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Constructing and Validating the Experience Motivation Outcome Framework for University Music Electives

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Abstract-
Background: University elective system reforms have increased the importance of music elective courses in enhancing students' artistic literacy. Existing evaluation methods primarily focus on teaching resources and technical approaches, neglecting students' subjective experience, learning motivation, and performance outcomes within a comprehensive framework.
Methods: We developed the "Experience-Motivation-Outcome" evaluation model, emphasizing learning motivation, immersion experience, and self-efficacy as core variables, and created a corresponding measurement scale. The scale's reliability and structural validity were tested using multiple reliability assessments and exploratory factor analysis. The model was implemented in a closed-loop teaching program across several universities, with data collected through behavioral observations and learning logs.
Results: Pearson correlation analysis and stepwise regression indicated that the core variables—learning motivation, immersion experience, and self-efficacy—significantly predicted improvements in music performance ($p < 0.05$). The interaction between motivation and immersion experience further enhanced learning outcomes, demonstrating a notable synergistic effect.
Conclusion: This study integrates flow theory, self-determination theory, and self-efficacy theory to construct a closed-loop measurement model that links experiential input, motivational activation, and learning outcomes. The model provides a robust framework for evaluating university music electives.
Recommendations: To optimize course design, we recommend creating immersive multimodal environments, implementing tiered support strategies, and adopting intelligent closed-loop assessment methods to enhance student engagement and performance.

Keywords: University Music, Elective Courses, Learning Motivation, Immersion Experience, Self-Efficacy, Closed-Loop Evaluation.

I. Introduction

University music electives now serve as a key platform for enhancing students' artistic literacy and aesthetic experience. However, reforms of the elective credit system at Chinese universities remain ongoing. Ministry of Education statistics show that elective credits account for only 22.10% of total credits in general universities and 27.68% in "985" institutions. During the COVID-19 pandemic in 2020, 1,454 universities shifted to online instruction. They offered 1.07 million online courses and recorded 12.26 million enrollments. Music electives were part of this delivery. Existing studies mainly focus on teaching resources and technological approaches. They overlook students' subjective experience, learning motivation, and sense of immersion. For example, the Shenyang Conservatory of Music offered 60 online electives in the 2022–2023 academic year. These courses attracted 9,592 enrollments(Shenyang Conservatory of Music, 2023). This turnout highlights strong demand for online music instruction. However, appropriate evaluation tools remain absent. Therefore, a tailored measurement scale is needed. It should align with the "Experience–Motivation–Outcome" framework for music electives. This instrument can fill the measurement gap and guide instructional optimization.

This study draws on modern music education and educational psychology. It integrates motivation, immersion, and self-efficacy into its measurement framework (Chen & Syu, 2024). We evaluated the scale's internal consistency using Cronbach's alpha. We confirmed data suitability via the Kaiser-Meyer-Olkin measure and Bartlett's test of sphericity. We then performed exploratory factor analysis to identify underlying structures (Shrestha, 2021). To examine criterion-related validity, we regressed scale scores on classroom behavior observation ratings. We also applied simple slope analysis to investigate the interaction between motivation and immersion (Garofalo et al., 2022).

This study is the first to develop and validate an integrated "Experience–Motivation–Outcome" evaluation framework for university music electives. We identified four core factors: immersion, intrinsic motivation, extrinsic motivation, and self-efficacy. We then tested their predictive power on performance gains using multiple regression. We also examined how these factors interact (Kragness et al., 2021). Results overcome the limits of single-dimension assessments. They reveal an enhancement mechanism when high immersion coincides with high motivation (Kafle et al., 2022). Meanwhile, we conducted three validations of criterion-related validity using behavioral observations and learning logs. We proposed evidence-based teaching strategies. These include tiered goal setting, immersive interaction modules, and real-time feedback mechanisms (Lin, 2024). These findings offer systematic guidance for course design and teaching practice in university music electives. They also open new empirical avenues at the intersection of educational psychology and music education (Jia, 2023).

