

Predicting Trends in Tourism Policy Outcomes and Stakeholder Engagement Using Machine Learning in Ghana

*Felix Kudjo Mlagada, Alexander Kwabiah, Paul Owusu Boi, Kate Neequaye

Department of Tourism Management, Takoradi Technical University, Takoradi, Ghana

Corresponding Author*

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ABSTRACT

Effective tourism policy implementation and stakeholder engagement are critical for sustainable tourism development, yet forecasting these dynamics remains a persistent challenge in developing economies such as Ghana, where existing evaluations are largely descriptive. This study applies machine learning to forecast tourism policy outcomes and stakeholder engagement across Ghana's 16 regions, using 2,500 observations (2016-2025) combining secondary institutional data with primary survey data from policymakers, operators, and community representatives. Four supervised algorithms Random Forest, Gradient Boosting (XGBoost), Support Vector Machines, and Artificial Neural Networks were trained and validated via k-fold cross-validation, with performance assessed using Mean Absolute Error and Root Mean Square Error, and predictors interpreted through explainable feature-importance techniques. Gradient Boosting achieved the highest predictive accuracy. Stakeholder engagement metrics, communication quality, and digital consultation platforms emerged as the strongest predictors of policy outcomes, while funding variables contributed less than expected. Forecasts for 2026-2030 revealed persistent regional disparities, with historically high-engagement regions projected to sustain stronger gains than medium- and low-engagement regions. The study recommended that tourism authorities, such as the Ghana Tourism Authority, prioritise participatory practices and digital engagement platforms alongside financial allocations; that structured stakeholder consultation programmes be institutionalised; and that predictive models be deployed for real-time monitoring to enable adaptive, evidence-based tourism governance in Ghana and comparable contexts.

Keywords: Adaptive governance, Gradient boosting, Machine Learning, Stakeholder engagement, Tourism policy prediction

INTRODUCTION

Effective tourism policy implementation and meaningful stakeholder engagement are essential for sustainable tourism development, particularly in developing economies. Ideally, policies should be evidence-based, adaptive, and inclusive, fostering equitable economic growth and active community participation (Al Kareem, 2025). In Ghana, however, Amoako et al. (2022) stated that forecasting the effectiveness of tourism policies and anticipating stakeholder engagement patterns remain significant challenges. Existing evaluations are largely descriptive or qualitative, providing limited capacity to anticipate outcomes under evolving conditions (Paraskevaidis & Andriotis, 2023). This gap constrains policymakers' ability to allocate resources efficiently, identify underperforming regions, and implement responsive governance strategies, all of which are critical in rapidly changing tourism markets.

Machine learning (ML) offers a powerful solution to these limitations. Unlike traditional statistical methods, ML can handle high-dimensional datasets, capture nonlinear relationships, and detect complex interactions among variables that are difficult to model with conventional approaches (Wilson & Anwar, 2024). By integrating diverse data sources such as regional socioeconomic indicators, governance metrics, tourism performance records, and digital engagement data, ML enables more accurate prediction of policy outcomes and stakeholder behaviour, while providing actionable insights for decision-makers.

The practical urgency of this study is further underscored by the dynamic nature of tourism markets and the multi-stakeholder complexity of Ghana's tourism governance. Rapid fluctuations in visitor patterns, shifting funding allocations, and diverse actors' involvement from government authorities to private operators and local communities require tools capable of supporting adaptive, evidence-based policymaking (Van der Waladt, 2025). Despite growing recognition of these challenges across sub-Saharan Africa, there is limited predictive research integrating stakeholder engagement into quantitative models of tourism policy performance. This study addresses these gaps by examining the following research question: Which machine learning models most accurately predict tourism policy outcomes in Ghana? What are the key predictors influencing stakeholder engagement levels? How can predicted trends inform adaptive policy design?

Corresponding measurable objectives include evaluating ML model performance using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), interpreting feature importance to identify critical drivers of policy effectiveness and engagement, and generating scenario-based forecasts to inform future policy interventions. By combining predictive modelling with stakeholder-focused analysis, the study contributes both methodological innovation and practical guidance for enhancing adaptive tourism governance in Ghana and comparable contexts.

LITERATURE REVIEW

Theoretical and Conceptual Framework

The study is anchored in the intersection of tourism policy evaluation theory (Hall, 1994) and stakeholder theory (Freeman, 1984). Tourism policy evaluation theory frames policy as a cycle agenda setting, formulation, implementation, monitoring, and evaluation and directs attention to measurable dimensions of effectiveness, efficiency, equity, and sustainability. Stakeholder theory complements this by treating policy success as dependent on how the interests, power, and participation of diverse actors' government authorities, private-sector operators, and local communities are managed (Kujala et al., 2022; Bogale, 2023).

