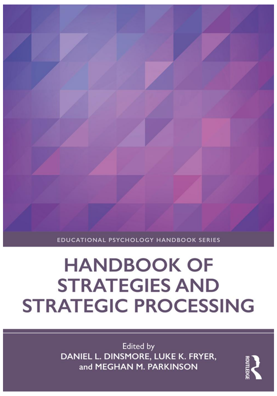

Handbook of Strategies and Strategic Processing

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Variable-centered Approaches

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VARIABLE-CENTERED APPROACHES

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Individuals' strategic processing, or strategy use, is a subject that has fostered increased research in recent years (Dinsmore, 2017). Effective strategic processing is beneficial in accomplishing tasks in a variety of domains. Students intentionally, purposefully, and effortfully use strategies to learn while navigating through content (Cho, Afferbach, & Han, 2018). Strategic processing has been linked to achievement outcomes, though the type and level of strategic processing matters in context (Dinsmore, 2017). Strategic processing is a valuable skill for learners of different ages. For example, in early childhood, learners use strategies to acquire and remember information (Nida, 2015). As another example, children in elementary school demonstrated they were able to respond to feedback in order to enhance strategy use in a dynamic testing situation (Resing & Elliott, 2011). Strategic processing affects learning outcomes for middle school students (Greene & Azevedo, 2009) and high school students, as well (Parkinson & Dinsmore, 2018). Additionally, the results of a recent meta-analysis showed that strategy use is a key variable associated with achievement in higher education (Schneider & Preckel, 2017).

This recent increase in research on strategic processing has led to a growing awareness that cognitive processes are not constrained by developmental stage, but are dynamic and malleable (Dinsmore, 2017). Because strategic processing is malleable, this provides the opportunity for students to learn more beneficial strategies. Researchers studying dynamic strategy use have capitalized on the malleability of strategic processing to identify and encourage students to use more beneficial strategies (e.g., practice testing and distributed practice) that encourage quality learning and achievement outcomes, rather than less beneficial strategies that encourage more shallow processing of the information (e.g., highlighting and rereading; Deekens, Greene, & Lobczowski, 2018; Dunlosky, Rawson, Marsh, Nathan, & Willingham, 2013).

People's strategic processing can change over time within and across learning tasks (Dinsmore, 2017). Given this, research methods that are capable of capturing dynamic processing are necessary (Dinsmore & Zoellner, 2018). However, such methods can produce a lot of data that can be challenging to analyze. Depending on the nature of the data and the research aims, these data may be analyzed in many ways, including variable-centered analyses (Laursen & Hoff, 2006) that allow for an understanding of relations among numerous variables of interest (e.g., strategic processing, motivation, learning). In this chapter, first we outline the differences between variable-centered and person-centered analyses in the context of studying strategy use and strategic processing. Then we discuss the different kinds of variable-centered analyses that can be used to understand and model strategy use and strategic processing data. Then, we conclude with a summary of observations about variable-centered analysis use in the extant literature, as well as practical implications and future directions.

VARIABLE-CENTERED VERSUS PERSON-CENTERED APPROACHES

There are two prevailing approaches to quantitative data analysis: variable- and person-centered. In statistical parlance, researchers employ variable-centered analytical methods to describe the associations between variables within populations that are assumed to be homogeneous regarding those variables' ability to predict a dependent outcome (Laursen & Hoff, 2006). These approaches involve analyses of relations between variables to produce a summarization of these relations, within a given set of parameters, to describe the entire population (Howard & Hoffman, 2018). For example, an R^2 statistic summarizes how much variance in an outcome variable can be explained by a set of predictor variables, for a particular sample assumed to represent a larger population. Variable-centered statistical methods include correlation, regression, path analysis, structural equation modeling, and growth models. Variable-centered methods can be used to investigate the associations between people's anxiety, knowledge of content, and frequency of deep strategy use. The hypotheses for this investigation might be: "There will be a negative relationship between anxiety and frequency of deep strategy use" and "There will be a positive relationship between people's knowledge of content and frequency of deep strategy use." A variety of different kinds of research questions pertaining to strategy use can be studied, including research questions about the efficacy of interventions (Yoon & Jo, 2014), strategy use change over time (Carr, Taasoobshirazi, Stroud, & Royer, 2011), the relation between strategy use and performance or knowledge gains (Greene, Deekens, Copeland, & Yu, 2018), and research questions pertaining to the relationship between strategy use and other learning phenomena (e.g., motivation; Bernacki, Byrnes, & Cromley, 2012).

