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The Role of Digital Intangible Culture Heritage Resources in Promoting Students' Innovative Ability in Higher Education Courses

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Abstract

The study is aimed at incorporating Web-AI (IESWS-LGBM) systems into the higher education curricula, specifically focusing on the development of creative thinking and innovation based on the use of digital ICH assets. The research was conducted on 52 undergraduates in the experiential learning program at the School of Ethnology and Sociology at Guangxi Minzu University. Additionally, 240 undergraduates from various branches of science, engineering, and arts were taught at a university in Southeast Asia. Specialized innovation courses focused on an AI application that provided audio for the digital assets of ICH. Although the strategy is unique to one institution, it is likely to be more beneficial and assist other colleges attempting to improve student creativity through the application of cultural elements in addition to the primary focus of the strategy. The research employed a mixed-methods design including pre-and post-tests, behavioral observation, questionnaires, interviews, and evaluations of projects. Quantitative data indicate a 26.4% increase in cognitive knowledge of ICH. Behavioral data shows that 92% of students reported increased levels of cultural motivation with 86% of the students being actively engaged. One of the most important aspects of the data is that 76% of the students in rubric-based exams evaluated the creativity criterion. The proposed model IESWS-LGBM has also demonstrated an increased accuracy (91.5%) in evaluating students' creativity compared to previous models. These results suggest that ICH with the help of technology is quite effective at promoting critical thinking, originality, and multicultural learning among students in institutions of higher education.

Keywords: Intangible Cultural Heritage, Innovation Ability, Higher Education, Experiential Learning, IESWS-LGBM, Digital Resources, Student Engagement.

1. Introduction

Intangible cultural heritage is presented in this convention as an interdisciplinary idea that represents the knowledge that has been crystallised from long-term production and living activities. Skill levels, real-world experiences, hobbies, spiritual perspectives, and more are all included, as is the continuation of civilisation and the observation of countries' evolutionary paths. It is considered a rare cultural resource for mankind and the "living fossil" of ancient civilisation [1]. However, the status of intangible cultural traditions is steadily decreasing due

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to the effects of economic modernisation and globalisation, making it imperative to address concerns pertaining to their transmission and preservation [2].

Students' creative skills must be developed immediately in the quickly changing higher education environment in order to fulfill the needs of the digital society knowledge economy. Since it allows people to think creatively, solve complicated issues, and adjust to change, innovation is widely seen as a critical competency for students in the twenty-first century [3]. But when it comes to encouraging students' creativity and invention, conventional teaching methods often fall short. In this regard, materials related to Digital ICH provide a fresh and revolutionary educational tool that may enhance instructional strategies and encourage learning that is focused on innovation [4].

According to UNESCO, traditions in oral arts, rituals, celebrations, practices, and knowledge related to culture, and traditional handicrafts are all considered forms of intangible cultural heritage. These cultural manifestations provide a wealth of multidisciplinary, immersive, and problem-based learning opportunities s and are firmly anchored in the values and inventiveness of the community [5,6]. The emergence of digital technologies has made it possible to conserve, portray, and distribute ICH aspects using digital formats such as immersive simulations, augmented reality apps, digital storytelling platforms, and virtual museums. By fusing cultural tales with contemporary digital media, these digital ICH tools open up new instructional opportunities and foster critical thinking, creative discovery, and student participation [7].

Education courses are fundamental to the long-standing accrual of human knowledge. The reference to courses, which are the basis of schooling is vital to ensuring the enhancement of the quality of education in general as well as providing a channel through which learning objectives can be achieved. It is through intangible cultural heritage that the essence of ethnic cultures is maintained and at the same time it provides a rich source of education. As a means of recognizing ethnic survival knowledge and vibrant culture, the incorporation of these distinctive cultural materials in the curriculum becomes a vehicle through which intangible cultural assets are taught and passed on in schools [8]. There is a new historical mission of the schools, which is the critically important goal of preserving and transmitting the intangible cultural heritage of ethnic minorities. In order to gain the highest value from the educational system within China, it is instrumental in specific strategy execution, local advantage exploitation, and environmental adaptation particularly in minority colleges [9]. These organizations significantly contribute to the diversity and richness of regional cultures by engaging in the protection and proliferation of local intangible cultural assets through the advantages they have by being in those locations and exploiting the available resources [10].

Integration of the digital ICH into the curriculum in higher education particularly in fields such as digital media, education, cultural studies, design and the arts, can potentially trigger the process of innovation. By engaging with this material, students are also likely to utilize modern technologies in analysing traditional cultural material, thus promoting technological literacy, interdisciplinary reasoning, and empathy with different cultures. Moreover, digital ICH projects frequently require collaborative work, research and creative production and are consequently well-suited to contemporary educational paradigms such as project-based learning, experiential education and constructivist learning. Therefore, students obtain not only an academic knowledge base but also innovative attitudes, digital skills, and imaginative problem-solving skills. Although there is a growing interest in digital heritage and its role in education, it remains to be researched in-depth how the effects of digital directly influence the innovative potential of the students. This difference is quite conspicuous in intelligent learning analytics and algorithmic educational evaluation. To model and predict the influence of digital ICH resources on students' creativity outcomes this study examines the use of machine learning, specifically an Improved Elephant Swarm Water Search algorithm optimised using Light Gradient Boosting Machine (IESWS-LGBM). The project seeks to offer analytically-epic, extendable, and sensible means of understanding and augmenting the capacity for innovation in university education by blending cultural training with artful computational methods.

Through this, both the fields of digital cultural heritage and educational technology are advanced given that the research holds significant potential in the assessment and enhancement of educational interventions, alongside the role of culture-driven digital material as a platform for innovation. It is expected that the findings will provide valuable insights for educators, cultural institutions, and curriculum designers who seek to engage students in creativity through culturally engaging digital learning opportunities.

1.1 Research Question

1. What is the current situation and the problems regarding the understanding of digital intangible cultural assets among higher education students?
2. Which curricular components are based on experiential theory, and how can they be implemented?
3. Has the understanding of digital intangible cultural heritage improved among students with the implementation of the curriculum using experiential theory?

1.2 Research Question

The digital intangible curriculum, rooted in experiential learning theory improves the understating of intangible cultural heritage among higher education students.