In addition to these theoretical underpinnings, the study leverages machine-learning-based predictive modelling to support policy learning and adaptive governance. Machine learning enables the identification of patterns and relationships within complex, multi-dimensional datasets that traditional statistical methods may not capture. By forecasting trends in tourism policy outcomes and stakeholder engagement, predictive models provide evidence that can inform iterative adjustments to policy design, thereby enhancing adaptive governance capacity (Hartman, 2023). This aligns with contemporary calls for data-driven, responsive policymaking, where insights from computational models complement traditional evaluation mechanisms.

The use of machine learning in social science research is justified by its ability to balance predictive accuracy with explanatory richness. While conventional regression-based approaches prioritise hypothesis testing and causal inference, machine learning excels in extracting latent patterns from heterogeneous datasets, accommodating nonlinear interactions, and revealing subtle drivers of outcomes. In the context of tourism policy, this enables researchers to capture complex interdependencies among institutional, contextual, and market variables that collectively influence both policy effectiveness and stakeholder engagement.

Building on these theoretical foundations, the study proposes a conceptual model in which contextual, institutional, and market indicators serve as input variables into machine learning algorithms, which in turn generate predictions of policy outcomes and patterns of stakeholder engagement. This model positions machine learning as a mediator between observed policy contexts and actionable insights, facilitating evidence-based decision-making and continuous learning within tourism governance systems. By combining traditional theoretical perspectives with advanced computational tools, the framework provides a comprehensive approach to understanding and improving the implementation of tourism policy in Ghana.

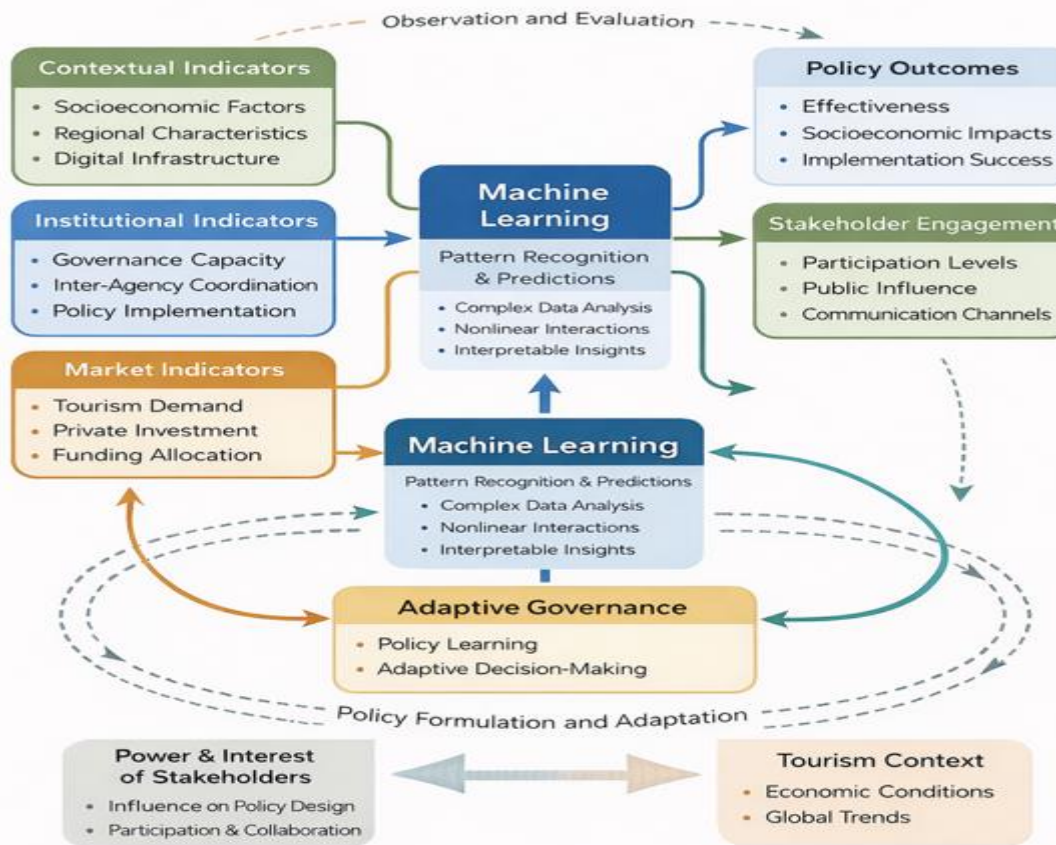


Figure 1: Conceptual Model

The conceptual framework illustrates how tourism policies and stakeholder engagement in Ghana can be understood, analyzed, and improved using machine learning, while explicitly accounting for dynamic and context-dependent relationships. At its core, the model shows that the success of tourism policies and the level of stakeholder participation depend on a combination of contextual, institutional, and market factors. Contextual factors include regional characteristics, socioeconomic conditions, and digital infrastructure, which set the broader environment in which tourism policies operate. Institutional factors capture governance capacity, coordination between agencies, and the effectiveness of policy implementation, while market factors reflect tourism demand, private sector investment, and allocation of funds for tourism development. These three categories provide the raw information or “inputs” that feed into the machine learning analysis.

