropleth of accommodation registrations and payment terminal density by district; (4) Correlation Matrix - interactive heatmap of r-values with time-stamped updates; (5) SWOT Dashboard - colour-coded quadrant display with time-stamped updates. The interface is completely responsive (Bootstrap 5), both can be piloted to the desktop of the destination management offices, and accessed by field staff via mobile devices.

2.7 Recommendation Layer (L5)

L5 has a content-based filtering recommender which creates customized heritage itineraries, by taking into account information on visitor profiles (country of origin, interests, time and money). The growing use of artificial intelligence in tourism also confirms the potential of data-driven systems for personalized recommendation and destination decision support [14]. TF-IDF representation of 47 heritage sites profiles (extracted as part of UNESCO sites and TripAdvisor listing) is compared with visitor profiles using cosine similarity. A keyword-targeted page summary generator is an auxiliary SEO content-brief generator, which is trained through the OpenAI API (GPT-4o) and is used to generate page outlines based on the five priority query clusters determined in the course of Section 5.2. L5 services are all exposed through FastAPI REST endpoints, allowing support of the existing web CMS of the destination.

3 MATERIALS AND METHODS

The SD-DMD analytics modules were empirically validated against a longitudinal secondary dataset obtained as: (1) The statistical compilations of the Bukhara Regional Tourism Department (2017-2024); (2) the national tourism statistics of the Statistics Committee of the Republic of Uzbekistan; (3) the reports of the UNWTO World Tourism Barometer. The data set comprises 14 KPIs in four categories. The temporal window 2017-2024 is used to include pre-pandemic baseline, disruption and recovery phase to perform a total analysis of CAGR and correlation as is done in L3 modules.

System Usability Scale (SUS)- a 10-item tool with proven validity and yielding scores ranging between 0 and 100 was also used in prototype usability evaluation [15]. Assessment was done on n= 15 domain-expert participants (regional tourism administrators, tour operators, researchers) through a structured task protocol with all five dashboard panels. The average scores of the SUS items were calculated according to the standard methodology: summation of the items scores multiplied by 2.5; comparison of the mean with benchmarks of grading (above 80.3 = excellent, 68-80.3 = good, less than 68 = ok/poor).

Limitations recognized in the analysis: the secondary official data could be used to underestimate informal-sector tourism; the pandemic-related anomaly (2020-2021) complicates the interpretation of trends; the correlational nature of the study prevents causal inference; the SUS sample, n = 15, is within the acceptable minimum but restricts the scope of generalization. Several additional limitations are noted here. The exact mechanism by which the L1 ingestion layer's Apache Kafka buffer feeds the PostgreSQL store in L2, and the specific data types transmitted through Kafka, are not fully detailed in the present architecture description and require further technical documentation. Similarly, the role of R (cor.test) alongside the Python-based analytics stack in L3 is not specified as either a separate module or a Python-invoked routine; this integration detail should be clarified in future documentation. The Pearson correlation coefficients reported in Table 3 were not accompanied by a formal test of normality for the underlying indicators, so the correlation results should be interpreted with this assumption in mind. In addition, the parallel drawn in the Discussion between the observed correlations (r = 0.89–0.91) and the theoretical models discussed by Tamirat and Zewdie [11] is conceptual rather than a direct quantitative comparison, since that source does not report comparable numerical correlation coefficients.

4 RESULTS

4.1 Tourist Flow Analytics Module Result

Table 2 presents the dashboard L3 CAGR module outputs of indicators of tourist flow. Aggregate arrivals increased 4.5 times (CAGR = 24.1 percent), and the pre-pandemic CAGR (2017-2019) was 69.4 percent and the recovery CAGR (2022-2024) was 27.9 percent. The international arrivals also increased 10.3 times (CAGR = 39.4%); the international share saw an increase in 2017 (13.4%), and 2024 (30.3%), which confirms progressive destination internationalization. The consequences of the pandemic were profoundly devastating, but temporary: the total number of arrivals dropped by 93.1 in 2020, and volumes returned to above 2019 levels in 2022.

4.2 Digital Infrastructure Correlation Results

The SD-DMD Pearson Correlation Engine computed bivariate associations between digital infrastructure indicators and tourist outcome variables (Table 3). Electronic accommodation connections showed strong positive correlation with aggregate arrivals ($r = 0.89$, $p < 0.01$). The composite Digital Score (aggregate of all infrastructure indicators, expanding 6.0-fold: 155 → 937 units) correlated with international arrivals at $r = 0.91$ ($p < 0.01$). Foreign currency payment terminal density correlated with foreign exchange revenue at $r = 0.87$ ($p < 0.01$). These associations, while non-causal, confirm that digital infrastructure expansion has accompanied - and likely facilitated - tourism growth, providing empirical grounding for the L5 recommendation module's prioritization of digital investment strategies.

