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Exploring New Paradigms in AI-Driven Multimedia Teaching of Marine Civilization across the Taiwan Strait: Comparative Perspectives from Mainland China and Taiwan

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ABSTRACT

This study focuses on how both sides of the Taiwan Strait (Mainland China and Taiwan) reshape maritime civilization education through artificial intelligence, exploring the key role of AI technology in digital teaching material translation, cultural content representation, and cross-domain teaching models. The research adopts a mixed-methods approach, combining expert interviews and Structural Equation Modeling (SEM) to verify the causal relationships among five dimensions: "policy culture, technology integration, cultural connotation, teaching practice, and cross-domain cooperation." The results show that technology integration serves as the mediating core of AI teaching transformation, significantly enhancing cultural interpretation and teaching effectiveness while promoting cross-strait cooperation dynamics. While policy culture provides institutional impetus, it requires technological and cultural translation mechanisms to transform into substantial teaching innovation. The research further constructs a five-ring model of "policy-driven—technology-mediated—culture-translated—teaching-practiced—cooperation-expanded," indicating that maritime civilization AI teaching should move toward narrative transformation that integrates cultural sensitivity and field adaptability. This framework can serve as an important reference for cross-strait smart education collaboration and cultural sustainability co-construction, while providing theoretical innovation and strategic insights for the global AI + maritime civilization cultural education field.

KEYWORDS

Cross-strait culture, Maritime civilization, Artificial intelligence, Digital media, New teaching paradigm.

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1. INTRODUCTION

SINCE the 21st century, the world has been facing unprecedented ecological transformation and knowledge reconstruction. The ocean, as the birthplace of human civilization and a key field for sustainable development, has increasingly highlighted the importance of its educational dissemination [1]. Against the backdrop of climate change, resource depletion, and international maritime competition and cooperation, how to enhance public awareness and action regarding maritime civilization through educational means has become an important issue in higher education and cultural communication. Meanwhile, the rapid development of Artificial Intelligence (AI) technology is profoundly changing the basic logic of education, communication, and cognitive systems, opening a new era of smart education.

In this historical context, the dissemination of maritime civilization should not remain limited to traditional narratives and static graphics, but should integrate multimedia sensory interaction, knowledge graph construction, and intelligent algorithm recommendations to promote deep integration of knowledge systems and perceptual experiences, responding to the learning characteristics and cultural absorption pathways of the digital generation [2-6]. Although there are differences between the two sides of the Taiwan Strait in maritime geography, cultural traditions, and educational systems, they both face the dual challenges of digital education transformation and maritime awareness enhancement. Therefore, collaborative exploration in artificial intelligence and multimedia teaching fields is particularly valuable and strategically forward-looking [7,8].

From the perspective of technological evolution, artificial intelligence has been widely applied in educational fields, including intelligent Q&A systems, personalized learning path recommendations, virtual teaching assistants, and immersive experience environment construction. Its core value lies in "data-driven cognition," "algorithm-enhanced interaction," and "systematic knowledge visualization" [9-11]. The educational content of maritime civilization encompasses interdisciplinary materials including geography, biology, history, culture, and philosophy, which urgently need AI for cross-modal integration and semantic-level analysis, thereby translating into understandable, perceptible, and internalizable knowledge experiences [12,13].

This study attempts to construct a composite teaching framework that integrates technology, culture, and education. First, it focuses on the institutional similarities and differences between Taiwan and Mainland China in the development trajectory of AI educational technology, analyzing their respective policy promotion, platform construction, and curriculum innovation practices regarding AI technology applications in teaching within higher education systems [14,15]. Second, through multimedia design and content analysis, it evaluates the perceptual experience, user engagement, and knowledge transmission efficiency of current multimedia teaching materials in maritime civilization education [16,17]. Furthermore, combining in-depth interviews and Structural Equation Modeling (SEM) methods, it verifies the impact mechanisms of AI intervention on educational indicators such as learning motivation, cognitive understanding, and cultural identity [18-20].
The application of artificial intelligence in teaching fields needs to address three core challenges: (1) Knowledge translation mechanisms: how to semantically deconstruct and visually reorganize the non-linear, cross-temporal knowledge content in maritime civilization through AI models; (2) Learner interactivity design: how to enhance students' cultural understanding and field experience through multimodal learning; (3) New paradigmatic teaching logic: AI systems are not just tools but may become "digital co-creators" in collaborative teaching, reconstructing teacher-student interaction logic and knowledge generation models [21-23].

To address the current challenges and opportunities in maritime education, this study aims to fill three critical research gaps. First, although AI and multimedia technologies are widely applied in general education, there is a lack of integrative frameworks specifically tailored to the cross-disciplinary and cultural-rich domain of maritime civilization. Second, current studies often neglect the learner's sensory experience and cultural identity formation in digital teaching environments. Third, few empirical studies conduct comparative analyses between regions with both shared cultural roots and divergent socio-political systems.

To bridge these gaps, this study sets out with the following objectives:

(1) To compare the institutional trajectories and policy implementations of AI-powered education between Taiwan and Mainland China,

(2) To analyze the effectiveness of multimedia teaching materials in conveying maritime civilization across different educational systems, and

(3) To evaluate the impact of AI interventions on students' motivation, cognitive processing, and cultural identity using qualitative interviews and SEM analysis.

In summary, this study is not only an attempt at technological innovation in teaching methods but also a response to the educational mission of maritime cultural revival and ecological civilization construction. Cross-media maritime teaching empowered by artificial intelligence is expected to break knowledge barriers, contextual isolation, and cultural misunderstanding, leading teachers and students from both sides of the strait toward deeper understanding and consensus, while providing a new path with Eastern wisdom and local empirical evidence for global educational paradigm reshaping.

1.1 Development Context of Maritime Civilization Education and Evolution of Multimedia Teaching

Maritime civilization, as an important component of human history and culture, encompasses multiple dimensions including history, humanities, geography, ecology, and technology [24]. In the educational systems of both sides of the strait, maritime civilization teaching inherits traditional narrative modes of geography and history subjects while increasingly integrating concepts of environmental education, sustainable development, and cultural heritage. However, traditional teaching is often limited to static materials and knowledge indoctrination, making it difficult to inspire students' deep resonance and critical thinking about maritime culture [25-27].

Since the 2000s, multimedia teaching technology has gradually been applied to maritime-themed teaching, such as 3D terrain simulation, marine ecosystem VR experiences, and interactive map platforms, providing learners with immersive and multi-sensory learning pathways. Especially in coastal universities in Taiwan and Mainland China, multimedia teaching has been regarded as a key tool for enhancing maritime awareness, promoting local identity, and inspiring exploratory spirit. However, most applications still remain at the technical level, lacking deep construction of cultural narratives and cross-domain integration strategies, indicating that current maritime civilization education needs to transcend information transmission and move toward value-oriented and critical thinking-based new teaching paradigms [28].

1.2 Application of Artificial Intelligence in Teaching and Cross-Strait Development Comparison

The application of Artificial Intelligence (AI) in educational contexts has rapidly evolved, progressing from early adaptive learning platforms and intelligent assessment systems to more sophisticated functions such as semantic understanding, learning style identification, and AI-driven virtual teaching assistants. In multimedia education, AI technologies—such as image recognition, voice interaction, knowledge graph construction, and generative content creation tools (e.g., ChatGPT and Midjourney)—enable increasingly personalized, interactive, and context-sensitive teaching experiences [4,29].

Across the Taiwan Strait, notable differences exist in the implementation and orientation of AI applications in education, which are closely tied to distinct policy environments and developmental strategies. In Mainland China, AI education initiatives are largely policy-driven, supported by top-down strategies that promote large-scale, systematized integration. Initiatives such as Huawei Education Cloud, smart classroom pilot programs, and AI-powered classroom evaluation platforms are representative of this approach. These efforts are typically embedded within national education modernization plans and emphasize efficiency, scalability, and technological infrastructure.

In contrast, Taiwan's application of AI in education is more decentralized and innovation-oriented, often emerging from local pilot programs and research-driven experimentation. AI is employed not only to enhance pedagogical effectiveness but also to cultivate cultural sensitivity and creativity. For example, Taiwanese educators and researchers have explored using AI to co-create digital materials that reflect regional cultures, marine ecosystems, and indigenous heritage—highlighting an emphasis on educational diversity, humanistic integration, and community-based engagement.

These policy and developmental differences reflect deeper epistemological divergences: while the Mainland emphasizes the scientification of knowledge and technological standardization, Taiwan tends to prioritize cultural narrativization and contextual learning. This divergence underscores not only the complementary potentials of both systems but also the challenges in forming an integrative AI education framework that bridges algorithmic logic with cultural depth and meaningful human interaction.

1.3 New Teaching Paradigm: From Cross-Domain Integration to Narrative Translation

In recent years, educational research has shifted toward new teaching paradigms centered on "cross-domain integration" and "narrative-driven" approaches, emphasizing that knowledge should not be taught in isolation but should be constructed within contexts, culture, and social practice. AI-assisted multimedia teaching systems, if only emphasizing technical efficiency, may easily become instrumentalized and decontextualized; only through cross-disciplinary knowledge integration and narrative translation strategies can learners' cultural perception, critical abilities, and innovative practice be activated [30].