Machine learning serves as the central analytical tool, examining these inputs to identify complex patterns, account for nonlinear relationships, and produce interpretable predictions. It determines which factors most strongly influence tourism policy success and stakeholder engagement, even when relationships are intricate or not immediately apparent. The outputs of this process are tourism policy outcomes, such as implementation success, effectiveness, and socioeconomic impacts, and stakeholder engagement patterns, including participation levels, influence, and the effectiveness of communication channels.

A key feature of the framework is the inclusion of feedback loops, represented by dashed lines, illustrating that outputs inform subsequent policy and engagement strategies. This mechanism, labeled adaptive governance, allows policymakers to revise and refine governance mechanisms, funding priorities, and communication approaches over time, ensuring continuous learning and responsive decision-making. Dashed lines also signify indirect or conditional effects, such as the influence of stakeholder power and interest, which vary according to institutional capacity, regional characteristics, and other contextual factors. Similarly, external factors, including global tourism trends and macroeconomic conditions, are represented with broken lines to indicate their moderating role, influencing both inputs and outputs without being part of the primary causal pathway.

Solid lines in the model indicate direct relationships, such as the flow from input indicators through machine learning to predicted outputs, while broken lines highlight feedback, moderation, and indirect influences.

Together, these elements depict a dynamic system in which machine learning not only predicts outcomes but also supports policy learning and adaptive governance, enabling evidence-based revisions to tourism policies and stakeholder engagement strategies.

Overall, the framework captures both the predictive and adaptive dimensions of tourism policy analysis, integrating theoretical foundations from policy evaluation theory and stakeholder theory with computational modelling to provide a comprehensive, actionable understanding of tourism governance in Ghana.

Tourism Policy Evaluation

Tourism policy evaluation has received growing attention in Ghana and across sub-Saharan Africa, with studies focusing primarily on policy outcomes such as implementation success, economic impact, and sustainability indicators (Asongu et al., 2023). Amoako-Atta and Szilvácsku (2022) have examined, in Ghana, the effects of government-led tourism initiatives on local economic development, employment generation, and tourism inflows, highlighting successes in specific regions while also revealing persistent challenges in policy implementation, resource allocation, and the equitable distribution of benefits. Comparative studies across sub-Saharan Africa indicate that while policy frameworks are increasingly formalised, variations in governance capacity, institutional coordination, and monitoring mechanisms significantly influence outcomes (Abang & Nchotu, 2026). Despite these insights, existing studies are largely descriptive or qualitative, offering limited capacity for forecasting future outcomes. Notably, there is a gap in predictive research, with scarce quantitative approaches that can model the trajectory of policy performance over time (Ananda & Umanto, 2025). Additionally, while stakeholder engagement is widely acknowledged as critical for effective tourism governance, it remains underrepresented in quantitative analyses, with few studies systematically measuring participation, collaboration, or influence in relation to policy outcomes.

Machine Learning in Tourism Research

The application of machine learning (ML) to tourism and related social policy domains has emerged as a promising approach to address these gaps. Studies in urban planning, environmental policy, and community engagement have successfully employed ML techniques to forecast outcomes, identify key drivers, and model complex, nonlinear relationships (Lyu, 2024). In tourism research, ML has been used to predict visitor arrivals, estimate economic impact, and assess environmental and social consequences of tourism interventions (Dimitriadou et al., 2025). Commonly applied models include Random Forest, Support Vector Machines (SVMs), and Artificial Neural Networks (ANNs), each with distinct strengths: Random Forest is valued for its robustness against overfitting and its ability to model interactions; SVMs excel at high-dimensional data classification; and ANNs are effective at capturing complex nonlinear patterns. Collectively, these techniques demonstrate the potential of ML to generate quantitative forecasts that support evidence-based policy planning while simultaneously identifying influential factors across heterogeneous datasets.