Alternatively, person-centered methods use the relations between observed variables along with differences between individuals to identify multiple homogeneous subpopulations within a larger heterogenous population (Fryer & Shum, this volume). Also inherent in these methods is the identification of the appropriate number of emergent subpopulations needed to optimize the accuracy of the resulting population summary. Common person-centered approaches include latent class, latent profile, and cluster analysis (Howard & Hoffman, 2018; Laursen & Hoff, 2006). Person-centered analyses might be used to answer research questions such as, "Are there two or more groups of participants in this sample that systematically differ in their use of five common studying strategies?" Person-centered analyses are often preferable to variable-centered analyses when the ratio of participants to strategic processing variables is small, or when researchers are interested in identifying homogeneous subgroups for further analysis. Once these groups have been identified, they can be compared across a number of other covariates or criterion variables, such as prior knowledge or academic performance. Both person- and variable-centered analyses are viable methods for understanding strategic processing. In this chapter we focus on variable-centered approaches.

VARIABLE-CENTERED ANALYSIS TECHNIQUES

Data from a variety of quantitative research designs (e.g., true experimental, quasi-experimental, non-experimental) can be analyzed using variable-centered techniques. Variable-centered analyses can be conducted in studies of strategy use across different time frames as well, including during one learning episode (e.g., Greene et al., 2018) or over multiple episodes (e.g., Carr et al., 2011). Further, variable-centered analyses have been used to understand strategic processing across a variety of contexts, from labs to classrooms to learning online. Strategy use can either be studied as an independent or a dependent variable within variable-centered processes. Before analyses begin, however, it is often necessary to aggregate strategy use data (Greene, Dellinger, Binbasaran Tüysüzoğlu, & Costa, 2013).

Data Aggregation

Researchers who study strategy use and strategic processing sometimes need to utilize data aggregation before analyzing their data. There can be many strategies observed in a sample, often more than ten (e.g., various memorization strategies, higher-order strategies; Dunlosky et al., 2013). In such cases, it can be a challenge to use variable-centered analyses to compare the efficacy of those strategies to one another, due to sample size needs. For example, if 13 strategies are observed in a sample, variable-centered analysis (e.g., research question: which of the 13 strategies is the strongest predictor of learning performance?) guidelines would suggest the need for a relatively large sample (i.e., 117 per Green, 1991). Aggregation can be used to address such challenges, particularly when the use of specific strategies is less important than whether particular types of strategies were used at all. For example, it may not matter whether one participant elaborates, another spaces practice, or a third participant self-tests. What matters is the number of times they invoke any of these effective strategies (Dunlosky et al., 2013). In this situation, it may be useful to create a macro-level aggregate variable (e.g., deep strategy use) comprised of the sum of the frequency of use of these micro-level strategies. In one study, micro-level strategy use data (e.g., frequency of summarizing) were aggregated into surface- and deep-strategy use macro-level variables in order to predict differences in learning outcomes (Deekens et al., 2018). In this study it was less important which specific strategy was used (e.g., taking notes, summarizing, etc.) than the number of times a participant invoked each type of strategy. In another study, the authors aggregated micro-level strategy use variables (e.g., type of note taking strategy) in order to describe the variety of strategies used in their given case or group (Hagen, Braasch, & Bråten, 2014). They found that intertextual knowledge elaboration use statistically significantly predicted deep-level comprehension outcomes when reading to construct an argument, whereas this relationship was not present in participants who used this strategy while reading to summarize.

Aggregation can be used to test posited relations in models of strategy use or self-regulated learning (SRL; Greene & Azevedo, 2009). Many of these models are conceptualized at the macro-level. For example, in Zimmerman's model of SRL, at a macro-level planning in the forethought phase is posited to drive strategy use in the performance phase (Zimmerman, 2013). Yet the data collected are often at the micro-level (e.g., a participant makes a subgoal as one kind of planning, whereas another student calibrates a task definition; one student uses an elaboration strategy during performance, whereas another uses highlighting), thus aggregating to the macro-level is necessary to test whether indeed macro-level planning predicts macro-level strategy use (Greene et al., 2013). In this way, micro-level data can be aggregated into macro-level data to test hypothesized relations in the model (e.g., changes in task understanding can affect the strategies used).

Data can also be aggregated by time or learning phase. For example, data from think-aloud protocols can be aggregated into types of strategies used during learning, as opposed to before or after learning (Greene, Robertson, & Costa, 2011). In sum, data aggregation allows for different, additional, or further analysis of data that can help inform research on strategy use. Once data have been aggregated, they can be analyzed using variable-centered techniques, just as non-aggregated data can be analyzed. In the remainder of this section, we describe various variable-centered analysis techniques, with examples of each to illustrate how they differ.

