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Factors Affecting Children's Learning Outcome from Family Tourism in Nakhon Ratchasima Province

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Abstract

This research aimed to identify key predictors of children's learning outcomes during travel experiences in Nakhon Ratchasima Province. Utilizing Social Cognitive Learning Theory (SCLT) as a theoretical framework, the study developed a random forest regression algorithm to analyze the complex relationships between various factors influencing children's learning during family tourism. The study employed a comprehensive survey of 921 families, collecting data on SCLT-related variables, travel characteristics, and demographic factors. The model consistently displayed high predictive performance (MSE values between 0.002 and 0.004) and explanatory power (R2 values between 0.994 and 0.995). According to a significant feature analysis, problem-solving abilities, time management, and cultural understanding are the most significant factors of children's learning outcomes. The research suggests that travel experiences, rather than family structure, have a greater influence on educational benefits than demographic factors. Tourism practitioners and policymakers can use this research to design more effective family-oriented travel experiences

Keywords: Family Tourism, Random Forest Regression, Children's Learning, Learning Outcome

Introduction

Family travel serves as an important form of informal education, helping children develop cultural awareness, problem-solving skills, adaptability, and global understanding [1-2]. Nonetheless, the specific mechanisms through which these outcomes occur-and the conditions that enhance them-are not yet well understood. Past research often focused on parental planning, with limited attention to children's active experiences during travel. More recent studies have begun exploring how travel impacts family relationships and overall quality of life, but the educational value for children remains under-researched [3].

Notably, most studies emphasize adult perspectives, often excluding children's voices and overlooking differences between nuclear and extended family experiences [4]. This study addresses these gaps by investigating children's learning outcomes from family tourism using Bandura's Social Cognitive Learning Theory (SCLT) [5]. According to SCLT, children learn through observation, imitation, and reinforcement in social contexts—elements commonly present in family travel. Interacting with new environments and observing adult behaviors during trips can enhance children's self-efficacy and learning.

These techniques enable the analysis of customer data to uncover preferences and satisfaction levels, allowing for personalized hospitality services [6]. The study employs Random Forest Regression (RFR), a machine learning method ideal for capturing complex, nonlinear relationships. RFR integrates multiple decision trees to enhance prediction accuracy and identify the travel experiences that most significantly impact children's cognitive and emotional development [7]. Compared to traditional approaches, RFR excels in managing large, diverse datasets and pinpointing critical predictors in complex, multidimensional environments.

This research draws on data from family travel experiences in Nakhon Ratchasima Province, a growing tourism area. While family tourism is increasing, several destinations lack structured learning activities for children. Initial observations demonstrate that families participate in leisure activities, but few opportunities support educational engagement. By integrating SCLT with RFR, this study identifies which travel factors—such as cultural exposure, parental involvement, or social interaction—most affect children's learning. The results will assist in design policies that aim to optimize the educational value of travel and strengthen child-centered tourism initiatives. They also demonstrate how combining psychological theory with machine learning can advance research in tourism and child development.

Objective

To investigate the impact of family tourism on children's Learning Outcomes from Family Tourism in Muaeng District, Nakhon Ratchasima Province

Literature Review

Family Tourism and Its Developmental Impacts

Family tourism, defined as parents and children traveling together for shared experiences, significantly boosts children's cognitive and emotional development. Research demonstrates it promotes learning through exposure to new environments, cultural interactions, and collaborative decision-making [8]. For example, [9] found that trips to cultural sites enhance children's understanding of social diversity and history, supporting observational learning as per Social Cognitive Learning Theory (SCLT). Additionally, [10] noted that family tourism strengthens interpersonal relationships and emotional resilience, key for socio-emotional growth. Studies conducted in Thailand, such as [11] Travel Factors Affecting the Travel Behavior of Family Groups in Bangkok after the COVID-19 Situation, have primarily emphasized decision-making factors rather than exploring children's learning outcomes. Nonetheless, there is a research gap in Nakhon Ratchasima Province, a province with attractions like Sala Loi Temple and Nakhon Ratchasima Zoo, where the impact of family tourism on children's development remains underexplored. Localized studies are needed to examine these effects in diverse settings.