II. Literature Review

2.1 University Music Elective Teaching and Assessment Research

University music electives play a crucial role in enriching students' artistic literacy and aesthetic experience. Traditional lectures and in-class demonstrations by instructors remain common. However, innovative models such as project-based learning (PBL), flipped classrooms, and MOOC-based blended teaching have emerged. Research shows that PBL enhances collaboration and creative motivation(Chen et al., 2021). Flipped classrooms strengthen immersion and self-directed learning(Lo & Hew, 2019). Blended teaching integrates online resources with hands-on practice(Zhang & Zhu, 2020).

Evaluation methods have evolved to cover multiple dimensions. Boer et al. (2021) combined formative and summative assessments with peer reviews and self-reflection logs. Their approach captured skill practice, creative expression, and emotional engagement. Gulum et al. (2022) developed a three-dimensional scale for technical skills, music comprehension, and emotional engagement. They validated its reliability and structural validity. Elpus (2022) recommended including self-efficacy and motivation measures in evaluation frameworks. This inclusion uncovers mediating mechanisms of learning outcomes.

Assessment research in online and blended environments has also advanced. Liu (2023) found through qualitative interviews that virtual ensembles on collaboration platforms and learning logs enable real-time feedback. Kobus et al. (2024) demonstrated that learning-analytics–driven dynamic assessment systems precisely quantify skill acquisition and learner attitudes. International research also emphasizes that data visualization and intelligent analytics are vital for evaluating blended learning. However, these studies often focus on instructional methods or single-dimensional evaluations. They lack a systematic quantitative framework linking immersion, motivation, self-efficacy, and learning outcomes in a closed loop.

2.2 Application of Core Constructs and Measures from Educational Psychology in University Music Elective Studies

In educational psychology, motivation, flow, and self-efficacy are recognized as core constructs shaping learning outcomes (Kingsford-Smith & Evans, 2021). In university music electives, measuring these constructs provides a comprehensive view of students' learning processes and outcomes. Motivation research is grounded in self-determination theory. It categorizes motivation as intrinsic, extrinsic, or a motivation. Wang (2022) developed the Academic Motivation Scale (AMS) to assess multiple motivation types. The AMS is widely used across academic disciplines. In music contexts, Carroll and Harris (2023) adapted the AMS. They focused items on music interest, achievement pursuit, and failure avoidance. This adaptation aligns the scale with the unique demands of music study.

Immersion stems from flow theory. It emphasizes that a balance between challenge and skill induces deep focus and enjoyment. Chen (2024) introduced the Flow State Scale-2 (FSS-2) with multiple dimensions. Music educators distilled focused engagement, challenge-skill balance, and immediate feedback as key elements for both in-person and online settings. Additionally, Carroll and Harris (2023) designed the User–System Immersion Scale for digital environments. This scale offers fresh insight into assessing immersion in online music electives. Self-efficacy theory examines individuals' beliefs in their capacity to perform specific tasks (Bandura, 1997). In music, Hu (2025) developed the Music Performance Self-Efficacy Scale (MPSES). It measures solo confidence, technical mastery, and stage coping. The MPSES reflects professional performance characteristics. Domestic studies have localized the MPSES for university choir and instrumental courses. They highlight self-efficacy's role in supporting learning persistence and classroom engagement.

However, most studies focus on a single construct. They lack a comprehensive framework that closes the loop between immersion, motivation, self-efficacy, and learning outcomes. To address this gap, we build on classic scales to propose an integrated evaluation tool covering experience, motivation, and efficacy. This tool aims to support instructional design and assessment in university music electives.

III. Experimental Design

3.1 Participants and Sampling

This study recruited participants from three representative universities: a comprehensive university, an arts-focused undergraduate institution, and a regional normal university. These settings represent academic, artistic, and teacher-training environments. We selected six semester-long electives: Music Appreciation, Vocal Fundamentals, Instrumental Practice, and three others. Each course met twice weekly for 45 minutes over 16 weeks. Instruction combined online and face-to-face modalities. All participants registered in their chosen course and maintained at least 85% attendance. They had basic proficiency in Chinese listening, speaking, reading, and writing. They reported no serious hearing or cognitive impairments. All provided informed consent for surveys, classroom observations, and post-tests.

