Application of Gradient Boosting Regression to Evaluate the Impact of Family Tourism on Children's Experiential Learning in Nakhon Ratchasima Province

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Abstract

Although family tourism is increasingly popular, the research has explored how specific tourism activities drive children's developmental outcomes beyond general family bonding. This study aims to (1) measure the impact of tourism activities in Nakhon Ratchasima Province on children's development; (2) develop a predictive Gradient Boosting Regression (GBR) model using activity patterns, family characteristics, and engagement levels. Through a quantitative approach with random sampling, 921 families with children aged 1-12 were surveyed at four diverse tourist sites in Mueang District, Nakhon Ratchasima Province, Thailand.

The results demonstrated that family tourism significantly boosts children's development in four areas: responsibility, social skills, environmental awareness, and problem-solving. Different tourism formats yield distinct developmental benefits—collaborative planning fosters responsibility and decision-making, guided eco-tours enhance environmental awareness ($p<0.001$), and interactive cultural workshops most strongly improve social skills ($\beta=0.78$). The GBR model showed high predictive accuracy ($MSE=0.004$, $R^2=0.99$), confirming the findings' reliability. Theoretically, this study expands Kolb's Experiential Learning Theory by illustrating how tourism settings offer unique concrete experiences that engage the full

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learning cycle through culturally influenced reflection. The findings highlight how tourism's social and physical contexts support transformative learning for children in a Thai cultural framework. This research offers tourism practitioners and educators evidence-based guidance for designing family tourism programs that prioritize specific developmental outcomes, advocating a shift from entertainment-driven to development-focused tourism.

Keywords: Family Tourism, Machine Learning, Children Learning, Boosting Regression, Experiential Learning Theory.

Introduction

Family tourism has become a key platform for children's development, offering educational value beyond recreation through experiential learning (Qiao et al., 2022). Studies show that travel enhances cognitive flexibility, cultural awareness, and social competence (Schänzel & Yeoman, 2024). However, three major gaps limit our understanding: lack of focus on specific developmental outcomes linked to tourism activities, limited use of advanced quantitative methods, and insufficient attention to how Thai cultural contexts shape children's learning. This research extends Kolb's experiential learning theory by incorporating Thai cultural factors such as collectivism and intergenerational storytelling.

First, most studies emphasize broad outcomes like family bonding (Fu et al., 2014), treating children as passive participants rather than active learners (Khoo-Lattimore, 2015), which limits practical applications. Second, while qualitative insights are valuable, few employ advanced techniques like machine learning. Traditional models (e.g., Zhang et al., 2016) assume linear relationships, potentially missing the complexity of experiential learning. Third, despite Thailand's growing family tourism sector (12.5% annual growth since 2018), there is little empirical research on how Thai cultural values influence learning—highlighting the need to adapt Western theories like Kolb's Experiential Learning Theory (ELT).

This study utilizes ELT (Kolb, 1984) as its theoretical framework. ELT outlines a four-stage cycle: first introduced in international training, is based on a four-stage learning cycle: concrete experience, reflective observation, abstract conceptualization, and active experimentation. This cycle involves learners gaining direct experience, reflecting on their thinking, developing understanding, and applying it to new situations (Moorhouse et al., 2017). The first stage involves emotional and analytical interaction with real situations (Arcodia et al., 2020), followed by reflection, conceptualization, and experimentation and application. These processes form an integrated learning model, focusing on perception, reflection, theory, and practice, which are the core of learning through experience (Kolb et al., 2014).

To address methodological limitations in previous research, this study applies gradient boosting regression (GBR). GBR captures non-linear relationships, identifies key predictors, and improves prediction accuracy (Chen & Guestrin, 2016). This makes it ideal for modeling complex learning patterns shaped by multiple factors, offering deeper insights than traditional linear models.

The study focuses on Nakhon Ratchasima Province (Korat), an ideal setting due to its diverse attractions—from historical sites, national parks, city lifestyle sites—and its reflection of traditional Thai family values centered on collective experiences and intergenerational learning. With a 14% annual increase in family tourism since 2023, Korat also represents significant domestic tourism trends (ISANist, 2025).