Social Cognitive Learning Theory (SCLT)

Social Cognitive Learning Theory (SCLT), developed by [12], explains children's learning through a triadic model of personal factors, environmental influences, and behavior. In family tourism, SCLT emphasizes how children gain knowledge and skills by observing parents, interacting with new settings, and reflecting on experiences [13]. For instance, visits to zoos or cultural sites foster observational learning, encouraging curiosity and cultural appreciation [14]. Research applying SCLT demonstrates that children's participation in travel decision-making enhances self-efficacy and cognitive growth [15], while shared experiences build emotional intelligence and empathy [6]. This framework is relevant to studying how family tourism in Nakhon Ratchasima Province shapes children's learning outcomes.

Random Forest Regression in Tourism Research

Random Forest Regression (RFR) is a machine learning method that can model complex, nonlinear relationships in large datasets [16]. It is particularly useful in tourism, where it can predict customer satisfaction and travel demand. RFR has been used to predict Southeast Asian tourist arrivals and to identify factors influencing children's learning outcomes. It has been used to link travel frequency and destination type to academic performance and to model the impact of travel experiences on emotional development [7]. Despite the growing body of research on family tourism and machine learning, several gaps remain. First, most studies focus on Western or urban contexts, with limited attention to rural or culturally diverse regions such as Nakhon Ratchasima Province [11]. Second, while SCLT has been widely applied in tourism, its integration with advanced machine learning techniques such as RFR is underexplored [15]. Third, there is a lack of research examining the combined effects of cognitive and emotional outcomes in children, particularly in the context of diverse tourism settings such as cultural sites, commercial hubs, and zoos [14]. The current study addresses these gaps by applying RFR within an SCLT framework to predict children's learning outcomes in Nakhon Ratchasima Province.

Figure 1. Research Framework

Methodology

Research Population and Sampling: The study targeted the 242,513 residents of Mueang District, Nakhon Ratchasima Province [17]. Initial sample size calculations, based on standard formulas, suggested a sample of 385. Nonetheless, this was insufficient for machine learning. Using specialized software [18], the required sample size was recalculated to 1,061, based on an effect size of 0.3, 61 latent variables, six observed variables, a p-value of 0.05, and a statistical power of 0.80.

Instrument: The survey was divided into two sections. The first section, based on Social Cognitive Learning Theory (SCLT), used a five-point Likert scale to evaluate factors such as whether family travel fosters understanding of cultural and social differences, supports children's time management skills, and incorporates the value of travel time (VTT) [19]. The second section collected demographic data, including family structure, children's ages, marital status, and children's participation in travel decision-making (CPTD). The instrument's quality was rigorously validated. Content validity was confirmed by three experts, achieving an Index of Item-Objective Congruence (IOC) of 0.50 or higher [20]. Reliability was established with a McDonald's Omega coefficient (ω = 0.959) and Guttman's $\lambda 6$ coefficient (0.964), indicating excellent internal consistency [21]. A pilot test with 30 families further ensured adherence to standard guidelines.

Data Collection: To capture a comprehensive understanding of family tourism experiences in Nakhon Ratchasima, a stratified sampling method was employed to ensure representation across four diverse tourist sites: Sala Loi Temple (a cultural site), a shopping mall (a commercial hub), Nakhon Ratchasima Zoo (a family-oriented attraction), and Save One Korat (a night market). A total of 1,061 questionnaires were distributed equally across these sites, aligning with recommendations for diverse sampling in tourism research and capturing varied family tourism experiences. Data collection took place on both weekdays and weekends between 9:00 AM and 4:30 PM, targeting families with children aged 0-5 and 6-12 years. This strategy aimed to capture a broad spectrum of family tourism experiences, aligning with recommendations for diverse participant perspectives in tourism research [22].

