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Examining the Impact of Preparation Difficulties on Postgraduate Entrance Exam Progress Among Foreign Language Students in the AI Era: A PLS-SEM Study

Wang Haitao
Lecture of School of Foreign Languages, Panzhihua University, Panzhihua, Sichuan, China
Pan ZhihuaUniversity 617000

ABSTRACT: *Generative AI has changed the job market that foreign language (FL) graduates in China face, and many now treat postgraduate study as a way to improve their prospects. What they struggle with while preparing for the entrance examination, and how those difficulties combine to slow preparation down, is less well understood, especially at local universities. Drawing on career decision-making difficulty theory and research on test anxiety, this study models five dimensions of preparation difficulty against perceived preparation progress. Sixty final-year FL students preparing for the 2027 National Postgraduate Entrance Examination completed the survey. Partial least squares structural equation modeling in SmartPLS 4 was used, with dimension merging and iterative indicator pruning as robustness checks. Only academic and psychological difficulties ($\beta = -0.258$, $p = .008$) and time and self-discipline difficulties ($\beta = -0.349$, $p = .015$) predicted progress. The refined model kept 20 indicators across five dimensions (composite reliability ≥ 0.73, all HTMT ratios below 0.85), and both significant paths held in the robustness specification. Open-ended responses pointed to senior-year course loads and administrative duties, which suggests that reducing coursework and protecting study time matter more than information campaigns or financial aid on their own.*

KEY WORDS: *AI anxiety, postgraduate entrance examination, foreign language students, preparation difficulties, PLS-SEM*

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I. INTRODUCTION

Generative AI, and in particular the large language models and machine translation systems built on it, has changed the demand for language-related work (Jiang & Li, 2026; Wang, 2026). As translation and routine content production are automated, foreign language (FL) majors have begun to doubt the market value of their linguistic training (Wang, 2026). A growing number respond by applying for postgraduate study: to add qualifications, to delay entry into a crowded job market, or to move toward specializations that seem less exposed to automation. The number of Chinese college graduates reached 12.7 million in 2026, and registrations for the National Postgraduate Entrance Examination (NPEE) have stayed at historically high levels despite a modest recent decline (Ministry of Education of China, 2026).

FL students at non-elite local universities decide to sit the NPEE for a mixture of reasons: anxiety about AI-related job displacement, a sense that a bachelor's degree has lost value, family expectations, interest in a subject, and the hope of moving to a better institution (Jiang & Li, 2026). The year of preparation that follows is demanding in its own right. Qualitative accounts point to a recurring set of problems: weak foundations in the politics paper and the second foreign language; poor access to reliable information about target institutions; competition between revision and coursework, practica, or part-time work; and rising distress (Wang, 2026). Any of these can slow progress and lower the chance of admission.

Research on FL students' career decisions, AI anxiety, and postgraduate aspirations has grown quickly (Jiang & Li, 2026; Wang, 2026), but important questions remain open. Few studies treat preparation difficulties as a multidimensional construct and compare their effects on progress inside a single structural model. Existing samples come mainly from elite or first-tier universities, so the position of students at local institutions, who carry heavier teaching loads, have less access to good tutoring, and work with tighter budgets, is largely

unexamined. AI anxiety, finally, is usually described as a motive for enrolling rather than a stressor that operates during preparation, and this second role has not been tested.

This study builds and tests a multidimensional model of NPEE preparation difficulties among FL students at a local public university in Sichuan Province, using PLS-SEM. Three questions guide the analysis: (1) which dimensions of preparation difficulty do FL students report; (2) which of those dimensions predict perceived preparation progress; and (3) what can local universities realistically do about them?

II. LITERATURE REVIEW AND HYPOTHESES

2.1 AI Anxiety and Career Decision-Making Among FL Students

Generative AI has raised widespread concern among FL majors about their career prospects. Working from career construction theory and the cognitive appraisal framework, Wang (2026) found that AI anxiety among English majors was associated with lower career adaptability and with greater difficulty in making career decisions. Jiang and Li (2026) showed that students' appraisals of AI, whether they read it as a challenge or as a hindrance, predicted employment anxiety and informal digital learning in different directions. For students who see AI mainly as a threat, postgraduate study often looks like a way to buy time and collect credentials that will protect them from displacement. But the shift from deciding to preparing creates pressures of its own, and the same anxiety that pushed a student to enroll can drain the attention and energy that preparation requires (Zeidner, 1998).

