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Path Analysis: The Predictive Relationships of Problem-based Learning Processes on Preservice Teachers' Learning Strategies

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ABSTRACT

Path analysis is used to provide estimates of the magnitude and significance of hypothesized causal connections among sets of variables displayed using path diagrams. It is an extension of multiple regression analysis and holds strength as a methodology as it allows researchers to assess both direct and indirect effects of multiple independent variables on one or more dependent variables. In this paper, path analysis is used to examine the predictive relations of preservice teachers' perception of key problem-based learning (PBL) processes and their learning strategies before and after their PBL experience. The sample involved in this study comprised of 1041 preservice teachers in the core Educational Psychology course using the PBL approach at a Teacher Education Institute in Singapore. The participants consisted of 333 males, 662 females, and 46 preservice teachers who did not indicate their gender. The mean age was 25.6 (SD = 5.41). The Motivated Strategies for Learning Questionnaire (MSLQ) by Pintrich, Smith, Garcia, and McKeachie (1993) was used to measure preservice teachers' learning strategies. It consisted of five subscales, namely rehearsal, elaboration, organization, critical thinking and metacognitive self-regulation. The Problem-based Learning Process Inventory (PBLPI) by Chua et al. (2016) was used to measure the key PBL processes, namely problem-posing, scaffolding, and connecting. Findings from the study suggested that in the PBL environment, (a) preservice teachers' pre-PBL metacognitive self-regulation played a pivotal role in determining preservice teachers' perceived importance of the key processes in enhancing their PBL experience; (b) the key PBL scaffolding and connecting processes were salient predictors of preservice teachers' subsequent post-PBL learning strategies; and (c) the key PBL processes played a mediating role in relating preservice teachers' pre-PBL learning strategies to their corresponding post-PBL factors. Implications for using path analysis for problem-based learning research will be discussed.

Keywords: path analysis, preservice teachers, problem-based learning processes, learning strategies

Path analysis consists of a family of models that depicts the influence of a set of variables on one another (Spaeth,1975), and it is most frequently used to analyze data relative to a prespecified causal model. The aim of path analysis is to provide estimates of the magnitude and significance of hypothesized causal connections among sets of variables displayed using path diagrams.

Path analysis is an extension of multiple regression analysis and is a statistical method often employed in research studies to investigate the predictive relationships between multiple variables underpinned by theoretical frameworks. With path analysis, researchers conduct a series of regressions to examine influences on dependent variables within the model. More often, dependent variables serve as independent variables for later regressions within the model. A regression is conducted for each dependent variable and effects are calculated across regressions for cumulative effects. As such, this statistical method often entails the investigation of hypothesised causal relationships, examining both the direct and indirect impacts of one or more independent variables on a dependent variable which often include the examination of mediators, providing a comprehensive understanding of the interplay between variables of the study.

In the context of education research, path analysis can be used to evaluate and refine theoretical models for education and assist researchers and educators in gaining knowledge and understanding of the complex relationships between various factors that impact learning processes and outcomes. For example, researchers might employ path analysis to examine the impact of factors like perceived teacher autonomy support, socioeconomic status, and peer relationships on student engagement and academic achievement. This analytical approach allows for a detailed exploration of the relationships between these constructs, shedding light on how they collectively influence students' educational outcomes. In a study by Nie et al. (2015), path analysis was used to test the importance of autonomy support and the mediating role of work motivation for well-being. Results from the path analysis supported the hypothesized model underpinned by Self-determination Theory (SDT), where autonomy support would be correlated with more autonomous forms of teacher motivation and that teacher motivation would, in turn, mediate the effects of autonomy support on indicators of work well-being such as job satisfaction.

Brief Development of Path Analysis

The concept of path analysis was first introduced by Sewall Wright (1921). He used this statistical analysis to understand the correlation and causal relationships between variables under study in the area of genetics. Generally, correlation does not imply causation, and Wright (1921) argued that the degree of relationship between variables is measured by the correlation coefficient to determine the direct influence along each separate path and the degree of variation for a given effect. to which variation of a given effect is determined by each cause. He cautioned the use of this method to imply causal relationships through the correlation coefficients, but suggested we should use the statistical findings together with qualitative information on the path relationship to investigate the implications of the hypothesized model.

In the 1960s and 1970s, path analysis was introduced to social sciences research (Blalock, 1961; Blau & Duncan, 1967; Duncan, 1966). Researchers Peter Blau and Otis Dudley Duncan were among the first to utilize path analysis in their research on the status attainment process. Specifically, path analysis was used to develop path models of the causal processes underlying educational and occupational outcomes.

In the 1970s and 1980s, path analysis was integrated into the broader framework of structural equation modeling (SEM). SEM is a multivariate statistical technique that combines factor analysis and path analysis to examine the relationships among latent variables (unobserved constructs) and observed variables (measured indicators; Jöreskog, & Sörbom, 1979; Kline, 2015). The integration of path analysis into SEM allowed researchers to test more sophisticated models involving both observed and latent variables.