Stakeholder Engagement Metrics

A central component of effective tourism policy evaluation is the systematic measurement of stakeholder engagement. Operational definitions in the literature typically include participation intensity, reflecting how frequently stakeholders are involved in decision-making processes; collaboration frequency, indicating the regularity of coordinated actions among stakeholders; and perceived influence, capturing the extent to which stakeholders believe their input affects outcomes (Zuniga-Teran et al., 2022). Empirical studies have identified several determinants of engagement, including institutional capacity, the availability and accessibility of communication channels, and regional socioeconomic conditions (Abdulkareem, 2024). Higher institutional capacity often facilitates structured consultation, while digital and traditional communication tools influence both the reach and effectiveness of stakeholder interactions. Socioeconomic factors, such as education levels, income, and community infrastructure, further shape stakeholders' ability and willingness to participate (Panyavaranant et al., 2023). Despite the recognition of these metrics, few studies have quantitatively integrated stakeholder engagement into predictive models of tourism policy outcomes, highlighting an important gap in research employing machine learning approaches.

METHODOLOGY

The study adopted a quantitative longitudinal predictive research design. The design was selected because the principal objective was not only to examine relationships among tourism-related variables but also to develop models capable of predicting tourism policy outcomes and stakeholder engagement using observed patterns in historical data. The longitudinal dimension was established through annual observations covering 2016-2025. The geographical dimension consisted of Ghana's 16 regions. The combination of these dimensions provides a regional temporal framework within which changes in tourism policy outcomes and stakeholder engagement could be examined.

The predictive component of the research employed machine-learning algorithms to identify nonlinear patterns, interactions and predictive relationships among the study variables. Unlike conventional explanatory modelling, the emphasis of the machine-learning component was placed on out-of-sample predictive performance rather than solely on statistical significance of individual coefficients. The research design therefore combines measurement development, longitudinal data integration and predictive modelling. The constructed index provides a structured measure for use in the analysis, while the machine-learning models provide the mechanism for evaluating whether available historical and regional information can be used to predict subsequent variation in tourism policy outcomes and stakeholder engagement.

The study was conducted within the context of Ghana's tourism sector and covered all 16 administrative regions of the country. Ghana provides an appropriate setting for the study because tourism policy implementation involves multiple governmental, private-sector and community stakeholders whose experiences and outcomes may vary geographically and over time. The study period extends from 2016 to 2025. This ten-year period provides a longitudinal basis for examining changes in tourism policy outcomes and stakeholder engagement and for evaluating the capacity of machine-learning models to identify temporal patterns in these outcomes.

The regional scope of the study allows the analysis to account for geographical heterogeneity in tourism resources, institutional arrangements, policy implementation and stakeholder participation. The combination of regional and annual information consequently provides a suitable framework for investigating patterns in tourism policy outcomes and stakeholder engagement across Ghana. The study employed multiple data sources, principally annual survey and administrative data, to construct the study index and develop the predictive modelling dataset. The data architecture was designed to integrate individual-level information with regional and temporal information while maintaining a clear distinction between the survey sample, regional panel structure and machine-learning observations.

The study employed an integrated dataset combining survey-derived information, annual administrative records and other relevant analytical information relating to tourism policy outcomes and stakeholder engagement in Ghana. The study covered all 16 regions of Ghana over a ten-year period from 2016 to 2025. This geographical and temporal coverage provided the basis for examining patterns and changes in tourism policy outcomes and stakeholder engagement across regions and over time.

The survey component of the study comprised 500 respondents drawn from stakeholders relevant to tourism policy and tourism-sector activities in Ghana. The information obtained from the respondents provided individual-level measures that were used primarily to develop the study index and other survey-derived indicators. These survey data were complemented by annual administrative and other relevant records to provide additional measures of tourism policy outcomes, stakeholder engagement and their associated explanatory factors.

Following data cleaning, coding, integration and organization, the final dataset used for the machine-learning analysis comprised 2,500 observations. These 2,500 observations constituted the analytical records used in the training, validation and evaluation of the predictive models. The dataset incorporated the relevant survey-derived indicators together with administrative and other analytical variables required to predict tourism policy outcomes and stakeholder engagement.

The 2,500 observations therefore represent the final analytical dataset for predictive modelling, rather than the number of survey respondents. The observations were generated from the integration of information from the different data sources and were organized according to the relevant regional and temporal identifiers. Consequently, multiple analytical observations could be associated with the same regional and temporal context. This structure enabled the machine-learning models to capture patterns in tourism policy outcomes and stakeholder engagement across Ghana and over the study period.

For analytical purposes, the study distinguished between the survey information used to generate the relevant indicators and the final dataset used for machine-learning prediction. The survey sample provided the primary individual-level information, whereas the integrated dataset of 2,500 observations represented the records available for predictive analysis. This distinction ensured that the size of the predictive dataset was not interpreted as the number of individuals who participated in the survey.