2.2 Dimensions of Preparation Difficulties

Drawing on work on test anxiety, academic self-efficacy, and career decision-making difficulties, together with interviews with 10 FL students at the study site, we treat NPEE preparation difficulties as a second-order construct with five first-order dimensions.

Academic and psychological difficulties. This dimension covers weak foundations in the NPEE subjects (politics, the specialized course, the second foreign language), difficulty in mastering professional content, and distress such as fear of failure, self-doubt, and test anxiety. Academic self-efficacy and test anxiety both predict exam performance in the existing literature (Zeidner, 1998); for FL students, the politics comprehensive paper and the specialized course add material that undergraduate training does not cover well.

Information and resource confusion. FL students often cannot get accurate and timely information about target universities: admission quotas, examination syllabi, reference books, and the preferences of potential supervisors. That asymmetry produces inefficient study plans, poor subject choices, and a good deal of uncertainty.

Time and self-discipline difficulties. Final-year students at local universities face competing demands on their time: compulsory coursework, teaching practica, administrative class meetings, and part-time employment. Self-regulatory problems such as procrastination and distraction narrow an already limited budget of study hours.

Economic and family pressure. Tutoring, review materials, application fees, and living costs during the gap year all cost money, and family expectations, stated openly or not, add to the strain. Students from lower-income families carry the heaviest load.

AI-era professional anxiety. This differs from the anxiety that precedes and drives the decision to enroll. What this dimension captures is continuing doubt about the long-term labor-market value of an FL master's degree, worry that AI will erode the returns on advanced language credentials, and uncertainty about how AI literacy should fit alongside language expertise.

2.3 Preparation Progress and Hypothesis Development

Perceived preparation progress is students' own judgment of how far their current work matches the schedule they set for themselves. It is self-reported, but it is a reasonable proximal measure of engagement and effectiveness, and in other high-stakes testing settings it tracks later exam performance. If preparation difficulties consume limited cognitive and emotional resources, each dimension should reduce progress. We therefore propose:

H1: Academic and psychological difficulties are negatively related to perceived preparation progress.

H2: Information and resource confusion is negatively related to perceived preparation progress.

H3: Time and self-discipline difficulties are negatively related to perceived preparation progress.

H4: Economic and family pressure is negatively related to perceived preparation progress.

H5: AI-era professional anxiety is negatively related to perceived preparation progress.

III. METHOD

3.1 Participants and Procedure

The study took place at a local public university in Sichuan Province, China, between September and October 2026. The sampling frame was all final-year FL majors (English, Translation, and Business English) registered on the university's internal NPEE intention-tracking system (N = 188). Data collection ran in two stages. In Stage 1 the academic affairs office distributed a demographic and intention registration form to all 188 registrants; after duplicate and test submissions were removed, 79 valid records remained. In Stage 2, students who had confirmed that they were actively preparing were invited to complete an online questionnaire on Wenjuanxing covering preparation difficulties and progress. Of the 66 responses received, six were dropped: one for patterned responding, four for duplicate submission, and one for partial missing data. The final sample was 60 responses, an effective response rate of 31.9% of the registered population and 76.0% of the Stage-1 confirmed subsample.

The sample included 48 women (80.0%) and 12 men (20.0%), a gender split typical of FL departments in Chinese universities. Mean age was 21.5 years (SD = 0.8). By major, 39 students (65.0%) studied English, 11 (18.3%) Translation, and 11 (18.3%) Business English. By class, 17 (28.3%) came from English Class 1, 22 (36.7%) from English Class 2, 11 (18.3%) from the Translation Class, and 10 (16.7%) from the Business English Class. The 10-times rule (Hair et al., 2022) requires a sample larger than ten times the number of structural paths aimed at any one construct; with five paths pointing at the endogenous construct, 60 cases meet the minimum for PLS-SEM.