2. Contribution

The proposed study enables a significant departure in the interrelationship between cultural learning, technological development, and machine learning by transforming an experiential learning-based curriculum that involves digital ICH resources in higher education. It gives a new paradigm for enhancing students' abilities regarding creative invention, cultural contribution, and conceptual understanding. Regarding methodology, it is also novel because it employs a hybrid model (Improved Elephant Swarm Water Search VarLightGBM, IESWS-LGBM) that is more accurate, precise, recalls, and F1-score metrics than the standard machine learning model to efficiently predict and estimate student innovation potential. The development of a multifaceted assessment system that considers both quantitative and qualitative approaches (tests, observations, interviews, and rubrics) in the study makes it possible to answer this question comprehensively. It also provides concrete evidence of the support that digital and pedagogically packaged cultural heritage material can provide towards in spurring higher-order thinking, participation and innovation among university students. For researchers in AI, legislators and educators wants to bridge the gap between student centered learning, cultural preservation and smart educational technology, their input cannot be more invaluable. Related Work

Table 1. Summary on Related Works

Reference	Key Findings	Limitations
[11]	The author focused on a human-centered paradigm for ICH transmission through games. It also identifies important VR game design elements (eudl.eu, dl.acm.org).	In the framework, student creativity outcomes and classroom trials are not evaluated.
[12]	This paper evaluate VR prototype that preserves Aipan art with anthropological support.	Ten-person sample, prototype stage, lack of learning or innovation evaluation
[13]	Active engagement can be improved by spatial audio interaction patterns (adaptive, progressive).	16 participants in a brief research with no metrics for originality or creativity.
[14]	With the help of physical exertion, haptic virtual reality boat racing enhances cultural comprehension.	Technique simulation is the main focus; creative or educational result analysis is not included.
[15]	Embodied cognition-based VR gestural engagement could increase cultural interest.	A prototype that is not standard to the innovation and metrics for educational success
[16]	Research trends in VR, AR, and MR have been discovered, and the application of immersive technology in cultural heritage is growing continually.	macro-level study; no direct assessment of the advantages of innovation or education
[17]	Students create own heritage tales and acquire skills for the future.	Contest case study; no control groups or long-term perspective
[18]	A VR system mayboost curiosity and contextual knowledge.	Emphasises the involvement rather than assessing students' creativity or higher-order abilities.
[19]	Immersive 3D heritage displays are produced via interdisciplinary VR animations.	Technical emphasis; little assessment of student results or innovative teaching
[20]	Compared to smartphones, VR headsets significantly boost engagement.	Engagement and novelty have an impact in isolation, with no connection to creativity or enhanced learning.

Table 1 explains the related works of key finding and limitations of existing methods chosen related to this study.

2.1 Research Gap

Although most previous research on ICH focuses on preservation, cultural sensitization, or tourism, it does not explore the use of digital ICH integration as a systematic pedagogical tool to enhance creativity and innovation among students across various disciplines. Through the ICH-based digital education model, which integrates ICH materials and interdisciplinary learning activities, this study provides empirical data sufficient to understand how cultural stories and traditions can help university students develop innovative thinking. Moreover, it also proposes some quantifiable measures of innovation outcome implications that play a minor role in earlier studies of ICH education. This will place the research at the nexus of maintaining culture, digital pedagogy, and capacity building through creativity, filling a disparate and nonexistent gap in the body of literature.

3. Proposed Work

Students were assessed for innovation capabilities using an adapted version of the ICAR framework, while the Torrance Tests of Creative Thinking served as foundations for the underlying evaluative elements. Each member of the cohort associated fluency, flexibility, originality, and elaboration with the participants' constructs of creativity and connected them to their respective projects. Furthermore, there were post-test and pre-test psychometric modified instruments, attitudinal post assumptions, and dispositions based on students' innovative post assumptions. Thus, reliable multi-faceted measures were collected. Measures that were authorized for the analysed outcomes used proxies to explain students' innovation development.

3.1 Population and Sample Group

3.1.1 Population

With the aims of this particular study, in the academic year 2024, the School of Ethnology and Sociology of Guangxi Minzu University accepted 280 first-year students, of which 240 were used for the purpose of analyzing the influence of ICH education on the creativity and understanding of students belonging to various fields including arts, engineering, education, science and more.

For studying the effect of the ICH innovation system digital transformation n participants were divided into an experimental group with 120 participants and a control group with 120 participants.

3.1.2 Sample Group

Randomly selected students’ participants for this study numbered 52 and were enrolled in the Spring 2024 semester of the ICH course. Active digital resources on ICH had already been modified and compiled by cultural and geographical divisions, and subsequently reviewed and categorized by levels of learning objectives in a controlled, systematic, and orderly manner. All participants were thus enabled to access professionally crafted culturally relevant materials through an LMS module to ensure a uniform learning outcome.

3.2 Research Process

Random sampling resulted in a selection of 52 participants. These students were enrolled in a class on intangible cultural heritage which was made available in the Spring semester of 2024.

Phase 1: Questionnaire

The present state of affairs review

- Interviewed 10 scholars on the ICH learning of the students.
- Questionnaire on the present knowledge and issues.
- Interview of the special opinions.
- Interpreted information to determine major problems and gaps in students knowledge.

Phase 2: Curriculum Development

- Reviewed literature on curriculum design and experiential learning.
- Components of the curriculum that were identified: principles, goals, content, the learning process, available resources and evaluation.
- Wrote curriculum ready to teach on ICH education.
- 5 expert scholars validated it.
- Curriculum reformed through the opinions of specialists.

Phase 3: Action and refinement

- 52 students underwent a pre-test concerning their understanding of ICH.
- Conducted 4 weeks (20 hours in total) of the delivered curriculum.
- Observed student behavior and spoke to the students during the lessons.
- Administered a post-test at the completion of the course.

This study employed a quantitative research methodology, incorporating pre- and post-test experimentation, statistical analysis, and a validated psychometric index of innovation to assess the impact of the digital ICH learning system (IESWS-LGBM) on students' innovation levels. The data were obtained through systematic exams in a variety of subjects in academic studies, which made it possible to provide an objective comparison between experimental and control groups.

3.3 Preprocessing

All data fed into the IESWS-LGBM model are guaranteed to be unambiguous, reliable, and relevant due to the appropriate preprocessing implemented. To understand the model's capacity to evaluate students' performance and behaviour, it involves encoding, data imputation, normalisation, and feature synthesis. Such measures analyse the performance and generalization of the model, thereby increasing the precision and trustworthiness of the evaluation of innovation in the digital education of ICH.

3.4 Proposed Method

Improved Light Gradient Boosting Machine (LGBM)

LGBM is the best gradient-boosting platform based on machine learning. It is thought to be better and able to grow more than older boosting methods. This speeds up training by using algorithms based on histograms, using less memory, and a leaf-wise growth method to keep trees from being too deep and overfitting. There are four strategies to make decision tree learning as successful as possible in Light GBM. By dividing continuous features into separate bins, ML accelerates the calculation and uses less memory. GOSS is a method that improves efficiency without losing too much accuracy. It does this by randomly picking cases with small gradients and keeping cases with large gradients. EFB reduces the number of attributes that can't be combined and the quantity of memory needed. To protect the model from overfitting, there needs to be a depth limit. However, the leaf-wise growth method makes the model more accurate by choosing the leaf that will be enlarged based on the most information acquired.