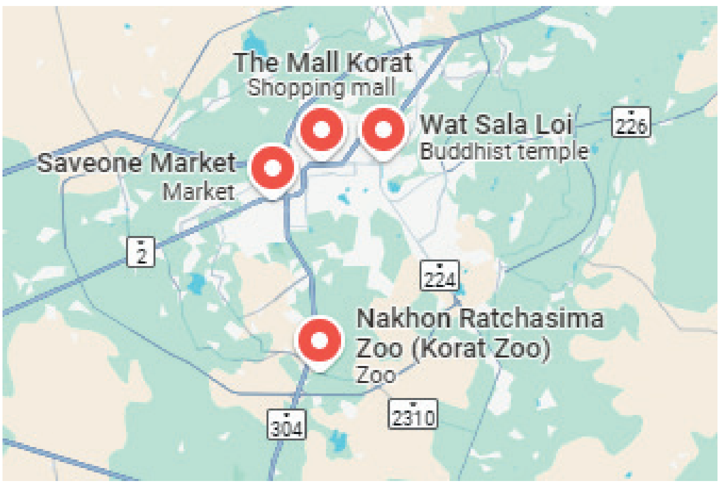

Figure 2. Research questionnaire collection location map (created by the author)

Data collection occurred between May and October 2024, resulting in a successful collection of 921 questionnaires (87%). This response rate surpasses typical response rates in tourism studies [23], indicating a strong engagement from participating families. The collected data, encompassing a wide range of family tourism experiences, provides valuable insights into the potential of family tourism to contribute to learning outcomes.

Data Analysis: The study utilizes Random Forest Regression (RFR) because of its ability to capability to manage complex, nonlinear relationships in social science data. Unlike traditional linear regression models, RFR can capture intricate interactions between variables without explicit specification. Its ensemble approach helps mitigate overfitting and provides robust predictions even with small sample sizes. Previous tourism research has successfully employed RFR to model complex phenomena [24].

Random Forest Regression (RFR) was used to evaluate the significance of children's learning outcome variables, value of travel time (VTT), family style, marital status, age of children, and children's participation in travel decision-making (CPTD) within family tourism. The model included children's learning outcomes as predictor variables, and its performance was assessed using key metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). These metrics were utilized to gauge the prediction error rate and overall performance of the regression model. The final model was selected based on the highest R^2 and the lowest values for MSE, RMSE, and Mean Absolute Percentage Error (MAPE). The relevance of variables in the final model was determined by evaluating the Mean Decrease in Accuracy (MDA), where variables with higher MDA were identified as strong predictors, and Out-of-Bag (OOB) error was utilized to assess model robustness and avoid overfitting [25].

Three distinct RFR models were created using dataset splits of 80%, 70%, and 60%. The models additionally incorporated feature significance permutation (50 iterations), utilizing 50% of training data per tree, with automatic feature selection per split. Features were scaled, and a seed value of 1 was set to ensure consistency. Additionally, the number of trees was optimized, with a maximum of 100 trees. The machine learning procedure adhered standard best practices, and all statistical analyses were carried using JASP (version 0.16.3.0).

Results

In the context of applying Social Cognitive Learning Theory (SCLT), value of travel time (VTT), family style, marital status, age of children, and children's participation in travel decision-making (CPTD) to family tourism, a model was developed and evaluated using different data splits to assess its predictive performance. The model leverages features related to children's learning experiences during family tourism, which are informed by SCLT's principles of observational learning, imitation, and reinforcement.

In the 80% data split scenario, the model was trained on 747 samples, with 83 samples used for validation and 92 samples used for testing. This split aimed to assess the model's performance when a larger portion of the data was dedicated to training, leaving a smaller set for validation and testing. The model configuration for this split included 84 trees and 4 features per split. This relatively high number of trees and features per split suggests a complex model structure that was able to capture intricate relationships within the data. The validation MSE for this split was 0.002, indicating a low level of error between the model's predictions and the observed validation data. Similarly, the test MSE was 0.003, demonstrating the model's ability to generalize well to the unseen test data. The out-of-bag (OOB) error, which provides an estimate of the model's overall predictive performance, was 0.003 for this split. This low OOB error suggests that the model exhibited high accuracy and robustness, with minimal variance between the training, validation, and test datasets.