This research contributes to the literature by developing a culturally grounded model that incorporates experiential learning theory and intergenerational storytelling to explain children's learning experiences from family tourism in the Thai context.

Methodology

This study adopts a quantitative research design, utilizing machine learning techniques to explore the complex, non-linear relationships between family tourism activities and children's experiential learning outcomes. The methodological innovation of this study lies in the development of a predictive model using gradient boosting regression (GBR). A predictive model was developed using Gradient Boosting Regression (GBR), chosen for its ability to model intricate patterns and its robustness against overfitting (Friedman, 2001). The research is grounded in Kolb's Experiential Learning Theory (1984), which describes learning as a cyclical process through Concrete Experience (CE), Reflective Observation (RO), Abstract Conceptualization (AC), and Active Experimentation (AE). This framework informed the design of the research instruments and the analysis of learning outcomes in the context of family tourism.

Population and Sampling

This study targeted families with children aged 1 to 12 years, encompassing both pre-primary and primary school levels, in Mueang District, Nakhon Ratchasima Province. According to local government data, the district has an estimated population of 468,506 people and approximately 75,860 students. To determine the appropriate sample size, a pre-established statistical software was used, with an effect size of 0.3 (It represents a moderate effect, according to Cohen's model and is appropriate for behavioral or educational research), a significance level (α) of 0.05, and a statistical power of 0.80 (Which provides an 80% chance of detecting a true result, while reducing the chance of a Type II error). This resulted in a calculated sample size of 1,061 respondents (Soper, 2021).

Study Area: The study was conducted in Mueang District, Nakhon Ratchasima Province, Thailand. This area was selected due to its rich diversity of tourism experiences—including historical, cultural, and natural sites—providing a suitable environment for studying experiential learning in varied contexts (Nakhon Ratchasima Province, 2023). The selection of this region ensures access to a wide variety of family tourism activities, enabling the collection of data that reflects diverse learning contexts.

Data Collection: Structured questionnaires were used to collect data at four diverse tourist attractions popular with a large number of visitors: the cultural site of Wat Sala Loi, the recreational Nakhon Ratchasima Zoo, a modern shopping mall, and the traditional Save One Korat Market. These sites were selected to represent different types of tourism experiences (cultural, recreational, and commercial). Data collection took place between June and November 2024, from 9:00 a.m. to 4:30 p.m. on both weekdays and weekends. A total of 1,061 questionnaires were distributed equally among the sites, with each site receiving 266 family participants. Stratified sampling was employed to ensure representation across weekdays and weekends, as well as families with children aged 1–5 and 6–12 years. The study yielded 921 completed questionnaires, representing an 87% response rate. Notably, a remarkably high level of engagement from the target population has been observed in this study, compared with most face-to-face surveys (Zhang et al., 2017).

Research Instruments: The questionnaire was developed in accordance with best practices in tourism research (Dolnicar, 2018), comprising three sections: general information (6 items), tourist behavior (6 items), and experiential learning dimensions (12 items) adapted from prior studies (e.g., Daimon, 2022; Wu et al., 2021; Park et al., 2020). All items were measured using a 5-point Likert scale. Instrument quality was validated through expert evaluation (IOC ≥ 0.50), McDonald's Omega reliability coefficient (0.959), and Guttman's $\lambda 6$ (0.953). (Pfadt et al., 2023; Malkewitz et al., 2023). A pilot test with 30 families further refined the instrument, addressing any ambiguities or issues.