Today, path analysis and SEM are widely used in social sciences research. The development of specialized software packages, such as LISREL, AMOS, Mplus, and Stata, has made it easier for researchers to conduct path analysis and SEM, further popularizing these techniques in empirical research.

In summary, path analysis has evolved from its initial application in genetics to a widely used statistical technique in various fields of research such as psychology, education, health sciences, etc. Its development has been driven by advances in computational technology and the integration with SEM, which has allowed researchers to test increasingly complex models and gain a deeper understanding of the relationships among variables.

Components and Process of Path Analysis

In path analysis, researchers posit a set of a priori structural relationships and test the ability of a solution based on this structure to fit the data by demonstrating that: (a) the solution is well defined, (b) parameter estimates are consistent with theory and a priori predictions, and (c) the $\chi 2$ and subjective fit indices are reasonable (McDonald & Marsh, 1990). Maximum likelihood or other estimation methods such as generalized least squares (GLS) or weighted least squares (WLS) could be used as the method of estimation for the models (Schumacker, & Lomax, 2004). The main components of path analysis include:

1. Variables: In path analysis, there are two types of variables—exogenous (independent) and endogenous (dependent) variables. Exogenous variables are not influenced by any other variables in the model, while endogenous variables are affected by one or more variables in the model (Byrne, 2010; Kline, 2015).
2. Path diagram: It is a visual representation of the hypothesized relationships between variables in the form of arrows (paths) connecting the variables. The arrows indicate the direction of the causal relationship between the variables (Byrne, 2010; Kline, 2015).
3. Path coefficients: Path coefficients are standardized regression weights that quantify the strength and direction of the relationships between variables. They are estimated from the observed data and are used to test the hypothesized relationships in the model (Kline, 2015).

4. Model fit: Model fit refers to the degree to which the proposed model represents the relationships among the observed variables (Marsh et al., 2004). A range of fit indices including the Comparative Fit Index (CFI), the Non-Normed Fit Index (NNFI; also called Tucker-Lewis Index; TLI), the Root Mean Square Error of Approximation (RMSEA), the χ^2 test statistic, and an evaluation of parameter estimates were used in the present research to assess model fit. The RMSEA index is less affected by sample size than the χ^2 test statistic, and values at or less than .08 and .05 are taken to reflect acceptable and excellent fit, respectively (see Marsh et al., 1996; Yuan, 2005). The NNFI and CFI vary along a 0-to-1 continuum in which values at or greater than .90 and .95 are typically taken to reflect acceptable and excellent fit to the data, respectively (McDonald & Marsh, 1990). The CFI contains no penalty for a lack of parsimony so that improved fit due to the introduction of additional parameters may reflect capitalization on chance, whereas the NNFI and RMSEA contain penalties for a lack of parsimony (Yuan, 2005).

5. Direct, indirect, and total effects: Direct effects refer to the causal impact of one variable on another without any mediation by other variables. Indirect effects are the causal effects that occur through one or more intervening variables (mediators). Total effects are the sum of direct and indirect effects, representing the overall impact of one variable on another (Byrne, 2010).

6. Mediation and moderation: Mediation analysis explores how independent variables impact dependent variables through mediator variables. Meanwhile, moderation analysis investigates the conditions under which the relationship between independent and dependent variables may vary, depending on the presence of a moderator variable (Baron & Kenny, 1986; Hayes, 2013).

To conduct a path analysis study, there is a need to first develop a hypothesized model based on literature review and theoretical framework to determine the relationships between the dependent and independent variables under study. Data with an adequate sample size to ensure statistical power of analysis is then collected (Westland, 2010). It is pivotal at this stage to embark on the process of data cleaning, checking for missing values, outliers, and assumptions of normality and multicollinearity (Byrne, 2010). There might be a need to create composite variables or factor scores to reduce the number of observed variables (Tabachnick & Fidell, 2013). Next, software like AMOS, Mplus, and R are used to estimate the path coefficients and test the relationships in the hypothesized model. At this stage, path analysis can be conducted using maximum likelihood estimation (MLE) or other estimation methods, such as generalized least squares (GLS) or weighted least squares (WLS; Schumacker & Lomax, 2004). This is followed by the assessment of model fit using the goodness-of-fit indices (Marsh et al., 2004). If the initial model does not fit the data well, revise the model based on the modification indices and theoretical considerations. This may involve adding or removing paths or specifying additional correlations among variables (Kline, 2015). This process of refinement is repeated until a good model fit for the hypothesized model is obtained. After establishing a model with good fit indices, investigate the path coefficients and their statistical significance to determine the strength and direction of the relationships between variables and assess the direct, indirect, and total effects of the variables on each other (Byrne, 2010). The findings are then presented in a clear manner using path models with the significant path coefficients stated and goodness-of-fit indices presented.

Path Analysis: A Plausible Statistical Method for PBL Study

Problem-based learning (PBL) is a student-centered pedagogical approach where students learn through solving authentic problems. In this approach, students are actively engaged in both self-directed and collaborative learning. This experience of solving real-world tasks engages students in an iterative cycle of collecting, connecting, and communicating information (Chua et al., 2015).