Under this trend, "AI + narrative design" is regarded as a potentially new teaching modality, utilizing AI generation technology (such as semantic expansion, text style conversion, and automatic image splicing), combined with cultural stories, historical contexts, and landscape changes, to form dynamic and interactive learning fields. This model not only helps break through traditional teaching content limitations but also provides expandable personalized learning journeys, enhancing students' knowledge construction and learning motivation [31,32].

However, current related practices mostly remain at the theoretical exploration or small-scale experimental stage, lacking integrated models specifically addressing the special knowledge systems and multimodal learning needs of "maritime civilization." The heterogeneity of the two sides of the strait in historical context, cultural perspectives, and teaching systems also provides a unique comparative perspective, helping to construct an AI-driven teaching paradigm that can respond to global maritime cultural education challenges [33].

This study adopts mixed research methods, conducting in-depth interviews with three educational experts from both sides of the strait who have backgrounds in AI applications and cultural teaching to construct a core element matrix for teaching innovation; then using Structural Equation Modeling (SEM) to verify the impact pathways of AI intervention on learning effectiveness, cultural perception, and teaching identity, combined with case analysis to propose new teaching paradigm prototype designs.

The purposes of this study are as follows:

1. Compare the development contexts and technological application gaps of "AI + cultural education" policies across the strait, constructing paradigmatic models for regional collaboration.
2. Extract core elements of maritime civilization teaching that can be AI-translated and multimedia-represented, designing digital teaching material frameworks with cultural depth and technical feasibility.
3. Construct a "content-technology-context" trinity intelligent teaching model, achieving transformation from "display-based teaching" to "co-creative learning."
4. Propose suggestions for cross-strait AI teacher collaboration platforms, such as establishing maritime civilization digital co-editing laboratories and cross-regional AI curriculum joint development mechanisms.
5. Respond to contemporary issues such as "knowledge democratization" and "technological ethics," promoting sustainable co-prosperity of artificial intelligence and maritime civilization in teaching fields.

Through this study, we expect to bring new dynamics combining artificial intelligence and maritime narrative to cross-strait digital cultural education, and at the intersection of digital humanities and educational technology integration, depict teaching paradigms with cultural roots, global vision, and technological foresight, realizing the vision of "AI empowering cultural education, civilization co-constructing digital future."

The research framework is shown in Figure 1 and the new paradigm of multimedia teaching of artificial intelligence ocean civilization across the Taiwan Strait is shown in Figure 2:

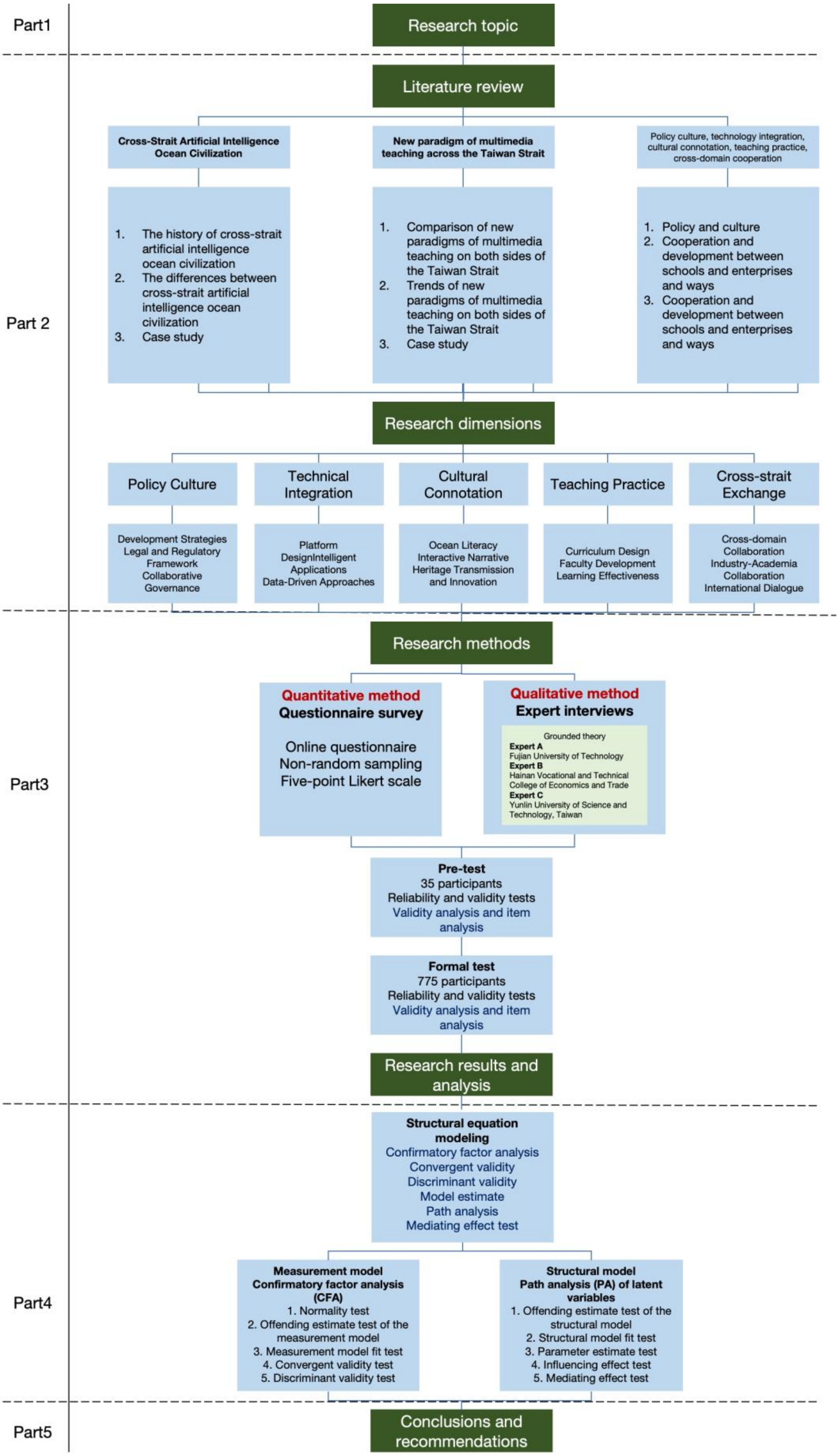

Figure 1. Research Framework.

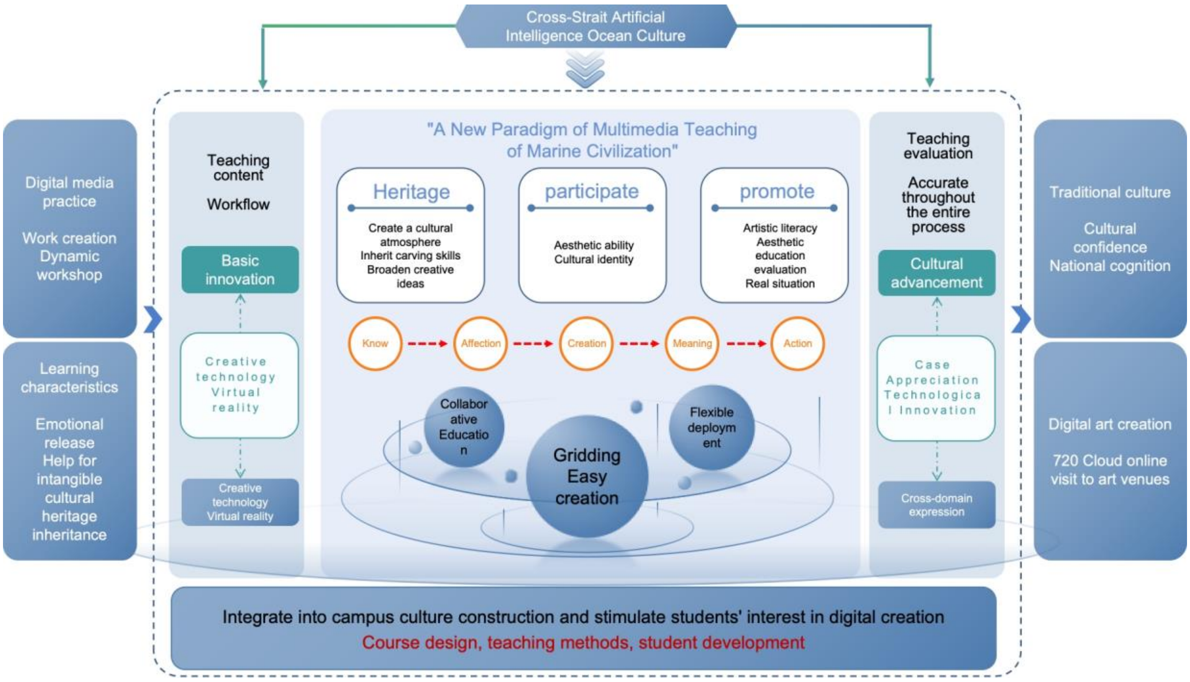

Figure 2. Cross-Strait Artificial Intelligence Maritime Civilization Multimedia Teaching New Paradigm.