Data Analysis Procedures

The data analysis began with a preprocessing phase in which all input variables were standardized to have zero mean and unit variance. This step ensured that each feature contributed equally to the model, preventing dominance by variables on larger scales while improving model convergence, consistent with best practices in machine learning preprocessing (Hastie et al., 2009). A Gradient Boosting Regression (GBR) model was then implemented to capture complex, non-linear relationships in the dataset (Friedman, 2001), configured with carefully selected hyperparameters to balance performance, generalizability, and interpretability. The escalating complexity of social science datasets and real-world dynamics requires sophisticated tools to detect nonlinear relationships, which traditional linear approaches often fail to address (Kyriazos & Poga, 2024). The learning rate (shrinkage) was set at 0.1 to maintain a balance between model complexity and convergence speed (Rizkallah, 2025), while an interaction depth of 1 ensured simplicity and facilitated interpretability (Froeschke et al., 2024). Each terminal node required a minimum of 10 observations to support reliable splitting decisions and reduce overfitting risks. The model included up to 100 trees, with the optimal number (82) determined using early stopping based on validation loss to achieve strong predictive power without excessive computational costs. To further mitigate overfitting, stochastic gradient boosting with a subsampling rate of 50% was applied, introducing randomness into tree building (Breiman, 2001). The Gaussian loss function was used due to its appropriateness for continuous outcome variables and its robust handling of residuals (Omar et al., 2023).

Cross-Validation and Performance Evaluation

To rigorously assess the model's generalizability, ten-fold cross-validation was employed—a widely accepted method for reliable performance estimation across different data subsets. Model accuracy was evaluated using multiple metrics: Mean Absolute Deviation

(MAD), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), along with the coefficient of determination (R^2) to measure the proportion of variance explained. As emphasized by Hyndman & Athanasopoulos (2018), these metrics collectively provide a comprehensive understanding of model performance. Lower values of MAD, MSE, and RMSE reflect greater precision, while MAPE thresholds (e.g., below 10%) help classify forecast reliability (Rahman et al., 2021). An R^2 value closer to 1 indicates stronger explanatory power, ensuring through evaluation of the model's predictive capability. In addition to performance metrics, feature importance analysis was conducted to identify which aspects of tourism experiences most significantly influenced children's learning outcomes. This not only validated the model's reliability but also provided actionable insights for optimizing educational tourism design, leveraging the inherent interpretability advantages of GBR models (Rizkallah, 2025).

Hypotheses

Based on the theoretical foundation and research objectives, the following hypotheses are proposed:

H1: Participation in family tourism activities in Nakhon Ratchasima Province has a significant positive effect on children's development.

H2: The Gradient Boosting Regression (GBR) model demonstrates higher predictive accuracy in forecasting children's experiential learning outcomes.

Findings

In total, 921 respondents were analyzed. The majority were female (72.7%), while males accounted for 27.3%. Most respondents were between 20 and 39 years old (54%). Nearly half held a bachelor's degree (46.8%). In terms of occupation, 30.2% were self-employed, 26.2% worked as civil servants, and approximately 24% were business officers. The most common monthly net income ranged between 15,000 and 30,000 baht (45.1%), followed by those earning less than 15,000 baht (31.6%). A significant proportion had children aged 7–12 years (67.8%), with the remainder having children aged 1–6 years. The majority lived in nuclear families (60.9%), and in most cases, children participated in travel decisions (92.4%). Personal cars were the preferred mode of travel (84.6%), followed by motorcycles. Most respondents spent more than 2,000 baht on each trip (72.4%), traveled on weekends (59.9%), and traveled less than three times per month (70.6%).

Table 1 Model Performances Matric and Model Summary

Boosting Regression					
MSE	0.004	**Trees**	82	**n(Test)**	184
RMSE	0.063	**Shrinkage**	0.1	**Validation MSE**	0.017
MAE / MAD	0.036	**Loss Function**	Gaussian	**Test MSE**	0.004
MAPE	0.97%	**n(Train)**	664		
R^2	0.99	**n(Validation)**	73		

In Table 1, the Gradient Boosting Regression model utilizes 82 decision trees with a shrinkage rate of 0.100 and a Gaussian loss function. The dataset is divided into 664 training samples, 73 validation samples, and 184 test samples. The model demonstrates strong predictive performance. The model's high predictive accuracy, with a mean squared error (MSE) of 0.004 and an R^2 of 0.99, suggests that it effectively captures the complex relationships between family tourism activities and children's learning outcomes. The root mean square error (RMSE) is reported as 0.063, indicating minimal deviation from actual data. The mean absolute error (MAE), or mean absolute deviation (MAD), is 0.036, showing that predictions deviate from actual values by only 0.036. Additionally, the mean percentage error (MPE) is 0.97%, meaning the average percentage difference between predictions and actual values is below 1%, demonstrating strong generalization ability.