4.3 Dashboard Usability Evaluation

The evaluation of the SUS (n=15 experts) resulted in a mean value of 81.3 (SD= 6.4) which is classified as Excellent according to the standard SUS interpretation (scores above 80.3), just above the Good/Excellent boundary. The percentage of tasks completion among the five dashboard panels varied between 87 percent (L5 Recommendation panel) to 100 percent (L1 KPI Overview); the underlying number of tasks per panel and their relative complexity were not equalized across panels, so this range should be read as an indicative rather than a strictly comparable measure. The mean task completion time with regards to the main user case, which was the generation of a CAGR and correlation report of a given pair of indicators, amounted to 4.2 minutes. The mapbox choropleth (L4 panel 3), was the highest-rated qualitative feedback among all the destination managers, and the SEO content-brief generator (L5), was the highest-utility among marketing staff. The findings indicate that the SD-DMD prototype demonstrates good usability and practical feasibility for limited pilot testing in regional tourism organizations.

5 DISCUSSION

The SD-DMD architecture is associated with a reported gap: no proven and open-source analytics platform is available with Central Asian UNESCO heritage destinations. The five-layered design can be used in accordance with UNWTO smart destination principles since it covers the entire range of tourism process - pre-visit (L5 SEO recommendations, personalized itineraries), during-visit (L4 real-time occupancy maps), and post-visit (L3 satisfaction correlation analysis). The SUS score of 81.3 confirms that the architectural complexity has been effectively abstracted into a convenient interface which is the first requirement in being adopted by regional tourism administrators whose digital literacy skill level is heterogeneous.

The results of empirical findings support and elaborate on earlier literature. Previous research on tourism and sustainable development in Uzbekistan has emphasized the importance of integrated destination-management approaches for strengthening regional tourism development and improving the long-term sustainability of tourist destinations [3], [16]. The fact that the correlation between digital infrastructure and tourist flows is strong (r = 0.89-0.91) aligns with theoretical models of digital marketing adoption in developing economies [11], whereas the scale of international visitors to Bukhara (10.3-fold, CAGR = 39.4) is significantly higher than that of Central Asia, meaning that the UNESCO status of the Bukhara city contributes to the multiplicative digital marketing effect. The high revenue multiplier (11.7 times) with CAGR of 42.1 plus the employment multiplier (24.3 times) means that the economic multiplier effect of tourism is high and it is an effective reason to continue investing in SD-DMD.

Table 1: SD-DMD layer architecture specification.

Layer	Components	Technologies	Output
L1: Data Ingestion	REST APIs, scraping agents, CSV import	Python (Scrapy), Apache Kafka, PostgreSQL	Raw tourism KPI streams; social media metrics
L2: ETL Pipeline	Cleansing, normalisation, deduplication	Apache Airflow, dbt, Pandas	Validated time-series dataset (14 KPIs, 2017–2024)
L3: Analytics Engine	CAGR module, correlation engine, SWOT scorer	Python (SciPy, NumPy), R (cor.test)	Growth metrics, Pearson r matrix, SWOT scores
L4: Visualisation	KPI dashboard, trend charts, heatmaps	React.js, D3.js, Chart.js, Mapbox GL	Interactive web dashboard (desktop + mobile)
L5: Recom-mendation	Content-based filtering, itinerary generator	Python (scikit-learn), OpenAI API, FastAPI	Personalized route recommendations; SEO content briefs

Table 2: Tourist flow metrics: SD-DMD analytics engine output (2017–2024).

Indicator	2017	2024	Factor	CAGR (%)
Total tourist arrivals	1,269,965	5,755,525	4.5×	24.1
International arrivals	169,617	1,745,200	10.3×	39.4
Domestic arrivals	1,100,348	4,010,325	3.6×	20.3
International share (%)	13.4%	30.3%	2.3×	-
Foreign exchange revenue (USD M)	37.2	436.3	11.7×	42.1

Note. Bukhara Regional Tourism Department (2024); computed by SD-DMD L3 Analytics Engine.

Table 3: Correlation Matrix: Digital Infrastructure vs. Tourism Outcomes.

Indicator Pair	r	p-value	Interpretation
E-accommodation connections × Total arrivals	0.89	< 0.01	Strong positive
Digital Score × International arrivals	0.91	< 0.01	Strong positive
Payment terminals × FX revenue	0.87	< 0.01	Strong positive
Tourism enterprises × Domestic arrivals	0.84	< 0.01	Strong positive

The limitations of L5 recommendation module should not be overlooked: the content-based filtering method, although successful in the context of structured heritage, lacks collaborative filtering (user history interaction) and real-time contextual clues (weather, event timetable). The future versions must be hybridized and integrate content-based and collaborative filtering, which would overcome a limitation known in single-paradigm recommender system in tourism settings [9].

The current validation does not encompass software-performance metrics (latency, throughput, ETL execution time, recommendation accuracy against held-out test sets). Full engineering validation - including load testing, fault-tolerance assessment, and L5 precision/recall benchmarking against a baseline recommender - is acknowledged as a priority direction for future work prior to operational deployment.