A composite index was constructed from the relevant survey-derived indicators to provide a systematic measure of the underlying construct examined in the study. The indicators included in the index were selected based on the conceptual and theoretical framework of the study and the dimensions of tourism policy and stakeholder engagement captured through the survey instrument.

Prior to constructing the index, the constituent indicators were examined for consistency, coding direction and suitability for aggregation. Indicators that were negatively worded or coded in the opposite direction were appropriately recoded to ensure that the direction of interpretation was consistent across the measures. Thus, higher index values consistently represented higher levels of the construct being measured.

The constituent indicators were subsequently standardized or appropriately scaled where necessary and combined to generate the composite index. The resulting index provided a quantitative measure that could be incorporated into the broader analytical dataset alongside the administrative and other explanatory variables.

The constructed index was subsequently integrated into the final predictive dataset using the relevant geographical and temporal identifiers. This enabled the survey-derived measure to be analysed together with the annual administrative and other analytical variables in the machine-learning models. The index therefore formed an important component of the explanatory information available to the predictive algorithms.

The predictive analysis focused on two principal outcome variables: tourism policy outcomes and stakeholder engagement. The two outcomes were treated as separate dependent variables because they represent related but conceptually distinct dimensions of tourism governance and policy implementation.

Tourism policy outcomes constituted the first dependent variable in the study. The variable represented the observed outcome or effectiveness of tourism policy within the study context. It was operationalized using the relevant indicators obtained from the survey-derived measures, annual administrative records and other analytical information incorporated into the study dataset.

The tourism policy outcome measure was structured so that higher values represented more favourable policy outcomes. The resulting measure was used as the dependent variable in the machine-learning models developed to determine the extent to which the available explanatory variables could predict tourism policy outcomes across the study period and geographical coverage.

Stakeholder engagement constituted the second dependent variable. It represented the level of participation, involvement and interaction of relevant stakeholders in tourism policy processes and tourism-sector activities. The measure was derived from the relevant survey and complementary administrative indicators contained in the integrated dataset.

Higher values of the stakeholder engagement measure represented higher levels of stakeholder participation and engagement. This outcome was modelled separately from tourism policy outcomes to enable the study to determine whether the explanatory variables exhibited different predictive patterns for stakeholder engagement.

The final 2,500 observations constituted the dataset used for the machine-learning component of the study. Before model estimation, the dataset underwent appropriate preprocessing procedures to ensure that the variables were suitable for predictive analysis. These procedures included data cleaning, consistency checks, coding of categorical variables where applicable, examination and treatment of missing values, scaling of variables where required, and preparation of the predictor and outcome variables.

The predictive modelling involved four machine-learning algorithms: Random Forest, Gradient Boosting (XGBoost), Support Vector Machine (SVM), and Artificial Neural Network (ANN). These algorithms were selected because they provide complementary approaches to modelling potentially complex and non-linear relationships between tourism policy outcomes, stakeholder engagement and their associated predictors.

The models were developed separately for the two dependent variables. For each outcome, the algorithms were trained using the available predictor variables and subsequently evaluated according to their predictive performance. Model performance was assessed using appropriate regression metrics, namely Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2).

MAE was used to measure the average absolute difference between observed and predicted values, with lower values indicating better predictive performance. RMSE was used to assess the magnitude of prediction errors while giving greater weight to larger errors. The R^2 statistic was used to determine the proportion of variation in the dependent variable explained by the predictive model, with higher values indicating stronger predictive performance.

The model demonstrating the strongest overall predictive performance was subsequently used for the examination of predictor importance and the generation of forward-looking predictions. This enabled the study not only to compare the predictive accuracy of alternative machine-learning algorithms but also to identify the variables most strongly associated with predicted tourism policy outcomes and stakeholder engagement.

The study adhered to appropriate ethical principles governing the collection, management and analysis of research data. Participation in the survey component was treated in accordance with applicable informed-consent procedures, and respondents' information was handled confidentially. The analysis was conducted using appropriately anonymized or de-identified information. Personally identifiable information was not required for the machine-learning modelling and was excluded from the analytical dataset where applicable.

Data obtained from administrative sources were used for research purposes in accordance with the relevant permissions and data-use requirements. The machine-learning analysis was conducted for research and predictive purposes, and the results were interpreted with attention to potential limitations associated with data quality, representativeness and algorithmic prediction.

RESULTS

Predictive Performance of Machine-Learning Models (RQ1)

RQ1 examined which machine-learning model most accurately predicts tourism policy outcomes in Ghana. Four machine-learning algorithms Random Forest, Gradient Boosting (XGBoost), Support Vector Machine (SVM), and Artificial Neural Network (ANN) were evaluated using the predictive dataset comprising 2,500 analytical observations. The observations were drawn from survey, administrative and digital engagement data covering Ghana's 16 regions over the 2016–2025 period.