2. RESEARCH METHODS

This study adopts a semi-structured expert interview method, focusing on how both sides of the Taiwan Strait utilize artificial intelligence technology in multimedia teaching construction and teaching paradigm innovation for maritime civilization themes. Experts from three major fields—digital humanities, educational technology, and smart learning applications—were invited for in-depth exchanges, with interviews lasting approximately 30 minutes. Through these interviews, the research team was able to extract similarities and differences in content construction strategies for maritime civilization education across the strait, AI application boundaries and potential, and feasible integrated new teaching paradigms for the future. The expert interview subjects are shown in Table 1.

Table 1. Expert Interview Subjects.

Code	Interviewee	Position	Institution	Years of experience	Related Directions/Research Achievements
A	Lin〇〇	Lecturer	Fujian University of Technology, School of Smart Ocean Science and Technology	3	Digital narrative and cultural multimedia teaching, marine-themed XR teaching material design, Taiwan local culture and educational technology integration research
B	Duan 〇〇	Associate Professor	Hainan College of Economics and Business, International Education College	15	AI in semantic understanding and cross-cultural learning applications, generative teaching material design, smart learning systems and human-computer interaction research
C	Wang 〇〇	Professor	National Yunlin University of Science and Technology, College of Design	25	Marine cultural education, cross-strait marine beliefs and folk teaching material construction, regional cultural teaching design and geographical digital teaching integration strategies

The interview outline of this study is based on the open coding principles of Grounded Theory, approaching from five major dimensions: conceptual, social, developmental, technical, and trend aspects. The interview question design balances theoretical depth with practical operability, extracting core elements through expert perspectives, ultimately focusing research topics on teaching content design logic, AI application scenarios, cultural narrative strategies, and teaching innovation models, serving as theoretical basis for subsequent quantitative questionnaire design and teaching model construction. The expert interview items are shown in Table 2.

Table 2. Expert Interview Items.

A. Conceptual Aspect	A-1 How do you define the relationship between "AI integration in teaching" and "digitalization of maritime civilization education"? Are there differences in understanding these two concepts in educational fields across the strait?
	A-2 Do you think AI-assisted teaching will reconstruct traditional ways of maritime cultural knowledge transmission? How can cultural authenticity be maintained in technological applications?
	A-3 What are the differences in maritime cultural narratives and teaching material design concepts across the strait? How do these differences affect the generation logic of AI teaching materials?
B. Social Aspect	B-1 How do you view the similarities and differences in social acceptance and value consciousness of maritime civilization as regional culture in education across the strait? Does this affect teaching promotion effectiveness?
	B-2 How do you view the role of communities and cultural institutions (such as cultural heritage museums, maritime museums) across the strait in promoting AI teaching cooperation? Is local participation a key factor in teaching success?
	B-3 Might AI intervention cause "knowledge intermediation gaps"? Especially in traditional communities like indigenous peoples, fishing villages, and ports, might technological gaps lead to cultural marginalization?
C. Developmental Aspect	C-1 Taiwan has introduced XR technology for marine teaching, while the mainland emphasizes AI + vocational education platform construction. What do you think are the practical benefits and challenges of these two strategies?
	C-2 Do both sides of the strait currently have shareable "smart teaching material resource libraries"? If not, how should cross-border sharing mechanisms be established?
	C-3 How do you think a multimedia course module compatible with AI applications and maritime knowledge content should be designed? Should cross-school, cross-regional alliances be established for promotion?
D. Technical Aspect	D-1 How should content accuracy and cultural sensitivity risks be assessed and controlled when AI-generated teaching materials (such as ChatGPT, Midjourney) are applied to maritime civilization narratives?
	D-2 Which AI technologies (XR, VR, semantic recognition) do you think have the most potential in maritime teaching? Why? Are there specific cases?
	D-3 Are there obvious technological gaps or development concept differences in AI teaching platform development across the strait? Will this affect the possibility of cooperative practice?
E. Trend Aspect	E-1 What do you predict will be the mainstream technologies and teaching forms for introducing AI in maritime civilization teaching across the strait in the next five years? Will there be new paradigm shifts?
	E-2 As the world is currently focusing on "ocean sustainability" and "blue education," do you think AI technology can effectively promote the integration of environmental education and cultural awareness?

	E-3 If we envision establishing a "Greater China Maritime Civilization Smart Education Alliance," what institutional and technological barriers do you think should be prioritized? Is there a foundation for policy support?

2.1 Structural Equation Modeling

This study adopts Structural Equation Modeling (SEM), integrating Confirmatory Factor Analysis (CFA) and Path Analysis to systematically quantify the multi-dimensional interaction mechanisms and efficiency transformation relationships involved in the process of AI integration into maritime civilization multimedia teaching across the strait. Additionally, this study designs a multi-group comparison model (multi-group SEM), using Taiwan and Mainland China as grouping variables to analyze structural stability and path strength differences of model dimensions under different policy systems, teacher role cognition, and AI teaching practice differences across the strait. Finally, SEM model results will be cross-validated with qualitative data from expert interviews to provide theoretical basis and strategic recommendations for future cross-strait educational innovation and cultural collaboration driven by artificial intelligence.

2.1.1 Questionnaire Design

This study focuses on university teachers, multimedia teaching designers, and teaching administrators in both Mainland China and Taiwan. To ensure representative and structured data collection, a stratified sampling method was adopted, considering differences in teacher ranks (e.g., assistant, associate, full professors), institutional levels (e.g., comprehensive universities, technological institutes), and regional digital education policy environments. A Likert five-point scale online questionnaire was employed to quantitatively examine key factors in AI-assisted maritime civilization teaching across the strait, including policy support, technology integration, teaching material innovation, cultural connotation, teaching practice, and cross-domain collaboration.

The sampling process began with a pilot study, during which 32 valid responses were collected. Based on Cronbach's α reliability analysis and Exploratory Factor Analysis (EFA), three items with factor loadings below 0.6 were removed to refine the instrument. The formal questionnaire ultimately consisted of 75 observed variables. Following Boomsma's (1985) guideline recommending a minimum sample size of ten times the number of observed variables for Structural Equation Modeling (SEM), a final sample of 812 valid responses was obtained—414 from Mainland China and 398 from Taiwan. This distribution ensured sufficient coverage and comparative validity across regions and respondent categories. Notably, questionnaire items D03, E02, and E14 were reverse-coded, with numerical conversion completed prior to statistical analysis. The full structure of the questionnaire is presented in Table 3.

Table 3. Questionnaire Item Design.

Policy Culture	
Development Strategies	
A01	Government promotes clear planning directions for AI integration in marine education.
A02	Both educational departments establish unified consensus on the development of AI in marine education.
A03	AI technology integration in curricula incorporates educational innovation strategies.
A04	Marine cultural works serve as distinctive educational resources with autonomous local characteristics.
A05	Local governments demonstrate innovative approaches to marine education without practical constraints.
Legal and Regulatory Framework	
A06	Both educational sectors establish comprehensive policy foundations with legal support regarding AI in marine education.
A07	Comprehensive safeguarding mechanisms exist for student privacy protection in AI-enhanced marine education.
A08	Cross-boundary data and digital content exchange tools comply with legal regulations.
A09	Schools implementing AI marine education equipment receive institutional guidance and support.
A10	Multimedia course content and cultural discussions follow independent core regulations.
Collaborative Governance	
A11	Education, technology, and cultural departments establish comprehensive cross-sector collaborative mechanisms.

