FEMALE PRESERVICE TEACHERS' ACHIEVEMENT GOALS AND PERFORMANCE ANXIETIES DURING IMPLEMENTING STEM EDUCATION PROJECTS FOR PRESCHOOL CHILDREN

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Abstract

Female preschool educators usually perceive themselves as less proficient in STEM, leading to heightened performance anxiety (PA), which in turn affects their achievement goals (AG). So, this study aims to examine the impact of PA on AG among female preservice preschool educators implementing STEM education projects. This research hypothesized that PA has both immediate and sustained effects on AG over multiple periods. Additionally, we posited that initial levels of PA and AG are interrelated and influence changes in each other over time. To test these hypotheses, data is collected from sixty female preservice preschool educators participating in a STEM education community for preschool children. Participants completed the Assessment Scale of STEM Education Learning Motivation for Preschool Teachers and the Assessment Scale of STEM Activity Performance for Preschool Teachers. The result of the path analysis model revealed satisfactory indices of goodness-of-fit, but the effects of PA on AG varied across different periods. The latent growth curve models also demonstrated a good fit, showing significant negative covariances between the intercepts and slopes of PA and AG. Specifically, PA exhibited a higher intercept but a lower slope compared to AG. The correlations between the intercepts and slopes of PA and AG were significant, though no significant connections were found between the intercepts and slopes of the two constructs. These findings suggest that while PA initially has a strong influence on AG, its impact diminishes over time, highlighting the complex and evolving relationship between PA and AG in preservice preschool educators engaged in STEM education projects.
Keywords: *achievement goal, female preservice teacher, latent growth curve model, performance anxiety, preschool children, STEM*

Introduction

Early exposure to STEM concepts can serve as a powerful catalyst for igniting children's natural curiosity, laying the groundwork for critical thinking and lifelong learning skills (Brenneman et al., 2019). In early childhood education, teachers play a pivotal role in shaping students' first encounters with STEM topics. As such, the efficacy of these early STEM educational initiatives depends significantly on the competence, confidence, and preparedness of educators (McClure et al., 2017). However, a notable challenge persists in the form of STEM-related anxiety among early childhood educators, especially among female preservice teachers. These educators frequently report low confidence in their ability to teach STEM subjects effectively, which may stem from limited experience or negative academic perceptions of STEM disciplines (Sullivan & Bers, 2015).

For female preservice teachers, STEM-related anxiety is often compounded by performance anxiety. Research indicates that female educators in training frequently experience heightened levels of performance anxiety compared to their male counterparts, which can lead to avoidance behaviors, undermining their achievement goals and potentially impacting their professional development (Legette & McCord, 2014; Putwain & Daly, 2014). Academic anxiety, as Freedman (2003) explains, is a negative emotional response triggered by past learning experiences perceived as challenging or discouraging, which may adversely affect future learning. Anxiety that originates from a fear of poor performance in STEM subjects can lead preservice teachers to avoid STEM-focused situations, creating a self-fulfilling cycle of avoidance and underperformance (Furner & Duffy, 2002).

This relationship between anxiety and performance in STEM is nuanced and often context-specific. Mueller (1992) found that individuals with higher performance anxiety struggle more with learning tasks, requiring more time and attempts to achieve proficiency compared to those with lower anxiety levels. Additionally, Eyring et al. (1993) discovered that task-specific anxiety, particularly in STEM, can slow the rate of learning, reinforcing feelings of inadequacy and creating barriers to effective teaching (Mitchell et al., 1994). Anxiety can thus inhibit preservice teachers' capacity to fully engage with STEM content, negatively affecting their professional growth and impacting the quality of STEM education they provide to young learners.

The interactions between anxiety and achievement goals are complex and appear to evolve over time. Aiken (1970) argued that there is a reciprocal relationship between emotional responses and academic achievement, while Ma and Xu (2003) proposed that there is a causal ordering between performance anxiety and achievement goals. In the case of female preservice teachers, high levels of performance anxiety could inhibit their willingness to take on STEM-related challenges, hindering their ability to develop a positive, growth-oriented relationship with these subjects. Although studies have explored the broader relationship between anxiety and academic success, less is known about how these dynamics specifically impact female preservice teachers in early childhood STEM education contexts.

This study seeks to address this gap by examining how performance anxiety and achievement goals interact over time in female preservice teachers, employing Latent Growth Curve Modeling (LGCM) to analyze these changes. By identifying critical points of intervention, this research aims to offer strategies for reducing anxiety and improving achievement orientation, ultimately supporting female preservice teachers as they develop competence and confidence in STEM teaching.

Research Focus

The focus of this research is to examine the trajectories of preservice preschool teachers' achievement goals and performance anxiety and their correlation across times.