In comparison, the 70% data split scenario utilized a slightly different configuration, with 83 trees and 4 features per split. This split allocated 666 samples for training, 118 for validation, and 138 for testing. The validation MSE for this split was even lower at 0.001, indicating an exceptional fit to the validation data. Nonetheless, the test MSE was 0.003, which was the same as the 80% split. This suggests that the model's generalization capabilities were consistent across the different data split scenarios. Interestingly, the OOB error for the 70% split was 0.005, slightly higher than the 80% split. This may indicate that the larger training set in the 80% split contributed to a more robust and stable model, whereas the 70% split, with a smaller training set, exhibited a small increase in overall predictive error.

In the 60% data split scenario, the model was trained on 590 samples, with 148 samples used for validation and 184 samples used for testing. This split aimed to assess the model's performance when a relatively smaller portion of the data was dedicated to training, while increasing the size of the validation and test sets. The model configuration for this split included 100 trees and 4 features per split. The relatively high number of trees, combined with the moderate number of features, suggests a complex model structure that was capable of capturing intricate relationships within the data. The validation MSE for this split was 0.004, indicating a low level of error between the model's predictions and the observed validation data. Interestingly, the test MSE was also 0.004, demonstrating the model's ability to generalize well to the unseen test data. The out-of-bag (OOB) error, which provides an estimate of the model's overall predictive performance, was also 0.004 for this split. This low OOB error, on par with the validation and test MSE, suggests that the model exhibited high accuracy and robustness, with minimal variance between the training, validation, and test datasets

Table 1. Model Summary

	Trees	Features per split	n(Train)	n(Validation)	n(Test)	Validation MSE	Test MSE	OOB Error
Split 80%								
	84	4	747	83	92	0.002	0.003	0.003
Split 70%	Trees	Features per split	n(Train)	n(Validation)	n(Test)	Validation MSE	Test MSE	OOB Error
	83	4	666	118	138	0.001	0.003	0.005
Split 60%	Trees	Features per split	n(Train)	n(Validation)	n(Test)	Validation MSE	Test MSE	OOB Error
	100	4	590	148	184	0.004	0.004	0.004

Table 2 presents the key performance metrics for the model developed. The model was evaluated across three different data split scenarios: 80%, 70%, and 60%. For the 80% data split, the Mean Squared Error (MSE) was 0.003, indicating a low level of error between the model's predictions and the actual observed values. The Root Mean Squared Error (RMSE) for this split was 0.055, providing an intuitive measure of the magnitude of the prediction errors. The Mean Absolute Error (MAE) and Mean Absolute Deviation (MAD) for the 80% split were 0.029, suggesting the model made relatively small absolute errors in its predictions. The Mean Absolute Percentage Error (MAPE) was 0.75%, further corroborating the model's high level of accuracy, as this percentage error is well below the 10% threshold for highly accurate forecasts. The coefficient of determination (R^2) for the 80% split was 0.994, indicating that the model was able to explain over 99% of the variance in the data, demonstrating its exceptional ability to capture the underlying relationships between the SCLT variables and the learning outcomes.

Comparing the performance across the different data splits, the 70% and 60% scenarios exhibited similar levels of predictive accuracy. The 70% split had an MSE of 0.003, the same as the 80% split, while the 60% split had a slightly lower MSE of 0.002, suggesting marginally better performance. The RMSE values were consistent at 0.055 for both the 80% and 70% splits, and 0.005 for the 60% split, further reinforcing the model's robust and stable performance. The MAE/MAD for the 70% split was 0.032, slightly higher than the 80% split, but the 60% split had a value of 0.045, indicating a moderate increase in the absolute magnitude of the errors. The MAPE for the 70% split was 0.85%, still well within the highly accurate range, while the 60% split had an impressive MAPE of 0.71%. Lastly, the R^2 values remained consistently high across all three data splits, with the 60% split achieving the highest R^2 of 0.995, followed by the 80% and 70% splits at 0.994.