A12	Both educational sectors possess ongoing periodic collaborative discussion forums.
A13	New territories and students receive comprehensive support for marine education research and learning environments.
A14	Industry research platforms integrate marine education promotion with practical application.
A15	Multi-party governance frameworks provide assistance for enhancing policy effectiveness.
Technical Integration	
Platform Design	
B01	AI marine education platforms operate with systematic interface design and functionality.
B02	Multimedia content and interactive learning achieve optimal integration.
B03	Support for personalized learning pathways enables systematic design optimization.
B04	Platforms enable real-time data collection and analytical support.
B05	Systems support cross-device access with seamless platform connectivity.
Intelligent Applications	
B06	AI foundation reporting supports quality medical research in marine education.
B07	Voice recognition and image processing technologies achieve maturity in educational applications.
B08	Intelligent tutoring enables automated response learning environments.
B09	Virtual reality integrates with AI to enhance marine learning scenarios.
B10	AI technologies provide scientific life-long learning updates in marine education with high effectiveness.
Data-Driven Approaches	
B11	Educational platforms possess comprehensive learning analytics capabilities.
B12	Learning data analysis supports predictive modeling and personalized risk assessment.
B13	Systems enable adaptive learning mechanisms with real-time responsiveness.
B14	Teachers receive real-time monitoring of educational effectiveness and data-driven feedback.
B15	Data analytics integration provides assistance for optimizing educational content precision.
Cultural Connotation	
Ocean Literacy	
C01	Educational materials present comprehensive marine historical knowledge through shared historical perspectives.
C02	Students develop understanding of marine ecosystems and human relationships.
C03	Educational applications integrate marine management, sustainability, and civilization development.
C04	Students utilize AI-driven interactive marine environmental information systems.
C05	Learning content integrates cultural depth with regional characteristics.
Interactive Narrative	
C06	Courses enable narrative-based storytelling approaches for conveying marine knowledge.
C07	Educational design incorporates situational guidance and marine resource elements.
C08	Systems enable interactive learning experiences for developing personalized chemical learning scenarios.
C09	Students develop multimedia creative works to express learning outcomes.
C10	Digital content integrates emotional engagement with cultural resonance.
Heritage Transmission and Innovation	
C11	Educational design enables students to explore and inherit marine cultural heritage.
C12	Integration of modern technology with historical materials enables cultural transmission.
C13	AI systems enable cultural heritage and innovative learning modalities.
C14	Students develop appreciation for creative activities and cultural understanding.
C15	Educational materials foster appreciation for local marine cultural identity.
Teaching Practice	
Curriculum Design	

D01	Course architecture possesses scientific and comprehensive depth.
D02	Educational design enables comprehensive technology integration and educational objectives.
D03	Students receive adequate support for marine education through responsive feedback (Reflection Questions).
D04	Educational content updates maintain synchronization with marine current events.
D05	Courses evaluate and incorporate academic practices with innovative expression.
Faculty Development	
D06	Teachers receive comprehensive AI marine education training programs.
D07	Teachers demonstrate application capabilities and workshop-based course design.
D08	Training addresses integration and collaborative development of educational capabilities.
D09	Teachers establish regular marine cultural and educational workshop experiences.
D10	AI platforms support teachers with continuous knowledge updates and feedback training.
Learning Effectiveness	
D11	Students demonstrate clear understanding and comprehension of marine civilization knowledge.
D12	Learning outcomes integrate practical application with innovative value creation.
D13	Students actively participate in interactive activities that enhance learning capabilities.
D14	Students develop comprehensive marine problem-solving and critical thinking abilities.
D15	Learning experiences support field research integration with cultural understanding.
Cross-strait Exchange	
Cross-domain Collaboration	
E01	Both educational sectors share AI educational content and knowledge resources.
E02	Students receive opportunities for cross-regional marine thematic collaboration (Reflection Questions).
E03	Teachers participate collectively in curriculum design discussions and educational practice.
E04	Bilateral school platforms enhance AI educational platform resource sharing.
E05	Cross-cultural educational activities promote marine educational activities through student dialogue.
Industry-Academia Collaboration	
E06	Enterprises participate in educational platform development and content design.
E07	Marine cultural enterprises provide case studies for educational materials.
E08	Practical applications and employment resource integration into educational platform regulations.
E09	Students receive opportunities to participate in AI-supported cultural industry projects.
E10	Schools collaborate with industry communities to evaluate learning effectiveness and capability enhancement.
International Dialogue	
E11	Educational platforms enable connections with international marine education institutions and curricula.
E12	Course systems enable student participation in international marine language competitions.
E13	Collaboration with international educational institutions enables shared research in AI educational models.
E14	Students develop multicultural linguistic capabilities for comprehensive global perspectives (Reflection Questions).
E15	Educational evaluation incorporates international standards and benchmarking guidance.

2.2 Research Hypotheses

The research hypotheses aim to verify the causal relationships and pathways among various dimensions in smart teaching transformation and maritime cultural digital heritage across the strait, exploring how artificial intelligence affects the interactive dynamics among teacher training mechanisms, digital teaching content construction, and student learning experiences.

The research hypotheses are as follows:

- H01: Policy culture has a significant positive impact on technology integration
- H02: Policy culture has a significant positive impact on cultural connotation

- H03: Policy culture has a significant positive impact on teaching practice
- H04: Policy culture has a significant positive impact on cross-domain cooperation
- H05: Technology integration has a significant positive impact on cultural connotation
- H06: Technology integration has a significant positive impact on teaching practice
- H07: Technology integration has a significant positive impact on cross-domain cooperation
- H08: Cultural connotation has a significant positive impact on teaching practice
- H09: Cultural connotation has a significant positive impact on cross-domain cooperation
- H10: Teaching practice has a significant positive impact on cross-domain cooperation

3. RESEARCH ANALYSIS

3.1 Expert Interview Analysis

This study explores key construction elements for introducing artificial intelligence into maritime civilization multimedia teaching across the strait through expert interviews, targeting maritime education, artificial intelligence applications, and teaching innovation fields, synthesizing interview recommendations from 3 experts from universities in design and vocational education fields across the strait. These 5 dimensions highlight institutional differences and practical collaborative potential for AI integration in maritime civilization teaching across the strait, serving as theoretical construction and application foundation for future cross-domain multimedia teaching innovation models. The expert interview summary elements are shown in Table 4.

Table 4. Expert Interview Summary Elements.

No.	Dimension	Key Points and Elements
1	Development Policy and Institutional Foundation	1. Different policy orientations: Mainland includes "AI + Education" in the "Education Digitalization Strategic Action," emphasizing platform construction and technology popularization; Taiwan uses the "Higher Education Sprout Project" to promote "cultural digital narrative" as the core of local innovation. 2. Curriculum system flexibility: Mainland promotes "AI profession + education application dual-track parallel," Taiwan emphasizes curriculum modularization and experimental teaching field flexibility. 3. Digital teaching material review process differences: Mainland adopts ministerial filing or platform review, Taiwan tends toward teacher-autonomous development and internal departmental review.
2	Teaching Material Translation and Cultural Depth Construction	1. Different cultural content handling strategies: Taiwan emphasizes cultural diversity and indigenous maritime perspective reproduction; Mainland focuses on "Chinese maritime rights historical perspective" and "Belt and Road" maritime narrative. 2. AI-generated content quality control mechanisms: Taiwan experimental labs encourage teachers to manually revise AI-generated texts, Mainland focuses on corpus cleaning and automated model review. 3. Teaching material development process: Taiwan teachers mostly use open resource collaboration (such as CC-licensed works), Mainland mostly integrates official platforms (such as smart education resource libraries) for material licensing and co-construction.
3	Teacher Digital Literacy and Teaching Innovation Capacity	1. Different digital capability focuses: Mainland emphasizes platform operation and system application capabilities, Taiwan emphasizes cross-modal narrative and visual design logic.

		2. Teacher AI application levels: Taiwan teachers emphasize the narrative possibilities of "AI as co-creator," Mainland teachers focus on the teaching effectiveness of "AI as auxiliary tool." 3. Differences in digital creative education backgrounds across the strait: Taiwan design and humanities teachers generally receive digital content editing training, Mainland teachers mostly come from technical engineering backgrounds.
4	Student Participation and Learning Model Differences	1. Learner role positioning: Taiwan students prefer role-playing, situational tasks, and virtual cultural interaction; Mainland students tend toward information-receiving and outcome-oriented learning. 2. Interactive design integration: Taiwan AI courses integrate design thinking and narrative games, Mainland tends toward fixed process modular learning. 3. Student creative outcome orientation: Taiwan tends toward group co-creation and cross-domain performance, Mainland emphasizes structured portfolios and standardized scoring.
5	Collaboration Mechanisms and Future Recommendations	1. Cross-strait institutional complementarity potential: Can combine Taiwan's cultural cultivation strength with Mainland's technology platform capabilities to co-build AI cultural teaching laboratories. 2. Co-construction standards and shared platforms: Recommend developing "AI Cultural Teaching Standard Reference System" and "Cross-Strait Co-built Knowledge Graph" to enhance cross-regional collaboration efficiency. 3. Digital ethics and review framework: Can collaborate to establish "AI Cultural Teaching Material Ethics Guidelines" and "Cross-Strait AI-Generated Content Review White Paper" to reduce cultural misunderstanding and narrative conflict risks.

3.2 Quantitative Analysis

3.2.1 Demographic Variables

To understand the basic situation of survey subjects, this study uses descriptive statistics to analyze basic information. The descriptive statistical analysis results are shown in Table 5.

Table 5. Descriptive Statistical Analysis.