Pretrain data is shown by, $X = \{(X_j, z_j)\}_{j=1}^{n}$. Finding an approximation function is the aimg ̂(x)that approximates g^*(x)to reduce the anticipated values of certain loss activities(z,g(x)), mathematical representation of the objective function as

$$\hat{g}(x) = \underset{e}{arg\, min} F_{z,x} K(z, g(x)) \quad (1)$$

In order to maximize predictions, this function minimizes the anticipated loss operation. The process of additive learning is stated as

$$g_S(X) = \sum_{s=1}^{S} g_s(X) \quad (2)$$

wherewhere $g_S(X)$shows the slow learner in parameters$s$, and $g_S(X)$is the last model after S boost iterations.

Regression tree summation is how LGBM creates a model. Optimization of leaf weight is calculated by

$$\omega_i^* = -\frac{\sum_{j\in J_i} h_j}{\sum_{j\in J_i} g_j + \lambda} \quad (3)$$

here, $h_j and g_j$are the loss operation's main and secondary gradients, maximizing the

tree's nodes,λ is the parameters in regularization Optimization of tree structures (high Values of Γ_S^*) is shown by

$$\Gamma_S^* = -\frac{1}{2}\sum_{i=1}^{I} \frac{(\sum_{j\in J_i} h_j)^2}{\sum_{j\in J_i} g_j + \lambda} \quad (4)$$

The quality of a feature split during tree development is gauged by the gain function, which is computed

$$\text{as}H = \frac{1}{2}\left(\frac{(\sum_{j\in J_i} h_j)^2}{\sum_{j\in J_i} g_j+\lambda} + \frac{(\sum_{j\in J_q} h_j)^2}{\sum_{j\in J_q} g_j+\lambda} + \frac{(\sum_{j\in J} h_j)^2}{\sum_{j\in J} g_j+\lambda}\right) \quad (5)$$

Improved LGBM is very fast to train and make accurate predictions because it is internally efficient making it adequate for deploying ML into production. It effectively forecasts highly crucial parameters of processes, supports adaptive real-time scheduling, workflow changes and improved overall production efficiency.

Improved Elephant Swarm Water Search (IESWS)

The IESWS method uses a metaheuristic optimization principle, fine-tuning process parameters in a manufacturing system with DT capabilities. The method presents the collective elephant swarms' social behavior and intelligence as a way of optimizing the system by reducing downtime and waste of materials across all means of activity.

Elephant Groups Process Solutions

A possible solution to process optimization in the optimization model is mapped out as different elephant groups, each corresponding to the dynamic variation of production parameters in order to optimize work and reduce the consumption of resources. The groups in which each elephant is included represent possible parameterization of various productive processes like scheduling, resource distribution, and work process optimization.

An elephant group's location inside the search area is shown as

$$U_{j,c}^{s} = U_{j1,}U_{j2,} \dots \dots \dots U_{jc} \quad (6)$$

where, $U_{j,c}^{s}$ represents thed-dimensional position of the j^{th}elephant group at iteration s.

Revised Velocity Using the Best Found Solutions

The second one is adapting the velocity of the given group of elephants based on local best solutions and world-class solutions so that the method of production can be optimized according to the DNA scheduling and inefficiencies of the production. The speed of each group of elephants is rejuvenated to maximize the decision-making that involves local and global search approaches that are denoted as,

$$U_{j,c}^{s+1} = U_{j,c}^{s} * \omega^{s} + \varepsilon \odot \left(H_{best,c}^{s} - W_{j,c}^{s}\right) \quad (7)$$

$$U_{j,c}^{s+1} = U_{j,c}^{s} * \omega^{s} + \varepsilon \odot (H_{besti,c}^{s} - W_{j,c}^{s}) \quad (8)$$

Production Parameters Revised

Optimized solutions are input into the algorithm continuously, allowing it to constantly adjust the critical production parameters in real-time to streamline and fine tune the workflow in environments, ensuring minimal downtime, and optimal process effectiveness. The production system is updated and is referred to as

$$\omega^{s} = \omega_{max} - \left\{\frac{\omega_{max} - \omega_{min}}{s_{max}}\right\} \times s \quad (9)$$

This procedure repeatedly improves machine learning models to forecast students' workflow, and IESWS dynamically updates it by

$$X_{j,c}^{s+1} = U_{j,c}^{s+1} + U_{j,c}^{s} \tag{10}$$

$$o(s) = o_{max} - \left(\frac{o_{max} - o_{min}}{s_{max}}\right) * s \tag{11}$$

where, $o_{max} = 1$, $o_{min} = 0$, $s_{max}$is the maximum count.

This strategy guarantees a more robust worldwide search at first and a more focused local search as iterations advance.

Velocity and Position Updates in IESWS

Maintain the same speed and position update in ESWS; control search flexibility and the new production system, as specified by

$$X_{j,c}^{s+1} = U_{j,c}^{s} * \omega^{s} + \epsilon \odot (H_{best,c}^{s} - X_{j,c)}^{s} \tag{12}$$

$$W_{j,c}^{s+1} = U_{j,c}^{s+1} + U_{j,c}^{s} \tag{13}$$

where, $(W_{j,c}^{s+1}$) - revised position at moment $(s + 1)$, position at moment -(s), Weight-controlling inertia exploration balance.

The IESWS-LGBM (Improved Elephant Swarm Water Search LightGBM) paradigm has a series of obvious advantages regarding its application in the domain of evaluating and promoting the inventiveness of students through the use of digital ICH education. Consequently, it is quite reliable in identifying children who are truly creative. Second, the insights of the Improved Elephant Swarm Water Search algorithm can be seamlessly integrated into Light GBM, allowing its hyperparameters to be successfully optimized, thus ensuring that the predictive model can recognize complex and non-linear trends in educational data, including the relationships between behavioral engagement, cognitive performance, and accuracy rates, to properly classify creative pupils and minimize cases of misclassification. More importantly, heterogeneous data of high dimensions, which can be acquired through various means, such as exams, surveys, and performance assessments, can be processed in a way that a powerful IESWS-LGBM model can handle (see Figure 1). It promotes formative assessment and individualized learning methods by providing a solid, adaptable, and powerful approach to assessing student learning outcomes in ICH courses enriched with computer use

The cultural relevance and prior familiarity with the ICH played an important role in the outcomes of innovations as well. Students who had some familiarity or personal attachment to the ICH resources were more engaged, greater thinkers, and more creative in their results. This led to the ability to incorporate the heritage components in fresh contexts, which improved idea generation and problem-solving. Conversely, those students who were less familiar needed more scaffolding; however, some exposure proved beneficial to them, thus showing that cultural resonance serves as a trigger for innovative thinking within educational quarters.