3.2 Measures

Preparation difficulties. A 27-item scale was built following standard psychometric procedure (DeVellis, 2017). Items were generated from semi-structured interviews with 10 FL students and from the existing literature, reviewed by three faculty members in FL education and psychometrics, and piloted with 20 students to refine wording. Respondents rated each statement on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree) for their experience over the previous month. The initial pool covered six dimensions: academic difficulties (5 items), information and resource confusion (5), psychological and emotional difficulties (6), time and self-discipline difficulties (4), economic and family pressure (3), and AI-era professional anxiety (4).

Perceived preparation progress. One face-valid item asked participants to rate their overall NPEE preparation progress on a 5-point scale (1 = severely behind schedule, 5 = fully on track). A single item is acceptable when the construct is concrete, unidimensional, and easy to judge about oneself (Hair et al., 2022).

Control and supplementary variables. Participants reported gender, major, class, target institution and major, whether they were switching disciplines, daily study hours, revision progress in each of the four NPEE subjects, willingness to attend one-to-one counseling, and backup plans in case they failed. One open-ended question asked them to describe difficulties that the scale did not cover.

3.3 Data Analysis Strategy

Analyses used partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4 (Ringle et al., 2022). PLS-SEM suited the design for three reasons: the study is exploratory and aims to identify salient predictors rather than test a tightly specified theory; the sample (n = 60) is modest, and PLS-SEM has more statistical power than covariance-based SEM at this size (Hair et al., 2022); and the model pairs reflective measurement with a single-item endogenous construct.

Assessment followed the standard two-stage procedure. The measurement model was first checked for internal consistency (Cronbach's α, composite reliability), convergent validity (average variance extracted, indicator loadings), and discriminant validity (HTMT ratios, the Fornell-Larcker criterion). The structural model was then evaluated for explanatory power (R^2, adjusted R^2), predictive relevance (Stone-Geisser Q^2 from blindfolding), overall fit (GoF), path coefficients, and effect sizes (f^2). Path significance was tested with 5,000 bootstrap resamples and no sign changes. Following Hair et al. (2022), we inspected both percentile and bias-corrected confidence intervals and report two-tailed significance at $\alpha = .05$.

Because the initial six-dimension, 27-item model showed low reliability on four dimensions and a discriminant validity violation between academic and psychological difficulties, the model was refined in two documented steps. The v2 model merged the two highly correlated dimensions and dropped two severely under-loading indicators (Q37 and Q42). The v3 model also dropped five indicators whose loadings stayed below 0.50 (Q17, Q20, Q26, Q36, and Q43), as the standard pruning guideline recommends (Hair et al., 2022). We kept v2 as the primary structural model because it retained more theoretical content and produced clearer significant paths, and used v3 to check measurement stability. Harman's single-factor test returned a first unrotated factor accounting for 26.8% of variance, well under the 50% threshold, so common method bias is not a serious concern here.

IV. RESULTS

4.1 Descriptive Statistics and Correlations

Table I reports means, standard deviations, and zero-order correlations for the six initial difficulty dimensions and perceived preparation progress. Overall preparation difficulty averaged 2.86 (SD = 0.39) on the 5-point scale, a moderate level. Academic difficulties drew the highest rating (M = 3.18, SD = 0.45), followed by psychological and emotional difficulties (M = 3.03, SD = 0.71), AI-era professional anxiety (M = 3.00, SD = 0.60), time and self-discipline difficulties (M = 2.78, SD = 0.52), information and resource confusion (M = 2.71, SD = 0.65), and economic and family pressure (M = 2.46, SD = 0.68). Perceived preparation progress averaged 3.13 (SD = 0.56), which suggests that most students saw themselves as moderately behind schedule.

The correlations ran in the expected direction. Every difficulty dimension correlated negatively with preparation progress, most strongly for academic difficulties ($r = -.43$, $p < .01$) and time and self-discipline difficulties ($r = -.44$, $p < .01$). Academic and psychological difficulties were closely related to each other ($r = .66$, $p < .01$); the discriminant validity problem this created is discussed below.