General Linear Models

The general linear model (GLM) is a term used to encapsulate models that rely on the notion that the relationships between a dependent or outcome variable and independent or predictor variables can be described as a linear function (Rutherford, 2011; Tabachnick & Fidell, 2013). GLM not only includes traditional linear models based on continuous data, like regression, but also incorporates models that utilize categorical data as predictors, such as analysis of variance (ANOVA).

GLM analysis techniques can be used to understand relations between strategy use or strategic processing and other variables of interest, including group membership (e.g., Student's t-test or ANOVA) as well as other continuous variables such as motivation either on their own (i.e., correlation) or in relation to multiple variables (i.e., multiple linear regression). In terms of GLM analyses, strategic processing variables can be either the predictor variable (e.g., how does frequency of strategic processing predict academic achievement?) or the criterion variable (e.g., how do men and women differ in their strategic processing?; what is the relationship between motivation, emotions, and strategic processing?).

Student's t-Test. Student's t-test is a common method used to determine if the difference between the means of two independent samples is statistically significant. However, Student's t-test functions under the assumption that samples are normally distributed and have equal variances. If t-tests are performed on data that do not adhere to these assumptions, the risk of erroneously reporting that the means are statistically significantly different (Type 1 error), and erroneously reporting that the means are statistically equal (Type II error), both increase (Gibbons & Chakraborti, 1991).

Ruffing, Wach, Spinath, Brünken, and Karbach (2015) used t-tests to determine if the use of learning strategies differed based on students' gender. They administered a 77-item inventory to educational science students to collect their self-reported use of learning strategies. The instrument was designed to produce 11 scales of learning strategy use, including effort, attention, time management, literature, learning environment, resource-management, organization, relationships, critical evaluation, cognitive strategies, and metacognition. Then, the data was grouped by gender and mean scores were calculated for each learning strategy scale. The gender-specific scale means could be compared using a t-test to determine if differences between the average male and female strategy use levels were statistically significant. They found female students reported more frequent use of effort, time management, organization, cognitive strategies, and metacognition, whereas male students reported performing the learning strategies of critical evaluation and relationships more often.

Analyses of Variance. ANOVA is used to determine if the differences between means (i.e., dependent variable) of three or more categorical groups (i.e., independent variable) are statistically significant (Rutherford, 2011; Tabachnick & Fidell, 2013). Variance due to additional predictor variables can be controlled by using analysis of covariance (ANCOVA; Rutherford, 2011). When researchers are interested in group differences across a number of dependent variables, a multivariate analysis of variance (MANOVA) should be used to evaluate the mean differences in composites of those dependent variables across independent variable categories (Tabachnick & Fidell, 2013). Finally, when dependent variables are captured from the same participants more than once, repeated-measures ANOVA or MANOVA can be used (Rutherford, 2011).

Anmarkrud, McCrudden, Bråten, and Strømsø (2013) used ANOVA to evaluate university students' think-aloud judgments of text relevance while reading conflicting documents about the scientific evidence regarding the health concerns of cell phone use. Text segments within the documents were coded as containing more or less relevant information and students' comments while reading them were coded as being either positive or negative judgments. To compare the frequency of positive and negative judgements across more and less relevant text segments a 2 (judgment type: positive or negative) × 2 (segment type: more relevant or less relevant) within-subjects ANOVA was performed. Anmarkrud et al. found that while reading more relevant text segments, students expressed a greater number of judgments and those judgments were more frequently rated as positive, whereas the judgments expressed when reading less relevant text were more frequently negative.

Vasilyeva, Laski, and Shen (2015) utilized a MANOVA to determine whether groups based on gender and age differed across multiple outcome measures. The outcomes measured for their study focused on first-graders' answer accuracy and use of four classifications of strategies (retrieval, counting, decomposition, other) while solving addition problems involving single-, mixed-, and double-digit numbers. Vasilyeva et al. found no differences between groups on the five outcome measures, allowing them to exclude those demographic variables from further analysis of the study's data.

Correlation. The bivariate correlation coefficient is used to measure size and directionality of the linear association between two variables. Most commonly reported as Pearson's *r*, correlation represents the degree to which two variables are related to each other. This measure of relationship ranges from −1 to 1, depending on the degree and valence of their correlation. Measures of variable correlation are omnipresent in reports of statistical findings and provide a foundation for more complex analytical methods, which has led to an underappreciation of their own utility and explanatory value (Lee Rodgers & Nicewander, 1988).