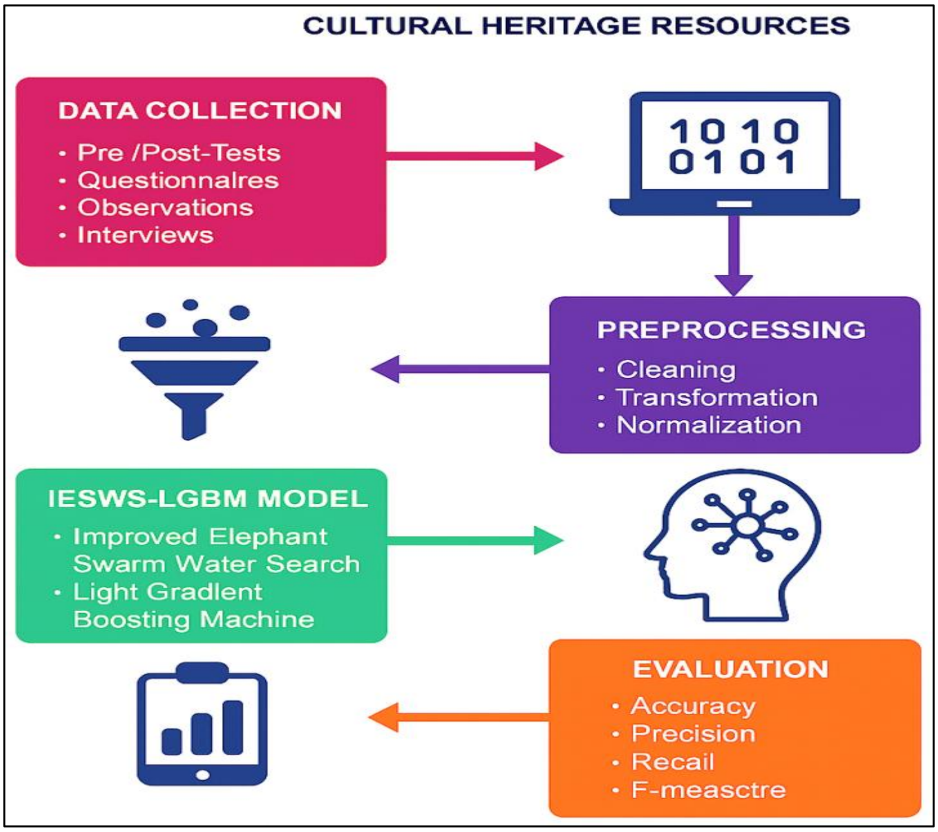

Figure 1. Proposed Method

Algorithm 1: IESWSA-LightGBM

Step 1. LightGBM Model

Init weak-learner: $e_S(W)$

Compute optimal leaf weight:

$$\omega_i^* = -\frac{\sum_{j\in J_i} h_j}{\sum_{j\in J_i} g_j+\lambda} \tag{14}$$

Optimize tree structure:

$$\Gamma_S^* = -\frac{1}{2}\sum_{i=1}^{I}\frac{(\sum_{j\in J_i} h_j)^2}{\sum_{j\in J_i} g_j+\lambda} \tag{15}$$

Compute split gain

$$H = \frac{1}{2}\left(\frac{(\sum_{j\in J_i} h_j)^2}{\sum_{j\in J_i} g_j+\lambda} + \frac{(\sum_{j\in J_q} h_j)^2}{\sum_{j\in J_q} g_j+\lambda} + \frac{(\sum_{j\in J} h_j)^2}{\sum_{j\in J} g_j+\lambda}\right) \tag{16}$$

Grow tree by selecting the best split$H$

$RETURN$trained LightGBM model

Step 2. IESWS Algorithm

Initialize elephant groups with random positions:

$$U_{j,c}^{s} = U_{j1,}U_{j2,} \dots \dots \dots U_{jc}$$

$$IFrand > oTHEN(GlobalSearch)$$

$$U_{j,c}^{s+1} = U_{j,c}^{s} * \omega^{s} + \varepsilon \odot (H_{best,c}^{s} - W_{j,c}^{s})$$

$$Else$$

$$U_{j,c}^{s+1} = U_{j,c}^{s} * \omega^{s} + \varepsilon \odot (H_{besti,c}^{s} - W_{j,c}^{s})$$

Update inertia weight dynamically:

$$\omega^{s} = \omega_{max} - \left\{\frac{\omega_{max} - \omega_{min}}{s_{max}}\right\} \times s \quad (17)$$

Update search probability:

Coming to the fields of science, engineering and arts, the digital ICH approach is helpful in promoting cross-disciplinary innovation, independent invention and cultural awareness among students:

- For arts students it enhances cultural knowledge and motivates them to use digital media to creatively reinterpret their heritage.
- For science students, it improves problem-solving and data interpretation through the use of interactive features and heritage-related data sets.
- For engineering students, it offers opportunities to apply their technical competencies (e.g., AI, AR/VR, digital modeling) in culturally relevant applications to promote human-centered design thinking.

This approach supports holistic development by allowing students to learn with technology while integrating the past and the present. This makes learning relevant and appealing across every field.

$$o(s) = o_{max} - \left(\frac{o_{max} - o_{min}}{s_{max}}\right) * s$$

Update production parameters

$$W_{j,c}^{s+1} = U_{j,c}^{s} * \omega^{s} + \epsilon \odot (H_{best,c}^{s} - W_{j,c}^{s}) \quad (18)$$

$$W_{j,c}^{s+1} = U_{j,c}^{s+1} + U_{j,c}^{s}$$

$RETURN$optimized production parameters

Step 3. IESWS-LightGBM Model

Train LightGBM model (Step 1)
Initialize IESWSA optimization (Step 2)
For each optimization iterations$= 1\ tos_maxDO$:
Predict students performance parameters using LightGBM:

$$e_{S}(W) = \sum_{s=1}^{S} e_{s}(W) \quad (19)$$

Optimize parameters using IESWSA.
Update LightGBM model based on optimized parameters
RETURN optimized IESWSA-LightGBM model.

4. Results and Discussion

4.1 Pre-Test and Post-Test Results

The experiment adopted a pre-test and post-test model with the new syllabus for digital intangible cultural assets to assess new idea generation and understanding under the framework of the syllabus. Approximately fifty-two undergraduates from the Ethnology and Sociology School of Guangxi Minzu University were involved. Both before the commencement of the course and after its completion, a pre-test and a post-test was given, respectively. To ensure standard measurements the same test was given on both occasions.