Table I. **Descriptive Statistics and Zero-Order Correlations Among Study Variables (n = 60)**

Variable	M	SD	1	2	3	4	5	6	7
1. Academic difficulties	3.18	0.45	—						
2. Psychological & emotional difficulties	3.03	0.71	.66**	—					
3. Information & resource confusion	2.71	0.65	.33**	.33*	—				
4. Time & self-discipline difficulties	2.78	0.52	.32*	.33*	.46**	—			
5. Economic & family pressure	2.46	0.68	.34**	.32*	.33**	.14	—		
6. AI-era professional anxiety	3.00	0.60	.10	.13	.22	.27*	.37**	—	
7. Perceived preparation progress	3.13	0.56	−.43**	−.27*	−.21	−.44**	−.10	−.20	—

Note. **p < .05; **p < .01 (two-tailed).*

4.2 Measurement Model Assessment

The initial model (v1: six dimensions, 27 indicators) had acceptable composite reliability (CR ≥ 0.70) on all six dimensions, but Cronbach's α fell below the conventional 0.70 on four of them (time and self-discipline α = .44; economic and family pressure α = .48; AI-era professional anxiety α = .58; academic difficulties α = .62), and AVE fell below 0.50 on five of six. Discriminant validity failed between academic and psychological difficulties (HTMT = 0.94, above the 0.85 threshold; the Fornell-Larcker criterion was also violated), and three indicators loaded below 0.40 (Q17 = .35, Q37 = .47 but theoretically misplaced, Q42 = .29).

Following a documented indicator-pruning and dimension-merging procedure (Hair et al., 2022), v2 merged the two overlapping dimensions into a single academic and psychological difficulties factor and removed Q37 (loading .47 on a three-item factor with a high cross-loading) and Q42 (.29). The v3 model removed Q17, Q20, Q26, Q36, and Q43, whose loadings stayed below 0.50 after re-estimation. Table II summarizes reliability and convergent validity for all three versions.

Table II. **Reliability and Convergent Validity Across Model Specifications**

Model	Construct	Items	α	CR	AVE
v1 (six dimensions, 27 items)	Academic difficulties	5	0.62	0.77	0.41
	Information & resource confusion	5	0.73	0.82	0.49
	Psychological & emotional difficulties	6	0.82	0.87	0.53
	Time & self-discipline difficulties	4	0.44	0.70	0.38
	Economic & family pressure	3	0.48	0.71	0.47
	AI-era professional anxiety	4	0.58	0.74	0.45
v2 (five dimensions, 25 items)	Academic & psychological difficulties	11	0.85	0.88	0.41
	Information & resource confusion	5	0.73	0.82	0.49
	Time & self-discipline difficulties	4	0.44	0.70	0.38
	Economic & family pressure	2	0.34	0.75	0.60
	AI-era professional anxiety	3	0.70	0.81	0.60
v3 (refined, 20 items)	Academic & psychological difficulties	9	0.85	0.88	0.46
	Information & resource confusion	4	0.76	0.85	0.58
	Time & self-discipline difficulties	3	0.43	0.73	0.47
	Economic & family pressure	2	0.34	0.75	0.60
	AI-era professional anxiety	2	0.74	0.88	0.79

Note. *α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. Cronbach's α for two-item subscales is a known biased underestimate of reliability and should not be read on its own; CR is the more appropriate index (Hair et al., 2022).*

Table III gives discriminant validity results for the refined v3 model. Every HTMT value fell below the conservative 0.85 threshold (the largest, 0.76, sat between academic-psychological and economic-family pressure), and the Fornell-Larcker criterion held for all construct pairs: the diagonal √AVE values exceeded the corresponding off-diagonal correlations. The violation seen in v1 was resolved.