Students activate their existing knowledge, integrate what they have learned within and beyond particular subject discipline, collaboratively co-construct knowledge, exhibit intrinsic motivation for learning, and develop cognitive, metacognitive, and social-emotional skills throughout their PBL experience. As such, path analysis is a statistical method suitable for studying PBL because it allows researchers and educators to examine the relationships between factors involved in the PBL learning process and their influence on students' learning outcomes..

Prior research studies which employ path analysis in PBL include examining the effectiveness of PBL intervention on learners' outcomes which include achievement such as subject content mastery, skills such as critical thinking andproblem-solving] skills, and motivational outcomes. In order to investigate the relationships between the variables using path analysis, it is necessary to construct a casual model based on a theoretical framework. In a study by Gijselaers, and Schmidt (1990), they constructed a casual model based on literature on student learning to evaluate the intervention based on input variables of prior knowledge, block-book (a guide book for students' learning activities) and tutor functioning, process variables of time and group functioning, and outcome variables of students' achievement and interest. According to the ideas of Cooley and Lohnes (1976, as cited in Gijselaers, & Schmidt, 1990) the assessment of PBL should explore the relationships between input variables, design variables, and output variables. These predictive relationships will then allow educators and researchers to make evidence-informed refinements to the pedagogical approach. Findings from this study purported the importance of a well-developed book guide that includes problems, resources, and information on the student learning activities on PBL processes and outcomes. In addition, this study also indicated the importance and impact of tutor functioning on students' group learning and interest.

Path analysis in PBL studies also allows researchers to identify mediating and moderating effects of variables in the PBL, such as tutor's scaffolding, student engagement, and motivation orientations on learning outcomes. In a study conducted by Chua and colleagues (2016), the researchers hypothesized the predictive relationships of key PBL processes of problem posing, scaffolding, and connecting on preservice teachers' learning strategies. One of the research objectives was to examine the mediating roles of PBL processes on preservice teachers' pre- and post-PBL learning strategies. Results from the study indicated the significant mediating role of PBL processes—the change in preservice teachers' use of learning strategies before and after their PBL experience was influenced by their perceptions of the key PBL processes.

In addition, this statistical method is used to explore temporal predictive relationships between key PBL variables. In a study by Rotgans and Schmidt (2011), PBL occurred in five stages, namely problem definition stage, initial self-study stage, initial findings sharing stage, self-study stageand presentation and elaboration stage. One of the study aims was to investigate the extent to which situational cognitive engagement in one PBL stage influenced the students' cognitive engagement in the subsequent PBL stages. In addition, they sought to explore the possibility that the relationships were not entirely sequential, such that early cognitive engagement may lead to engagement at the later stages. Findings from the study indicated that students' cognitive engagement is strongly related to their cognitive engagement in the immediate next stage. That is, if a student is cognitively engaged during the problem definition phase, he or she is likely to be engaged during the next phases as well. In addition, there were also some weaker non-sequential relationships between the early PBL stages and the later stages. Overall, 81% of the variance in the last situational cognitive engagement measure could be explained by the preceding ones. This study seems to suggest that students' cognitive engagement would increase as the students progress with their PBL.

In summary, path analysis is an important tool for studying PBL, as it allows researchers to investigate the complex relationships between various factors involved in the PBL process and their effects on student outcomes. By identifying the mediating and moderating variables and through their direct and indirect effects, researchers can gain valuable insights into the mechanisms through which PBL influences learning and develop evidence-based recommendations for improving PBL practices.

An Illustrative Example: The Predictive Relationships of Problem-based Learning Processes on Preservice Teachers' Learning Strategies

In a rapidly evolving world driven by swift technological progress, how can we prepare teachers with the competencies to design learning environments for the holistic development of their students? In Singapore, we aim to develop teachers to be self-directed learners, active collaborators, and metacognitive reflective practitioners who assume ownership of their professional growth. It is thus pivotal that the initial teacher preparation program equips preservice teachers with innovative pedagogical approaches such as BLroblem-based learning, which develop their cognitive, metacognitive, problem-solving, and collaborative skills. Problem-based learning is a pedagogical approach that uses real-life problems (rather than content) as the focal points for learning, where students become active problem-solvers, and teachers become facilitators of their students' learning (Boud & Feletti, 1996).

According to Svinicki (2007), examining the processes within PBL that support learners' learning is pertinent. Instead of taking a broad stroke of PBL as a whole intervention, researchers should examine the contributing processes in PBL and how they support learners' learning (Albanese, 2000; Norman & Schmidt, 2000). The relationships between these contributing processes and learners' cognitive measures can provide insights on how to scaffold and develop learners' cognitive and metacognitive skills to be effective problem-solvers and self-directed, reflective learners.