Research Aim

To achieve the aim of understanding the overtime impacts of performance anxieties on preservice teachers' achievement goals during STEM education project, this study has had two main objectives:

1. To explore whether preservice teachers' achievement goals are affected by performance anxieties across time.
2. To examine the longitudinal associations of preservice teachers' performance anxieties and achievement goals.

Research Questions

This study addresses two main research questions:

1. Do preservice teachers' achievement goals vary in response to performance anxiety over time? Additionally, what is the magnitude of both immediate and sustained effects of performance anxiety on these goals?
2. Are there longitudinal associations between preservice teachers' performance anxiety and their achievement goals? Specifically, what are the baseline associations, and how do these associations change over time?

Research Methodology

General Background

This study employed a secondary analysis method to explore the trajectories of female preservice preschool teachers' psychological states, specifically performance anxiety and achievement goals, during the implementation of STEM education projects. Secondary data analysis enables the re-examination of existing data sets to uncover new insights, particularly useful in longitudinal studies such as this one. In this research, several statistical models, including path analysis and latent growth curve models were employed to trace the development of PA and AG over time. These models were chosen because of their capacity to capture both immediate and sustained effects of psychological factors on teacher performance in STEM settings.

LGCM, in particular, allows for the examination of individual change over multiple time points and the identification of factors contributing to these changes. This method is well-suited for understanding complex, dynamic relationships, such as those between PA and AG, providing a detailed picture of how these constructs evolve and interact over the course of a teacher's training. In addition, the use of path analysis models with explicit variables provides insights into both the direct and indirect effects of PA on AG across different periods. The first time point is in the beginning of the Fall 2023 semester, the second time point is in the middle of the same semester, and the third time point is in the end of the same semester.

Sample

A pre-testing phase was conducted to ensure the instruments' readability and logical organization. The pre-test involved 20 undergraduate students with characteristics similar to the final study sample, allowing for necessary adjustments to the questionnaire items for clarity and relevance.

Purposeful sampling was used to select participants, focusing on college students majoring in early childhood education and child development who were actively engaged in STEM education projects and enrolled in teacher training programs centered on STEM. These 60 female preservice preschool educators, part of a STEM education community for preschool children in Taichung City, Taiwan, received comprehensive training that included designing STEM activities, creating STEM kits, and implementing these activities in preschool settings.

Data on participants' performance, motivation, performance anxiety, and achievement goals were collected at three distinct time points to capture developmental changes during their training. The longitudinal dataset enables an in-depth examination of how PA and AG evolve and interact over time in response to STEM training and classroom experiences.

Instrument and Procedures

Data were collected using two main instruments: the "Assessment Scale of STEM Education Learning Motivation for Preschool Teachers" (Sung, 2024) and the "Assessment Scale of STEM Activity Performance for Preschool Teachers." (Sung, 2024) Each instrument was adapted to the context of the study and aimed to measure the participants' AG and PA, respectively.

Achievement Goal Subscale: The "Assessment Scale of STEM Education Learning Motivation for Preschool Teachers" (Sung, 2024) included the AG subscale, designed to assess participants' motivation toward engaging with STEM activities. Responses were rated on a 5-point Likert scale ranging from "Always" to "Never" and "Very Often" to "Rarely." This scaling allowed for the quantification of attitudes and motivational orientations in relation to STEM activities. Sample items in the AG subscale included statements such as:

- "STEM activities have increased my willingness to face challenges."
- "Challenging STEM activities motivate me to learn."
- "I love linking concepts in STEM activities."

These items were intended to capture various aspects of AG, such as intrinsic motivation, interest, and perceived competence in STEM.

Performance Anxiety Subscale: PA was measured using the "Assessment Scale of STEM Activity Performance for Preschool Teachers," (Sung, 2024) with items reflecting the participants' anxiety levels related to their STEM-related tasks and responsibilities. This subscale also used a 5-point Likert scale anchored with "Not much," "Little," "Somewhat," "Much," and "A great deal." Sample items included:

- "When I do my homework, I feel nervous and under pressure."
- "I become very nervous before a presentation, even if I am well prepared."
- "I worry that I will receive a poor grade in writing papers."

These items were designed to identify specific sources of anxiety, including evaluation apprehension, performance concerns, and general nervousness associated with STEM activities.

Validation of Instruments

A confirmatory factor analysis (CFA) with a bootstrapped method was conducted to ensure the construct validity of both subscales. The CFA results indicated a satisfactory construct validity for the PA subscale ($\chi^2 = 1.019$, $df = 2$, $p = .601$) and the AG subscale ($\chi^2 = 5.131$, $df = 2$, $p = .077$), with all factor loadings exceeding the recommended threshold of 0.7. The composite reliabilities were calculated at .884 for the PA subscale and .843 for the AG subscale, indicating high internal consistency. Additionally, the average variance extracted (AVE) values were .656 for PA and .574 for AG, meeting the criteria proposed by Fornell and Larcker (1981) and Hair et al. (2019) for satisfactory convergent validity. These validation procedures ensured that the instruments reliably measured the intended constructs.