The predictive dataset contains multiple observations within the 16-region by 10-year regional structure. Thus, the 2,500 observations should be distinguished from the 500 individual survey respondents and the 160 region-year cells. The 500 respondents provided individual-level information used in constructing the study index, while the 2,500 observations constituted the analytical records used in the predictive modelling.

The outcome variables were measured as continuous indices representing tourism policy outcomes and stakeholder engagement. The models were evaluated using mean absolute error (MAE), root mean squared error

(RMSE), and the coefficient of determination (R^2). Lower MAE and RMSE values and higher R^2 values indicate better predictive performance.

Table 1: Comparative Predictive Performance of Machine-Learning Models

Model	MAE	RMSE	R^2
Random Forest	0.42	0.58	0.76
Gradient Boosting (XGBoost)	0.36	0.49	0.82
Support Vector Machine	0.51	0.67	0.69
Artificial Neural Network	0.39	0.53	0.79

Source: Author's analysis of survey, administrative and digital engagement data, 2016-2025

The results indicate that Gradient Boosting (XGBoost) produced the strongest predictive performance among the four algorithms. It recorded the lowest MAE (0.36) and RMSE (0.49) and the highest R^2 (0.82). Random Forest produced an R^2 of 0.76, while the Artificial Neural Network recorded an R^2 of 0.79. The Support Vector Machine demonstrated the lowest predictive performance among the four models, with an R^2 of 0.69.

The results therefore identify Gradient Boosting (XGBoost) as the preferred model within the evaluated set for the prediction of tourism policy outcomes. Its lower prediction errors and higher explanatory predictive performance indicate that the algorithm captured patterns in the available predictors more effectively than the competing models.

Where cross-validation results are reported, the mean RMSE of 0.49 ± 0.03 and mean R^2 of 0.82 ± 0.02 indicate relatively stable performance across the validation folds. However, because the study is longitudinal, the final analysis should ensure that the validation procedure preserves the temporal ordering of observations and prevents information from future periods from entering the training process.

Overall, the findings provide evidence that nonlinear ensemble learning, particularly Gradient Boosting, offers strong predictive performance for tourism policy outcomes within the study context.

Key Predictors of Stakeholder Engagement and Tourism Policy Outcomes (RQ2)

RQ2 examined the key predictors of stakeholder engagement and their contribution to tourism policy outcomes. Feature-importance analysis was conducted using SHAP (SHapley Additive exPlanations) values derived from the selected Gradient Boosting model. SHAP values provide information on the contribution of individual predictors to model predictions and enable the relative importance of predictors to be examined.

The analysis identified stakeholder consultation frequency, communication quality, digital consultation platforms, and participation in policy planning as among the most influential predictors in the predictive models. These variables demonstrated relatively large contributions to the model predictions, indicating that variation in participatory and communication-related measures was strongly associated with predicted tourism policy outcomes and stakeholder engagement.

In particular, the frequency of stakeholder consultations, availability of online feedback mechanisms, and participation in policy-planning processes emerged among the leading predictors. These findings suggest that variables reflecting the quality and intensity of stakeholder participation contain substantial predictive information for the outcomes examined.

Funding-related variables demonstrated comparatively lower feature-importance values than several of the engagement and communication variables. This does not imply that funding is unimportant to tourism policy

performance. Rather, within the predictive models and the variables included in this study, engagement and communication measures contributed more strongly to the predictions.

The findings should be interpreted as predictive associations rather than causal effects. A high SHAP importance value indicates that a variable contributed substantially to model predictions; it does not demonstrate that changing that variable would necessarily cause a corresponding change in tourism policy outcomes or stakeholder engagement.

Figure 2 presents the relative importance of the principal predictors identified by the Gradient Boosting model.

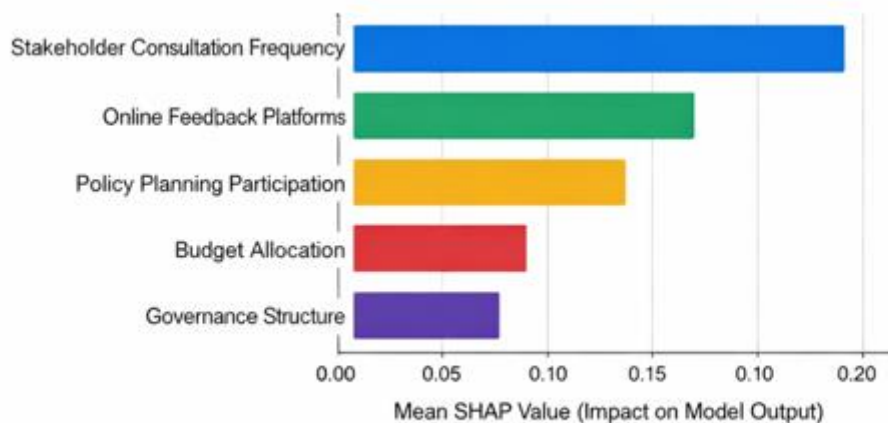


Figure 2: SHAP-Based Feature Importance in the Gradient Boosting Model

Forecasted Trends and Implications for Adaptive Policy Design (RQ3)