Table III. **Discriminant Validity of the Refined Measurement Model (v3, n = 60)**

Construct	1	2	3	4	5
1. Academic & psychological diff.	**0.68**	0.37	0.71	0.76	0.32
2. Information & resource confusion	.28	**0.76**	0.68	0.58	0.37
3. Time & self-discipline difficulties	.41	.40	**0.69**	0.65	0.33
4. Economic & family pressure	.46	.31	.22	**0.77**	0.76
5. AI-era professional anxiety	.27	.29	.18	.37	**0.89**

Note. *Diagonal (bold) = √AVE; below the diagonal = construct correlations; above the diagonal = HTMT ratios. All HTMT values are below 0.85, indicating satisfactory discriminant validity.*

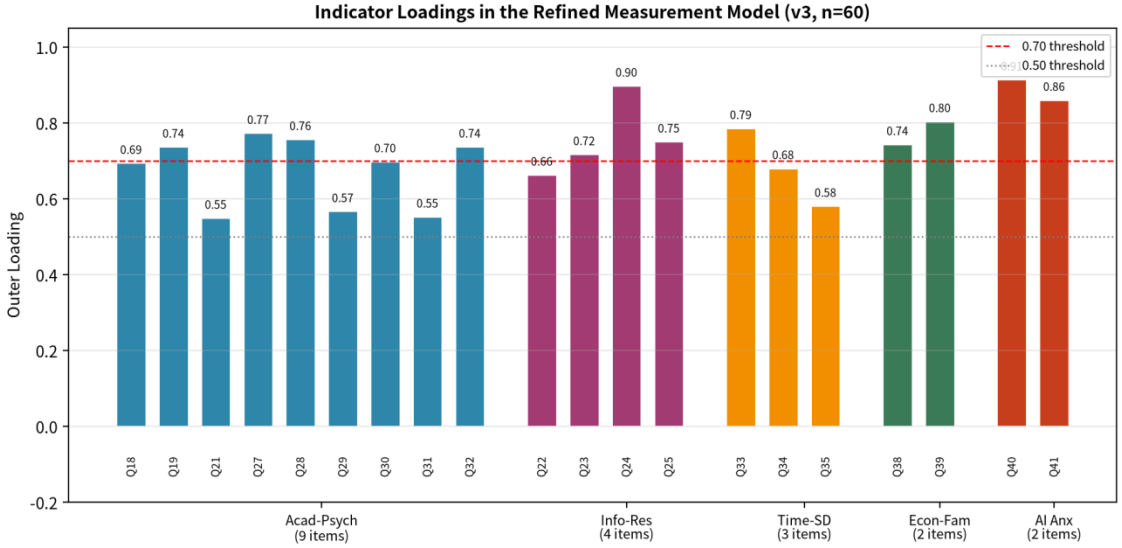


Figure 1: Indicator outer loadings for the refined measurement model (v3). The dashed red line marks the 0.70 benchmark; the dotted gray line marks the 0.50 minimum.

4.3 Structural Model Results

The structural model was estimated first with v2, which kept more theoretical coverage while meeting acceptable measurement quality. Figure 2 shows the path diagram with standardized coefficients, and Table IV reports path coefficients, bootstrap intervals, and effect sizes for v2 and v3. The v2 model accounted for 25.9% of the variance in perceived preparation progress (R^2 = .259, adjusted R^2 = .191). Stone-Geisser Q^2 from blindfolding (omission distance D = 7) was 0.099, indicating small-to-moderate predictive relevance, and the GoF was 0.344.