Using bivariate correlation, Askell-Williams, Lawson, and Skrzypiec (2012) evaluated survey responses to study the relationship between Australian secondary school students' self-reported use of cognitive and metacognitive strategies and their self-assessment of how they coped with their homework. Askell-Williams et al. found statistically significant, positive correlations between student's coping status and the use of both cognitive and metacognitive strategies, indicating that "students who reported using higher levels of cognitive and metacognitive strategies were more likely to report that they were coping well with school work" (p. 442). After identifying these positive relationships, the researchers used ANOVA to compare students grouped at the extreme ends of the "coping with homework" scale and found that students who reported coping very well with homework were statistically more likely to report using metacognitive strategies than those students who were not coping well with homework.

Multiple Linear Regression Models. Unlike t-tests and bivariate correlation measures, multiple linear regression (MLR) allows researchers to test multiple predictors at once and look at the unique relationship of each predictor with the criterion variable, over the combined relations of the others. MLR models are used to predict criterion variable values by calculating coefficients for the included predictor variables that minimize the sum of the squared differences between them. Often included in the reported results of a regression is the proportion of variation in the criterion variable that is explained by the model (i.e., R^2; Rutherford, 2011; Tabachnick & Fidell, 2013).

Roelle, Schmidt, Buchau, & Berthold, (2017) described how the use of MLR allowed them to measure an unexpected effect of their experimental intervention that was not initially apparent when they analyzed their data using ANCOVA. In the third experiment discussed in their article, Roelle et al. tested the effects of providing high school students with either information about regulation strategies or the dangers of making overconfident judgments of learning (JOLs), or both. Although the results of ANCOVA indicated that only providing students with information about the use of regulation strategies had a statistically significant positive effect on the number of elaborations students made, the treatment did not have a statistically significant effect on posttest results. In contrast, a statistically significant positive effect on posttest results was found for providing information about the dangers of making overconfident JOLs and additionally the interaction of the two treatments also showed a significant positive effect on posttest scores. To further understand the relationships between their two treatments, the frequency of students' elaboration use, and posttest results, Roelle et al. used MLR. Its ability to test multiple predictors and their interactions made MLR particularly well-suited for this situation.

Using posttest scores as the dependent variable, Roelle et al. (2017) produced an MLR model that included pretest scores, the two treatment groups (i.e., information about regulation strategies and information about the dangers of making overconfident JOLs), an interaction term for the two treatments, the number of elaborations performed, and finally an interaction term between being informed about making overconfident JOLs and elaborations performed. The resulting MLR model produced statistically significant positive coefficients for pretest scores, elaboration use, and the interaction of the JOLs treatment on elaboration use. Though at first an ANCOVA indicated that the overconfident JOLs treatment had no effect on the use of elaboration, the results of an MLR revealed that the JOLs treatment had a statistically significant effect on the use of elaboration. In sum, conducting an MLR revealed that understanding the dangers of making overconfident JOLs was not enough to have a statistically significant effect in this learning situation, and that participants also benefitted from learning regulation strategies in order to produce more effective elaborations. Thus conducting an MLR gave more details of the relationship between having knowledge about overconfident JOLs, strategic processing, and learning outcomes.

Count Data

Many studies of strategic processing have involved self-report data regarding strategy use, which are often normally distributed and amenable to GLM analyses (e.g., Askell-Williams et al., 2012). On the other hand, some studies of strategic processing involve counts of the number of times participants use particular strategies, either via observation (e.g., Hagen et al., 2014), participants' think-aloud verbalizations of strategy use (Greene et al., 2018), or via trace data from computer-based learning environments (Bernacki, 2018). For example, think-aloud protocols conducted during learning events can be coded into behaviors (i.e., monitoring strategy use), and those coded data can be transformed into quantitative data by totaling up or tallying the data (Creswell & Plano Clark, 2018). Researchers can use count data to assess behavior, to compare behavioral measures to self-report measures, and to predict learning and performance outcomes from these data (Gall, Gall, & Borg, 2007; Greene et al., 2011). Often, count data are not normally distributed, and when used as a criterion variable, they violate a basic assumption of GLM analyses. In this case, researchers must use statistical techniques that can compensate for these non-normal distributions of data, such as Generalized Linear Model analyses. In one study, researchers conducted strategy use intervention to see if the instruction received by the students in the intervention group affected subsequent strategy use (Yoon & Jo, 2014). The researchers found that the instructed learning strategy was used more frequently in the treatment group than the comparison group by comparing frequency of count data. In sum, many studies involving strategy use or strategic processing include some measure of the frequency of those behaviors. When the outcome measure is a frequency, it is often the case that the data are non-normally distributed, and in those cases count models should be considered, rather than GLM.

