Problems in Academic Motivation Research and Advantages and Disadvantages of Their Solutions

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In this article, problems in current academic motivation research and their solutions are discussed. From a theoretical standpoint, it is argued that the field suffers from a lack of comprehensive models that are capable of capturing the full dynamics underlying observed behaviors. Different theoretical orientations among researchers often result in a rather arbitrary inclusion or exclusion of variables which leads to the misspecification of models. A lack of discriminant validity among motivational constructs exacerbates the problem. Furthermore, the issue of motivational influences on specific phases of information-processing and their interaction with different types of knowledge has largely been neglected. From a measurement perspective, heavy reliance on self-reporting questionnaires is once again criticized. It is argued that such practice overlooks motivational fluctuation both over time and across domains, assuming a greater degree of generalization of academic motivation without empirical support. Several solutions are suggested for each problem and their advantages and disadvantages are considered.

Recent developments in academic motivation research have advanced our understanding of the psychological processes that presumably underlie various patterns of achievement behavior. We now have a number of reasonable, although far from complete, explanations of why two people may display drastically different reactions to seemingly identical experiences. Possible cause, or causes, for such diversity can be conceived of easily by resorting to one or more of the following theories of motivation: Causal attributions (Weiner, 1985), theories of intelligence and achievement-goal orientations (Dweck, 1986, 1989; Dweck & Leggett, 1988), and perceived self-efficacy (Schunk, 1990, 1991b), to name just a few. However, as the field progresses toward a deeper understanding of motivational phenomena, several problems have called for our attention.

LACK OF A COMPREHENSIVE MODEL

One of the problems facing current academic motivation research is that despite a proliferation of theories and models testing specific relationships and hypotheses (Schunk, 1990), no single model can capture the full dynamics
of motivated behaviors. This seems, in part, due to different theoretical orientations of investigators working in the field, who tend to emphasize a particular dimension of motivational phenomena over the others.

Models with Different Theoretical Orientations

One set of such models can be categorized as cognitive models of academic motivation. Investigators who take primarily cognitive approach to motivation research place greater weight on understanding learners’ covert thought processes, often overlooking the impact of social and contextual variables. Weiner’s attribution theory of motivation and emotion (1985), for example, carefully delineates the processes of how learners’ causal ascriptions influence their cognitive, affective, and behavioral consequences following an outcome. Predictions are formulated solely based upon an analysis of causal dimensions of each attribution.

Another example with a similar approach is Salomon’s (1983, 1984) conceptualization about the role of perception and its influence on the amount of invested mental effort (AIME). He claimed that it was learners’ perceptions, beliefs, and preconceptions toward a particular class of media that were primarily responsible for different motivational patterns. Both Weiner’s (1985) and Salomon’s motivational analyses assign a major role to learners’ subjective perceptions and beliefs with no explicit provision for the roles played by social or situational variables.

There are numerous other models that take a similar stance. Some of them reserve room for contextual variables. Boekaerts’ (1991) heuristic model of affective learning process can be a good example. Although learners’ subjective competence and their cognitive appraisals of learning situation still assume major responsibility for predicting a motivational outcome, characteristics of learning task and its context are nevertheless hypothesized to wield an influence on such cognitive processes. Likewise, Dweck’s model of achievement motivation (Dweck, 1986, 1989; Dweck & Leggett, 1988) is a cognitive model in essence, with acknowledgment of the potential impact from social and situational variables. These theories, however, still do not provide specific hypotheses or predictions regarding the roles played by social and contextual factors.

The other set of models that is rapidly increasing in the literature takes a social–cognitive approach, often represented by a goal theory of motivation. Unlike those previously described, these models formulate and test specific hypotheses regarding the nature and direction of influence from social and contextual variables. Ames (1992; Ames & Archer, 1988), for example, identified three classroom structures that contributed to adoption of different achievement goals: task, authority, and evaluation and recognition. She argued that meaningful tasks with an appropriate level of challenge, teachers who reward autonomy, and effort- and progress-based evaluations should lead to
a mastery goal orientation that is conducive to further learning and development. Schunk’s (1989; 1991a) and Zimmerman’s (1989; Zimmerman, Bandura, & Martinez-Pons, 1992) models of self-regulated learning are other examples which tried to incorporate personal, behavioral, and environmental factors and their triadic reciprocality into account.