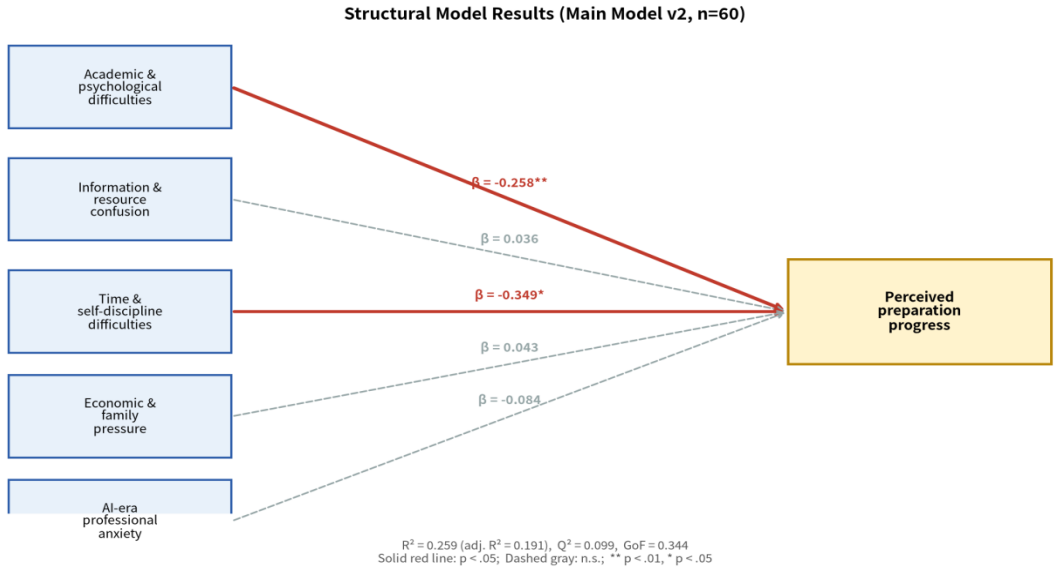


Figure 2: Structural model results for the v2 main model (n = 60). Values are standardized path coefficients (β). Solid red arrows mark significant paths; dashed gray arrows mark non-significant paths. **p < .01, *p < .05.

Table IV. **Structural Model Path Coefficients, Significance, and Effect Sizes**

Path	β	p	95% CI	f^2
v2 main model (25 items, R^2 = .259)				
Academic & psychological diff. → Progress	−0.258	.008	[−0.503, −0.064]	0.064
Information & resource confusion → Progress	+0.036	.829	[−0.221, 0.275]	0.001
Time & self-discipline diff. → Progress	−0.349	.015	[−0.655, −0.078]	0.115
Economic & family pressure → Progress	+0.043	.770	[−0.305, 0.344]	0.002
AI-era professional anxiety → Progress	−0.084	.605	[−0.319, 0.247]	0.008
v3 robustness model (20 items, R^2 = .253)				
Academic & psychological diff. → Progress	−0.214	.027	[−0.451, −0.032]	0.042
Information & resource confusion → Progress	−0.058	.564	[−0.294, 0.150]	0.003
Time & self-discipline diff. → Progress	−0.327	.024	[−0.610, −0.043]	0.104
Economic & family pressure → Progress	+0.061	.683	[−0.291, 0.359]	0.004
AI-era professional anxiety → Progress	−0.102	.485	[−0.340, 0.218]	0.011

Note. *β = standardized path coefficient; CI = 95% percentile bootstrap confidence interval based on 2,000 resamples; f^2 = Cohen's effect size (0.02 = small, 0.15 = medium, 0.35 = large).*

Two paths were significant in the v2 model. Academic and psychological difficulties reduced perceived preparation progress (β = −0.258, p = .008, 95% CI [−0.503, −0.064], f^2 = 0.064), supporting H1, and time and self-discipline difficulties did the same (β = −0.349, p = .015, 95% CI [−0.655, −0.078], f^2 = 0.115), supporting H3. H2, H4, and H5 were not supported: information and resource confusion (β = +0.036, p = .829), economic and family pressure (β = +0.043, p = .770), and AI-era professional anxiety (β = −0.084, p = .605) showed no detectable effect on progress. The positive but non-significant coefficient for economic and family pressure may mean that students under greater family pressure also receive more structured support, which offsets part of the strain.

4.4 Robustness Check

After seven low-loading indicators were removed, v3 produced a similar pattern (Table IV, lower panel). Academic and psychological difficulties (β = −0.214, p = .027) and time and self-discipline difficulties (β = −0.327, p = .024) stayed significant and negative; the other three dimensions stayed non-significant. Explanatory power was comparable (R^2 = .253, Q^2 = 0.082, GoF = 0.367). Table V lists the predictive-power indices for all three specifications. The two dominant paths kept their sign, magnitude, and significance across specifications, which is the main evidence that the core result is robust.