Name	Option	Frequency	Percentage (%)	Cumulative Percentage (%)
Gender	Male	414	53.4	53.4
	Female	361	46.6	100.0
Age	18-20 years	189	24.4	24.4
	21-40 years	186	24.0	48.4
	41-65 years	209	27.0	75.4
	Over 65 years	191	24.6	100.0
Region	Mainland	374	48.3	48.3
	Taiwan	401	51.7	100.0
Education Level	College/University	245	31.6	31.6
	Master's	261	33.7	65.3
	Doctorate	269	34.7	100.0
Education Category	Natural Sciences	384	49.5	49.5
	Social Sciences	391	50.5	100.0
Marital Status	Previously Married	366	47.2	47.2

	Currently Unmarried	409	52.8	100.0
Monthly Income	Under 10,000	208	26.8	26.8
	10,000-20,000	181	23.4	50.2
	20,000-30,000	203	26.2	76.4
	Over 30,000	183	23.6	100.0
	Total	775	100.0	

3.2.2 Reliability Analysis

Scale data is selected for reliability and validity analysis, using Cronbach's Alpha to analyze data reliability. In reliability analysis, Cronbach's Alpha coefficient generally needs to reach above 0.7 to reflect high questionnaire reliability, allowing for further in-depth analysis of related correlations. From the table below, it can be seen that the Cronbach's Alpha coefficients for each dimension and the total questionnaire are all greater than 0.7, while CITC is greater than 0.4, and the Cronbach's coefficients after deletion are all smaller than the dimension's Cronbach's coefficient, indicating high overall questionnaire reliability with no items needing removal. The reliability analysis is shown in Table 6.

Table 6. Reliability Analysis.

Dimension	Item	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	Cronbach's Alpha	Overall Cronbach's Alpha
Policy Culture	A01	52.61	137.152	0.785	0.964	0.966	0.961
	A02	52.63	136.114	0.819	0.964		
	A03	52.61	136.407	0.805	0.964		
	A04	52.58	136.202	0.809	0.964		
	A05	52.60	136.980	0.796	0.964		
	A06	52.59	136.536	0.813	0.964		
	A07	52.59	136.374	0.807	0.964		
	A08	52.61	136.651	0.796	0.964		
	A09	52.60	135.910	0.815	0.964		
	A10	52.60	136.163	0.810	0.964		
	A11	52.59	136.840	0.797	0.964		
	A12	52.59	136.382	0.800	0.964		
	A13	52.64	136.862	0.800	0.964		
	A14	52.58	136.089	0.811	0.964		
	A15	52.61	139.138	0.677	0.966		
Technology Integration	B01	45.44	184.118	0.772	0.960	0.963	
	B02	45.39	183.868	0.781	0.960		
	B03	45.44	183.717	0.783	0.960		
	B04	45.35	184.450	0.761	0.960		
	B05	45.39	184.942	0.771	0.960		
	B06	45.41	184.146	0.774	0.960		
	B07	45.42	183.734	0.787	0.960		
	B08	45.35	184.815	0.780	0.960		

	B09	45.40	182.837	0.791	0.960	
	B10	45.46	183.512	0.785	0.960	
	B11	45.42	184.347	0.779	0.960	
	B12	45.37	185.019	0.766	0.960	
	B13	45.43	184.229	0.777	0.960	
	B14	45.37	183.027	0.802	0.960	
	B15	45.45	183.478	0.776	0.960	
Cultural Connotation	C01	45.09	202.350	0.806	0.963	0.966
	C02	45.06	203.777	0.788	0.964	
	C03	44.99	204.200	0.793	0.964	
	C04	45.03	204.396	0.788	0.964	
	C05	45.05	202.645	0.804	0.964	
	C06	45.02	203.432	0.795	0.964	
	C07	45.01	202.406	0.803	0.964	
	C08	45.01	201.878	0.808	0.963	
	C09	45.04	204.175	0.781	0.964	
	C10	45.02	203.740	0.790	0.964	
	C11	45.03	203.655	0.787	0.964	
	C12	45.02	203.475	0.796	0.964	
	C13	45.04	202.575	0.798	0.964	
	C14	45.00	204.050	0.787	0.964	
	C15	45.04	203.028	0.793	0.964	
Teaching Practice	D01	43.14	178.808	0.788	0.962	0.965
	D02	43.25	178.285	0.785	0.962	
	D03	43.21	179.138	0.786	0.962	
	D04	43.24	177.880	0.790	0.962	
	D05	43.23	177.819	0.792	0.962	
	D06	43.19	178.775	0.781	0.962	
	D07	43.21	178.990	0.776	0.962	
	D08	43.19	178.235	0.790	0.962	
	D09	43.20	178.545	0.784	0.962	
	D10	43.22	178.159	0.798	0.962	
	D11	43.24	178.153	0.801	0.962	
	D12	43.21	179.272	0.778	0.962	
	D13	43.22	178.807	0.788	0.962	
	D14	43.19	178.477	0.796	0.962	
	D15	43.17	178.366	0.784	0.962	
Cross-domain Collaboration	E01	44.24	156.760	0.777	0.960	0.963
	E02	44.24	156.872	0.780	0.960	
	E03	44.25	157.521	0.772	0.960	
	E04	44.24	156.560	0.785	0.960	
	E05	44.29	156.786	0.768	0.960	
	E06	44.26	156.593	0.776	0.960	
	E07	44.24	157.324	0.769	0.960	

E08	44.25	157.294	0.774	0.960
E09	44.25	157.023	0.782	0.960
E10	44.26	157.027	0.775	0.960
E11	44.27	156.784	0.778	0.960
E12	44.23	157.227	0.770	0.960
E13	44.28	156.070	0.807	0.960
E14	44.24	156.284	0.784	0.960
E15	44.27	155.905	0.796	0.960

3.2.3 Validity Analysis

Factor analysis method is used for validity analysis. In validity analysis, generally speaking, when KMO value remains above 0.7, the questionnaire analysis is suitable for factor analysis. From the table below, it can be seen that the KMO test value is .975>0.7, and Bartlett's sphericity test Sig is 0.000, significantly effective at the 0.001 level, suitable for factor analysis. The KMO and Bartlett's test is shown in Table 7.

Table 7. KMO and Bartlett's Test.

KMO Measure of Sampling Adequacy		0.975
Bartlett's Test of Sphericity	Approx. Chi-Square	49226.426
	Degrees of Freedom (df)	2775
	Significance	0.000

Through further in-depth analysis, from the table below it can be concluded that the total variance explained by factors extracted from the service quality scale is 67.00%, indicating good factor explanatory ability, and the 5 extracted factors can relatively completely preserve original data information. Meanwhile, the first factor loading extraction variance before rotation is 19.483%, below 40%, indicating the questionnaire does not have serious common method bias. The total variance explained is shown in Table 8.

Table 8. Total Variance Explained.

Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**			**Rotation Sums of Squared Loadings**		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	19.483	25.978	25.978	19.483	25.978	25.978	10.253	13.671	13.671
2	9.784	13.046	39.023	9.784	13.046	39.023	10.168	13.557	27.228
3	7.693	10.257	49.281	7.693	10.257	49.281	10.061	13.414	40.642
4	6.997	9.329	58.610	6.997	9.329	58.610	9.889	13.185	53.827
5	6.293	8.390	67.000	6.293	8.390	67.000	9.880	13.173	67.000
6	0.607	0.809	67.809						
7	0.591	0.788	68.597						
8	0.576	0.768	69.366						

9	0.559	0.745	70.111
10	0.545	0.726	70.837
11	0.535	0.713	71.549
12	0.534	0.712	72.261
13	0.520	0.694	72.955
14	0.520	0.693	73.648
15	0.511	0.681	74.329
16	0.497	0.663	74.992
17	0.489	0.652	75.644
18	0.473	0.631	76.275
19	0.471	0.628	76.903
20	0.469	0.626	77.529
21	0.461	0.615	78.144
22	0.455	0.607	78.751
23	0.442	0.589	79.340
24	0.436	0.582	79.922
25	0.433	0.578	80.499
26	0.429	0.572	81.071
27	0.422	0.563	81.634
28	0.411	0.548	82.182
29	0.409	0.545	82.728
30	0.400	0.533	83.260
31	0.394	0.525	83.785
32	0.389	0.519	84.305
33	0.387	0.516	84.821
34	0.380	0.507	85.328
35	0.367	0.489	85.816
36	0.362	0.482	86.299
37	0.352	0.469	86.768
38	0.351	0.469	87.237
39	0.348	0.464	87.701
40	0.346	0.462	88.162
41	0.341	0.455	88.617
42	0.331	0.441	89.059
43	0.326	0.435	89.493
44	0.320	0.427	89.920
45	0.315	0.420	90.340
46	0.313	0.418	90.758
47	0.307	0.410	91.168
48	0.303	0.404	91.572
49	0.295	0.393	91.965
50	0.292	0.390	92.355
51	0.287	0.383	92.737
52	0.286	0.381	93.118
53	0.278	0.371	93.489

54	0.273	0.364	93.853
55	0.271	0.361	94.214
56	0.265	0.353	94.567
57	0.262	0.350	94.917
58	0.257	0.343	95.260
59	0.250	0.333	95.593
60	0.245	0.326	95.919
61	0.239	0.318	96.238
62	0.234	0.312	96.550
63	0.230	0.306	96.857
64	0.228	0.304	97.161
65	0.219	0.292	97.453
66	0.211	0.282	97.734
67	0.211	0.281	98.016
68	0.208	0.278	98.293
69	0.199	0.265	98.558
70	0.197	0.263	98.821
71	0.196	0.261	99.082
72	0.182	0.243	99.325
73	0.174	0.232	99.558
74	0.172	0.229	99.787
75	0.160	0.213	100.000

According to the factor loadings in the table below, it can be seen that all items of the service quality scale fall within their corresponding preset dimensions, indicating good construct validity of the questionnaire, and the data obtained from the questionnaire can be used for further analysis. Overall, the entire questionnaire has high reliability and validity, is reliable and effective, and can be used for research analysis. The rotated component matrix is shown in Table 9.