This study investigates explicitly the predictive relations of preservice teachers' perceptions of PBL processes and their learning strategies before and after PBL. According to Chua, Tan, and Liu (2016), there are three distinct component PBL processes: Problem Posing, Scaffolding and Connecting. From the pedagogical lens of PBL, the quality and design of the problem scenario will impact the participants' learning process (Sockalingam, et al., 2011; Sulaiman, et al., 2004). Problem Posing purported the importance of putting careful thought into the planning, crafting, and representation of the problem scenario in the PBL process. In a PBL environment, solving ambiguous, open-ended, and complex tasks often have heavy cognitive demands on the learners. As such, there is an immense need to support the problem-solving process during PBL through scaffolding. Scaffolding is another distinct PBL process, and it refers to the intentional instructional support, such as question prompts, cognitive and metacognitive cues, explanatory information, and specific goals, templates, and feedback at every stage of the PBL process (Chua et al., 2016; Scardamalia & Bereiter, 1994). Finally, Connecting is the third PBL process, and it refers to the learners' connective processes of making meaningful links, co-constructing knowledge with their peers through active sharing and contextualization. The PBL process of Connecting is catalytic in connecting different learners' perspectives, connecting new and prior knowledge, connecting to meta-awareness, and thinking about how one is learning and changing.

Learning strategies refer to learners' use of different cognitive and metacognitive strategies. Learning strategies in this study are measured by five subscales, namely rehearsal, elaboration, organization, critical thinking, and metacognitive self-regulation. Rehearsal refers to the strategies that are used for simple tasks and activation of information in the working memory. Elaboration includes strategies such as paraphrasing, creating analogies, and summarizing. These strategies build connections between items to be learned. Organization refers to strategies that help learners select and construct connections among the information to be learned. This includes strategies such as clustering, outlining, and selecting main ideas. Critical thinking refers to learners' analysis and application of prior knowledge to solve problems and make decisions. Metacognitive self-regulation refers to learners' awareness, knowledge and control of cognition.

The research question for this study is: What are the predictive relations of preservice teachers' perception of key PBL processes and their learning strategies before and after PBL? In order to answer this question, the hypothesized model looking into the predictive relations of key PBL processes on preservice teachers' learning strategies (see Figure 1) was conceptualized. This model is guided by the general understanding of the PBL cycle, empirical evidence from the literature review, and logical temporal sequencing of pre-PBL and post-PBL measures.

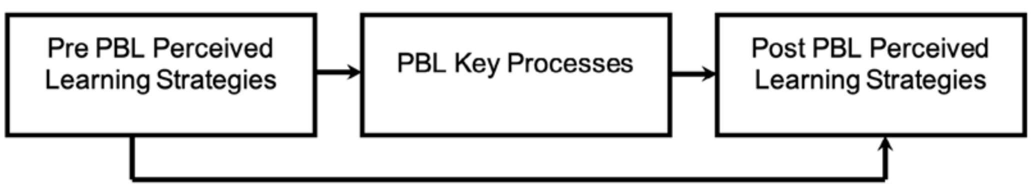


Figure 1. Hypothesized Model and Constructs Examining the Predictive Relations of Preservice Teachers' Perception of Key PBL Processes and their Learning Strategies Before and After PBL

Research Method

Research Sample

The sample involved in this study comprised 1041 preservice teachers in the core Educational Psychology course across programs in Singapore using the PBL approach. The participants consisted of 333 males, 662 females, and 46 preservice teachers who did not indicate their gender. The mean age was 25.6 (SD = 5.41).

Measures

The measure used for this study was the learning strategies section of the Motivated Strategies for Learning Questionnaire (MSLQ) by Pintrich, Smith, Garcia, and Mckeachie (1993) and the Problem-based Learning Process Inventory (PBLPI) by Chua, Tan, and Liu (2016). Preservice teachers rated each item on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree)

Results

As a preliminary analysis, the correlations between all the variables are first examined. Table 1 presents the correlations among learning strategies and key processes of Problem Posing, Scaffolding, and Connecting embedded in the PBL environment. The correlations between pre-PBL learning strategies and the key PBL processes of Problem Posing, Scaffolding, Connecting were significant and positive, ranging from $r = .16$, $p < .01$ to $r = .32$, $p < .01$. The correlations between key PBL processes to post-PBL learning strategies were also significant and positive, ranging from $r = .21$, $p <$

.01 to $r = .57$, $p < .01$. Furthermore, the correlations between pre-PBL learning strategies to post-PBL learning strategies were significant and positive, ranging from $r = .19$, $p<.01$ to $r = .58$, $p < .01$. These correlations provided preliminary support to the relationships proposed in the hypothesized model (see Figure 2) and justified further investigation using a path analysis that controlled for shared variances among the variables.