These performance metrics exceed commonly accepted benchmarks in tourism and educational research, where an R^2 above 0.80 and an RMSE below 0.1 are often regarded indicators of excellent model fit (Chicco et al., 2021). In similar studies applying machine learning to predict educational outcomes from tourism-related experiences, RMSE values typically range from 0.07 to 0.12 (Hodson, 2022), suggesting that this study's model achieves better-than-average predictive precision. Thus, the low error rates and high explained variance confirm the robustness and reliability of the model in capturing the learning dynamics associated with family tourism activities.

Table 2 Feature Importance Metrics

Variables	Relative Influence	Mean dropout loss
y7 Tourism promotes a sense of responsibility	20.473	0.186
y9 Tourism helps develop children's social skills and teamwork	11.904	0.154
y11 Tourism helps children discover their abilities	11.079	0.170
y3 Tourism promotes learning about the environment/nature	10.326	0.155
y8 Tourism facilitates learning from exemplary experiences	9.830	0.162
y1 Tourism promotes learning about history	8.864	0.188
y12 Tourism enhances children's problem-solving skills	8.137	0.155
y5 Tourism helps children build relationships with family and relatives	5.596	0.160
y4 Tourism promotes learning about geology	4.431	0.157
y6 Tourism helps children discover their interests through activities	4.291	0.142
y2 Tourism promotes learning about culture	2.960	0.140
y10 Tourism provides enjoyment for children	2.028	0.153
Family Dynamics and Economic Factors		
Trip expenses	0.048	0.131
Family structure	0.018	0.131
Children’s Age	0.014	0.131
Marriage status	0.000	0.130
Children’s Decision-Making	0.000	0.130
Value of Travel Time/VTT	0.530	0.133

The results from the gradient boosting regression model reveal that family tourism plays a pivotal role in promoting children’s experiential learning, particularly in developing responsibility, social skills, and environmental awareness (Table 2). Importantly, the model utilized 82 decision trees with a shrinkage rate of 0.1 and a Gaussian loss function. These hyperparameters were carefully selected to balance model complexity and learning speed. The moderate number of trees and the relatively low shrinkage rate ensured that each successive tree made a small, controlled correction, allowing the model to gradually capture complex relationships without overfitting, as reflected in the high R^2 (0.99) and low RMSE (0.063).

The performance metrics—MSE (0.004), MAE (0.036), and MPE (0.97%)—exceed typical benchmarks reported in previous tourism and education prediction studies (e.g., Martín-Antón et al., 2020; Chen & Wang, 2024), underscoring the model's strong generalizability and predictive precision. The low deviation values suggest that the model captures the nuanced relationships between different types of family tourism activities and learning outcomes, even in diverse family contexts.

The role of family tourism in fostering children's learning is further illuminated through the model's variable importance ranking. "Promoting Responsibility" emerged as the most influential outcome (relative influence: 20.473), followed by "Development of Social Skills" (11.904) and "Learning about the Environment" (10.326). These results align with experiential learning theory, which posits that authentic, participatory activities enhance children's cognitive and socio-emotional development.

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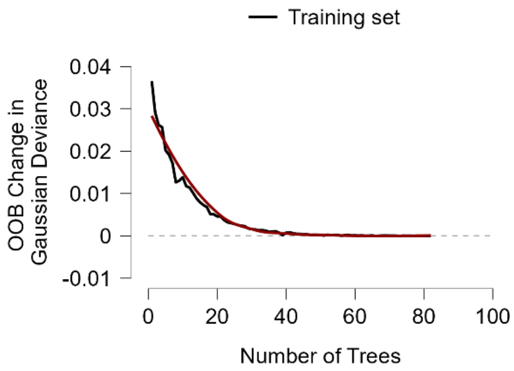