Table V. **Predictive Power Indices Across Model Specifications**

Model	R^2	Adj. R^2	Q^2	GoF
v1: 6 dimensions, 27 items (initial)	0.302	0.223	0.144	0.372
v2: 5 dimensions, 25 items (main)	0.259	0.191	0.099	0.344
v3: 5 dimensions, 20 items (robustness)	0.253	0.184	0.082	0.367

Note. *R^2 = proportion of variance explained; Q^2 = Stone-Geisser predictive relevance (blindfolding, D = 7); GoF = Tenenhaus goodness-of-fit index.*

Table VI. **Summary of Hypothesis Testing (v2 Main Model)**

Hypothesis	Path	β	p	Result
H1	Academic & psychological diff. → Progress	−0.258	.008	Supported
H2	Information & resource confusion → Progress	+0.036	.829	Not supported
H3	Time & self-discipline diff. → Progress	−0.349	.015	Supported
H4	Economic & family pressure → Progress	+0.043	.770	Not supported
H5	AI-era professional anxiety → Progress	−0.084	.605	Not supported

Note. *Two-tailed significance based on 2,000 bootstrap resamples; significance threshold α = .05. In the v3 robustness check, both supported paths remained significant at p < .05.*

4.5 Qualitative Insights

Answers to the open-ended question filled in detail that the scale could not capture. The barriers students named most often were heavy senior-year coursework and compulsory administrative activities, which matches the quantitative weight of time and self-discipline difficulties. Two responses illustrate the pattern:

> *"Why does our department still schedule so many compulsory courses and pointless cadre meetings in the final year? Other departments have almost no classes. We simply cannot focus on reviewing."*
>
> *"I only decided to take the exam in September, and I'm extremely worried about running out of time. The four subjects all need large amounts of memorization, and I can barely keep up."*

Other themes appeared repeatedly: the cost of off-campus tutoring, the difficulty of finding accurate information about target institutions, and doubt about whether an FL master's degree would still be worth having in the AI era. These responses fit the dimensional structure of the scale, but as predictors of progress they did not reach significance, most likely because students varied a good deal in how strongly they reported them.

V. DISCUSSION

5.1 Key Findings and Interpretation

This study asked how five dimensions of preparation difficulty relate to perceived preparation progress among FL students at a local Chinese university who were preparing for the NPEE. Two results carry most of the weight.

Academic and psychological difficulties and time and self-discipline difficulties were the only consistent negative predictors of progress, with medium and small-to-medium effects respectively. Both results fit the test anxiety and self-regulated learning literatures (Zeidner, 1998) and carry them into a setting, the NPEE among FL majors, that has not been studied in this way. The decision to merge academic and psychological difficulties was driven by their high intercorrelation ($r = .66$), but it also makes sense on its own terms: for FL students at local institutions, perceived academic weakness and emotional distress look like one experience of being overwhelmed rather than two separate barriers.

AI-era professional anxiety did not significantly predict progress, even though students endorsed it at a moderate level ($M = 3.00$). One reading is that it works mainly as a motive at the enrollment-decision stage, pushing students toward postgraduate study, and that once preparation is under way, nearer pressures such as time scarcity and academic-psychological strain dominate day-to-day progress. This fits the appraisal framework of Jiang and Li (2026): students who have committed to the NPEE may already treat the graduate credential as an adaptive answer to AI, which removes much of the anxiety's force. A second and more mundane possibility is statistical power. With $n = 60$ and a bivariate correlation of only $r = -.20$ with progress, the study was underpowered to detect a small-to-medium effect for this dimension.

Economic and family pressure also showed no detectable negative effect, and its sign was positive though non-significant. Preparing for the NPEE costs less, directly, than an overseas graduate application, and family pressure often comes with family support, financial or otherwise, that cancels part of its impact (Wang, 2026). Information and resource confusion likewise failed to reach significance. Free and abundant online resources (Bilibili, Xiaohongshu, Zhihu) now supply much of what institutional information channels once provided.