The hypothesized model (see Figure 2) explored the predictive relationships between preservice teachers' learning strategies and key PBL processes. The significant paths were identified and the derived model as reflected in Figure 3 fit the data well (χ^2 = 87.31, df = 33, TLI = .99, CFI = .99, RMSEA = .04). All standardized path coefficients and R^2 are presented in Figure 3. The beta coefficient (β) in path analysis measures how a change in one variable can impact the change in another variable. β ranges from -1 to +1, indicating the strength and direction of the relationship between the two variables. For example, a β value of +1 indicates a strong positive relationship, meaning as the one variable increases, the other variable also increases by an equal amount (Kline, 2015). The R-squared (R^2) value ranges from 0 to 1 and is usually expressed as a percentage. It represents the proportion of the variance in the dependent variable that can be explained from the independent variable(s) in a path model (Kline, 2015).

As shown in Figure 3, the predictive paths from preservice teachers' pre-PBL learning strategies to their perceptions of key PBL processes indicated that preservice teachers' pre-elaboration significantly predicted Problem Posing (β = .18, $p < .001$) and Connecting (β = .17, $p < .001$), whereas their pre-metacognitive self-regulation significantly predicted Problem Posing (β = .13, $p < .001$), Scaffolding (β = .30, $p < .001$) and Connecting (β = .20, $p < .001$). Further, the predictive relations from perceptions of key PBL processes to post-PBL learning strategies suggested that preservice teachers' perception of Scaffolding significantly predicted post-PBL Rehearsal (β = .07, $p < .05$), post-PBL Organization (β = .07, $p < .01$) and post-PBL Metacognitive self-regulation (β = .06, $p < .01$); preservice teachers' perception of Connecting significantly predicted post-PBL Rehearsal (β = .20, $p < .001$), post-PBL elaboration (β = .40, $p < .001$), post-PBL organization (β = .30, $p < .001$), post-PBL critical thinking (β = .29, $p < .001$) and post-PBL metacognitive self-regulation (β = .33, $p < .001$). It is important to note that these predictive paths from preservice teachers' perceptions of key PBL processes to their post-PBL learning strategies were significant over and above the variance explained by their pre-PBL learning strategies (both corresponding and non-corresponding dimensions), showing the importance of preservice teachers' perceptions of key PBL processes in predicting their post-PBL learning strategies.

Table 2 shows that, alongside the direct effects of pre-PBL learning strategies on subsequent post-PBL learning strategies, preservice teachers' pre-PBL learning strategies also had indirect effects on their post-PBL learning strategies through the mediating role of their perceptions of key PBL processes. The direct predictive relations of preservice teachers' pre-PBL learning strategies on their post-PBL learning strategies, particularly on the corresponding dimensions (e.g., the auto-regressive path from pre-PBL elaboration to post-PBL elaboration) were larger than their indirect predictive relations (i.e., β = .24 for direct effects and β = .08 for indirect effect). This being said, there were some instances where the indirect effects of pre-PBL learning strategies on post-PBL learning strategies were larger than their direct effects. For example, the indirect effect of pre-PBL elaboration on post-PBL metacognitive self-regulation (β = .06) was significant whereas its direct effect was nonsignificant. This, again, demonstrates the significant mediating role of preservice teachers' perceptions of key PBL processes in linking their pre-PBL and post-PBL learning strategies.