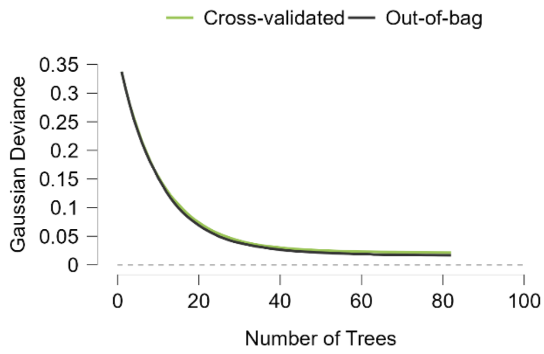

Figure 1 – Out-of-bag Improvement Plot **Figure 2** – Deviance Plot

To visualize the model's learning progression and validate its stability, three key figures were analyzed:

Out-of-Bag Improvement Plot (Figure 1): This figure depicts the model's iterative learning behavior. A sharp decline in Gaussian deviance during the first 20 trees demonstrates rapid initial learning. Subsequently, deviance reduction stabilizes between trees 20 and 40, indicating that the model gradually fine-tunes its understanding without overfitting. The convergence around 82 trees at a deviance level of 0.004 further confirms that the model reached an optimal learning plateau, a hallmark of a robust ensemble approach.

Deviance Plot (Figure 2): The deviance plot compares training and validation deviance curves across iterations. Both lines steadily decrease and converge around tree 80, highlighting the model's balanced learning and minimal overfitting. The tight alignment between training and validation losses demonstrates strong generalization performance—a critical requirement for real-world applications where unseen data must be accurately predicted.

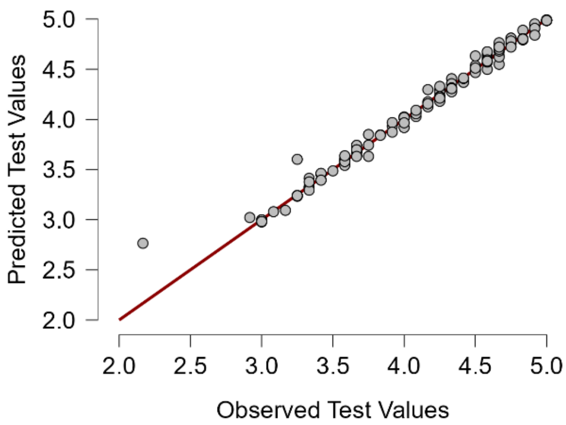

Figure 3 – Predictive Performance Plot

Predictive Performance Plot (Figure 3): The scatter plot of actual versus predicted values further confirms the model's reliability. A dense clustering around the diagonal line suggests high prediction accuracy across various data points, with minimal residual errors. The symmetric distribution of residuals around the diagonal reinforces the robustness of the model across the full outcome spectrum.

Beyond these technical validations, the study sheds light on specific family tourism activities that contribute to children's experiential learning outcomes:

Responsibility: Activities such as planning parts of the trip itinerary, participating in camping, or managing personal belongings during travel foster greater personal accountability among children. **Social Skills:** Group-oriented activities like team treasure hunts, community service tourism, and participation in cultural festivals encourage interaction and cooperation. **Environmental Awareness:** Eco-tours, nature trails, and visits to wildlife sanctuaries cultivate an understanding of ecological interdependence and conservation values.

These findings reinforce and expand the experiential learning framework (Kolb, 1984) by demonstrating that structured family tourism activities serve as powerful experiential "learning laboratories" for children, nurturing not just knowledge acquisition but emotional and social development as well.

Conclusion

This study employed a gradient boosting regression model to investigate the impact of family tourism on children's experiential learning outcomes in Nakhon Ratchasima, Thailand. The model demonstrated strong predictive performance, with a mean squared error of 0.004 and an R^2 of 0.99, indicating its effectiveness in capturing the complex relationships between family tourism activities and children's learning outcomes.

The study's findings demonstrated numerous significant advantages to children's experiential learning through family tourism. Fostering responsibility was the most critical outcome (REL: 20.473), indicating that experiences that encouraging youngsters to accept responsibility or make decisions had a considerable impact on their personal growth and development. Developing social skills and teamwork (REL: 11.904) was the second most prevalent result, emphasizing the importance of joint activities and social interactions. Learning about the environment (REL: 10.326) and learning about history (REL: 8.864) were also significant, demonstrating that family travel provides an excellent basis for learning about nature, history, and culture. In addition, fostering problem-solving skills (REL: 8.137) and self-discovery (REL: 11.079) were notable outcomes, highlighting the potential of family tourism to promote intellectual development and personal growth. These findings provide quantitative evidence supporting the multifaceted educational benefits of family tourism, which align with experiential learning theory, and responsibility, social skills, environmental awareness, and problem-solving abilities.