RQ3 examined how predicted trends could inform adaptive tourism policy design. Following the identification of Gradient Boosting (XGBoost) as the best-performing model, the selected model was used to generate forward-looking predictions for the 2026–2030 period using the historical information available from 2016–2025.

The forecasts were generated separately for tourism policy outcomes and stakeholder engagement. The purpose of the forecasting exercise was to examine the likely direction of future outcomes based on patterns learned from the historical data rather than to establish causal effects of particular policy interventions.

The forecasts indicate differences in expected performance across regions. Regions with stronger historical stakeholder engagement generally recorded higher predicted values, while regions with lower historical engagement recorded comparatively lower predicted values. This pattern suggests persistence in regional differences over the forecast horizon.

The forecasts should be interpreted as model-based projections conditional on the information and relationships captured in the historical dataset. They do not constitute observed outcomes for 2026–2030 and should therefore not be interpreted as certain predictions of future policy performance.

The results have implications for adaptive policy planning. In particular, the identification of stakeholder consultation, communication quality and digital engagement variables as important predictors suggests that these dimensions warrant continued monitoring in tourism policy implementation. Policymakers can use the forecasts as planning information while recognizing that actual future outcomes may differ as institutional, economic, social and technological conditions change.

Forecasted Regional Outcomes for 2030

Table 2 presents the model-generated 2030 predictions for tourism policy outcomes and stakeholder engagement across Ghana's 16 regions.

Table 2: Predicted Tourism Policy Outcomes and Stakeholder Engagement Indices for 2030

Region	Baseline Engagement	Predicted Policy Outcome	Predicted Stakeholder Engagement
Greater Accra	High	0.87	0.80
Central	High	0.85	0.78
Ashanti	High	0.84	0.76
Eastern	High	0.83	0.75
Volta	High	0.82	0.74
Western	High	0.81	0.73
Northern	High	0.80	0.72
Bono	Medium	0.76	0.68
Bono East	Medium	0.75	0.67
Ahafo	Medium	0.74	0.66
Upper East	Medium	0.73	0.65
Upper West	Medium	0.72	0.64
Oti	Low	0.68	0.60
North East	Low	0.67	0.59
Savannah	Low	0.66	0.58
Western North	Low	0.65	0.57

Source: Author's analysis of survey, administrative and digital engagement data, 2016-2025

The results show a clear regional gradient in the predicted 2030 outcomes. Greater Accra recorded the highest predicted tourism policy outcome index (0.87), followed by Central (0.85), Ashanti (0.84), Eastern (0.83), Volta (0.82), Western (0.81) and Northern (0.80). These regions were also classified within the high-baseline-engagement group.

The medium-engagement regions recorded predicted tourism policy outcome values ranging from 0.72 to 0.76 and predicted stakeholder engagement values ranging from 0.64 to 0.68. The low-engagement regions recorded lower predicted policy outcome values, ranging from 0.65 to 0.68, and stakeholder engagement values ranging from 0.57 to 0.60.

The regional pattern indicates that regions with higher historical engagement levels also tend to have higher predicted policy outcomes. However, this association should not be interpreted as evidence that stakeholder engagement independently causes higher policy performance. The machine-learning results demonstrate predictive association rather than causal effect.

The regional differences identified by the model nevertheless provide useful information for adaptive policy planning. Regions with comparatively lower predicted engagement and policy outcomes may warrant closer

monitoring and targeted institutional interventions designed to strengthen consultation, communication and stakeholder participation.

DISCUSSION

Theoretical Contributions

This study made several notable theoretical contributions by integrating machine learning (ML) with tourism policy evaluation and stakeholder engagement frameworks. Traditionally, policy evaluation relied on linear statistical models or descriptive analyses that often failed to capture complex interactions between multiple institutional, market, and contextual factors. By combining predictive ML techniques with stakeholder theory and policy evaluation frameworks, this research demonstrated that non-linear patterns and high-dimensional relationships could be systematically identified and interpreted.