Table 9. Rotated Component Matrix.

	Component				
	1	**2**	**3**	**4**	**5**
A01	0.812				
A02	0.844				
A03	0.830				
A04	0.832				
A05	0.823				
A06	0.834				
A07	0.832				
A08	0.819				
A09	0.838				
A10	0.834				
A11	0.817				
A12	0.822				
A13	0.826				

A14	0.833			
A15	0.708			
B01				0.791
B02				0.783
B03				0.797
B04				0.776
B05				0.776
B06				0.778
B07				0.806
B08				0.778
B09				0.790
B10				0.795
B11				0.796
B12				0.774
B13				0.786
B14				0.808
B15				0.788
C01		0.799		
C02		0.791		
C03		0.797		
C04		0.800		
C05		0.813		
C06		0.797		
C07		0.802		
C08		0.816		
C09		0.782		
C10		0.787		
C11		0.793		
C12		0.794		
C13		0.810		
C14		0.797		
C15		0.793		
D01			0.802	
D02			0.795	
D03			0.799	
D04			0.800	
D05			0.799	
D06			0.795	
D07			0.792	
D08			0.796	
D09			0.792	
D10			0.799	
D11			0.809	
D12			0.787	
D13			0.789	

D14	0.797	
D15	0.790	
E01		0.781
E02		0.779
E03		0.771
E04		0.786
E05		0.776
E06		0.783
E07		0.770
E08		0.784
E09		0.789
E10		0.781
E11		0.786
E12		0.782
E13		0.812
E14		0.790
E15		0.807

Note: Extraction method: Principal Component Analysis

Rotation method: Kaiser normalized Varimax rotation

Rotation converged in 6 iterations

3.2.4 Correlation Analysis

To understand whether there are significant correlations among teaching practice, cultural connotation, technology integration, policy culture, and cross-domain cooperation, Pearson correlation analysis is used. The correlation analysis is shown in Table 10.

Table 10. Correlation Analysis.

	Teaching Practice	**Cultural Connotation**	**Technology Integration**	**Policy Culture**	**Cross-Domain Cooperation**
Teaching Practice	1				
Cultural Connotation	0.334**	1			
Technology Integration	0.228**	0.301**	1		
Policy Culture	0.090*	0.092*	0.142**	1	
Cross-Domain Cooperation	0.299**	0.287**	0.325**	0.156**	1

Note: ** Correlation is significant at the 0.01 level (2-tailed)

This table shows Pearson correlation coefficients and their significance levels among five variables (teaching practice, cultural connotation, technology integration, policy culture, cross-domain cooperation).

- Teaching practice shows significant positive correlations with cultural connotation (0.334), technology integration (0.228), policy culture (0.090), and cross-domain cooperation (0.299).
- Cultural connotation shows significant positive correlations with technology integration (0.301), policy culture (0.092), and cross-domain cooperation (0.287).Author information.

- Technology integration shows significant positive correlations with policy culture (0.142) and cross-domain cooperation (0.325).

3.2.5 Confirmatory Factor Analysis

Confirmatory factor analysis is used to analyze the questionnaire. Generally speaking, in confirmatory factor analysis, standardized factor loadings need to be greater than 0.6, composite reliability CR greater than 0.7, and average variance extracted AVE greater than 0.5 to reflect good composite reliability and construct validity among data.

According to the table below, it can be seen that the confirmatory factor analysis fit indices meet ideal values, indicating reliable analysis results. The confirmatory factor analysis is shown in Table 11.

Table 11. Confirmatory Factor Analysis.

	CMIN/DF	GFI	IFI	RMSEA	CFI	TLI
Ideal Value	≤3.00	≥0.90	≥0.90	≤0.08	≥0.90	≥0.90
Fit Index	1.221	0.902	0.988	0.017	0.988	0.987

According to the table below, it can be seen that the standardized factor loadings of each item and the CR and AVE values of each dimension all meet standards, indicating good composite reliability and construct validity among data. The standardized factor loadings are shown in Table 12.

Table 12. Standardized Factor Loadings.

Variable	Item	Standardized Factor Loading	CR	AVE	Square Root of AVE
Policy Culture	A15	0.689	0.967	0.659	0.812
	A14	0.825			
	A13	0.814			
	A12	0.815			
	A11	0.813			
	A10	0.825			
	A09	0.830			
	A08	0.812			
	A07	0.823			
	A06	0.829			
	A05	0.811			
	A04	0.823			
	A03	0.819			
	A02	0.835			
	A01	0.800			
Technology Integration	B01	0.787	0.963	0.632	0.795
	B02	0.797			
	B03	0.799			
	B04	0.777			
	B05	0.787			
	B06	0.791			
	B07	0.802			

	B08	0.797			
	B09	0.808			
	B10	0.801			
	B11	0.795			
	B12	0.781			
	B13	0.793			
	B14	0.818			
	B15	0.791			
Cultural Connotation	C01	0.822	0.966	0.655	0.809
	C02	0.803			
	C03	0.808			
	C04	0.802			
	C05	0.818			
	C06	0.809			
	C07	0.819			
	C08	0.823			
	C09	0.796			
	C10	0.805			
	C11	0.801			
	C12	0.811			
	C13	0.812			
	C14	0.802			
	C15	0.808			
Teaching Practice	D15	0.802	0.965	0.645	0.803
	D14	0.801			
	D13	0.801			
	D12	0.805			
	D11	0.807			
	D10	0.796			
	D09	0.791			
	D08	0.806			
	D07	0.800			
	D06	0.814			
	D05	0.817			
	D04	0.793			
	D03	0.804			
	D02	0.811			
	D01	0.799			
Cross-domain Collaboration	E01	0.811	0.963	0.633	0.796
	E02	0.800			
	E03	0.823			
	E04	0.786			
	E05	0.793			
	E06	0.791			
	E07	0.798			

E08	0.789
E09	0.785
E10	0.793
E11	0.783
E12	0.802
E13	0.788
E14	0.797
E15	0.793

3.2.6 Discriminant Validity

Finally, the AVE square root of dimensions is compared with correlation coefficients between dimensions. According to the comparison, it can be seen that the AVE square root of each dimension is greater than the correlations between dimensions, indicating that internal correlations within dimensions are greater than correlations between dimensions, showing good discriminant validity of the data. In summary, the reliability and validity of the data are good and suitable for further analysis. The discriminant validity is shown in Table 13.

Table 13. Discriminant Validity.

	Teaching Practice	**Cultural Connotation**	**Technology Integration**	**Policy Culture**	**Cross-Domain Cooperation**
Teaching Practice	0.803				
Cultural Connotation	0.346	0.809			
Technology Integration	0.236	0.312	0.795		
Policy Culture	0.094	0.097	0.146	0.812	
Cross-Domain Cooperation	0.311	0.297	0.337	0.161	0.796

3.2.7 Structural Equation Model Analysis

This study adopts Structural Equation Modeling (SEM) to verify research hypotheses, aiming to explore the causal relationships and pathway mechanisms among key dimensions in the process of cross-strait application of artificial intelligence in maritime civilization multimedia teaching construction. SEM, as an important multivariate analysis tool, can effectively handle complex relational structures composed of latent variables (such as "teaching innovation cognition," "AI technology acceptance," "learning motivation," "cultural identity," and "learning effectiveness"). This model analyzes based on covariance matrices of characteristic variables, can simultaneously handle multiple endogenous variables (dependent variables), and fully considers interactive influences and internal structural variations among other variables when calculating path coefficients, thereby avoiding limitations of traditional regression analysis that ignores system integrity.

In this study, through theoretical construction and preliminary expert interviews, a model structure of five major latent variables was constructed, further deriving hypothetical relationships among various dimensions. SEM model verification helps deeply analyze the educational transformation logic triggered by AI integration into maritime civilization teaching and reveals collaborative pathways and strategic opportunities under institutional differences across the strait. The structural model diagram is shown in Figure 3.