These social–cognitive models of academic motivation provide us with practical instructional strategies that can direct learners to more adaptive motivational paths. Unfortunately, they sometimes lack detailed specification of construct definitions evidenced in other cognitive theories. For example, Blumenfeld (1992) pointed out that while Ames’ (1992) description of three classroom structures affecting students’ goal orientations provided us with a useful framework for devising practical interventions, the dimensions of each of these structures still needed to be elaborated more fully. The difficulty faced by social–cognitive theorists stems, in part, from the countless number of social factors that need to be considered in these relatively recent theoretical formulations and, in part, from the potential disparity among researchers, practitioners, and students on how these social and contextual factors (and each of their dimensions) are perceived and interpreted.

In summary, it is evident that different theoretical orientations often lead academic motivation researchers to different conclusions as to which potentially relevant variables to include in or exclude from their conceptualizations. This rather arbitrary inclusion or exclusion of variables makes it difficult to envision a single model that can explicate various motivational phenomena despite a generous number of theories and models that are now available in the literature.

**Motivational Constructs without Discriminant Validity**

What exacerbates the aforementioned problem is the ever-increasing number of motivational constructs that lack discriminant validity (d’Ydewalle, 1987; Graham & Golan, 1991). Many researchers are too quick to invent their own set of labels without carefully examining those found in the literature. It may sometimes be the case that they do not like what they see even after paying them a careful consideration. This causes what can be aptly called “a conceptual mess” for those who try to draw a coherent whole out of the relevant literature.

Two most commonly used terms in current academic motivation research are those that denote major adaptive and maladaptive patterns of achievement orientation. At one end of the motivational continuum, there are learners who seek challenging tasks, persist in the face of obstacles, and whose ultimate goal lies in learning and mastering new skills. At the other end, there are those who avoid challenging tasks in fear of displaying low ability, slacken effort at the presence of potential failure, and whose goal is to validate superior ability over or to avoid negative judgments from others. Although it is recently
recognized by some researchers that those who cherish both goals—that of learning and looking good—thrive in classrooms, it is still customary to classify learners into the two major kinds of achievement orientations that are maximally different. Ames (1992; Ames & Archer, 1987, 1988) attributed these contrasting styles to mastery- and performance-oriented goals, whereas Dweck (1986, 1989; Dweck & Leggett, 1988) described the same phenomena using such labels as learning- and performance-goals. Nicholls (1984) employed yet another set of terms; task- versus ego-involvement.

Another area in academic motivation research where distinction among constructs often gets blurred is that related to the self or to subjective perceptions. This becomes obvious when definitions of such constructs are compared. For instance, Schunk (1991b) defines self-efficacy as ‘‘an individual’s judgment of his or her capabilities to perform given actions (p. 207).’’ Boekaerts (1991) presents a similar construct called subjective competence defined as ‘‘a person’s knowledge, beliefs, and feelings about his capabilities and skills’’ (p. 2). Another related construct is perceived control suggested by Skinner (Skinner, Wellborn, & Connell, 1990), which is further classified into ‘‘three qualitatively different’’ sets of beliefs: strategy beliefs that are ‘‘beliefs about the extent to which certain potential causes are effective in producing outcomes,’’ capacity beliefs that are ‘‘beliefs about the extent to which the person has access to the potential known causes,’’ and control beliefs that are ‘‘beliefs about the extent to which the person can produce desired outcomes, without reference to any explicit categories of causes (p. 23).’’ As academic motivation researchers, we have to extract from these definitions the decisive characteristics of subjective competence, if any, that can distinguish itself from self-efficacy or from capacity beliefs and vice versa. The situation worsens when investigators employ certain constructs in their study without providing a defensible rationale for such decision as well as clear conceptual and operational construct definitions.

Although several authors acknowledge conceptual similarities and differences among these labels (e.g., Ames, 1992; Boekaerts, 1991; Schunk, 1991b), that alone is not enough for others to realize the extent to which theoretical formulations behind those labels agree to each another. As Ames (1992) justly pointed out, predictions derived from mastery- versus performance-goal distinction (e.g., Ames & Archer, 1988) are almost identical to those derivable from learning- versus performance-goal orientation description suggested by Dweck (e.g., Dweck & Leggett, 1988). It is still not clear, however, whether Ames also accepts Dweck’s contention that roots of these contrasting achievement orientations rest in differing theories of intelligence that learners endorse. This problem can seriously hamper any attempt to synthesize findings from the current literature which can eventually guide researchers to the construction of a more general conceptual model of academic motivation.
Motivational Influences on Information-Processing: A Neglected Topic

Compared to the amount of effort invested in disentangling psychological processes that link motivational orientations to different achievement strivings, the impact from the same motivational factors on cognitive processes that are potentially responsible for different levels of academic attainment remains largely unexplored (Corno & Mandinach, 1983; Graham & Golan, 1991).