Table 2. Model Performances Metrics

	MSE	RMSE	MAE/ MAD	MAPE	R^2
80%	0.003	0.055	0.029	0.75%	0.994
70%	0.003	0.055	0.032	0.85%	0.994
60%	0.002	0.005	0.045	0.71%	0.995

Table 3 demonstrates the feature importance metrics from the Random Forest model. In the 80% data split, z6 ("Family travel enhances understanding of cultural and social differences") had the highest impact on model accuracy (MDA = 0.042), indicating its central role in predicting children's learning outcomes. Other top variables included z8

("Understanding time management," MDA = 0.038) and z2 ("Problem-solving skills," MDA = 0.035), emphasizing the relevance of cognitive and social-emotional development within the SCLT framework.

Moderately important variables were z5 ("Fosters love for learning," MDA = 0.031), z7 ("Analytical thinking," MDA = 0.025), and z3 ("Environmental responsiveness," MDA = 0.021). Meanwhile, variables like z1 (language skills), z4 (understanding nature), z9 (lifestyles and cultures), z10 (creativity), and z11 (learning new things) had lower MDAs (0.017–0.031), indicating less influence in this model configuration.

In 70% and 60% splits, the significance rankings shifted slightly, with z2 (Tourism helps foster a love of learning), z5 (Family tourism helps build an understanding of cultural and social differences), and z3 (Tourism enhances children's analytical thinking) gaining prominence. Nonetheless, z6 (Tourism helps children learn about the lifestyles and cultures of people in different places), z8 (Tourism promotes children's creativity), and z4 (Tourism helps children gain a better understanding of nature and the environment) remained consistently influential across all splits. Non-SCLT variables—such as value of travel time (VTT), family style, marital status, child's age, and child participation in travel decisions (CPTD)—had relatively low MDAs, suggesting they were less predictive of learning outcomes compared to SCLT-based variables.

Table 3. Feature Importance Metrics

Variables	Mean decrease in accuracy		Mean decrease in accuracy		Mean decrease in accuracy
Spilt 80%		Spilt 70%		Spilt 60%	
z6	0.042	z2	0.047	z2	0.039
z2	0.035	z5	0.032	z8	0.035
z8	0.038	z3	0.034	z6	0.036
z5	0.031	z8	0.027	z5	0.037
z7	0.025	z6	0.029	z3	0.032
z3	0.021	z4	0.020	z4	0.029
z1	0.022	z7	0.028	z9	0.022
z4	0.031	z9	0.025	z7	0.029
z9	0.017	z11	0.025	z1	0.020
z10	0.022	z1	0.021	z10	0.024
z11	0.019	z10	0.022	z11	0.022

Table 3. Feature Importance Metrics (continue)

Variables	Mean decrease in accuracy		Mean decrease in accuracy		Mean decrease in accuracy
	VTT	0.001	VTT	0.002	VTT
	Marriage status	2.699×10^{-4}	Marriage status	2.342×10^{-4}	Marriage status
	Children's age	3.225×10^{-4}	Children's age	6.655×10^{-4}	Children's age
	Family structure	1.263×10^{-4}	Family structure	2.955×10^{-4}	Family structure
	CPTD	8.629×10^{-5}	CPTD	7.655×10^{-6}	CPTD

The Impact of Family Tourism on Children's Learning Outcomes

Using Social Cognitive Learning Theory (SCLT) as a framework, this study found that family tourism positively influences children's development across several key areas, as demonstrated by predictive model performance and variable relevance:

1. Traveling to culturally diverse destinations enhances children's understanding of different lifestyles and values. Based on the 80% data split, variable **z6** – *"Family tourism helps understanding cultural and social differences"* – showed the highest importance (MDA = 0.042), emphasizing the role of observational learning and empathy development as emphasized in Social Cognitive Learning Theory (SCLT).