Data Analysis

The analysis employed a three-wave dataset to examine the trajectories of PA and AG among the preservice preschool teachers. The study focused on three primary statistical models to investigate the temporal changes and relationships between these variables:

1. Path Analysis Model:

The path analysis model was used to explore both the immediate and sustained effects of PA on AG across the three time points. This model explicitly incorporated all observed variables and covariates, allowing for the identification of direct and indirect pathways through which PA might influence AG. The path analysis provided an initial understanding of the structural relationships between PA and AG, including how these variables potentially interact over time.

2. Unconditional Latent Growth Curve Model

To capture the dynamic nature of PA and AG over time, an unconditional LGCM was fitted. In this model, PA and AG were treated as time-invariant variables measured at three different time points. Two factors were estimated: (1) Growth Intercept Factor: Representing the initial level of each variable. (2) Growth Slope Factor: Representing the rate of change over time.

This model allowed the examination of individual differences in the starting points (intercepts) and growth trajectories (slopes) of PA and AG, providing insights into how these constructs develop throughout the teacher training process.

3. Conditional Latent Growth Curve Model

Building on the unconditional model, the conditional LGCM examined the relationships between the growth factors of PA and AG. This model investigated whether changes in one construct (e.g., PA) were associated with changes in the other (e.g., AG) over time. By including the correlations between the intercepts and slopes of PA and AG, this model provided a more nuanced understanding of their interdependence. The nested structure of the conditional LGCMs allowed for comparison between different configurations of the model, facilitating the identification of the most suitable model to represent the data.

Model Testing and Estimation

All three models were subjected to testing for their goodness-of-fit using indices such as chi-square (χ^2), degrees of freedom (*df*), root mean square residual (RMR), root mean square error of approximation (RMSEA), goodness-of-fit index (GFI), and comparative fit index (CFI), following guidelines from Hair et al. (2019) and Hu and Bentler (1998). The maximum likelihood estimation (MLE) method was employed in a two-step process:

Measurement Model Analysis: This step assessed the relationships between each construct (PA and AG) and its measures to confirm the validity of the constructs.

Structural Model Analysis: This step examined the relationships between PA and AG, checking the hypotheses related to their longitudinal associations and dynamic changes over time (Jöreskog, 1993). Model equivalence and fit comparisons were made to select the best-fitting model.

This robust methodological approach ensured a comprehensive analysis of the trajectories of PA and AG among female preservice teachers in a STEM context, addressing both their immediate effects and long-term interrelationships. The insights gained from this analysis can inform strategies for reducing anxiety and fostering positive achievement goals during teacher training programs.

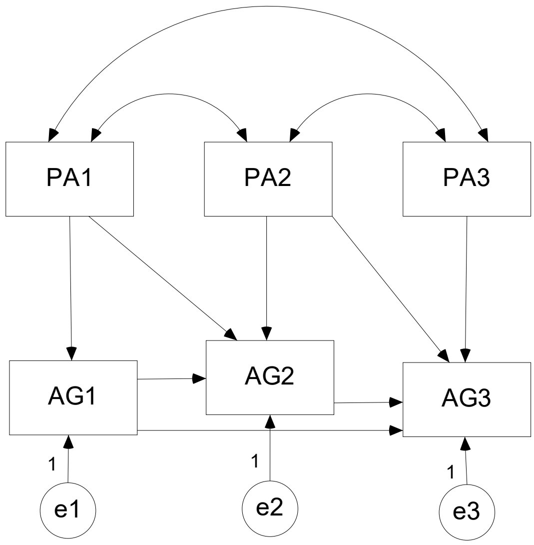
Research Results

Path Analysis Model

Path analysis models were employed to address the first research question, which aimed to capture the complex dynamics between PA and AG, including how PA at an earlier time point affects AG both immediately and in subsequent periods. The hypothesized model is presented in Figure 1, and the default setting posits that PA exerts both immediate and sustained effects on AG, while AG itself demonstrates temporal effects across successive time points.

Figure 1

Default Setting of Path Analysis Model



The default path analysis model was structured around four main sets of effects:

(1) Immediate Effects of PA on AG: This pathway examines how PA at each specific time point (PA1, PA2, PA3) directly impacts AG at the same time point (e.g., PA1 → AG1, PA2 → AG2, PA3 → AG3).

(2) Sustained Effects of PA on AG: This pathway investigates the delayed impact of PA on AG at later time points (e.g., PA1 → AG2, PA2 → AG3).

(3) Temporal Effects of AG: This component examines the continuity of AG over time, analyzing how AG at one time point affects AG at the subsequent time point (e.g., AG1 → AG2, AG2 → AG3).