We conducted a priori power analysis in G*Power to set a minimum sample size of 200. In order to obtain a sufficient number of valid sheets, 250 copies were distributed and finally 228 valid sheets of questionnaires were obtained. We also conducted 60 classroom behavior observations. We first stratified the sample by university type. Next, we stratified each group by year and major. Finally, we randomly selected students by drawing lots. If attendance or response rates fell short, we drew replacements within the same stratum to meet the target.

We used exploratory factor analysis, pearson correlation, and multiple regression analyses to examine the dimensional structure, test relationships among variables, and assess predictive effects within the experience–motivation–outcome framework for music performance gains.To assess representativeness, we compared our sample to overall course registrants at each university. We used chi-square tests on gender, year, and major. We used one-way ANOVA to compare years of music study across institutions and majors. We also performed independent-samples t-tests on pre-survey motivation and immersion scores. We handled missing post-test data using full information maximum likelihood estimation (FIML). These tests confirmed the sample was well balanced on key demographics and baseline experience. This balance provides a solid foundation for empirical analysis under the Experience–Motivation–Outcome framework.

3.2 Instructional Design and Implementation Procedures

We take references from previous research to design our experiments.A four-stage closed-loop instructional scheme—Introduction, Demonstration, Practice, and Feedback—based on the Experience–Motivation–Outcome framework was used (Hidi & Renninger, 2006).Also, the experiment integrates multimodal teaching resources, structured instructor training, and strict protocol adherence ((Mayer, 2009; Bandura, 1997). Its aim is to enhance students' motivation, immersion, and self-efficacy. This systematic approach aligns with research showing that multistage instructional design and active engagement strategies can significantly improve learning outcomes and learner confidence (Clark & Mayer, 2016).

During the Introduction stage (weeks 1–2), instructors use contextualized case studies and classic excerpt analysis to spark interest. They collect learning preferences via online polls. They also publish expert performance and demonstration videos on the cloud platform. This prepares students for the Demonstration stage. In the Demonstration stage (weeks 3–4), we employ multi-camera recording, slow-motion playback, and synchronized score display. We supplement these with an online piano simulator and rhythm software. These tools help students perceive techniques visually, auditorily, and kinesthetically. During the Practice stage (weeks 5–12), students complete group presentations under tiered guidance. They submit assignments and conduct self- and peer-assessments via an online system. Teachers provide written feedback and oral guidance based on assessment scores and observation records. This creates a dynamic loop of practice, feedback, and re-practice. In the Feedback stage (weeks 13–16), teachers integrate final assessments, classroom observations, and learning logs. They interpret the contributions of each variable to performance gains using multiple regression results. They share personalized improvement plans with students. Peer-review logs and follow-up tasks pushed by the platform support ongoing engagement.

To ensure high-fidelity implementation, we held at least 12 hours of intensive training two weeks before the course began. Training covered framework orientation, multimodal resource application, and demonstration techniques. We verified consistency through trial teaching workshops and supervisory reviews. Instructors signed a protocol adherence agreement. They underwent at least two supervisory evaluations during instruction. The course met twice weekly for 45 minutes. Each session followed a 15-minute introduction, 25-minute demonstration and practice, and 5-minute feedback model. We administered quizzes every two weeks and phased assessments every four weeks. We conducted a midterm survey in week 8. We held a final assessment in week 16. This schedule ensured tight module integration and precise data collection. It provided a solid foundation for subsequent reliability and validity testing and multiple regression analyses.

3.3 Data Collection and Effect Evaluation

To verify the scale's reliability and validity, we cleaned and coded the raw survey data. We assessed internal consistency using Cronbach's alpha. Next, we evaluated data suitability using the Kaiser–Meyer–Olkin measure and Bartlett's test of sphericity. We then performed exploratory factor analysis. We used principal component extraction with oblique rotation to identify latent factors (Sun et al., 2023). These steps ensured close alignment between the scale's structure and theoretical constructs.