Graham and Golan (1991) conducted a series of experiments in an attempt to address this issue. They reported that there was little difference in learners’ ability to encode given information regardless of their motivational state but that ego-involving state significantly impaired learners’ ability to access already stored information. They speculated that this might be the reason for different academic achievement often documented in empirical studies which compared learners with adaptive versus maladaptive motivational orientations. The importance of this study lies in the fact that it proved the very existence of motivational influences on learners’ specific information-processing capabilities.

Although Graham and Golan’s study (1991) concerned mainly the processing of declarative information, it will be interesting to see whether there are different effects of motivational orientations on processing procedural types of knowledge. It is suspected that processing of declarative information may be more impeded by maladaptive motivational orientations because it requires greater cognitive resources compared to that of procedural knowledge. Similarly, procedural knowledge in its cognitive stage where it largely remains as declarative representation of conditions and actions (Gagné, Yekovich, & Yekovich, 1993) may be more prone to the motivational impact than highly automatized procedures.

Such a detailed analysis of motivational influences on information-processing promises a fruitful line of research that can lead us to the fuller understanding of this complicated phenomena and should thus constitute an important dimension of any broader model of motivation.

Solution 1: An Integrative Approach

One possible solution for integrating numerous motivational constructs and findings into a unified course of investigative endeavor appears to be to create a general model that can guide future research on motivation, learning, and instruction. The need for such a comprehensive model which can fully incorporate the dynamic interactions among motivational variables has been suggested repeatedly (e.g., Clark & Bong, 1996; Corno & Mandinach, 1983; Marshall, 1992; Meece, Wigfield, & Eccles, 1990; Schunk, 1990). So far, however, there has not been a systematic approach that explicitly compares and contrasts predictions and hypotheses generated by numerous theories and models. As pointed out earlier, it is demonstrated by the generous number
of models and constructs existing in the literature, sometimes with striking resemblance to each other.

Recent efforts to combine scattered findings into a coherent body have brought a social–cognitive approach to motivation (e.g., Ames, 1992; Zimmerman, 1989; Zimmerman et al., 1992). These models take into account influences from various social and contextual factors on learner’s motivation in addition to those emanating from cognitive variables. Although far from exhaustive in their specifications, they provide a helpful future direction the field has to move on. Formulation of a more comprehensive model should start from careful selection and labeling of motivational constructs based on empirical testings and should continue evolving through constant revisions. Integration of existing theories and constructs will become inevitable. As a result, the model should be able to reflect cognitive, social, affective, and other conceivable dimensions of motivational influence on both overt and covert processes. Such a model can guide and encourage researchers to put more concerted efforts for unveiling diverse patterns of motivated behavior by providing them with a clearer means of communication.

Potential disadvantage of the integrative approach is that there is a danger of overlooking some unknown complexities of or hidden disparities between variables that appear to be identical. Great caution is required when one seeks to establish a unified set of motivational constructs. When there exists a discrepancy among those constructs, no matter how subtle it may be, it is difficult to justify the integration.

Some may point out that such a macro-approach can be too unwieldy when conducting a study that can yield any meaningful results. This argument sounds legitimate from a practical point of view. It is not feasible to analyze all the constructs and their interactions in a single study. However, variables of interest can be selected and their relationships can be tested without losing sight of the big picture. This allows an examination of intra- as well as interdimensional interactions among constructs that is not possible in isolated approaches.