Path Analysis

Compared to GLM, path analysis, also called path model analysis, allows researchers to model and investigate equivalent as well as more complex relations among predictor and outcome variables (Kline, 2014). In regression, all predictors are modeled to correlate with one another, and each predictor has its own unique path modeled as directly connecting the predictor to the outcome variable. Each path has an estimated regression coefficient, which can be tested for statistical significance. Each of these regression coefficients represents the unique relationship between the predictor and the outcome variable, after controlling for all other predictors in the regression. For example, a researcher may be interested in how the frequency of use of two deep strategies, such as elaboration and self-testing, as well as two surface strategies, such as highlighting and summarization, each predict academic achievement (Dinsmore, 2017; Dunlosky et al., 2013). A regression approach can be conducted using an equivalent path model, where the analysis would produce six correlations among the four strategies, as well as four path model coefficients, one for each strategy (see Figure 21.1). In statistical parlance, such a model is saturated, because every variable (i.e., predictors and outcome) is connected to every other variable.

However, in regression models only one formulation of the variables is possible (i.e., all predictors related to the outcome directly). Researchers often have more complex conceptualizations of the relations among phenomena, such as positing mediators between variables (e.g., Pintrich, 2000). For example, rather than assuming that each strategy acts only directly on academic achievement, the researcher may posit instead that the two surface strategies are correlated, with each predicting use of elaboration, which in turn predicts self-testing, which in turn is the only predictor of academic achievement (see Figure 21.2). In this conceptualization, two deep strategies serve as mediators of the relationships between the two surface strategies and academic achievement. To test these ideas, the researcher would use path analysis where the posited model would include only a single correlation (i.e., the two surface strategies), with one path from each surface strategy to elaboration, a single path from elaboration to self-testing, and a single path from self-testing to academic achievement. This more nuanced model, compared to the regression-equivalent path model, is not saturated