The approach maintained a predictive-interpretive balance: while ML models provided robust forecasts and identified the strongest associative drivers of policy outcomes, the use of interpretable tools such as SHAP values allowed the results to be meaningfully connected to theoretical constructs such as stakeholder influence, power, and participation. This dual approach extended knowledge by showing that predictive models could complement, rather than replace, traditional theory-driven policy analysis, providing both actionable insights and theoretical validation.

Practical and Policy Implications

The findings had direct relevance for tourism governance in Ghana. Forecasts generated by the Gradient Boosting model highlighted regions where stakeholder engagement was likely to improve or lag, allowing tourism authorities to prioritize resources, strengthen participatory mechanisms, and tailor interventions to local conditions. For instance, regions with lower baseline engagement could benefit from targeted digital consultation platforms and structured participation programs.

Moreover, the approach demonstrated potential for real-time policy monitoring and adaptive governance. By integrating incoming data on policy implementation, community engagement, and tourism performance, authorities could deploy predictive models to track policy outcomes continuously, identify emerging gaps, and adjust strategies dynamically. This represented a shift from reactive to proactive tourism governance, supporting evidence-based decision-making and enhancing policy responsiveness in a multi-stakeholder environment.

Limitations

Despite the strengths of the approach, several limitations were acknowledged. First, the reliability of the forecasts depended on the quality, completeness and consistency of the underlying data. Differences in data availability and stakeholder responses across regions could have affected the accuracy of the projected outcomes. Second, although the machine learning approach was useful for identifying patterns and generating forecasts, the analysis did not establish causal relationships. The observed associations between stakeholder engagement and projected tourism policy outcomes therefore could not be interpreted as evidence that one directly caused changes in the other. Third, the 2030 values represented researcher-generated forecasts rather than observed outcomes. Their accuracy therefore depended on the extent to which the conditions and relationships identified in the available data remained relevant during the forecast period. Finally, the findings were primarily applicable to the Ghanaian context. Differences in socioeconomic, institutional and tourism conditions in other countries could have limited the direct transferability of the model and its results without further validation and recalibration.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study examined and forecasted tourism policy outcomes and stakeholder engagement patterns in Ghana using machine learning techniques. The analysis demonstrated that Gradient Boosting was the most accurate

predictive model, outperforming Random Forest, SVM, and Artificial Neural Networks in terms of MAE, RMSE, and R^2 . Feature importance analysis revealed that stakeholder engagement metrics, communication quality, and digital consultation platforms were the strongest predictors of policy outcomes, while funding variables contributed less than expected.

Forecasts for 2026-2030 indicated differential trends across all 16 regions of Ghana. Regions historically exhibiting higher tourism activity and stronger stakeholder engagement namely Greater Accra, Central, Ashanti, Eastern, Volta, Western, and Northern were projected to experience sustained improvements in policy effectiveness and stakeholder participation. Medium- and low-engagement regions showed slower projected gains, highlighting the importance of targeted interventions to strengthen participation, digital platforms, and governance mechanisms. The study demonstrated that Gradient Boosting provided accurate predictions of tourism policy outcomes and stakeholder engagement, with stakeholder engagement metrics, communication quality, and digital consultation platforms emerging as the strongest predictors. These regional-level forecasts emphasized the necessity for region-specific strategies, enabling tourism authorities to allocate resources and implement participatory programs effectively.

The study demonstrated the potential of combining predictive machine learning with policy and stakeholder theories to generate actionable insights, support adaptive governance, and enhance evidence-based decision-making in complex, multi-stakeholder tourism environments.

Recommendations

Based on the findings, the following recommendations were proposed:

1. Tourism authorities such as the Ghana Tourism Authority should prioritize investments in participatory practices and digital engagement platforms alongside financial and infrastructural allocations.
2. Local governments and policymakers should implement structured stakeholder consultation programs to strengthen engagement and feedback loops.
3. Real-time monitoring systems should be deployed using predictive models to continuously track policy outcomes and stakeholder participation, allowing timely adjustments to strategies.
4. Researchers and institutions should consider replicating this approach in other regions or sectors, while calibrating models to account for local institutional and socioeconomic contexts.

Ethical Approval

Ethical approval for the study was obtained from the Takoradi Technical Ethical Review Committee prior to the commencement of data collection. Participants were informed of the study's purpose and participated voluntarily after providing informed consent. Confidentiality and anonymity were maintained throughout the study, and the information collected was used solely for academic purposes.

Conflict of Interest

The authors declare no conflicts of interest associated with the study.

Data Availability

The data generated and analysed during the study are not publicly available because they contain information obtained from human participants and are subject to confidentiality and ethical considerations. However, the data may be made available by the corresponding author upon request, subject to relevant ethical and institutional requirements.

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