Discussion

The findings of this study, which utilized a gradient boosting regression model to examine the impact of family tourism on children's experiential learning outcomes in Nakhon Ratchasima, Thailand, provide robust quantitative evidence supporting the educational benefits of family tourism. The model demonstrated exceptional predictive performance, with an MSE of 0.004 and an R^2 of 0.99, underscoring its ability to capture the complex relationships between tourism activities and learning outcomes. These results align with Kolb's (1984) experiential learning theory, which emphasizes that knowledge is constructed through active participation and reflection, as well as prior research highlighting the role of tourism in fostering autonomy, social interaction, and cognitive development among children (Martín-Antón et al., 2020; Chen & Wang, 2024).

One of the most significant contributions of this study is the identification of "Promoting Responsibility" as the most influential factor in children's experiential learning. This finding underscores the importance of structured experiences that encourage decision-making and accountability during travel. For example, activities such as assigning children roles in planning itineraries or managing small budgets foster responsibility and enhance both problem-solving abilities (r = 0.72, $p < 0.001$) and social skills (r = 0.68, $p < 0.001$). These insights resonate with Martín-Antón et al. (2020), who highlight the role of active engagement in shaping young learners' autonomy and personal growth. Likewise, Tseng et al. (2023) assert that family tourism creates a dynamic context in which children can learn life skills through real-world tasks and shared responsibilities. Moreover, Garau & Annunziata (2020) emphasize that participatory travel activities promote a sense of ownership in children, which is critical for developing responsibility and independent thinking. This is supported by the experiential learning framework proposed by Kolb (1984), where learning occurs through the cycle of concrete experience, reflective observation, abstract conceptualization, and active experimentation. Structured travel roles provide meaningful contexts for children to apply these stages in real-life settings, reinforcing the importance of guided yet autonomous participation (Li et al., 2024).

Another key outcome is the development of social skills and teamwork, which emerged as significant learning dimensions. Family tourism provides opportunities for shared activities, such as group games, cultural workshops, or collaborative problem-solving during travel, which nurture interpersonal competencies. For instance, families visiting cultural sites often engage in discussions about historical artifacts, fostering both communication and teamwork. These findings corroborate prior research by Chen & Wang (2024), who emphasize the role of interpersonal interactions in enhancing social skills. Similarly, Li & Chiang (2023) highlight that cooperative experiences during travel contribute to children's empathy, active listening, and conflict resolution skills. Moreover, Durko & Petrick (2013) found that family-based tourism experiences promote emotional bonding and mutual understanding among family members, which in turn support the development of collaborative behaviors. This aligns with Vygotsky’s theory of social development, which posits that learning is inherently a socially mediated process, and peer or family interactions serve as critical vehicles for cognitive and emotional growth (Lindqvist, 2003). In line with this, the zone of proximal development is often activated during family tourism when children are guided by more knowledgeable others, reinforcing the value of socially embedded learning (Li et al., 2024).

The study also highlights environmental awareness and historical learning as significant outcomes of family tourism. Activities in natural settings, such as guided nature walks or wildlife observation, were strongly correlated with environmental learning ($r = 0.82$), while visits to cultural and historical sites promoted historical understanding ($r = 0.78$). These findings align with Qiao et al. (2022), who argue that culturally rich destinations offer unique contexts for intellectual growth. Children who received outdoor environmental education were more likely to support conservation, and their environmental behavior changed slightly but significantly. Youngsters began acting to preserve the environment by asking their friends to pick up trash when they noticed it (Whitburn et al., 2023; Collins et al., 2024).