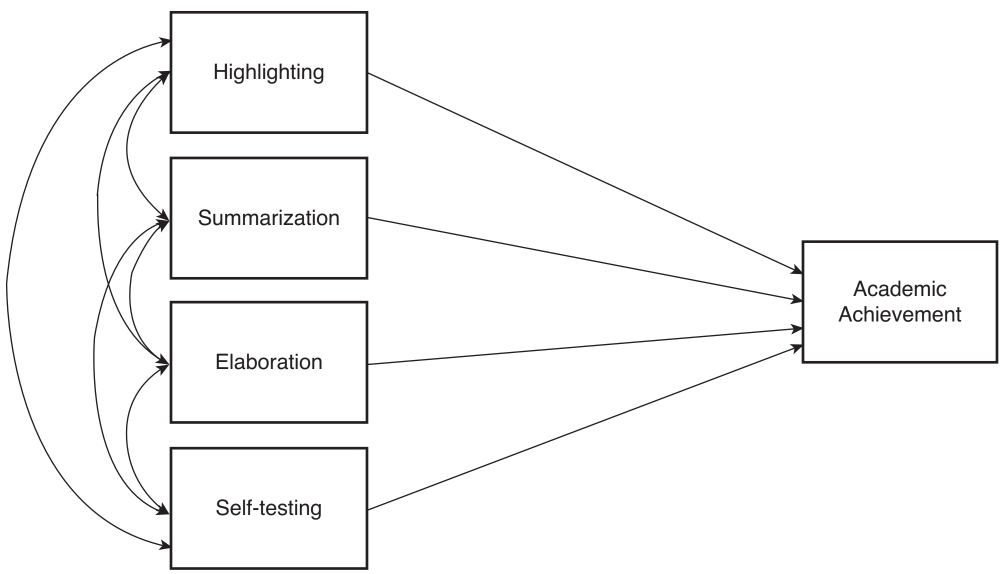

Figure 21.1 Example Path Model of a Regression Analysis

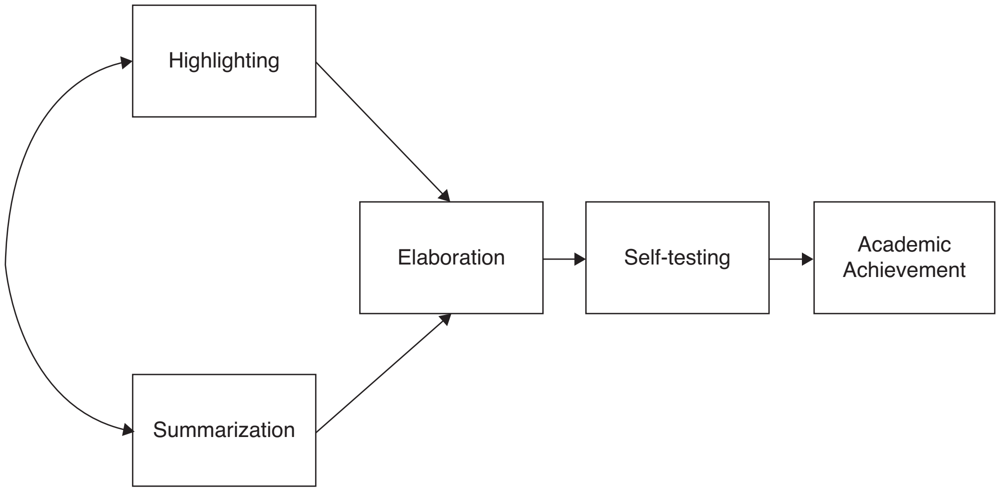

Figure 21.2 Example Path Model Analysis

because there are possible paths that are not specified (e.g., a path from highlighting to self-testing, or from elaboration to academic achievement). Models that are not saturated can be more thoroughly tested for data-model fit than saturated models, and compared to other specifications (e.g., deep strategy use predicting surface strategy use, which in turn predicts academic achievement) to determine which specification best represents relations in the data. Thus, path models and their associated analyses allow researchers to test more complex models than GLM methods such as regression, and often allow for more rigorous tests and comparisons of different conceptualizations of the relations among variables. On the other hand, to be estimated successfully, path model analysis often requires a larger sample size than GLM models (Kline, 2014).

Bernacki et al. (2012) used trace data from college students' use of a technology-enhanced environment to study relations among strategy use, self-reported motivation, and learning performance. The trace data represented counts of college student participants' use of highlighting, note taking, and definition tools, as well as monitoring tools such as accessing a list of learning goals. Bernacki et al. (2012) could have used a regression model in their analysis, but that would not have allowed them to test their hypotheses regarding how motivation predicts strategy use, which they posited would then predict learning, a common consequential order in models of self-regulated learning (SRL; Schunk & Greene, 2018). By using path model analysis, they were able to discover that approach-based motivation was positively related to strategy use, whereas avoidance-based motivation was negatively related. Further, highlighting was the only strategy use variable that predicted learning. Finally, they found acceptable data-model fit for this model, indicating its superiority to a saturated model, adding evidence regarding the validity of their conceptualization.

Deekens et al. (2018) posited a similar model in the second of two studies in their article, arguing that the relationship between pre and posttest measures of learning would be mediated first by the frequency of monitoring, which in turn would predict the frequency of deep and surface strategy use, with both strategy use variables predicting posttest performance. Again, a path analysis model allowed them to examine a common consequential ordering of variables in SRL theory, where prior knowledge positively predicts the frequency of monitoring, which in turn would positively predict deep strategy use while negatively predicting the use of surface strategies. As Dinsmore (2017) and others have argued, Deekens et al. posited that deep strategy use would positively predict posttest performance, whereas surface strategy use would negatively predict performance. These authors found support for their path model, despite a relatively small sample size likely leading to power concerns. A standard regression model would not have allowed for tests of relations between prior knowledge and monitoring, or monitoring and strategy use, as the path model analysis did. In sum, path models allow researchers to more closely adhere to theoretical relations in their analysis and can provide unique insights regarding contingent relations among strategy use and other variables of interest in learning (e.g., motivation, prior knowledge, monitoring; Ben-Eliyahu & Bernacki, 2015).

Structural Equation Modeling

Structural equation modeling is quite similar to path model analysis in that researchers can posit and test complex relations among variables, including mediation (Kline, 2014). However, path model analysis involves only measured variables, which are likely to contain significant amounts of error variance in addition to true score variance. In structural equation modeling, one or more measured variables are replaced with a latent variable constructed of two or more measured variables. The process of estimating the latent variable from the associated measured variables enables researchers to produce an estimate of the error variance in each measured variable, and remove it, thus producing a latent variable that, in theory, is a more accurate and pure representation of the underlying construct (i.e., all true score variance, no error score variance).