(4) Covariance Among PA Measurements: The model also includes covariances among PA measurements across time points (e.g., PA1 ↔ PA2, PA1 ↔ PA3, PA2 ↔ PA3) to account for the potential interrelationships between different time points of PA.

1. Nested Models for Path Analysis

To identify the most suitable model for explaining the data, we created and tested a series of nested models (Model 1a to Model 1e), each progressively introducing more complexity. The specific settings of these nested models are outlined below:

(1) Model 1a (Basic Model): This model serves as the baseline, where only the variances of the exogenous variables are freely estimated. All regression weights and covariances were fixed to zero.

(2) Model 1b: This model extends Model 1a by allowing all covariances to be freely estimated while keeping the other parameters fixed.

(3) Model 1c: Building upon Model 1b, this model allows the parameters for temporal effects (e.g., AG1 → AG2, AG2 → AG3) to be freely estimated.

(4) Model 1d: In addition to the temporal effects, Model 1d permits the parameters for the sustained effects of PA (e.g., PA1 → AG2, PA2 → AG3) to be freely estimated.

(5) Model 1e (Full Model): This model further includes the immediate effects of PA on

AG, allowing all relevant parameters to be freely estimated. It represents the most comprehensive model for examining both immediate and sustained effects, as well as temporal effects of AG.

2. Model Comparison and Fit Indices

The model fit indices for each of the nested models are provided in Table 1. Although the chi-square tests of model fitness were rejected for all models, Model 1e demonstrated the best fit among the nested models, as indicated by the chi-square value, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Consistent Akaike Information Criterion (CAIC), and Expected Cross-Validation Index (ECVI) values. Specifically, Model 1e had the lowest values across these fit indices, supporting its selection as the best-fitting model for the dataset. The differences in the fitness indices between Model 1e and the other nested models were statistically significant, further validating the robustness of Model 1e.

Table 1
Comparison of Nested Model 1

Model	χ2	*df*	*p*	AIC	BCC	EVIC
Model 1a	684.6	15	<.001	696.4	696.9	2.33
Model 1b	393.2	12	<.001	411.2	411.7	1.38
Model 1c	243.0	9	<.001	267.0	267.5	0.89
Model 1d	176.6	7	<.001	204.6	205.2	0.68
Model 1e	30.3	4	<.001	64.3	65.1	0.22

3. Model 1e: Best-Fitting Model

For Model 1e, the absolute fit indices revealed a chi-square value of 30.27 ($df = 4$, $p < .001$) and a χ^2/df ratio of 7.57. Although the chi-square and χ^2/df values were not ideal, other fit indices suggested an acceptable model fit. The GFI was .968, indicating that the model accounted for a significant proportion of the observed variances and covariances. The RMR was .043, which is less than .05, suggesting that the discrepancy between the predicted and observed matrices was minimal. Furthermore, the RMSEA was .148, indicating a moderate fit.

The relative indices of model fit were also assessed, with NFI = .956, RFI = .834, IFI = .961, TLI = .853, and CFI = .961. These indices were generally within acceptable ranges, indicating that Model 1e offered a substantial improvement from the null model toward the theoretical perfect model. Collectively, these fit indices supported Model 1e as the most robust model for exploring the relationship between PA and AG.

4. Estimated Coefficients of Model 1e

The estimated coefficients of Model 1e, displayed in Figure 2, reveal several key findings:

(1) Immediate Effects: The immediate effect of PA on AG varied across time points. At time-point 1, the coefficient was negative and significant (PA1 → AG1 = -0.33, $p < .001$), suggesting that higher PA at the initial stage significantly lowered AG. However, at time-point 2, the effect was non-significant (PA2 → AG2 = -0.01, $p = .850$), indicating a temporary decline in PA's influence on AG. By time-point 3, the

effect regained significance (PA3 → AG3 = -0.47, $p < .001$), suggesting a resurgence of PA's negative impact on AG as the training progressed.

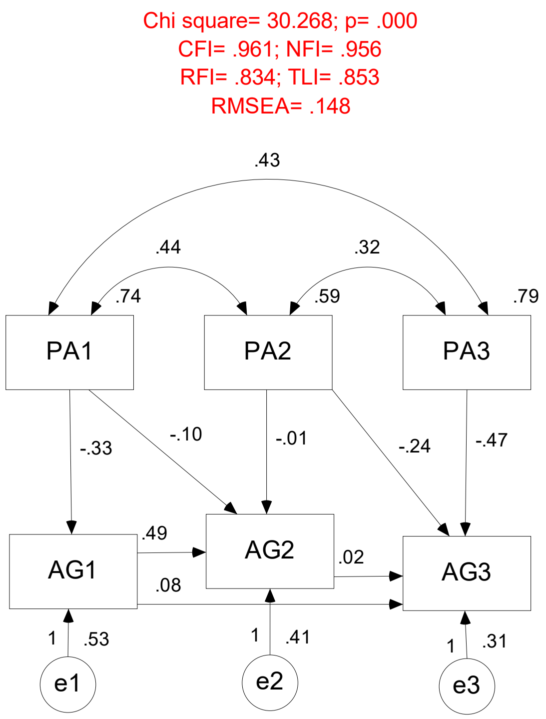
(2) Sustained Effects: The sustained effect of PA on future AG showed mixed results. The effect of PA1 on AG2 was weak and marginally non-significant (PA1 → AG2 = -0.10, $p = .088$). Conversely, the effect of PA2 on AG3 was stronger and statistically significant (PA2 → AG3 = -0.241, $p < .001$). These results suggest that sustained anxiety has a more pronounced impact on AG later in the program.