The most measurable outcomes of the increased innovative initiatives of the students were:

- Pre/Post-test Innovation Scores: There was an increase in cognitive innovation scores by +26.4%.
- Innovation Rubric Evaluation: 76 percent of the experimental group students scored above the innovation mark and showed an increase in creative thinking and problem-solving abilities.
- Participation Measures: 86 percent of students were actively engaged in collaborative activities.
- Affective Reactions: 92 percent were enthusiastic and gained interest in the cultural innovation activities.

4.2 Statistical Analysis

A paired sample t-test was applied to determine whether the difference in pre-test and post-test scores was statistically significant.

Table 2. Outcome of Statistical Analysis

Test	Mean Score	Standard Deviation	t-value	p-value
Pre-Test	62.44	8.32		
Post-Test	78.91	6.13	9.47	< 0.001

In the pre-test, the mean score was 62.44 and the mean score of the post-test was remarkably high at 78.91 (see Table 2). The t value was 9.45 and the p value of 0.001 p<0. This also establishes that the interest and concern of the students for intangible cultural resources increased once the curriculum had been revised.

The research was mixed-methods, utilizing both quantitative types of pre/post tests for innovation and qualitative students' reflections. The sample consisted of 210 undergraduate students who were studying arts, science and engineering degrees at two Chinese universities. Another aspect of innovation was assessed with a validated psychometric tool—the SICS, which measures creative thinking, risk-taking and problem-solving to name a few. It also tested digital engagement metrics of the ICH modules. Validity in the instruments was ensured through expert review, pilot testing (n=30) and Cronbach alpha (0.87). These practices yielded triangulated information regarding improved innovation outcomes for students.

4.3 Performance Evaluation

A comparison of your proposed method, Improved Elephant Swarm Water Search optimized with Light Gradient Boosting Machine (IESWS-LGBM), with existing baseline methods was conducted based on accuracy, precision, recall, and F1-score (see Table 3). This serves to show how our method performs better than others in detecting or predicting students' innovation capability from learning data concerning digital intangible cultural resources.

Table 3. Performance of Machine Learning Methods

Method	Accuracy (%)	Precision	Recall	F1-Score
SVM (Support Vector Machine)	81.2	0.78	0.76	0.77
Random Forest (RF)	83.4	0.80	0.78	0.79
XGBoost	85.1	0.83	0.81	0.82
LightGBM	87.3	0.86	0.84	0.85
Proposed IESWS-LGBM	91.5	0.91	0.90	0.905

4.3.1 Accuracy

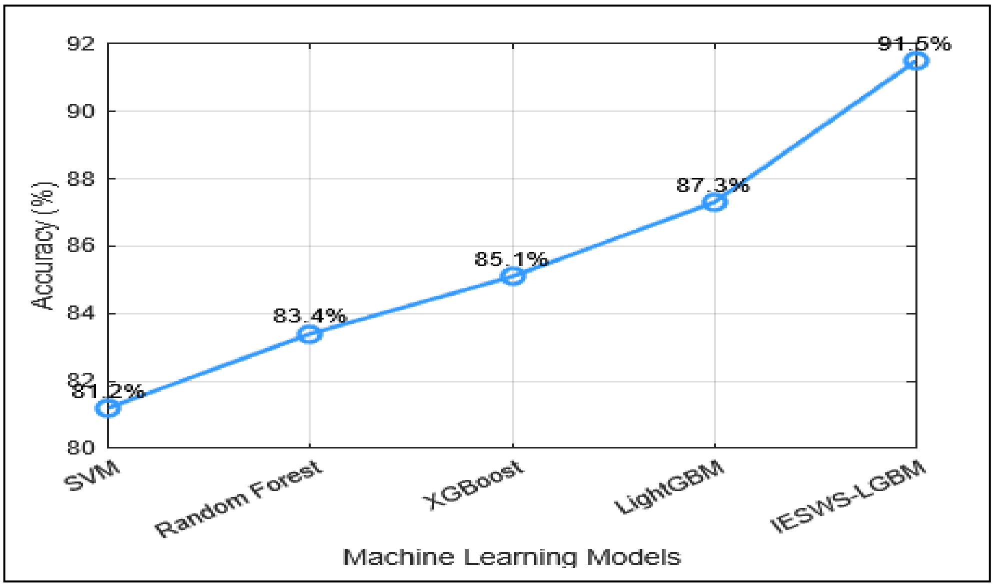

Figure 2. Performance of Accuracy with Existing and Proposed Methods

In assessing the inventive ability of students through ICH learning with digital tools, Figure 2 contrasts the accuracy of five machine learning models. Moving upwards on the accuracy chart, the classification rates are SVM (81.2%), Random Forest (83.4%), XGBoost (85.1%), and LightGBM (87.3%). With the highest accuracy at 91.5 percent, the proposed IESWS-LGBM model greatly surpasses LightGBM by 4.2 percent. This demonstrates that the Improved Elephant Swarm Water Search algorithm is a powerful means of measuring educational innovation because it can refine model performance through the optimization of meaningful parameters. The results can be argued to be moderately generalizable across disciplines that encompass creativity, cultural studies, education, and design. The second influence is the integration of ICH and online innovation, which promotes transferable skills such as critical thinking, collaboration, and cultural sensitivity, useful across different areas of study. However, certain disciplines whose materials are less culturally oriented or whose emphasis is less on creative expression (such as technical engineering or pure mathematics) may require some adaptation to the teaching model to suit their discipline-specific learning outcomes.