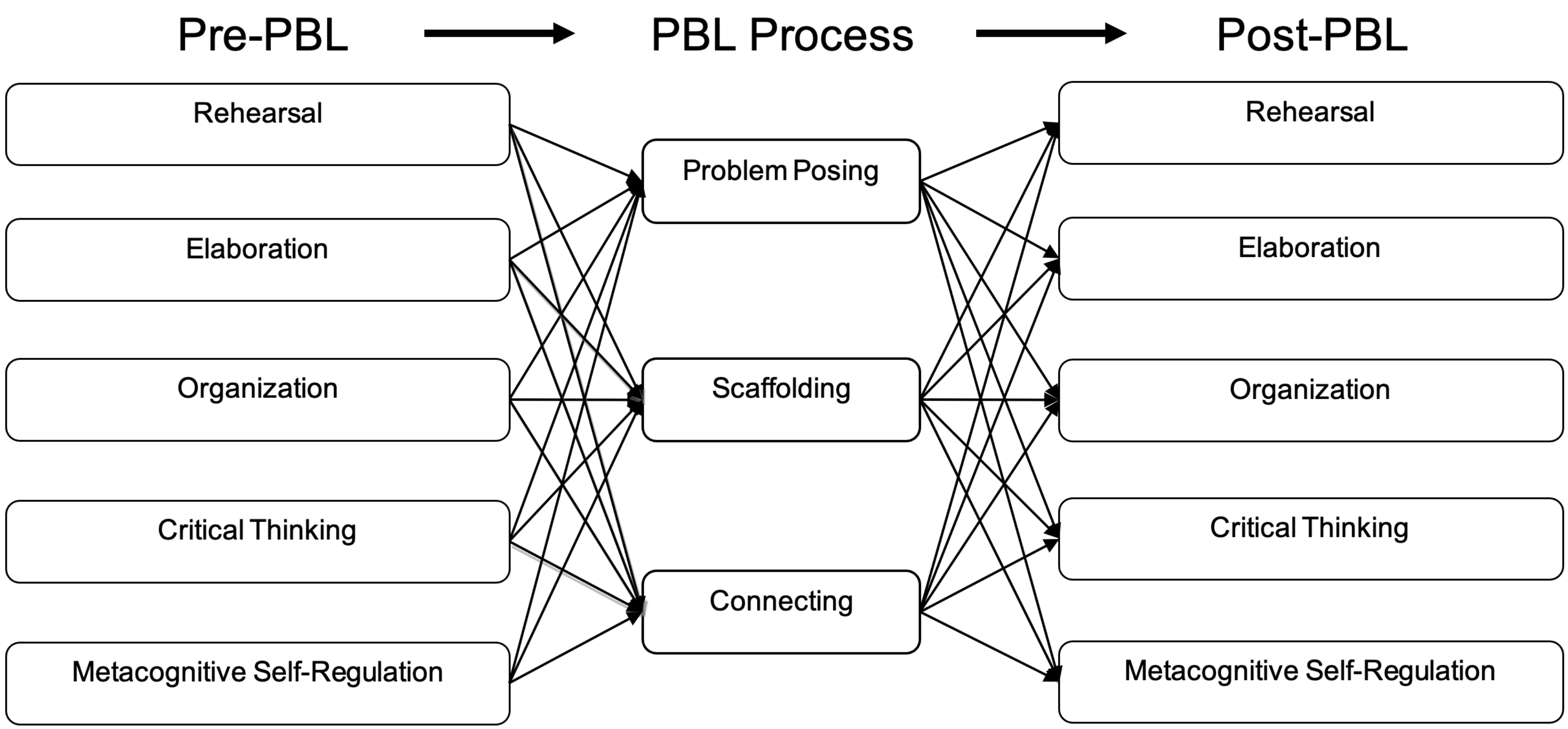
Taken together, preservice teachers' pre-PBL learning strategies explained around 8% of the variance in their perception of Problem Posing, around 11% of the variance in their perception of Connecting, and around 9% of the variance in their perception of Scaffolding. In terms of the variance in post-PBL learning strategies, pre-PBL learning strategies and the key PBL processes explained around 32% of the variance in students' post-rehearsal, around 47% in post-elaboration, around 40% in post-organisation, around 39% in post-critical thinking, and around 44% in post-metacognitive self-regulation.

	M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Pre-RE	3.15	.66	1												
2. Pre-ELB	3.63	.58	.40**	1											
3. Pre-ORG	3.47	.67	.53**	.67**	1										
4. Pre-CRI	3.43	.60	.28**	.71**	.47**	1									
5. Pre-MSR	3.35	.54	.47**	.72**	.64**	.66**	1								
6. Post-RE	3.29	.67	.53**	.26**	.34**	.19**	.34**	1							
7. Post-ELB	3.70	.54	.28**	.53**	.45**	.42**	.50**	.52**	1						
8. Post-ORG	3.60	.62	.34**	.46**	.55**	.31**	.46**	.58**	.72**	1					
9. Post-CRI	3.56	.58	.20**	.47**	.32**	.54**	.49**	.43**	.73**	.55**	1				
10. Post-MSR	3.49	.53	.31**	.46**	.42**	.42**	.58**	.59**	.79**	.71**	.74**	1			
11. PP	3.90	.70	.16**	.28**	.25**	.18**	.25**	.21**	.42**	.35**	.26**	.35**	1		
12. SC	3.38	.78	.20**	.24**	.25**	.17**	.30**	.27**	.37**	.35**	.28**	.38**	.54**	1	
13. CO	3.91	.63	.22**	.32**	.29**	.22**	.32**	.34**	.57**	.47**	.42**	.50**	.61**	.55**	1

Note. RE = Rehearsal, ELB = Elaboration, ORG = Organization, CRI = Critical Thinking, MSR = Metacognitive Self-regulation, PP = Problem Posing, CO = Connecting, SC = Scaffolding