(3) Temporal Effects of AG: The temporal effect of AG was strong at the initial stages, with AG1 significantly predicting AG2 (AG1 → AG2 = 0.49, $p < .001$). However, this effect weakened substantially over time, becoming non-significant by the next interval (AG2 → AG3 = 0.02, $p = .751$). The effect of AG1 on AG3 was marginal (AG1 → AG3 = 0.08, $p = .096$), indicating a diminishing influence of early AG on later achievement.

5. Interpretation of Results

The analysis of Model 1e indicates that PA has a complex, fluctuating impact on AG throughout the training period. The significant negative effects at time-points 1 and 3 highlight the critical influence of initial anxiety and the resurgence of anxiety toward the end of the training. The weakening of effects at the intermediate stage might be attributed to factors like procrastination or temporary adaptation to the program's demands. The findings underscore the importance of addressing PA continuously and systematically to support the development of AG in preservice teachers.

Figure 2
Estimated Coefficients of Parameters of Path Analysis Model 1e



Longitudinal Associations among the Baselines and Changes in Preservice Teachers' Performance Anxiety and Achievement Goals

The initial path analysis model was only partially adequate in fitting the dataset, suggesting that a regression model limited to explicit variables might not fully capture the impact trajectory of performance anxiety on achievement goals for preservice preschool teachers. To gain a more comprehensive understanding, we employed a latent variable approach, allowing us to explore the repeated measures of performance anxiety and achievement goals through their underlying latent factors.

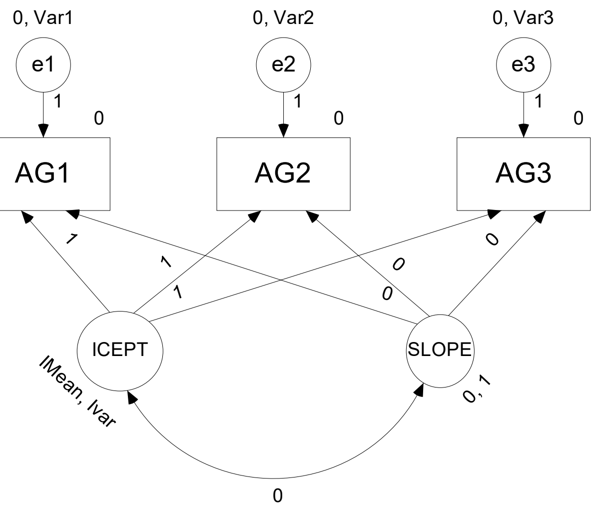
The Latent Growth Curve Model is particularly advantageous in the present study as it systematically explains how performance anxiety and achievement goals evolve over three waves of data collection (Willett & Sayer, 1994). LGCM is suitable for modeling longitudinal data, especially when within-subject variations are dependent and between-subject variations may change over time (Wang, 2009). This methodological approach helps uncover the inherent growth patterns in both performance anxiety and achievement goals.

1. Unconditional Latent Growth Model (Default Setting)

The default setting of the unconditional latent growth model, illustrated in Figure 3, includes two variations: one with only a latent intercept factor and another incorporating both latent intercept and slope factors.

In the model with only an intercept factor, achievement goals at three different time points (AG1, AG2, and AG3) are measured. The factor loadings for the intercept factor are fixed at 1, indicating that this factor uniformly influences all repeated measures. Here, the latent intercept factor captures the initial level of the outcome, while the slope growth factor and the covariance between the intercept and slope factors are set to zero.

Figure 3
Default Setting of Latent Growth Curve Model



In contrast, the model that incorporates both intercept and slope factors retains the fixed intercept loadings but introduces a slope factor that also points to AG1, AG2, and AG3. The factor loadings of the slope factor are scaled according to the timing of the outcome measures, coded as 0, 0.4, and 1 for the achievement goal model. This setup allows the slope factor to represent the trajectory of change over time. For the performance anxiety model, the factor loadings of the slope are coded as 0, 0.75, and 1, indicating a different pattern of change over the three measurement points.