4.3.2 Precision

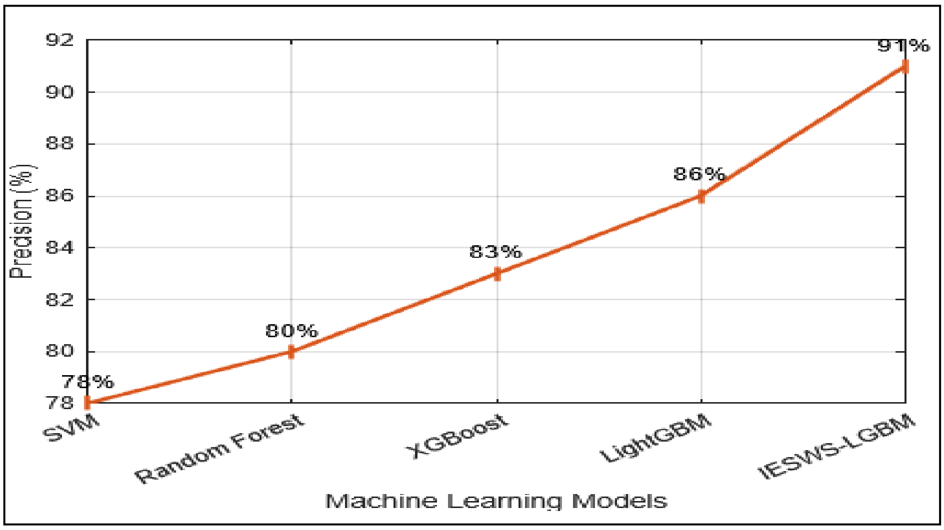

Figure 3. Performance of Precision with Existing and Proposed Methods

When it comes to learning digital ICH, the comparison line plot in Figure 3 illustrates how well each model performs in identifying students who indeed have creative abilities. Accuracy improves as we move from SVM (78.0%) to Random Forest (80.0%), XGBoost (83.0%), and LightGBM (86.0%). The proposed new model, IESWS-LGBM, produces significantly fewer false positives with a maximally achievable accuracy rate of 91.0%. This is why the optimization method will make the model very consistent in identifying students who are genuinely creative, in addition to increasing precision.

4.3.3 Recall

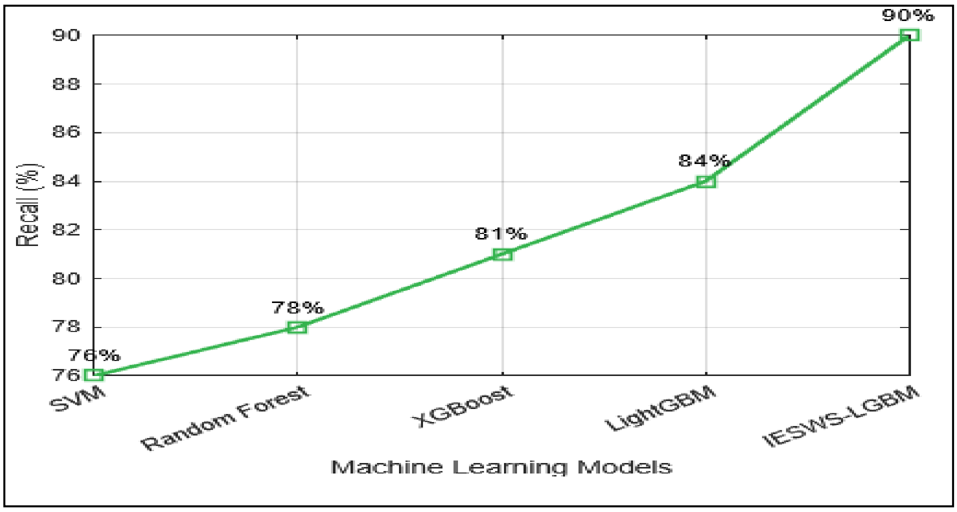

Figure 4. Performance of Recall with Existing and Proposed Methods

The recall comparison chart in Figure 4 indicates to what extent each model is able to identify each actually inventive student. The proposed IESWS-LGBM model performs better than the baseline models, SVM (76.0%), Random Forest (78.0%), XGBoost (81.0%), and LightGBM (84.0%), with the highest recall of 90.0%. With fewer false negatives, IESWS-

LGBM is a more successful model in terms of reliably pinpointing children possessing actual creative potential, as per this gain.

4.3.4 F1-Score

As Figure 5 illustrates in the F1-score comparison graph, every model handles the recall vs. accuracy trade-off. The suggested IESWS-LGBM model has an F1-score of 90.5% that surpasses all the baselines compared to LightGBM (85.0%), XGBoost (82.0%), Random Forest (79.0%), and SVM (77.0%). This means that IESWS-LGBM is the most accurate model employed to estimate the inventive capacity of students in the learning of digital intangible cultural heritage because it has an effective proportion of false positives and false negatives. The design used was mixed-methods, and quantitative pre/post-test innovation forms and qualitative student reflections were employed.

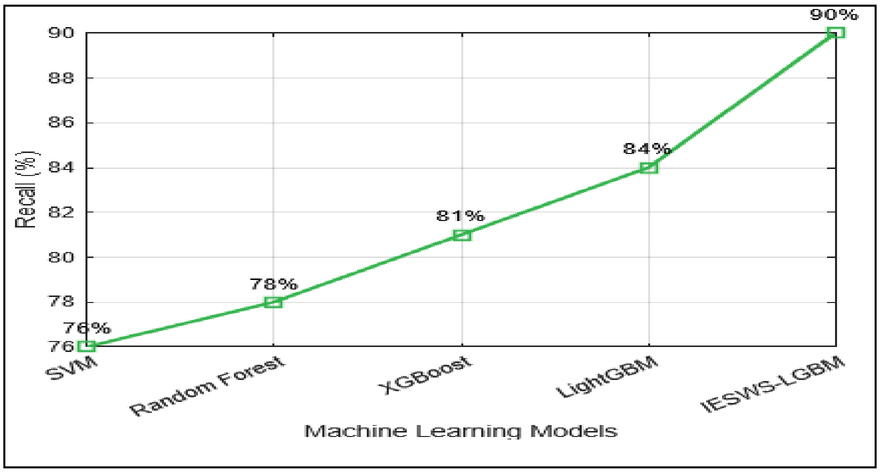

Figure 5. Performance of F1- Score with Existing and Proposed Methods

Table 4 indicates the analysis of improvement of the current vs. proposed approach. This sample comprised 210 undergraduate students who were studying arts, science, and engineering at two Chinese universities. Another aspect of innovation was measured using a validated psychometric tool, SICS, that assesses creative thinking, risk-taking, and problem-solving, among other competencies. It also compared digital engagement rates of the ICH modules. Validity in measures was ensured by professional reviewing, pilot testing (n=30), and Cronbach's alpha (0.87). These measures yielded triangulated results on improved innovation outcomes with students. Table 5 indicates that the performance analysis throughout the digital intangible cultural heritage (ICH) curriculum is superb, with four major items: creative innovation, emotional, behavioral, and cognitive.