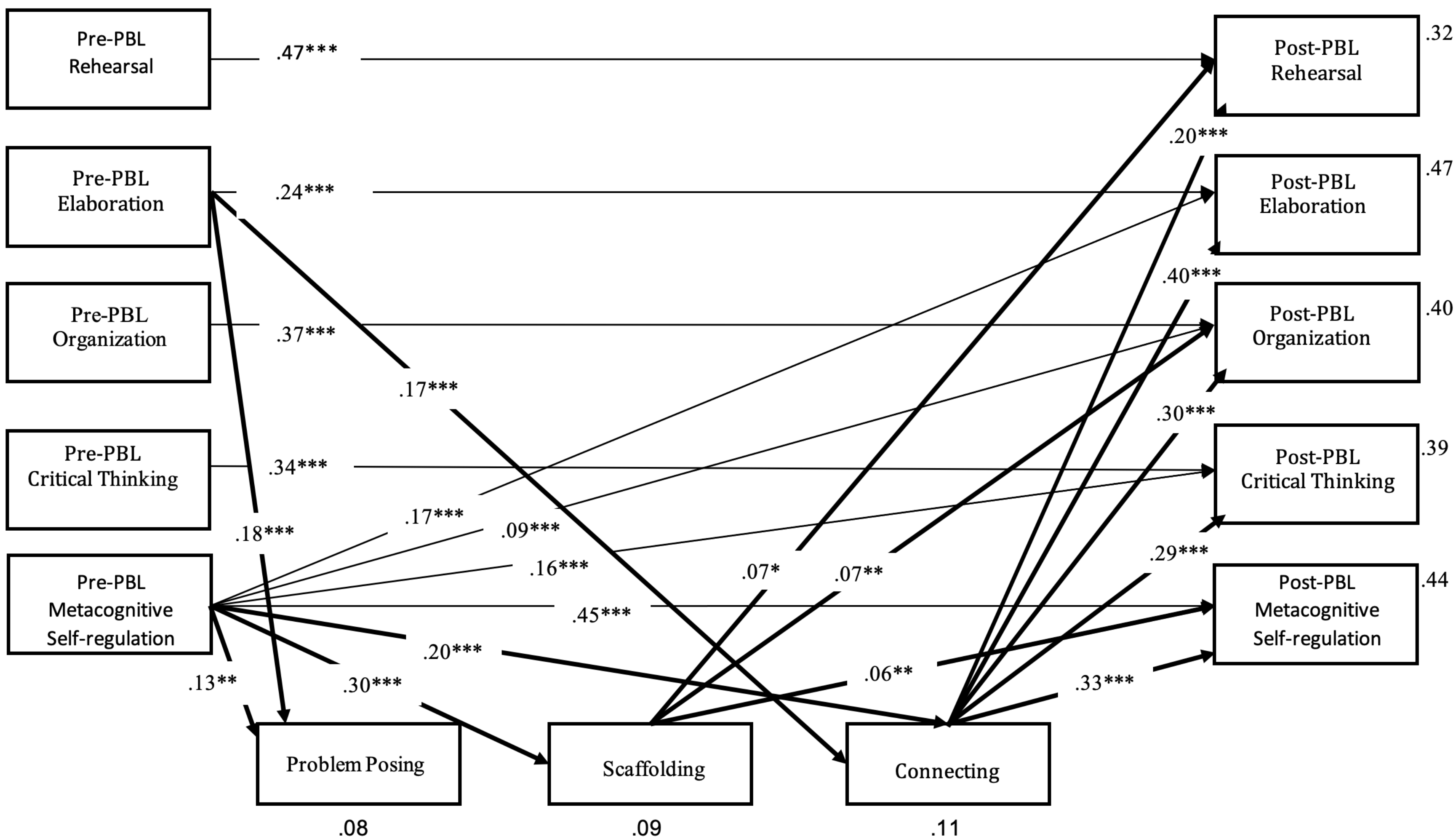
** $p<.01$

Table 1. Descriptive Statistics and Zero-order Correlations for LS and PBL processes



Note. The direct paths from pre-PBL Learning Strategies to post-PBL Learning Strategies (corresponding and non-corresponding dimensions) are not shown in the figure for clarity purposes.

Figure 2. Theoretical Model and Constructs Showing the Relations between Preservice Teachers' Pre-PBL Learning Strategies, Key PBL Processes, and Post-PBL Learning Strategies



Note. Only significant standardized regression coefficients are presented in this figure, ***p <.001, **p <.01,*p <.05 , R^2 was presented at the upper right side of the criterion variables.

Figure 3. Path Model of the Relations between Pre-PBL Learning Strategies, Key PBL Processes, and Post-PBL Learning Strategies.

Predictor	Criterion	Direct effect	Indirect effect	Total effect
The predictive relations of pre-PBL learning strategies on key PBL processes				
Pre ELB	PP	.18	-	.18
Pre MSR		.20	-	.20
Pre MSR	SC	.30	-	.30
Pre ELB	CO	.17	-	.17
Pre MSR		.20	-	.20
The predictive relations of key PBL processes on post-PBL learning strategies				
SC	Post RE	.07	-	.07
CO		.20	-	.20
PP	Post ELB	.07	-	.07
CO		.40	-	.40
SC	Post ORG	.07	-	.07
CO		.30	-	.30
CO	Post CRI	.29	-	.29
SC	Post MSR	.06	-	.06
CO		.33	-	.33

Table 2. Standardized Direct, Indirect and Total Effects in the Model for Learning Strategies in the PBL Environment

The predictive relations of pre-PBL learning strategies on post-PBL learning strategies

Pre RE	Post RE	.47	-	.47
Pre ELB		-	.03	.03
Pre MSR		-	.06	.06
Pre ELB	Post ELB	.24	.08	.32
Pre MSR		.16	.09	.25
Pre ELB	Post ORG	-	.05	.05
Pre ORG		.37	-	.37
Pre MSR		.09	.08	.17
Pre ELB	Post CRI	-	.05	.05
Pre CRI		.34	-	.34
Pre MSR		.16	.06	.22
Pre ELB	Post MSR	-	.06	.06
Pre MSR		.45	.08	.53