2. Model Comparison and Results

The results of the LGCM for achievement goals indicate that the model with both intercept and slope factors outperforms the intercept-only model. The goodness-of-fit indices for the model with intercept and slope factors are $\chi^2 = 0.06$ ($df = 1$, $p = .806$), AIC = 16.1, and BCC = 16.3. In contrast, the intercept-only model yields $\chi^2 = 294.6$ ($df = 4$, $p < .001$), AIC = 304.6, and BCC = 304.7. The significant difference in the fit between these two models ($\Delta\chi^2 = 294.5$, $\Delta df = 3$, $p < .001$) demonstrates that including a slope factor is crucial for accurately modeling changes in achievement goals. The estimated means of the intercept (2.7, $t = 62.4$, $p < .001$) and slope (1.0, $t = 19.8$, $p < .001$) suggest that both the initial level and the rate of change in achievement goals are significantly greater than zero.

Similarly, the LGCM for performance anxiety reveals that the model incorporating intercept and slope factors is superior. For this model, the indices are $\chi^2 = 19.8$ ($df = 1$, $p \leq .001$), AIC = 16.1, and BCC = 16.3, whereas the intercept-only model produces $\chi^2 = 61.7$ ($df = 4$, $p < .001$), AIC = 35.8, and BCC = 36.0. The difference in fit ($\Delta\chi^2 = 294.5$, $\Delta df = 3$, $p < .001$) reinforces the importance of modeling the change trajectory. The estimated means for the intercept and slope are 3.4 ($t = 69.4$, $p < .001$) and 0.2 ($t = 5.9$, $p < .001$), respectively, indicating that the initial level and the rate of change in performance anxiety are also significantly positive.

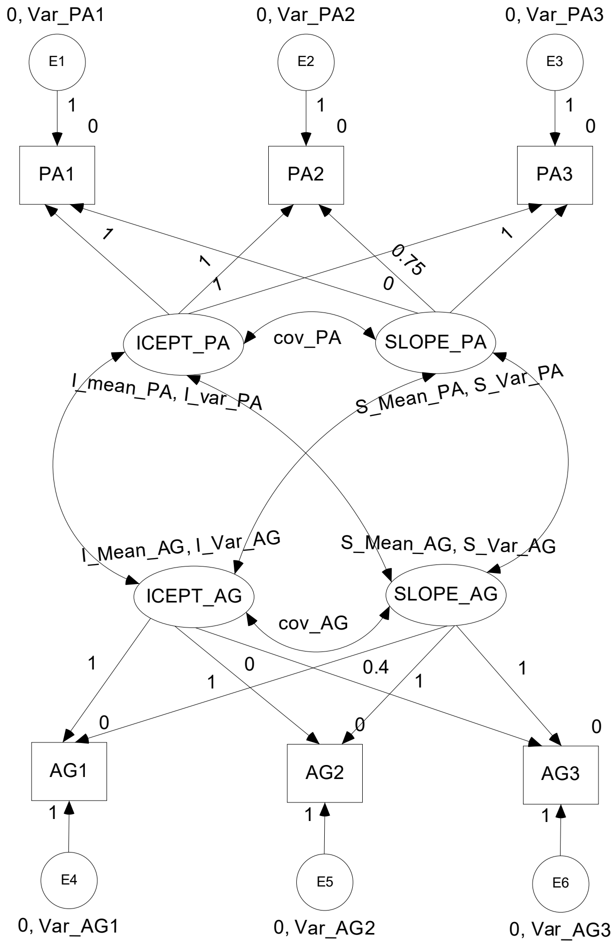
Given the significance of both the initial levels and rates of change for performance anxiety and achievement goals, it becomes essential to explore their trajectory further. To investigate the relationship between the trajectories of performance anxiety and achievement goals, we constructed a series of conditional latent growth curve models. These models integrate both intercept and slope factors to examine the correlations between the trajectories, as shown in Figure 4. Various competing models (Model 2a, Model 2b, Model 2c, etc.) were compared using different parameter constraints.

3. Setting and Comparison of Competing Models

The settings for the competing models (Model 2) are as follows:

(1) Model 2a: All covariances among achievement goal (AG) and performance anxiety (PA) factors are fixed to 0.
(2) Model 2b: AG factors' covariances with the PA intercept factor are fixed to 0, with other covariances freely estimated.
(3) Model 2c: AG factors' covariances with the PA slope factor are fixed to 0, with other covariances freely estimated.
(4) Model 2d: Covariances between the intercepts (Intercept_AG < > Intercept_PA) and slopes (Slope_AG < > Slope_PA) are fixed to 0.
(5) Model 2e: Covariances between Intercept_PA < > Slope_AG and Slope_PA < > Intercept_AG are fixed to 0.
(6) Model 2f: All covariances between AG factors and PA factors are freely estimated.