For example, many SRL researchers have used the Motivated Strategies for Learning Questionnaire (Pintrich, Smith, Garcia, & McKeachie, 1991) to measure participants' perceptions of their motivation and strategy use (Vermunt, this volume). This questionnaire includes numerous self-report, Likert-type scale items intended to measure motivation (e.g., "In a class like this, I prefer course material that really challenges me so I can learn new things" and "If I study in appropriate ways, then I will be able to learn the material in this course") as well as learning strategy use (e.g., "When studying for this course, I often set aside time to discuss course material with a group of students from the class" and "I ask the instructor to clarify concepts I don't understand well"). In theory, each item is a good but not perfect measure of the underlying latent construct of motivation or learning strategy use. Summing scores across multiple strategy use items would include both true score and error variance in the total. Structural equation modeling allows researchers to estimate and remove the error variance from each individual item, including only true score variance in the estimate of participants' score on the latent variable. This latent variable is a more accurate and statistically stronger estimate than any of its individual measured variable indicators. Structural equation models can be conceptualized, tested, reconceptualized, and compared similarly to path analysis models. However, structural equation modeling often requires even larger sample sizes than path model analysis.

Baas, Castelijns, Vermeulen, Martens, and Segers (2015) used the self-report Children's Perceived Use of Self-Regulated Learning Inventory (Vandevelde, Van Keer, & Rosseel, 2013) to measure elementary school students' surface and deep learning strategies as well as their relations among monitoring, scaffolding, and evaluation. This inventory included two items the authors used to measure perceived use of surface learning strategies, and another eight items used to measure perceived use of deep learning strategies. They used structural equation modeling to determine whether the items appropriately measured each latent perceived strategy use variable, and then they evaluated relations among those latent variables and other phenomena of interest such as scaffolding, monitoring, planning, and product evaluation. They found that scaffolding positively related to perceived use of both surface and deep learning strategies, thus supporting the idea that helping students understand what they need to do next when learning (i.e., scaffolding) is associated with self-reported increases in the perception of strategy use. It is important to note that despite common misconceptions, structural equation modeling does necessarily allow researchers to make causal claims (e.g., scaffolding caused students to perceive greater use of strategies). Causal claims are dependent upon the design of the study (i.e., experimental versus non-experimental designs), rather than the type of analysis technique used (e.g., regression, path model analysis, structural equation modeling; Murnane & Willet, 2010).

Greene, Costa, Robertson, Pan, and Deekens (2010) used a structural equation model to examine relations among college students' knowledge gains while using a computer-based learning environment, SRL processing including strategy use as captured via think-aloud protocol data (Greene et al., 2018), and implicit theories of intelligence (Dweck & Master, 2008). The authors found that planning, monitoring, and strategy use could be used as measured indicators of a latent SRL variable, and that this variable mediated relations between prior knowledge, implicit theory of intelligence, and posttest performance. This posited model allowed these researchers to test common assumptions about SRL (i.e., SRL mediates relations between individual differences and learning performance; Pintrich, 2000) that would have been impossible to assess with a regression model.

Growth Curve Modeling

Often, researchers wish to measure changes in strategy use over time, for example in studies of children's strategic processing as they age through elementary school (Carr & Alexeev, 2011). This change over time can be estimated using growth curve modeling, which is akin to a structural equation modeling approach to GLM repeated measures analysis. In growth curve modeling, the participants' initial performance ability and their rate of change over time are treated as latent variables that can be more accurately estimated after removing error variance from the repeated measures. Carr and Alexeev captured students' use of both cognitive and manipulative mathematics strategies in 2nd, 3rd, and 4th grades and then used growth curve modeling to find statistically significant change in the frequency of observed strategy use over that time period. Their analyses extended beyond the scope of this chapter, revealing previously unobserved differences in students that related to 4th grade mathematics competency, as well. The use of growth curve modeling allowed the authors to more accurately discern how strategy use changed over time, and how that change related to covariates such as fluency, accuracy, gender, and subsequent measures of mathematics competency.

CURRENT AND FUTURE DIRECTIONS FOR VARIABLE-CENTERED APPROACHES TO STRATEGIC PROCESSING RESEARCH

In sum, variable-centered analyses are statistical methods used to prepare or analyze data from previously identified groups (Laursen & Hoff, 2006). Whereas the goal of using person-centered analyses (e.g., cluster analysis and latent class analysis) is to identify previously unobserved groups based upon common patterns within the data, the goal of variable-centered analyses is to explore, compare, or contrast extant groups within the data. Data aggregation prepares data for analyses. The analyses we outlined in this chapter include GLM analyses (i.e., t-tests, ANOVA, multiple linear regression), count models, path analysis, structural equation modeling, and growth curve models.