Note. Learning Strategies: RE = Rehearsal, ELB = Elaboration, ORG = Organization, CRI = Critical Thinking, MSR = Metacognitive Self-Regulation; Key PBL Processes: PP = Problem posing, CO = Connecting, SC = Scaffolding

$^{*}p<.05$

Table 2 continued. Standardized Direct, Indirect and Total Effects in the Model for Learning Strategies in the PBL Environment

Discussion

Problem-based learning motivates and engages learners' learning through the use of authentic, stimulating, and contextualized real-life problems (Dunlap, 2005). It is an iterative, continuous process of linking new knowledge, reshaping understanding, and knowledge building through interactions with each other and with the problem of practice (Barrows, 1984, 1985, 1986, 1992; Barrows & Tamblyn, 1980; Dunlap, 2005; Walton & Matthews, 1989). Through this apprenticeship for real-life problem solving, students acquire knowledge, skills and self-efficacy required by professionals in the workplace (Schunk, 1989)

The findings reported provide empirical evidence that pre-PBL learning strategies had predictive relations on their perceptions of key PBL processes, subsequently predicting their post-PBL learning strategies. In particular, preservice teachers' pre-PBL elaboration and pre-PBL metacognitive self-regulation played significant roles in predicting their perception of key PBL processes as demonstrated by path coefficients (β) greater than .1 and $p < .001$. The salient roles of key PBL processes in predicting post-PBL learning strategies were also established in this study. In particular, the Connecting process (demonstrated by path coefficients (β) > .1 and $p < .001$) had the most prominent predictive relations on post-PBL learning strategies. It is important to note that these predictive paths from preservice teachers' perceptions of key PBL processes to their post-PBL cognitive outcomes are significant and relatively substantial over and above the variance explained by pre-PBL cognitive factors (corresponding and non-corresponding dimensions). In addition to the direct effects of pre-PBL learning strategies on subsequent or post-PBL learning strategies, there were indirect effects through the mediating roles of preservice teachers' perceptions of the key PBL processes. This is supported by the fact that the indirect effect of pre-PBL elaboration on post-PBL metacognitive self-regulation (β = .06) was significant whereas its direct effect was nonsignificant. This showed the significant role of preservice teachers' perceptions of key PBL processes in linking their pre-PBL learning strategies to their post-PBL learning strategies. That is, changes in the level of preservice teachers' learning strategies before and after the PBL experience are, in part, determined by their perceptions of key PBL processes.

As discussed above, pre-PBL learning strategies and the key PBL processes explained around 32% of the variance in students' post-rehearsal, around 47% in post-elaboration, around 40% in post-organization, around 39% in post-critical thinking, and around 44% in post-metacognitive self-regulation. This showed the importance of preservice teachers' prior learning strategies and PBL processes in determining their use of post-PBL learning strategies. Specifically, this study indicates that in the PBL environment, (a) preservice teachers' pre-PBL cognitive factors play pivotal roles in determining their perceived importance of the key processes (Problem Posing, Scaffolding, and Connecting) in enhancing their PBL experience; (b) these key PBL processes are salient predictors of preservice teachers' subsequent post-PBL cognitive factors; and (c) the key PBL processes play a mediating role in relating preservice teachers' pre-PBL learning strategies to their corresponding post-PBL factors.

Conclusion

This paper illustrated the use of path analysis to examine the temporal predictive relationships between preservice teachers' pre-learning strategies, PBL processes, and post-learning strategies. Through the examination of the temporal relationships between key constructs in a PBL environment, there is a substantive contribution to PBL research through the following key findings:

1. It is important to break down PBL into key learning processes to understand how the PBL environment impacts preservice teachers' learning strategies development. In this study, the key processes of Problem Posing, Scaffolding, and Connecting were identified. The identification of these processes allows PBL researchers and educators to (a) be cognizant of their presence and thus make mindful and intentional enhancements/refinements to enhance learners' PBL experience, and (b) assess and evaluate learners' outcomes based on their relationships with these key processes rather than the whole PBL intervention, thus allowing comparisons to be made across different PBL approaches.
2. The preservice teachers' prior learning strategies is important in determining how much they will benefit from the key PBL processes, namely Problem Posing, Scaffolding and Connecting inherent in the PBL environment. Specifically, different dimensions of preservice teachers' prior learning strategies appear to be related to the degree to which they had favorable perceptions of key PBL processes. This points to the importance of preservice teachers' cognitive and metacognitive readiness for PBL experience. The implication for practice is to equip learners with the cognitive and metacognitive strategies necessary to break down the complexity of the problem-solving processes inherent in a PBL environment to maximize learners' engagement.
3. The key PBL processes of Problem Posing, Scaffolding and Connecting play a pivotal role in mediating preservice teachers' changes in learning strategies before and after PBL.

The provided research example highlights that path analysis is effective in examining the connections between key constructs in a study. Through these identified relationships, researchers can articulate the practical implications and suggest directions for future research.

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