2. Travel exposes children to unfamiliar situations that demand reasoning, adaptability, and decision-making-key cognitive skills emphasized in Social Cognitive Learning Theory (SCLT). These real-world encounters encourage the development of critical thinking and problem-solving abilities. Variables **z2** (*problem-solving skills*) and **z7** (*adaptive thinking and situational response*) consistently ranked among the most important across all data splits. Notably, **z2** had the highest Mean Decrease in Accuracy (MDA = 0.047) in the 70% data split, emphasizing its strong predictive value. Meanwhile, **z7** showed steady importance across the 60%, 70%, and 80% splits, reflecting children's enhanced capacity to adjust and respond effectively to new and complex situations through travel experiences.

3. Participating in travel planning encourages children to engage in scheduling, organizing, and setting priorities-essential components of time management. These practical tasks align with Social Cognitive Learning Theory (SCLT) by promoting self-regulation through experiential learning. Variable **z8** (*time management through travel experiences*) demonstrated consistent importance across all data splits, with a particularly strong impact in the 60% split model (MDA = 0.035). It also appeared in the 80% (MDA = 0.038) and 70% (MDA = 0.027) splits, reinforcing tourism's role in helping children develop structured thinking and effective time-use strategies.

4. Motivation and Love for Learning: Novel experiences gained through travel stimulate children's curiosity and foster intrinsic motivation-key drivers of lifelong learning as outlined in Social Cognitive Learning Theory (SCLT). Engaging with new environments and cultures can ignite a genuine interest in learning beyond the classroom. Variables **z5** (*interest in learning through travel*) and **z11** (*positive learning attitude*) emphasize this impact, consistently showing notable importance across all data splits. Specifically, **z5** recorded MDA values of 0.031 (80%), 0.032 (70%), and 0.037 (60%), while **z11** showed stable relevance with MDA values of 0.019 (80%), 0.025 (70%), and 0.022 (60%). These findings suggest that travel plays a meaningful role in encouraging enthusiasm and a positive mindset toward education.

Figure 3 demonstrates the relationship between the number of trees and the Out-of-bag Mean Squared Error for both the training and validation sets. All three graphs show a rapid decrease in error values as the number of trees increases. After reaching a certain number of trees, the error values tend to stabilize, indicating similar trends. Each graph has distinct characteristics. Graph 1 has a Y-axis range from 0 to 0.025 and an X-axis range from 0 to 100 trees, demonstrating a quick drop in error until about 20 trees, where it stabilizes around 0.005. Graph 2 experiences a rapid decline until 10-15 trees and starts at a higher initial error compared to Graph 1. Graph 3 has a Y-axis range from 0 to 0.020 and an X-axis up to 80 trees, demonstrating a decrease up to around 20 trees, followed by slight fluctuations before stabilizing at approximately 0.005. Overall, Graph 1 displays the most stable results, Graph 2 has the highest initial error but decreases most rapidly, and Graph 3 exhibits the greatest fluctuations between the two datasets.