6 CONCLUSIONS

In this paper, the SD-DMD a five-layer smart destination digital marketing dashboard was proposed, and its analytics modules were tested on an eight-year empirical dataset of Bukhara region, Uzbekistan (2017-2024). Key findings: (1) The system architecture provides reproducible analytics of CAGR computation, Pearson correlation, SWOT scoring, interactive visualization and content-based recommendation in prototype-level web application (2) It is confirmed that the significant increase in heritage tourism (4.5x aggregate arrivals, 10.3x international arrivals, 11.7x FX revenue) is significantly correlated with digital infrastructure expansion ($r = 0.89$-0.91, $p < 0.01$). (3) Evaluation of SUS prototype (means = 81.3) supports its feasibility for pilot use by regional destination management organizations.

The proposed SD-DMD demonstrates the feasibility of integrating tourism analytics, visualization, and recommendation support within a single prototype platform for heritage destinations. While the empirical results for Bukhara region are encouraging, further engineering validation is required, including latency, throughput, ETL, and recommender benchmarking, before full operational deployment. Nevertheless, the prototype may serve as a practical foundation for future pilot implementations supporting evidence-based tourism management in Uzbekistan.

REFERENCES

[1] UNWTO, World Tourism Barometer, vol. 22, no. 1. World Tourism Organization, 2024, [Online]. Available: https://doi.org/10.18111/wtobarometereng.

[2] N. Sonuc and S. Suer, “Smart tourism destinations and digitalization of cultural heritage for sustainability,” in Smart Cities for Sustainability. Emerald Publishing, 2023, pp. 189-208, [Online]. Available: https://doi.org/10.1108/S1877-636120230000033010.

[3] M. Musaev, “Economic and mathematical analysis of development of pilgrimage tourism in Bukhara region,” AIP Conference Proceedings, vol. 3377, no. 1, Art. no. 020014, 2025, [Online]. Available: https://doi.org/10.1063/5.0299571.

[4] UNWTO, Digital Transformation in Tourism, 2023, [Online]. Available: https://www.unwto.org/digital-transformation.

[5] H. Bekele and S. Raj, “Digitalization and digital transformation in the tourism industry: A bibliometric review and research agenda,” Tourism Review, vol. 80, no. 1, 2024, [Online]. Available: https://doi.org/10.1108/TR-07-2023-0509.

[6] S. K. Deb et al., “Promoting tourism business through digital marketing in the new normal era,” European Journal of Innovation Management, vol. 27, no. 3, pp. 775-799, 2024, [Online]. Available: https://doi.org/10.1108/EJIM-04-2022-0218.

[7] C. M. Hall and C. Cooper, “Making tourism smart in the age of artificial intelligence,” Current Issues in Tourism, vol. 28, no. 1, pp. 1-5, 2025, [Online]. Available: https://doi.org/10.1080/13683500.2025.2460922.

[8] A. Velentza and T. Metaxas, “The role of digital marketing in tourism businesses: An empirical investigation in Greece,” Businesses, vol. 3, no. 2, pp. 272-292, 2023, [Online]. Available: https://doi.org/10.3390/businesses3020018.

[9] B. Armutcu et al., “Tourist behaviour: The role of digital marketing and social media,” Acta Psychologica, vol. 240, Art. no. 104025, 2023, [Online]. Available: https://doi.org/10.1016/j.actpsy.2023.104025.

[10] Y. Lu, G. Mi, H. Lu, and Y. Wang, “Immersive technologies in built heritage spaces,” Buildings, vol. 15, Art. no. 3481, 2025, [Online]. Available: https://doi.org/10.3390/buildings15193481.

[11] S. Tamirat and S. Zewdie, “Digital Marketing in Developing and Emerging Economies: A Systematic Review of Introductory Phase Features Evaluated by a double blind review system,” International Journal of Marketing Communication and New Media, vol. 11, p. 49, Jan. 2023.

[12] O. K. Khurramov, S. A. Fayzieva, F. K. Saidova, B. B. Khalilov, and S. K. Fayzieva, “Directions for improvement digital tourism and tourism info structure in Uzbekistan,” Journal of Critical Reviews, vol. 7, no. 5, pp. 366-369, 2020, [Online]. Available: https://doi.org/10.31838/jcr.07.05.72.

[13] S. Hamidov, B. Mamurov, D. Khodjaeva, and S. Tadjieva, “Processes of management of competitiveness of ecotourism destinations and methodology of its assessment,” E3S Web of Conferences, vol. 587, Art. no. 05021, 2024, [Online]. Available: https://doi.org/10.1051/e3sconf/202458705021.

[14] D. Buhalis, D. Leung, and R. Law, “Artificial intelligence for tourism,” Annals of Tourism Research, vol. 99, Art. no. 103528, 2023, [Online]. Available: https://doi.org/10.1016/j.annals.2023.103528.

[15] J. Brooke, “SUS: A quick and dirty usability scale,” in Usability Evaluation in Industry, P. Jordan et al., Eds. London, U.K.: Taylor & Francis, 1996, pp. 189-194.

[16] S. Tadjieva, J. Tokhirov, O. Khurramov, and Z. Juraeva, “Tourism and sustainable development studies in Uzbekistan,” E3S Web of Conferences, vol. 403, Art. no. 08027, 2023, [Online]. Available: https://doi.org/10.1051/e3sconf/202340308027.