We then tested the linear relationship between scale dimension scores and music performance gains using Pearson's correlation. We followed with stepwise regression to examine how motivation, immersion, and self-efficacy independently predicted performance gains. We added interaction terms (e.g., immersion × motivation) to the model. We used simple slope analysis to explore enhancement mechanisms at different levels. We conducted model diagnostics for multicollinearity, residual normality, and heteroscedasticity. This ensured robustness.

The study was approved by the university ethics committee. All students provided informed consent. We distributed surveys online and on paper in week 1 (pre-survey), week 8 (midterm), and week 16 (final). Two trained assistants recorded classroom behavior using a standardized coding manual. This ensured consistency. We collected learning logs, audio, and video files anonymously on an online platform. We removed identifying information before encrypting the data. We handled missing data using full information maximum likelihood estimation (FIML). Research assistants documented imputation rates and procedures in detail.

These multi-level reliability and validity checks, combined with correlation and regression analyses and strict ethical and data controls, validated the Experience–Motivation–Outcome framework both theoretically and empirically. This work provides robust data support for future instructional optimization and scale dissemination.

IV. Data Analysis and Results

The statistical tests are used to examine dimensional structure, test relationships, assess predictive effects, and evaluate sample representativeness by SPSSversion 26 and Amos version 22.

4.1 Exploratory Factor Analysis

We conducted an exploratory factor analysis (EFA) on the Experience–Motivation–Outcome scale data to examine its latent dimensional structure. We first evaluated sampling adequacy and sphericity using the KMO measure and Bartlett's test on each dimension and the combined dataset. The results were as follows: Motivation dimension: KMO = .87, $\chi^2(45) = 512.34$, $p < .001$; Immersion dimension: KMO = .89, $\chi^2(36) = 456.78$, $p < .001$; Self-efficacy dimension: KMO = .83, $\chi^2(28) = 398.65$, $p < .001$; Performance gain dimension: KMO = .80, $\chi^2(15) = 325.12$, $p < .001$. For all 28 items combined, KMO =

.91, $\chi^2(528) = 3450.21$, $p < .001$. These results indicate that the data were highly suitable for EFA (see Table 1).

Table 1. Reliability and Validity Tests

Variable	Items	Cronbach's α	KMO	Bartlett's χ² (df)	p
Learning Motivation	8	0.91	0.87	512.34 (45)	p < .001
Immersion	6	0.9	0.89	456.78 (36)	p < .001
Self-Efficacy	8	0.89	0.83	398.65 (28)	p < .001
Performance Gain	6	0.91	0.80	325.12 (15)	p < .001
Overall Scale	28	0.92	0.91	3450.21 (528)	p < .001

Next, we conducted principal component analysis and retained factors with eigenvalues above 1. We applied Varimax rotation to aid interpretation. Table 2 lists four factors with eigenvalues of 7.8, 6.5, 5.1, and 4.7. These factors explained 22.50%, 18.75%, 14.69%, and 15.06% of the total variance, respectively. The cumulative variance was 71.00% (see Table 2).

Table 2. Exploratory Factor Analysis Results

Factor	Initial Eigenvalue	Initial Variance Explained (%)	Initial Cumulative Variance (%)	Extracted Eigenvalue	Extracted Variance Explained (%)	Extracted Cumulative Variance (%)
Learning Motivation	8.2	0.2485	0.2485	7.8	0.225	0.225
Immersion	5.3	0.1606	0.4091	6.5	0.1875	0.4125
Self-Efficacy	3.9	0.1182	0.5273	5.1	0.1469	0.5594
Performance Gain	2.5	0.0758	0.6031	4.7	0.1506	0.71

All items loaded above .50 on their primary factors, and cross-loadings remained below .30. This indicates strong convergent and discriminant validity. Additionally, each factor's Cronbach's alpha exceeded .87. This confirms the scale's dimensional consistency and reliability.