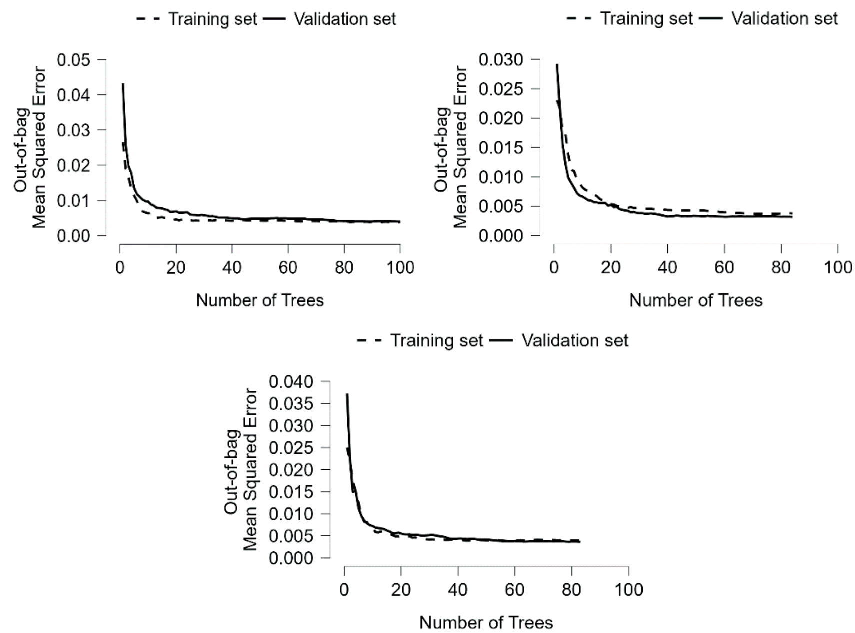

Figure 3. Out-of-bag Mean Squared Error Plot (80%, 70%, 60%)
(calculated by the author)

Discussion

The study uses Social Cognitive Learning Theory (SCLT) to explore the impact of family tourism on children's learning outcomes. SCLT emphasizes observational learning, self-efficacy, and environmental influences, which are particularly relevant in family travel [26]. The Random Forest Regression (RFR) model was used to capture complex and nonlinear relationships in tourism-related learning. The results validate that experiential family travel significantly contributes to children's development, aligning with experiential learning theories [27]. The model outperforms traditional regression models in social science research due to its ability to handle multicollinearity and high-dimensional data [28].

One of the most noteworthy findings is the strong influence of cultural understanding on learning outcomes. The high significance of this variable (z6) suggests that children who engage in culturally diverse travel experiences are more likely to develop empathy, open-mindedness, and global awareness. This may be because family tourism exposes children to environments where they must interact with different customs, values, and behaviors—stimuli often absent in routine daily life. In line with Bandura's concept of observational learning, children internalize these cultural norms by watching and imitating how their parents navigate unfamiliar social contexts [29]. The researcher believes that the novelty and intensity of these cultural encounters heighten children's attention and retention of learning, thus leading to more pronounced developmental gains [30].

Similarly, the strong predictive power of problem-solving skills and analytical thinking can be explained by the unstructured and unpredictable nature of tourism experiences. Children often face minor challenges during travel—such as navigating maps, making choices in unfamiliar restaurants, or adjusting to delays. Unlike the structured classroom environment, these situations require spontaneous thinking and real-time decision-making [31]. The researcher contends that this dynamic context simulates real-world problem-solving more effectively than traditional educational settings. These cognitive challenges, coupled with the supportive presence of parents as co-participants, provide an ideal "scaffolded learning" experience in Vygotsky's terms, allowing children to extend their capabilities [26].

In addition, the significance of time management skills as a predictor of learning outcomes can be attributed to the role children play in planning and executing daily travel activities. The researcher posits that when children participate in scheduling travel itineraries—such as determining which sites to visit and when—they begin to internalize concepts of temporal sequencing, priority-setting, and punctuality [32]. These are skills rarely taught explicitly in early childhood but emerge naturally through collaborative family planning. Furthermore, the consequences of poor time management during travel (e.g., missing transportation or skipping attractions) provide natural feedback mechanisms that reinforce these skills without the negative connotations often associated with academic failure [33].

The study also found that intrinsic motivation and love for learning were significantly influenced by family tourism experiences. This outcome may be due to the autonomy children feel when exploring new environments, as well as the joy of discovering new information outside the formal school curriculum. The researcher interprets these findings through the lens of Self-Determination Theory, which emphasizes the role of autonomy, competence, and relatedness in fostering motivation [34]. Travel offers children the freedom to explore (autonomy), the opportunity to master new social and cognitive tasks (competence), and emotional bonding with caregivers (relatedness), all of which fuel internal motivation to learn. In this way, tourism acts as a powerful natural reinforcer of learning behaviors, often leaving a lasting impact on children's attitudes toward education [35].