Figure 4
Variables and Paths of the Correlation between Two Latent Growth Curve Models



The model fit indices of the competing models are presented in Table 4. Model 2e emerges as the best-fitting model, with $\chi^2 = 54.8$ ($df = 9$, $p < .001$), AIC = 90.8, BCC = 91.6, and EVIC = .304. When compared to Model 2f, the chi-square difference test indicates equivalence ($\Delta\chi^2 = 1.6$, $\Delta df = 2$, $p = .449$). However, Model 2e is preferred due to its lower AIC, BCC, and EVIC values, confirming it as the optimal model for explaining the relationship between performance anxiety and achievement goal trajectories.

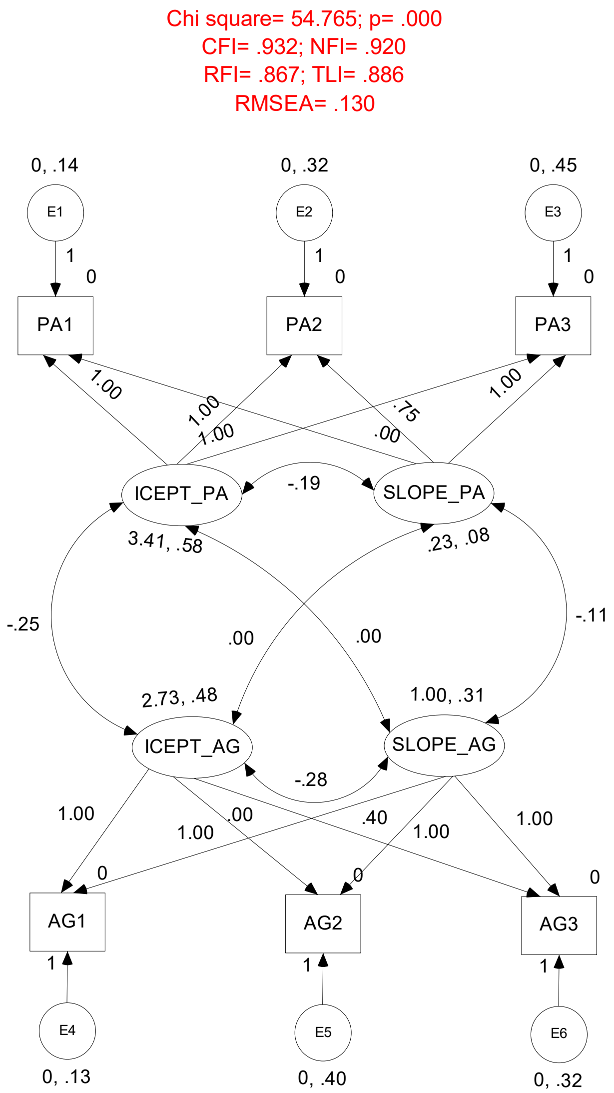
Table 4
Comparison of Nested Model 2

Model	χ^2	*df*	*p*	AIC	BCC	EVIC
Model 2a	282.8	11	< .001	294.8	295.6	.986
Model 2b	134.8	9	< .001	170.8	171.6	.571
Model 2c	64.9	9	< .001	100.9	101.8	.337
Model 2d	93.0	9	< .001	129.0	129.9	.431
Model 2e	54.8	9	< .001	90.8	91.6	.304
Model 2f	53.2	7	< .001	93.2	94.1	.312

4. Interpretation of Model 2e

The estimated coefficients for Model 2e are presented in Figure 5. The covariances between the intercepts and slopes of AG and PA reveal a significant negative association: Intercept_AG <-> Intercept_PA = -0.25 (t = -8.1, p < .001) and Slope_AG <-> Slope_PA = -0.11 (t = -4.4, p < .001). These findings suggest that the initial levels of performance anxiety have a significant association with achievement goals and that this association persists in their rates of change over time.

Figure 5
Estimated Coefficients of Parameters of Model 2e



Interestingly, the near-zero covariance between the intercept factor of performance anxiety and the slope factor of achievement goals implies that the decline in achievement goal rate of change is not primarily driven by the initial status of performance anxiety. Similarly, the weak association between the intercept of achievement goals and the slope of performance anxiety indicates that the change in performance anxiety may be influenced by long-term factors rather than an immediate effect of the initial achievement goal status.

For fixed effects, the means of the intercepts for performance anxiety and achievement goals are 3.41 and 2.73, respectively, while the means of the slopes are 0.23 and 1.00. This suggests that while performance anxiety starts at a higher level, its rate of change is slower than that of achievement goals. For random effects, the variances of intercepts for performance anxiety and achievement goals are 0.58 and 0.48, respectively, with slope variances of 0.08 and 0.31. Thus, performance anxiety displays a broader range of initial levels but a narrower range of change compared to achievement goals.