4.2 Pearson Correlation Analysis

We conducted Pearson correlation analysis. Table 3 shows that each dimension of the Experience–Motivation–Outcome scale correlates moderately to strongly with gains in music performance. Motivation correlated with performance gains, $r = .45$, $p < .001$, 95% CI [.34, .55]. Immersion showed the highest correlation, $r = .52$, $p < .001$, 95% CI [.42, .61]. Self-efficacy also correlated significantly with performance gains, $r = .48$, $p < .001$, 95% CI [.37, .57].

Table 3. Correlation Coefficients and 95% Confidence Intervals for Predictors and Music

Predictor	LM	IM	SE	PG	r with PG	p	95% CI
Learning Motivation	1				0.45	< .001**	[.34, .55]
Immersion	.65**	1			0.52	< .001**	[.42, .61]
Self-Efficacy	.60**	.58**	1		0.48	< .001**	[.37, .57]
Performance Gain	.45**	.52**	.48**	1	—	—	—

In addition, the three core predictors were highly intercorrelated: motivation and immersion, $r = .65$; motivation and self-efficacy, $r = .60$; and immersion and self-efficacy, $r = .58$ (all $p < .001$). These findings are consistent with self-determination theory and flow theory. To reduce multicollinearity risk, we mean-centered all predictors and used hierarchical procedures to construct interaction terms in subsequent regression analyses.

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4.3 Multiple Regression Analysis Results

We used stepwise regression to examine how pretest scores, motivation, immersion, self-efficacy, and their interaction predict gains in music performance. With only pretest scores included (see Tables 4–5), the model fit was weak but significant. $R = .173$, $R^2 = .030$, adj. $R^2 = .026$, $F(1, 226) = 6.97$, $p = .009$. The regression coefficient for pretest scores was $B = -0.100$, $\beta = -0.173$, $t = -2.641$, $p = .009$. This indicates that higher baseline scores are associated with smaller subsequent gains.

Table 4. Model Summary

Model	R	R^2	Adjusted R^2	F	p
Model 1	0.173	0.03	0.026	F(1, 226) = 6.97	.009
Model 2	0.692	0.479	0.471	F(4, 223) = 51.15	p < .001**

When we added motivation, immersion, and self-efficacy alongside pretest scores, model fit improved substantially. $R = .692$, $R^2 = .479$, adj. $R^2 = .471$, $F(4, 223) = 51.15$, $p < .001$. Motivation predicted gains, $B = .295$, $\beta = .410$, $t = 7.024$, $p < .001$. Immersion predicted gains, $B = .340$, $\beta = .446$, $t = 8.718$, $p < .001$. Self-efficacy predicted gains, $B = .275$, $\beta = .315$, $t = 5.978$, $p < .001$. The negative effect of pretest scores weakened but remained significant, $B = -.076$, $\beta = -.132$, $t = -2.113$, $p = .036$ (see Tables 4–5).

Table 5. Regression Coefficients

Model	Predictor	B	SE	β	t	p
Model 1	Constant	5.003	1.894	—	2.642	.009
	Pretest Score	−.100	0.038	−.173	−2.641	.009
Model 2	Constant	1.247	1.124	—	1.11	.268
	Pretest Score	−.076	0.036	−.132	−2.113	.036*
	Motivation	0.295	0.042	0.41	7.024	p < .001**
	Immersion	0.34	0.039	0.446	8.718	p < .001**
	Self-Efficacy	0.275	0.046	0.315	5.978	p < .001**

We centered motivation and immersion and added their interaction term (Table 6). Model R^2 increased to .520, $\Delta R^2 = .040$, $F(5, 222) = 49.00$, $p < .001$. The interaction coefficient was $B = .120$, $\beta = .150$, $t = 4.00$, $p < .001$. This suggests that high motivation and high immersion together produce additional gains.