The study found that demographic factors like age, family structure, and marital status did not significantly predict learning outcomes in children. This suggests that children's experiences during travel are more significant than their demographics. This contradicts traditional developmental psychology assumptions that focus on static traits (e.g., age or socioeconomic background) over dynamic experiences [36]. The study suggests that intentional travel experiences can equalize educational opportunities. The RFR model's consistent performance across different data splits and ability to identify nuanced patterns in large datasets emphasize its value in tourism research. This balance is crucial in social sciences where data is often noisy and multidimensional.

Conclusion

This study explored the impact of family tourism on children's learning outcomes using a powerful combination of Social Cognitive Learning Theory (SCLT) and machine learning techniques, specifically Random Forest Regression (RFR). By analyzing data from 922 families in Nakhon Ratchasima Province, the study identified key SCLT-related factors that significantly predicted children's learning experiences during family travel. The study revealed that cultural understanding, problem-solving skills, and time management, all central to SCLT, were strong predictors of children's learning outcomes. The RFR model consistently achieved high accuracy (R^2 values exceeding 0.99) and low error rates across various data splits, indicating its robustness. The quality and nature of the travel experience proved to be more influential on learning outcomes than demographic factors such as family structure or children's ages. This suggests that enriching experiences, such as cultural immersion activities and opportunities for problem-solving, are key to maximizing learning potential. The findings strongly suggest that family tourism can serve as an effective educational tool, contributing to children's cognitive and social-emotional development.

Implications

1. Cultural Immersion Activities: Family tourism packages should include structured cultural immersion activities where children can directly engage with local communities, traditions, and practices. Examples include participation in local festivals, guided tours by local artisans, or interactive workshops such as traditional craft-making or cooking.

2. Problem-Solving Scenarios: Tourism providers can incorporate educational games and challenges that encourage children to develop problem-solving skills during the trip. This could include treasure hunts in historical sites, escape room experiences within a cultural context, or nature-based problem-solving tasks such as navigating a jungle trail with maps and compasses.

3. Time Management Workshops: Family-oriented resorts or tourist destinations could offer time management workshops or programs specifically designed for children. For example, daily activities could be structured with morning planning sessions where children and parents are encouraged to create schedules for exploring the destination.

4. Collaborative Learning: Incorporating collaborative activities that require children to work together can enhance their social and communication skills. For instance, guided group activities such as collaborative art projects or community service can help them bond and learn from one another.

Limitations

Despite the strong predictive performance of the model, there are several limitations to this study. First, the data was collected from a specific geographic location—Mueang District, Nakhon Ratchasima Province—which may limit the generalizability of the findings to other regions or cultural contexts. Second, the study focused primarily on social cognitive learning theory, potentially overlooking other crucial dimensions such as physical or environmental learning experiences. Additionally, while Random Forest Regression is a powerful tool for predictive modeling, its "black box" nature makes it challenging to interpret the precise relationships between variables beyond feature significance.

Future Research

Future research should address the study's limitations by broadening the geographic scope to include diverse cultural contexts and regions. Conducting longitudinal studies would be beneficial to explore how repeated family tourism experiences impact long-term learning outcomes in children. Additionally, integrating other machine learning models, such as neural networks or hybrid approaches, could yield deeper insights into the relationships between variables and improve predictive accuracy. Future studies should also investigate additional dimensions of learning, including emotional and physical development, to provide a more holistic understanding of how family tourism influences children's growth. Tracking children's learning over time and across various cultural contexts would further substantiate the claims made in this paper. Therefore, while the results are promising, they should be interpreted with caution until further research can replicate and expand upon these findings.

Human Research Ethics Certification

The researcher obtained human research ethics approval from the Research Committee of Vongchavalitkul University, certificate number COA. 111/2567. The researcher considered the protection of the rights of research participants concerning risk prevention, benefits, confidentiality, and privacy. Participation was voluntary, and participants could refuse or withdraw without providing reasons. The data presentation was in aggregate form.

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