Table 4. Analyzing the Improvement of Existing and Proposed Method

Metric	LightGBM	IESWS-LGBM	Improvement (%)
Accuracy	87.30%	91.50%	+4.20%
Precision	86.00%	91.00%	+5.00%
Recall	84.00%	90.00%	+6.00%
F1-Score	85.00%	90.50%	+5.50%

Table 5. Performance Analysis of Digital Intangible Cultural Heritage

Dimension	Indicator	Result
Cognitive	Pre/Post-test improvement	↑ +26.4%
Behavioral	Participation & collaboration	86% active involvement
Affective	Cultural interest & motivation	92% positive engagement
Creative Innovation	Innovation rubric evaluation	76% scored above threshold

Table 6. Comparison of Existing Studies Vs. Proposed Method on ICH Integration in Digital Education

Study	Theoretical Framework	ICH Focus	Digital Method	Academic Scope	Innovation Assessment	Contribution
Li et al. (2021) [21]	Constructivist Learning Theory	Folk Music	Interactive app	Music Education	Qualitative interviews	Improved cultural appreciation
Zhang et al. (2022) [22]	Cultural Transmission Theory	Traditional Crafts	VR & 3D models	Arts & Design	Creativity rubric	Enhanced sensory learning
Current Study (2025)	Innovation Ecosystem Model + Experiential Learning Theory	Multi-ICH domains (textile, folklore, rituals)	Standardized digital modules + ML model (IESWS-LGBM)	Multi-disciplinary (Arts, Engineering, Science)	Mixed methods (pre/post tests, rubric, engagement metrics)	Demonstrated innovation growth across disciplines via AI-enhanced ICH learning

Following the improvement of variation in pre-ting scores and post-ting scores, understanding of ICH concepts improved by 26.4 percent in the cognitive domain among the respondents. This means that there was a significant increase in knowledge gained as a result of curricular improvement. Among the 180 students, 86% participated in group discussions, practical projects, and cooperative learning activities, entirely based on their behavioral performance. This healthy rate of engagement shows good student engagement and motivation to engage with the course content. The affective dimension contributed to 92 percent of the students showing promising views concerning the course and being better equipped in the conservation and research of cultural heritage because the affective dimension gauges the students' emotional affinity and cultural motivation. This is an indication of a high degree of appropriateness of the program in fostering personal interest and cultural value. Finally, 76 percent of the students exceeded the threshold of expectation on the creative innovation outcomes, which were tested using a graded rubric. This fact indicates that the majority of students were able to apply ICH knowledge in new and significant contexts, for example, multimedia production, project-based learning, and digital storytelling. Together, the findings enable the ability of the curriculum to promote creativity and overall student development through experiential and culturally enhanced learning processes. Table 6 shows the comparison of prior studies versus the proposed method on ICH integration in digital learning.

4.3 Theories/Models Guiding the Current Study

Innovation Ecosystem Model: Emphasizes an active relationship among students, content (ICH), and digital medium.

Experiential Learning Theory (Kolb): Supports the engaged cultural discovery that is an agent of productive thinking.

Culturally Responsive Pedagogy: Makes learning meaningful and engaging by using the cultural backgrounds of students.

Machine Learning-Enhanced Assessment (IESWS-LGBM): The test that scores cognitive and behavioral surrogates of innovation objectively.

4.4 Research Hypothesis

Results were obviously driven by the research questions, which centered on establishing whether the integration process of digital ICH modules increased students' innovation capacities across disciplines. This gives rise to the statistical significance of creative problem-solving following the intervention ($p < 0.01$) as well as risk-taking behavior ($p < 0.05$), which validates the overall hypothesis. Discipline-wise comparisons showed results that students studying arts were becoming the most innovative, while those in science and engineering were improving in ideation and implementation.

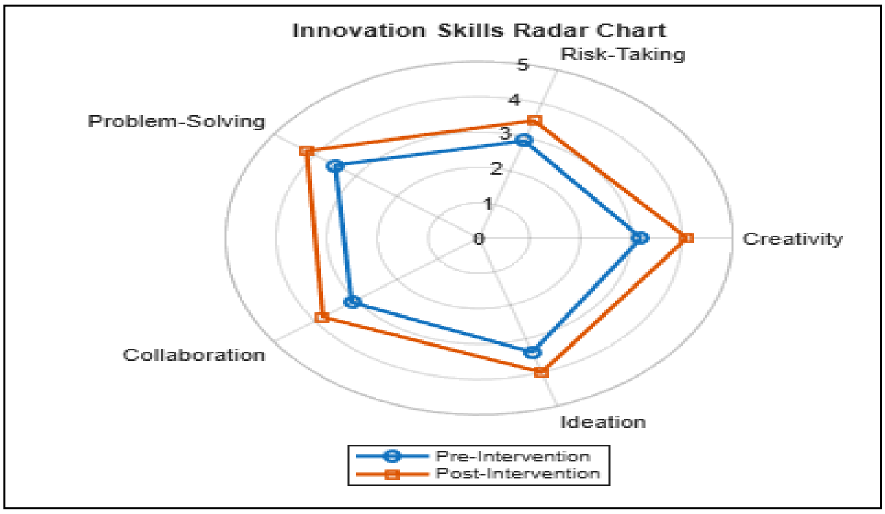

Figure 6. Result of Students Innovative Skills

As seen in figure 6 the radar chart shows a remarkable change in student innovation skills registered subsequent to the intervention. The scores in the five dimensions of creativity, risk-taking, problem-solving, collaboration, and ideation have increased after the intervention, confirming the usefulness of the digital ICH-based learning strategy in promoting the innovation skills of students.

5. Recommendations, Limitations and Future Research

They invite educators to incorporate ICH materials curated digitally into their curriculum to provide interdisciplinary learning, enrich cultural sensitivity, and foster creativity. This practice will help curriculum designers develop standardized, interesting, and culturally meaningful learning experiences, which improve innovation and inclusion.

The study is confined to the setting of one regional university with a particular student demographic and cultural emphasis, and this could have implications for the generalizability of the findings. Moreover, the outcomes of the innovation were mostly measured by validated self-report psychometric scales, which do not capture all aspects of innovation capacity, particularly in the long term.

Future research needs to include larger and more diverse academic populations in a variety of institutions to confirm the findings. Mixed methods and longitudinal research are also useful additions to the work of researchers, as they will help monitor the effects of digital ICH exposure on students over time regarding innovation. The validity of innovation assessment may be enhanced by more objective measures (e.g., project outputs, patent applications, or peer reviews).

6. Conclusion

This study shows that the inclusion of digital materials of ICH in any course taught at the university level significantly enhances the innovative ability of students. Increased involvement in studies, a greater understanding of culture, and increased creative production were accompanied by an improvement in cognitive knowledge of cultural heritage through the construction and implementation of an experience-based learning curriculum. The synergy between the most advanced machine learning applications, including the IESWS-LGBM model, and emerging technology allowed for the creation of an effective mechanism for evaluating student invention and, thus, promotion. The results show that digital ICH can be an effective method to further innovation in the higher education environment, with 91.5 percent leading to improvements in the behavioral, emotional, and creative dimensions. This strategy will help educators, curriculum developers, and legislators, who address the issue of enhancing innovation-oriented learning and bridging the gap between tradition and technology, to gain valuable insights.