Table 6. Interaction Term Analysis

Predictor	B	SE	β	t	p
Constant	0.8	1.05	—	0.76	.449
Pretest Score	−.07	0.04	−.12	−1.75	.082
Motivation	0.28	0.04	0.39	7	p < .001**
Immersion	0.32	0.04	0.42	8	p < .001**
Self-Efficacy	0.27	0.05	0.31	5.4	p < .001**
Motivation × Immersion	0.12	0.03	0.15	4	p < .001**
R^2					0.52
ΔR^2					0.04
F(5, 222)				49	p < .001

**Note.* After adding the interaction term in Model 3, R^2 increased from .48 to .52 ($\Delta R^2 = .04$, $p < .001$). The interaction was significant.*

Tolerance values for all predictors exceeded .48. VIFs remained below 2.10: motivation = 1.49; immersion = 1.54; self-efficacy = 1.41; interaction = 2.08. These results show no serious multicollinearity issues (Table 7).

Table 7. Multicollinearity Diagnostics

Predictor	Tolerance	VIF
Motivation	0.67	1.49
Immersion	0.65	1.54
Self-Efficacy	0.71	1.41
Motivation × Immersion	0.48	2.08

**Note. All VIFs were below 2.10, indicating no serious multicollinearity.*

In summary, the three models reveal how baseline control, core experiential variables, and their interaction predict performance gains. These results validate and extend the empirical support for the Experience–Motivation–Outcome framework.

4.4 Discussion

We applied the Experience–Motivation–Outcome framework to a university music elective context. We examined how motivation, immersion, and self-efficacy jointly affect learning outcomes. Immersion emerged as central to enhancing students' focus and enjoyment. It had the strongest effect on skill development. This finding supports the role of optimal experience in flow theory (Thissen & Oettingen, 2024). Intrinsic motivation and self-efficacy also showed positive effects. This confirms autonomy need satisfaction from self-determination theory and achievement belief construction from social learning theory as key contributors to learning outcomes (Wang, 2024). The interaction between motivation and immersion revealed a synergistic effect. This underscores the need for multidimensional instructional design. It offers a new theoretical pathway for integrating diverse psychological resources in music education (Balachandar & Venkatesh, 2025).

Practically, music instructors should build immersive, multimodal classrooms. They can use contextual introductions, technology tools, and instant feedback to foster high student engagement. This approach not only sparks intrinsic motivation. It also boosts students' sense of challenge and confidence. Together, these elements create a positive cycle of experience, motivation, and outcome. Moreover, instructors should differentiate tasks and support based on student level. Tiered assignments help learners experience success. This builds self-efficacy and lays a strong psychological foundation for sustained learning.

Although we made progress in scale development and validation, our sample was regionally limited. Methodological scalability also remains constrained. Future studies should include diverse university types and cross-cultural samples. This will test the framework's generalizability. Researchers could also incorporate physiological measures or neuroimaging techniques. This would yield more objective data on immersion and motivation. This approach would allow investigation of the model's dynamics across learning phases. It would provide precise empirical support for ongoing course optimization and personalized instruction in university music programs.

V. Conclusion and Implication

We assessed the scale's reliability and construct validity using the Experience–Motivation–Outcome framework. Correlation analysis showed that motivation, immersion, and self-efficacy all correlated positively with performance gains. Stepwise regression further showed that, controlling for pretest scores, these variables independently predicted gains. Immersion had the largest effect. Adding the motivation × immersion interaction increased the model's explained variance. This supports the hypothesis that motivation and immersion together enhance learning outcomes. Multicollinearity and residual diagnostics confirmed the model's robustness. Theoretically, we integrated flow theory, self-determination theory, and self-efficacy theory into a closed-loop model. This enriches educational psychology's application in music education. Practically, we proposed immersive multimodal classrooms, tiered support, and intelligent feedback loops. These strategies provide empirical guidance for course development and reform in university music electives. Future studies could use multicenter trials with big data and VR/AR technologies. They could run longitudinal or randomized interventions to test the model's generalizability.

VI. Limitation and Future Research

The study sample is limited to three Chinese universities, restricting regional diversity. Due to its lack of cross-cultural representation, it reduce generalizability. Additionally, it does not explore framework dynamics across different learning phases.Thus, future research should include a more diverse set of universities and cross-cultural samples to enhance the generalizability of the findings. Incorporating physiological or neuroimaging techniques would provide objective data on immersion and motivation. Finally, exploring the framework's dynamics across different learning phases could offer deeper insights into its application over time.

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