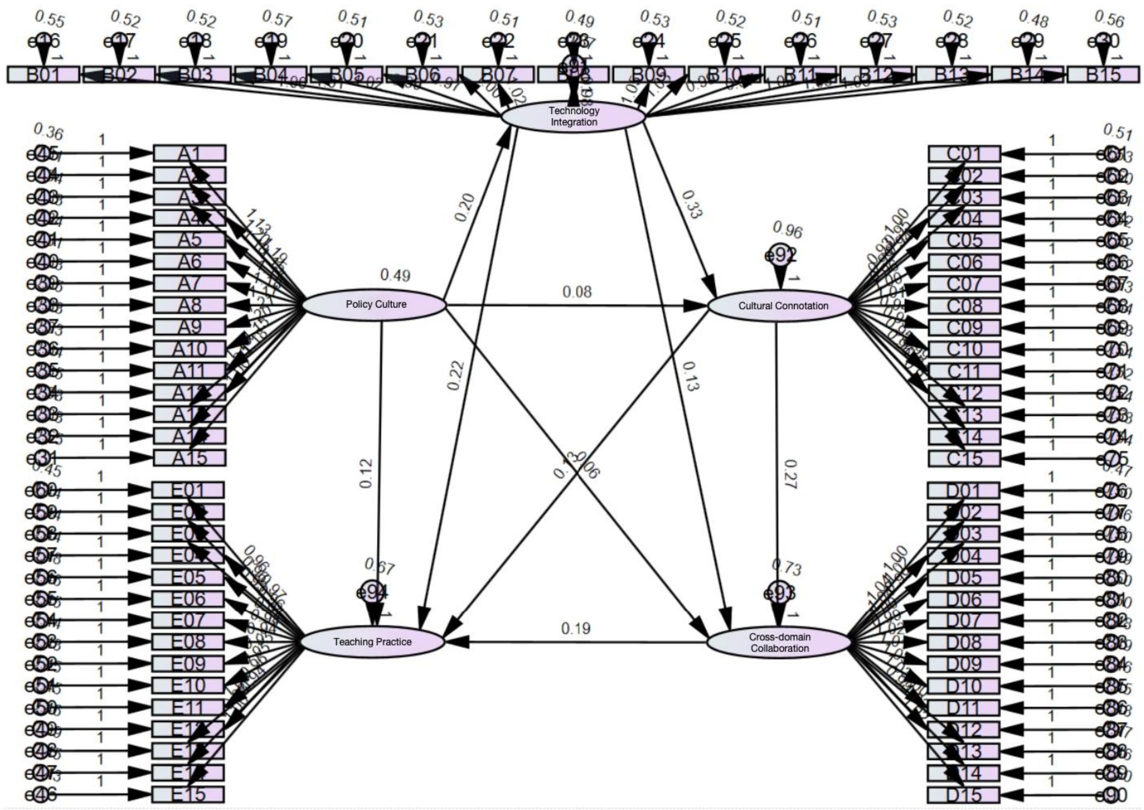

Figure 3. An example of figure.

Structural equation modeling is used to verify the path coefficients of the model. According to the table below, it can be seen that all fit indices of the model reach ideal values, indicating good model fit. The path coefficients are shown in Table 14.

Table 14. Path Coefficients.

	CMIN/DF	GFI	IFI	RMSEA	CFI	TLI
Ideal Value	≤3.00	≥0.90	≥0.90	≤0.08	≥0.90	≥0.90
Fit Index	1.221	0.902	0.988	0.017	0.988	0.987

(1) Policy Culture → Technology Integration (H01)

Standardized Estimate (SE): 0.146

Unstandardized Estimate: 0.196

Significance (P): ($p < 0.01$)

Conclusion: Supported

Interpretation: Policy culture has a significant positive effect on technology integration. For every one-unit increase in teaching practice, cultural connotation level increases by 0.196 units.

(2) Policy Culture → Cultural Connotation (H02)

Standardized Estimate (SE): 0.053

Unstandardized Estimate: 0.077

Significance (P): 0.143 (not significant)

Conclusion: Not supported

Interpretation: The direct effect of policy culture on cultural connotation is not significant, and may require indirect influence through other mediating variables (such as cultural connotation).

(3) Policy Culture → Teaching Practice (H03)

Standardized Estimate (SE):

Unstandardized Estimate: 0.123

Significance (P): 0.201

Conclusion: Not supported

Interpretation: Policy culture has no significant effect on teaching practice.

(4) Policy Culture → Cross-domain Collaboration (H04)

Standardized Estimate (SE): 0.095

Unstandardized Estimate: 0.136

Significance (P): 0.006 ($p < 0.05$)

Conclusion: Supported

Interpretation: This indicates that policy culture has a direct positive effect on cross-domain collaboration.

(5) Technology Integration → Cultural Connotation (H05)

Standardized Estimate (SE): 0.304

Unstandardized Estimate: 0.334

Significance (P): ($p < 0.001$)

Conclusion: Supported

Interpretation: Technology integration significantly enhances technology integration level. For every one-unit increase in cultural connotation, cultural connotation level increases by 0.334 units.

(6) Technology Integration → Teaching Practice (H06)

Standardized Estimate (SE): 0.136

Unstandardized Estimate: 0.134

Significance (P): ($p < 0.001$)

Conclusion: Supported

Interpretation: The direct effect of technology integration on teaching practice is significant.

(7) Technology Integration → Cross-domain Collaboration (H07)

Standardized Estimate (SE): 0.230

Unstandardized Estimate: 0.222

Significance (P): ($p < 0.001$)

Conclusion: Supported

Interpretation: Technology integration directly promotes cross-domain collaboration. For every one-unit increase in cultural connotation, cross-domain collaboration increases by 0.230 units.

(8) Cultural Connotation → Teaching Practice (H08)

Standardized Estimate (SE): 0.299

Unstandardized Estimate: 0.267

Significance (P): ($p < 0.001$)

Conclusion: Supported

Interpretation: Cultural connotation has a significant direct effect on teaching practice.

(9) Cultural Connotation → Cross-domain Collaboration (H09)

Standardized Estimate (SE): 0.149

Unstandardized Estimate: 0.131

Significance (P): ($p < 0.001$)

Conclusion: Supported

Interpretation: Cultural connotation level significantly enhances cross-domain collaboration. For every one-unit increase in technology integration level, cross-domain collaboration increases by 0.131 units.

(10) Teaching Practice → Cross-domain Collaboration (H10)

Standardized Estimate (SE): 0.196

Unstandardized Estimate: 0.193

Significance (P): ($p < 0.001$)

Conclusion: Supported

Interpretation: Teaching practice has a significant positive effect on cross-domain collaboration. For every one-unit increase in policy culture, cross-domain collaboration increases by 0.193 units.

Hypothesis verification was conducted, and the path results can be seen according to the following table (Table 15):

Table 15. Path Results Summary.

Hypothesis	Path	SE	Estimate	S.E.	C.R.	P	Conclusion
H01	Policy Culture → Technology Integration	0.146	0.196	0.050	3.889	***	Supported
H02	Policy Culture → Cultural Connotation	0.053	0.077	0.053	1.465	0.143	Not Supported
H03	Policy Culture → Teaching Practice	0.045	0.059	0.046	1.279	0.201	Not Supported
H04	Policy Culture → Cross-Domain Cooperation	0.095	0.123	0.045	2.759	0.006	Supported
H05	Technology Integration → Cultural Connotation	0.304	0.334	0.041	8.088	***	Supported
H06	Technology Integration → Teaching Practice	0.136	0.134	0.037	3.650	***	Supported

H07	Technology Integration → Cross-Domain Cooperation	0.230	0.222	0.036	6.174	***	Supported
H08	Cultural Connotation → Teaching Practice	0.299	0.267	0.034	7.823	***	Supported
H09	Cultural Connotation → Cross-Domain Cooperation	0.149	0.131	0.033	3.941	***	Supported
H10	Teaching Practice → Cross-Domain Cooperation	0.196	0.193	0.037	5.274	***	Supported

4. DISCUSSION

(1) Policy culture has positive promoting effects on technology integration and cross-domain cooperation but fails to directly drive teaching practice - Responding to and breaking through practical blind spots in the "Education Digitalization Strategy" (2021) and "Higher Education Sprout Project" (2022)

Previous research pointed out that although educational policies across the strait highly value digital transformation, there still exists disconnection between policy and practice in cultural education fields. This study's SEM empirical findings show that "policy culture" has significant positive impacts on "technology integration" (H01) and "cross-domain cooperation" (H04), but lacks direct influence on "teaching practice" (H03) and "cultural connotation" (H02). This result highlights that while policy provides important support for promoting AI integration in education, it is difficult to effectively transform into specific teaching innovation outcomes without establishing culturally-oriented institutional interfaces (such as cross-strait co-review mechanisms and digital teaching material ethics review frameworks), echoing previous research by Chen Qiyuan (2020) emphasizing "cultural governance gaps" .

This reveals that policy culture needs technology integration as mediation to effectively penetrate teaching practice and cultural construction, suggesting that future policy design across the strait should shift from "technology-driven logic" to "cultural participation logic," strengthening the three-tier progressive relationship of policy-technology-culture [34].

(2) Technology integration as key mediating variable for teaching innovation - Extending Anderson & Dron's (2011) AI teaching model logic

Anderson and Dron (2011) proposed AI's future role as "co-instructor," and this study further verifies "technology integration" as an important mediating bridge promoting "cultural connotation" (H05), "teaching practice" (H06), and "cross-domain cooperation" (H07), particularly AI+XR applications in multimodal content construction of maritime mythology, fishing village folklore, and port migration history, demonstrating high semantic reconstruction and immersive translation efficiency [35,36]. This result also aligns with Manovich's (2021) observations on "digital narrative algorithmization" trends, confirming that AI is no longer just an auxiliary tool but participates as a "cultural re-performance actor" in teaching narratives.