The residual variances for the observed variables are within a normal range, being 0.14, 0.32, and 0.45 for performance anxiety across the three time points, and 0.13, 0.40, and 0.32 for achievement goals.

5. Interpretation of Results

The findings support the use of Model 2e as the most fitting conditional latent growth curve model for this dataset. Despite some limitations in absolute fit indices (e.g., χ^2 and χ^2/df), the relative fit indices (e.g., NFI, RFI, IFI, CFI) are within satisfactory levels, indicating that Model 2e offers a robust framework for understanding the longitudinal interplay between performance anxiety and achievement goals among preservice preschool teachers.

Discussion

This study provides important evidence about the longitudinal effects of performance anxiety on achievement goals among female preservice teachers involved in STEM education projects. The path analysis model underscores that PA exerts a significant, sustained negative influence on AG, illuminating the inhibitive role that academic anxiety can play in limiting engagement and future learning potential. This aligns with Freedman's (2003) findings that heightened performance anxiety often leads individuals to avoid environments associated with complex learning challenges, potentially stifling meaningful participation in STEM contexts. Such avoidance, as noted by Civelek et al. (2003), can perpetuate disengagement and reinforce negative associations with STEM subjects.

Supporting Mueller's (1992) findings, the present study demonstrates that elevated levels of performance anxiety are correlated with challenges in mastering STEM-related tasks. Similarly, Eyring et al. (1993) observed that task-specific anxiety can impede learning progression. This study reveals that the negative correlations between PA and AG are especially pronounced at critical project junctures (time points 1 and 3), where participants were required to conceptualize and implement STEM projects. Many preservice teachers lacked foundational STEM knowledge, amplifying anxiety, particularly around assignment submission, as noted in Furner and Duffy's (2002) research on STEM-related anxiety.

Interestingly, the path analysis reveals a fluctuating impact of PA on AG, with a temporary reduction in PA influence around time-point 2. This suggests that situational and emotional factors may moderate PA, allowing for a brief enhancement in AG during the middle phase of the project, as noted in Mitchell, et al.'s (1994) research on performance and anxiety. The latent growth curve model further elucidates these temporal dynamics, supporting Ma and Xu's (2003) assertion of a causal link between PA and AG. The analysis also shows significant relationships between the intercepts and slopes of PA and AG. Specifically, while AG begins at a moderate level and increases over time, PA starts high but gradually decreases as preservice teachers become more familiar with STEM tasks, potentially gaining confidence through repeated exposure.

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However, the absence of significant correlations between the intercepts and slopes of PA and AG suggests that while initial anxiety levels may shape early achievement goals, subsequent changes in anxiety do not directly precipitate equivalent changes in AG. This pattern supports Aiken's (1970) theory that emotional responses and achievement are reciprocally related but may not necessarily evolve in parallel. These findings open new avenues for research. Future studies might explore mediating variables such as motivation, self-efficacy, and peer support to clarify the conditions under which PA influences AG in early childhood STEM education.

Overall, this study advances understanding of the impact of performance anxiety on achievement goals among female preservice teachers in STEM. The findings highlight the importance of incorporating scaffolded STEM experiences into teacher training programs to help mitigate PA by fostering gradual familiarity and competence. By creating environments where preservice teachers engage confidently with STEM content, such programs can enhance both STEM education quality and the professional growth of future educators.

Conclusions and Implications

This study contributes to our understanding of the dynamic relationship between performance anxiety and achievement goals among preservice preschool teachers. The findings indicate that the impact of PA on AG is dynamic, varying across time points. Path analysis models reveal that the negative relationship between PA and AG is particularly pronounced at the beginning and end of the assessment periods, with a temporary reduction in the mid-project stage. The latent growth curve model further elucidates these temporal patterns, showing significant negative covariances between the intercepts and slopes of PA and AG. Specifically, while PA exhibits a higher intercept and a decreasing slope, AG begins at a moderate level and increases over time. These results underscore that PA initially has a strong influence on AG, but its effect changes over time.

Several practical implications emerge from these findings. First, given that high initial PA can inhibit AG, future research could focus on strategies such as stress management, coping mechanisms, and confidence-building to better prepare educators for training with a positive mindset. Cognitive-behavioral interventions may also be effective in equipping preservice teachers with tools to manage anxiety proactively. Furthermore, while PA and AG are correlated, their independent rates of change suggest that research could investigate not only strategies for reducing anxiety but also methods for enhancing AG. This could include setting clear, achievable goals, providing consistent feedback, and celebrating incremental successes to motivate preservice teachers. Lastly, future research might examine these dynamics in diverse teacher populations and varied educational contexts to further refine support mechanisms for STEM educators.

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Declaration of Interest

The authors declare no competing interest.

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