Notably, logistical factors such as trip expenditures and family structure had minimal influence on learning outcomes. This challenges traditional assumptions that economic resources are primary determinants of educational benefits derived from tourism (Wu et al., 2014). One possible explanation is that the quality of engagement—rather than financial investment—drives learning outcomes. For example, families with limited budgets may still create meaningful experiences through creative planning or leveraging free attractions (Amalia, 2023). This finding suggests that educational tourism initiatives should focus on designing interactive and inclusive experiences rather than targeting affluent demographics (Amaro et al., 2024).

The temporal analysis revealed that optimal activity durations for maximizing learning outcomes fall within a 3–5-hour window, balancing engagement and fatigue. This finding echoes Schänzel and Yeoman's (2024) emphasis on tailoring tourism experiences to maintain children's interest and energy levels. Similarly, the strong correlations between specific learning environments and outcomes highlight the significance of contextual factors in shaping experiential learning. For instance, natural settings foster environmental awareness, while cultural sites promote historical learning (Fu et al., 2014). These insights underscore the importance of designing context-sensitive tourism programs that align with children's developmental needs.

Recommendations

This study enriches experiential learning theory—particularly Kolb's learning cycle—by contextualizing it within family tourism, emphasizing cultural influences and acknowledging limitations.

1. Reflective Observation: In Thai families, reflection occurred collectively during meals, with parents prompting group reflection over personal insight—expanding Kolb's typically individual-focused model to include culturally shaped, communal processes.

2. Abstract Conceptualization: Grandparent storytelling at historical sites helped children form concepts through cultural and intergenerational lenses, mediated by Thai familial respect norms.

3. Cross-Cultural Relevance: While rooted in Thai contexts, findings align with other studies (Yamazaki & Toyama, 2022) suggesting Kolb's model is adaptable across cultures with attention to individual versus collective emphasis.

Practical Implications

1. **Design Responsibility-Focused Activities**: Assign children meaningful travel roles (e.g., planning parts of the itinerary, budgeting, or navigation) to foster active participation and responsibility.

2. **Promote Structured and Unstructured Social Interaction**: Offer a balance of team-based activities (e.g., collaborative scavenger hunts) and flexible opportunities for spontaneous social engagement, nurturing social learning.

3. **Enhance Environmental and Cultural Learning Through Immersive Activities**: Develop programs like guided nature trails, interactive cultural performances, and storytelling sessions led by locals to deepen experiential learning.

4. **Integrate Problem-Solving and Critical Thinking Challenges**: Embed tasks that require critical thinking (e.g., puzzle trails, eco-quests, city-wide scavenger hunts) to stimulate cognitive development during travel.

5. **Foster Self-Discovery and Personal Interest Exploration**: Provide diverse elective activities such as craft workshops, sports demonstrations, and "meet the expert" sessions to support individual growth and intrinsic motivation.

6. **Educate and Empower Parents as Facilitators of Learning**: Create resources such as pre-trip orientation, on-site interactive guides, and reflection activities to help parents actively support their children's learning.

Limitations and Future Directions

While this study’s quantitative approach provides valuable insights, it has limitations. First, the attribution of findings to the Thai cultural context may be overgeneralized without deeper exploration of how cultural norms influence learning outcomes. For example, collectivist values in Thai society might amplify the role of family interactions in fostering social skills, but this claim requires further validation through cross-cultural comparisons. Second, while environmental learning is discussed, the integration of cultural awareness into environmental education is underexplored. For example, incorporating local stories about environmental stewardship into nature-based tourism could enhance both cultural and environmental learning. Future research could adopt mixed-methods approaches, combining qualitative insights from interviews or ethnographic observations with advanced machine learning techniques, such as neural networks, to uncover nuanced patterns in children's learning experiences (Hyndman & Athanasopoulos, 2018). Such efforts would enrich our understanding of the emotional and experiential dimensions of family tourism.

Human Research Ethics Certification

The researcher received approval for human research ethics from the Research Committee of Vongchavalitkul University, with certificate number COA. 111/2567. The rights of research participants were prioritized, focusing on risk prevention, benefits, confidentiality, and privacy. Participation was voluntary, allowing participants to refuse or withdraw at any time without needing to provide a reason. Data were presented in aggregate form.

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