This proposes a four-stage transformation path of "technology integration-cultural connotation-teaching practice-cross-domain cooperation," highlighting that AI integration needs to couple with cultural resources to trigger genuine learning field transformation, filling gaps in previous research that mostly focused on operational aspects (such as platform development) [37,38].

(3) Cultural connotation as core variable for transforming learning dynamics and enhancing teaching identity - Responding to "non-linear knowledge architecture" problems in maritime cultural transmission

According to this study's interviews and quantitative analysis, cultural connotation significantly positively influences teaching practice (H08) and cross-domain cooperation (H09), indicating that cultural narrative situational introduction and local identity construction help deepen students' learning motivation and teachers' teaching identity [39,40]. This aligns with Zheng Qinmo's (2023) viewpoint that "local maritime memories can stimulate cultural identity in XR translation" and matches Griffiths et al.'s (2018) "story-driven education" teaching philosophy [41].

Incorporating "cultural connotation" as a core dimension in AI teaching effectiveness models, contrasting with most research still focusing on technology usability or learning effectiveness evaluation (such as Zawacki-Richter et al., 2019), provides a systematic perspective of "cultural field-learning participation-identity construction" [42].

(4) Teaching practice transformation requires technology-culture dual collaborative strategies - Challenging traditional "display-based teaching" logic, moving toward "co-creative learning"

The SEM model confirms that "teaching practice" significantly influences "cross-domain cooperation" (H10) and is highly coupled with cultural connotation (H08) and technology integration (H06). Interviews indicated that Taiwan teachers generally excel in narrative-oriented, cross-modal design thinking; Mainland teachers excel in platform planning and process arrangement, showing high complementarity in teaching strategy design across the strait [30,43,44].

Responding to Wang Sihua's (2020) theoretical trend of "moving from traditional teaching to innovative collaborative learning fields," and proposing that AI integration must be based on dual complementarity, suggesting development of AI teaching module design frameworks centered on "co-creative tasks" [45,46].

(5) Cross-domain cooperation as strategic hub driving maritime civilization intelligent education ecosystem - Transcending "inter-school cooperation" toward "cultural system collaboration networks"

This study shows "cross-domain cooperation" is driven by multiple factors including policy culture, technology integration, cultural connotation, and teaching practice, serving as an output indicator for the overall AI+cultural education ecosystem. This aligns with OECD's (2022) "Hybrid Learning Ecosystem" trend, emphasizing that policy planning, enterprise participation, local culture, and international dialogue need integrated promotion [25,47].

This first constructs a dynamic five-ring model including "policy-technology-culture-teaching-cooperation," expanding existing research that often narrows cross-domain cooperation to "cross-school resource sharing," further proposing strategic recommendations such as "Greater China Smart Cultural Education Alliance" and "AI Cultural Narrative Database Sharing Platform," responding to global cultural teaching reconstruction needs in the post-pandemic era [48].

Research Recommendations and Limitations

This study provides foundational insights into the cross-strait construction of maritime civilization multimedia teaching through artificial intelligence. However, several methodological limitations must be acknowledged, which may affect the generalizability and robustness of the findings:

(1) Sample Selection Bias and Representativeness

The current sampling strategy predominantly focused on teachers and related personnel in the educational sectors of Mainland China and Taiwan, relying on non-random sampling methods such as expert interviews and online questionnaires. This approach, while practical, restricts the diversity of perspectives and potentially compromises the external validity of the results. Future studies are encouraged to adopt more inclusive and randomized sampling strategies, incorporating participants from varied geographic regions, institutional types, and professional backgrounds to enhance representativeness and cross-contextual applicability.

(2) Limited International Perspective

The expert interviews were conducted primarily with scholars and practitioners engaged in digital education, AI applications, and maritime teaching within Mainland China and Taiwan. This regional focus omits the valuable insights of international scholars, which may limit the breadth of comparative understanding. Future research should aim to include international experts in maritime civilization education and AI-enhanced pedagogy to enrich the global relevance and cross-cultural depth of the study.

(3) Depth and Rigor of Data Analysis

While the study employed a first-order structural equation model (SEM) to examine relationships among latent variables, the analytical framework remains relatively basic and does not delve into potential mediating or moderating effects. To enhance explanatory power and theoretical robustness, future studies are recommended to employ higher-order SEM models or multigroup analysis. This would allow for a more nuanced understanding of indirect effects, model stability, and cross-variable interactions within multimedia teaching paradigms.

(4) Lack of Stratified Contextual Differentiation

The comparative analysis between the two regions (Mainland China and Taiwan) focused primarily on overarching system structures and policy orientations, without accounting for sub-regional or institutional variations. Differences such as urban vs. rural contexts, or between vocational, technical, and academic institutions, were not specifically addressed. Future research should incorporate stratified analyses based on educational levels and regional characteristics, enabling the development of more context-sensitive AI teaching models and localized pedagogical strategies.

(5) Absence of Experimental Validation

Although the study proposes a conceptual framework for a new multimedia teaching paradigm integrating AI and maritime cultural content, it lacks empirical validation through field implementation. To substantiate the practical effectiveness of the proposed model, future research should employ quasi-experimental designs or longitudinal case studies in actual classroom environments. This would enable assessment of learning outcomes across cognitive, emotional, and skill-based dimensions, thereby offering stronger empirical support for pedagogical innovation.

5. Conclusion

This study explores the cross-strait development of maritime civilization multimedia teaching through artificial intelligence (AI) and emerging educational paradigms. Utilizing a mixed-methods approach—including expert interviews and Structural Equation Modeling (SEM)—the study identifies institutional, pedagogical, and technological distinctions between Mainland China and Taiwan, and proposes a five-ring dynamic development framework: policy-driven → technology-mediated → culture-translated → teaching-transformed → cooperation-expanded. This framework offers a practical roadmap for cross-strait educational innovation.

(1) Key Findings and Implications

The results show that "policy culture" plays an essential but indirect role in promoting AI teaching. Its limited direct influence on "cultural connotation" and "teaching practice" suggests that current policies on both sides of the strait overly emphasize technological infrastructure while neglecting cultural contextualization and educational system reform. In contrast, "technology integration" emerges as a vital enabler, exerting significant positive effects on "cultural connotation," "teaching practice," and "cross-domain cooperation." This reveals AI’s growing role as a co-narrator and translator of culture, not just a passive tool.

(2) Cultural Connotation and Educational Transformation

"Cultural connotation" significantly stimulates learning motivation and reinforces teacher identity. Its positive influence on "teaching practice" and "cross-domain cooperation" highlights the necessity of integrating local narratives and values into curriculum design. Despite divergent narrative logics between Mainland and Taiwan educational materials, semantic translation and immersive AI tools can bridge gaps and foster shared digital cultural discourse. This implies that policy frameworks should support AI-enhanced cultural translation tools and promote co-development of culturally adaptable teaching materials.

(3) Toward Sustainable Cross-Domain Cooperation

As an outcome variable, "cross-domain cooperation" embodies the synergistic effect of all influencing variables. This suggests that smart cultural education must evolve beyond isolated school collaborations into structured alliances among industry, academia, government, research, and cultural sectors. Concrete initiatives should include:

A. Establishing cross-strait joint AI curriculum development centers, particularly within maritime and cultural heritage fields.
B. Developing cooperative funding schemes for co-produced multimedia content and teaching platforms.
C. Setting up an intergovernmental cultural-education AI policy taskforce, responsible for harmonizing ethical standards, data use policies, and joint platform governance.

(4) Policy Recommendations for Implementation

To translate these findings into actionable cross-strait strategies, we propose the following specific recommendations:

A. Policy Synchronization: Establish a cross-strait policy dialogue mechanism focused on cultural AI education, with annual roundtables co-hosted by Ministries of Education and cultural institutions.

B. Teacher Training: Launch joint AI literacy and cross-cultural pedagogy certification programs for teachers, incentivized through mutual recognition and exchange programs.

C. Content Co-Creation Platforms: Develop a bilingual, AI-assisted platform for co-editing teaching materials on maritime culture, supported by a shared digital asset repository.

D. Local Innovation Pilots: Support region-specific AI teaching pilot zones (e.g., Fujian and Penghu) that test adaptive cultural content with community participation.

E. Global Partnerships: Position the cross-strait alliance within broader international maritime education networks, leveraging UNESCO or APEC frameworks to scale cultural-AI integration globally.

In sum, this study provides a strategic and structural foundation for AI-empowered, culturally rich educational transformation across the Taiwan Strait. By translating abstract frameworks into concrete policy tools and multi-actor collaborations, the research offers a pathway toward sustainable, inclusive, and context-sensitive digital education ecosystems. The vision of "AI empowering culture, education co-constructing civilization" becomes actionable when grounded in institutional reform, cross-border alliances, and participatory content innovation.

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