5.2 Theoretical Implications

The first point for theory is that the dimensions of difficulty do not weigh equally on progress. Time constraints and the merged academic-psychological factor dominate, while information deficits and macro-level anxiety do not. That ordering suggests resource depletion and self-regulation are the more proximal mechanisms in this population, and it argues for measuring preparation difficulties as a set of distinct dimensions instead of a single global burden.

The second point concerns AI anxiety itself. It behaves differently at the preparation stage than at the decision stage, and treating it as one construct across both would hide that difference. Career-construction research on AI anxiety should therefore separate the pre-decisional variety, which drives enrollment, from the post-decisional variety, which in this sample did not predict progress at all. The instrument developed here also extends CDDQ-style frameworks, which were built for general career indecision, to a high-stakes examination context.

5.3 Practical Implications

The strongest lever available to local universities is curricular. Reducing compulsory senior-year coursework and administrative obligations during the fall semester would attack the constraint that predicted lagging progress most strongly. Several elite universities already run 'exam-preparation semesters' with reduced course loads, and local institutions could adopt the same arrangement. Academic support should then be aimed at the hardest subjects (politics and the specialized course) through faculty-led review workshops or peer tutoring, rather than leaving students to commercial tutoring that widens financial inequality. Counseling services matter as well, and should be expanded and made easier to reach during the peak months from October to December, given how closely academic weakness and distress are tied together in these data. Information confusion did not predict progress in this sample, but alumni information sessions and a maintained database of target-institution materials cost little and address a problem that students raised often. Finally, bursaries for review materials or examination fees would ease financial pressure for students from lower-income families, even though the effect on measured progress was not significant.

5.4 Limitations and Future Directions

Several limitations qualify these findings. The sample ($n = 60$) sits at the lower bound for PLS-SEM, which limits the power to detect small effects and makes the bootstrap estimates imprecise; the results should be treated as exploratory. All measures were self-reported at a single time point, so common method variance and reverse causality (students who are behind may report more difficulties) cannot be ruled out; Harman's test was

reassuring, but multi-wave designs are needed to settle the direction of the relationships. The preparation-difficulties scale, despite repeated refinement, still showed weak internal consistency on the time and self-discipline subscale (α = .43 to .44 across specifications), which probably reflects the small number of retained items (three to four) and the fact that time management and self-discipline are not the same thing; this subscale needs to be expanded and revalidated with larger samples. The study was conducted at one local university, so the findings may not transfer to elite universities, where resources are more plentiful, or to non-FL majors. Progress was measured with a single self-report item; mock exam scores or study-time diaries would provide firmer evidence. And because the design is cross-sectional, no causal claim can be made; experimental or quasi-experimental evaluations of support interventions would be the next step.

VI. CONCLUSION

AI-related anxiety about employment and the continuing flow of Chinese FL students into postgraduate applications form the background to this study, which identifies academic-psychological distress and time and self-discipline constraints as the two barriers that matter most for NPEE preparation progress at a local university. Information gaps, economic and family pressure, and AI-era professional anxiety all appear in students' accounts, but none of them predicts progress independently once the two dominant barriers are in the model. The clearest institutional implications are to cut the senior-year course load, protect dedicated study time, and strengthen academic and psychological support during the peak months. Helping students through preparation itself, rather than treating postgraduate enrollment as the outcome to be explained, is where local universities have the most room to act.

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Conflict of Interest: The authors declare no conflict of interest.

Ethics Approval: The study was approved by the Institutional Review Board of Panzhihua University (Approval No. [XXX]). Informed consent was obtained from all participants before data collection.

Data Availability: The data that support the findings of this study are available from the corresponding author on reasonable request.

Author Contributions: Conceptualization, Wang Haitao; methodology, Wang Haitao; software, Wang Haitao; formal analysis, Wang Haitao; investigation, Wang Haitao; data curation, Wang Haitao; writing (original draft), Wang Haitao; writing (review and editing), Wang Haitao; supervision, Wang Haitao.

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