In this chapter, we explained the purpose of and process for using variable-centered analyses to study strategy use and strategic processing. Researchers were able to answer key research questions about strategy use through variable-centered analytic methods. For example, Bernacki and colleagues' (2012) study used path analysis to analyze trace data from college students' use of a technology-enhanced environment to study relationships among strategy use, self-reported motivation, and learning performance. Using path model analysis meant they were able to discover that approach-based motivation was positively related to strategy use, and avoidance-based motivation was negatively related. Additionally, variable-centered analyses provided other affordances for research, such as analyzing use of count data. Sometimes studies of strategy use involve counts of the number of times participants use particular strategies. These can be counts of strategy use via observation (e.g., Hagen et al., 2014), participants' think-aloud verbalizations of strategy use (Greene et al., 2018), or from trace data from computer-based learning environments (Bernacki, 2018). Researchers can analyze count data that is non-normally distributed through generalized linear model analyses. Also, variable-centered analyses can be used to model complex relations among numerous measured variables (e.g., path analysis), to understand latent variables and structures (e.g., SEM), as well as how strategic processing changes over time (e.g., repeated-measures ANOVA, growth modeling). Variable-centered analyses of strategic processing data have been and likely will continue to be a prominent way of understanding how people enact strategies, as well as the precursors and consequences of such enactment.

Future Directions for Research

There are opportunities to expand the use of variable-centered analyses for strategy use in future research. We identified many researchers who utilized self-report surveys and questionnaires about strategy use (e.g., Askell-Williams et al., 2012; Mirzaei et al., 2014; Ruffing et al., 2015). However, strategy use is dynamic and not stable. Researchers studying strategy use that incorporates behavioral data have an opportunity to capture learning behaviors as they occur, via think-aloud protocols (Anmarkrud et al., 2013), eye fixations on a page (Arya & Feathers, 2012), or other methods. Capturing these strategic processing behaviors as they occur can be more useful than self-report data because it allows for modeling the dynamic nature of strategy use, and can afford an understanding of the sequential and contingent nature of strategic processing (Ben-Eliyahu & Bernacki, 2015; Binbasaran Tüysüzoğlu & Greene, 2015). In the future, variable-centered analyses, such as path modeling, could be used to understand how people leverage feedback to dynamically adjust the depth of their strategy use (Dinsmore, 2017), such as when frequent difficulty with formative assessments leads to participants shifting from surface- to deep-strategy use.

Often, researchers have studied how strategy use predicts achievement or learning outcomes (e.g., Carr et al., 2011). However, there are fewer studies that exist where researchers have considered strategy use itself as the outcome variable (e.g., Greene et al., 2011; Vasilyeva et al., 2015). In the future, researchers may study strategy use as an outcome in itself more often, rather than establishing the relationships between strategy use and other variables (e.g., GPA). Given the established relationship between strategy use and performance outcomes, more research is needed on how to foster effective strategic knowledge and processing among those who would otherwise struggle to enact without support (Bjork, Dunlosky, & Kornell, 2013).

In the future, we encourage diversifying methodological and analytical techniques in the field of strategy use. We identified many studies that utilized quasi-experimental designs (Aghaie & Zhang, 2012) or experimental studies (Cantrell et al., 2014), but fewer case studies. It may be that qualitative research is needed to better understand why people do and do not enact effective strategic processing, and what variables are most important to capture and analyze (e.g., self-efficacy for strategy use; Zimmerman, 2013). Likewise, mixed methods might enhance the knowledge base and research quality in the field of strategy use. For example, researchers might use mixed methods to iterate between what participants actually do when studying (i.e., quantitative data derived from observation) and what they think they are doing (i.e., qualitative investigations of participants' impressions and experience). Such mixed methods research designs may afford greater insight into the variables associated with proper calibration and metacognitive knowledge during strategic processing (Pieschl, Stallmann, & Bromme, 2014).

In addition to methodological and analytical diversification, diversification of samples is also an area of further exploration. For example, Vasilyeva et al. (2015) analyzed cross-cultural differences in strategy use between US and Taiwanese students. They found that Taiwanese children used retrieval practice more than US children. Such research is necessary to understand how strategy use varies across contexts, and why. However, such work must necessarily be conducted from a perspective derived from within the culture, rather than imposing ideas derived from one culture onto another (King & McInerney, 2018).

Conclusion

In conclusion, strategy use data comes in different forms, and some of these data can be analyzed with variable-centered analyses. The variable-centered analyses described here include general linear model approaches such as correlational and regression analyses, path analyses, structural equational models, and growth models. Data aggregation can be used to make strategy use data more amenable to variable-centered analyses, although in some cases count-based analyses must be used. Though the variable-centered analyses most appropriate for a given situation are determined by the research question, the type of data collected, and the goal of the research methods used, we demonstrated in this chapter how variable-centered analyses can be used to answer questions about the nature of strategy use and its relationships with other variables. Specifically, we look forward to seeing how researchers incorporate new applications of analytic methods for understanding strategic processing data.

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