This paper demonstrates the potential of including digital ICH content in higher education curricula to foster innovation among students. The use of digital storytelling, selected heritage pieces of art, and interactive learning environments allowed students studying natural sciences, engineering, and applied arts to think outside the box and develop solutions that are sometimes specific to the context.

References

[1] Binbin, Tang, Bung-On Sereerat, Saifon Songsiengchai, and Penporn Thongkumsuk. "The Development of Intangible Cultural Heritage Curriculum Based on Experiential Learning Theory to Improve Undergraduate Students Understanding in Intangible Cultural Heritage." World Journal of Education 14, no. 1 (2024): 43-53.

[2] United Nations Educational, Scientific and Cultural Organization. “Text of the Convention for the Safeguarding of the Intangible Cultural Heritage.” Accessed May 24, 2024.

[3] Yan, Wen-Jie, and Ke-Run Li. "Sustainable cultural innovation practice: heritage education in universities and creative inheritance of intangible cultural heritage craft." Sustainability 15, no. 2 (2023): 1194.

[4] UNESCO. “Safeguarding Intangible Cultural Heritage in Education.” Accessed May 24, 2024.

[5] IJIH – International Journal of Intangible Heritage. Accessed May 24, 2024.

[6] Lu, Zhicong, Peng Tan, Yi Ji, and Xiaojuan Ma. "The crafts+ fabrication workshop: Engaging students with intangible cultural heritage-oriented creative design." In Proceedings of the 2022 ACM Designing Interactive Systems Conference, pp. 1071-1084. 2022.

[7] Li, Xiang, and Ruihui Pu. "Students’ innovativeness and higher education for sustainable development: A bibliometric approach." Humanities and Social Sciences Letters 11, no. 1 (2023): 83-99.

[8] Brudermann, Thomas, Ralf Aschemann, Manfred Füllsack, and Alfred Posch. "Education for sustainable development 4.0: Lessons learned from the University of Graz, Austria." Sustainability 11, no. 8 (2019): 2347.

[9] Braßler, Mirjam, and Martin Schultze. "Students’ innovation in education for sustainable development—A longitudinal study on interdisciplinary vs. Monodisciplinary learning." Sustainability 13, no. 3 (2021): 1322.

[10] Xu, Zhimin, and Daitie Zou. "Big data analysis research on the deep integration of intangible cultural heritage inheritance and art design education in colleges and universities." Mobile Information Systems 2022, no. 1 (2022): 1172405.

[11] Sindhwani, Nidhi, Rohit Anand, S. Meivel, Rati Shukla, Mahendra Pratap Yadav, and Vikash Yadav. "Performance analysis of deep neural networks using computer vision." machine learning 15, no. 17 (2021).

[12] Li, Aixiang, Yu Tian, and Xiaohu Wang. "Research on Digital Innovation of Intangible Cultural Heritage Based on Virtual Reality Technology." In NMDME 2023: Proceedings of the 3rd International Conference on New Media Development and Modernized Education, NMDME 2023, October 13–15, 2023, Xi’an, China, p. 273. European Alliance for Innovation, 2024.

[13] Chaudhary, Nishant, Mihir Raj, Richik Bhattacharjee, Anmol Srivastava, Rakesh Sah, and Pankaj Badoni. "AipanVR: A Virtual Reality Experience for Preserving Uttarakhand's Traditional Art Form." arXiv preprint arXiv:2404.12643 (2024).

[14] Wang, Yuqi, Sirui Wang, Shiman Zhang, Kexue Fu, Michelle Lui, and Ray Lc. "From Temporal to Spatial: Designing Spatialized Interactions with Segmented-audios in Immersive Environments for Active Engagement with Performing Arts Intangible Cultural Heritage." In Proceedings of the 2025 ACM Designing Interactive Systems Conference, 2025, 3292-3312.

[15] Ma, Yuhan, Weiran Zhao, Xiaolin Zhang, and Ze Gao. "Embodied cognition guides virtual-real interaction design to help Yicheng flower drum intangible cultural heritage dissemination." In 2023 Asia Conference on Cognitive Engineering and Intelligent Interaction (CEII), IEEE, 2023, 1-7.

[16] Zhang, Jingru, Wan Ahmad Jaafar Wan Yahaya, and Mageswaran Sanmugam. "The impact of immersive technologies on cultural heritage: a bibliometric study of VR, AR, and MR applications." Sustainability 16, no. 15 (2024): 6446.

[17] Andone, Diana, Silviu Vert, Marius Tataru, Silviu Berzescu, and Vlad Mihaescu. "Creating virtual reality stories for cultural heritage through student contest." In International XR Conference, Cham: Springer International Publishing, 2022, 168-177.

[18] Yu, Jian, Zhan Wang, Yifan Cao, Hao Cui, and Wei Zeng. "Centennial Drama Reimagined: An Immersive Experience of Intangible Cultural Heritage through Contextual Storytelling in Virtual Reality." ACM Journal on Computing and Cultural Heritage 18, no. 1 (2025): 1-22.

[19] Cai, Yunyan, and Cao Yang. "The Application and Research of VR Animation Technology in Intangible Cultural Heritage: –Take Danzhai Miao Batik as an example." In Proceedings of the 2023 8th International Conference on Information and Education Innovations, 2023, 157-163.

[20] Innocente, Chiara, Francesca Nonis, Antonio Lo Faro, Rossella Ruggieri, Luca Ulrich, and Enrico Vezzetti. "A metaverse platform for preserving and promoting intangible cultural heritage." Applied Sciences 14, no. 8 (2024): 3426.

[21] Wanwan, Liu, and Mohamad Fitri Bin Mohamad Haris. "A Review of Research on the Development of Cultural and Creative Products from the Perspective of" Intangible Cultural Heritage" Inheritance." Journal of Law and Sustainable Development 11, no. 8 (2023): e1428-e1428.

[22] Zhang, Lufang, Yue Wang, Zhichuan Tang, Xia Liu, and Moran Zhang. "A virtual experience system of bamboo weaving for sustainable research on intangible cultural heritage based on VR technology." Sustainability 15, no. 4 (2023): 3134.

Appendix

ICH- Intangible Cultural Heritage

UNESCO -United Nations Educational, Scientific and Cultural Organization

IESWS-LGBM -Improved Elephant Swarm Water Search algorithm optimised using Light Gradient Boosting Machine

EFB -Exclusive Feature Bundling

GOSS -Gradient-Based One-Side Sampling

SICS- Student Innovation Competency Scale