**Solution 2: Multiple Models That Represent Separate Dimensions of Motivational Phenomena**

Another solution may be to construct several models, each of which reflects a separate dimension of motivation. Although not as complete as the comprehensive model proposed above, these models should display greater depth and breadth in their own dimensions. For instance, information-processing model of motivation will be able to relate motivational variables, their interactions, and their potential impact on cognitive processes to the general principles of information-processing (Graham & Golan, 1991). Likewise, social–cognitive and affective models of motivation are readily conceivable. Among these, the social–cognitive model of academic motivation seems to be the
one that can be realized in the nearest future as reflected in an optimism expressed by those currently engaged in the enterprise (e.g., Ames, 1992; Blumenfeld, 1992; Marshall, 1992). In fact, we are witnessing recent burgeoning of models on self-regulated learning (e.g., Schunk, 1991a; Zimmerman, 1989) in social–cognitive motivation research. There is also an increasing interest in emotions and their relations to motivation (Weiner, 1990).

A major advantage of this approach lies in the relative ease for carrying out an investigation that fully incorporates variables specified for a given dimension. The model as a whole, therefore, can be tested and revised easily. An obvious disadvantage is that it cannot capture potential interactions among variables that belong to separate dimensions. For example, effects of goal-setting on specific aspects of information-processing or that of self-regulation on subsequent emotions can be neglected in a model that represents only a single dimension.

Solution 3: Use of Path Analysis and Structural Equation Modeling

One of the notable developments in the field of educational psychology, or of psychology as a whole, is the advent of path analytic techniques. Structural equation modeling, in particular, can solve many of the problems discussed above. Specifically, path analysis and structural equation modeling allow researchers to put to a test the hypothesized causal relationships in nonexperimental research, to establish discriminant and predictive validity of constructs, and to decompose the effects operating among variables, all of which enable them to revise, refine, and reconstruct the theoretical model (Pedhazur, 1982; Weinberg, 1982).

For example, Pajares and Miller (1994) successfully demonstrated the predictive utility of academic self-efficacy beliefs on students’ academic performance over and beyond what could be accounted for by a conceptually similar construct, academic self-concept, using path analysis. The aim of their study was to examine the impact of gender, prior experience in math, math self-efficacy, math self-concept, perceived usefulness of math, and math anxiety on math performance. The investigators postulated that although the constructs of interest were all cognitive mechanisms that were presumed to influence students’ academic achievement to a certain degree, self-efficacy beliefs would emerge as the strongest predictor of an outcome as well as a mediator of the other constructs.

The results confirmed their predictions. Specifically, mathematics self-efficacy exerted the strongest positive influence on math performance compared to other variables. It also mediated the impact of gender and prior math experience on mathematics self-concept, perceived usefulness, and math performance. The impact of math self-concept on math performance was only modest after the effects of math self-efficacy was controlled for. Interestingly, math anxiety was dropped from path analysis due to its high correlation with math self-concept ($r = .87$).
This study proved the usefulness of path analytic techniques in establishing discriminant and predictive validity of psychological constructs.

Although both path analysis and structural equation modeling are suitable methods for testing causal models, structural equation modeling has several critical advantages over path analysis (Pedhazur, 1982; Pedhazur & Schmelkin, 1991). The term path analysis usually refers to a situation in which each construct is represented by a single indicator. Such an analysis is based on very narrow assumptions, the most unrealistic of which might be that each variable is measured perfectly without error. Structural equation modeling is the first attempt to take into account the measurement error. It allows the inclusion of multiple indicators for each construct specified in the model, assuming that each set of indicators shares a common underlying factor that is not directly observable. This feature is very useful when one tries to come up with a comprehensive model of academic motivation. As pointed out previously, the danger of such an integrative approach is in the possibility of missing some unknown disparities among seemingly identical variables. By using structural equation modeling, it becomes possible to include several related measures in the analysis that presumably represent slightly different facets of the same underlying construct.

WHAT IS THE NATURE OF ACADEMIC MOTIVATION AND HOW CAN WE MEASURE IT?

The term, motivation, is so commonly used in everyday life, people seldom think about what they mean by it exactly even as they use it. The same case applies to academic motivation researchers. What do we really mean when we talk about motivation? What are the best descriptors of motivation and motivated behavior? The problem arises because a conceptual definition alone is not enough to conduct a study that involves hypothetical constructs.

Current academic motivation research predominantly depends on questionnaire studies that are correlational and one-shot in nature which often preclude a possibility to disclose any unknown dynamics beyond the measurement setting (Blumenfeld, 1992). Heavy reliance on a single scale for measuring a motivational construct tends to aggravate the problem.

Is There a Single Measure That Best Represents a Motivational Construct?

There are so many indicators and scales that purport to reflect the same motivational construct that it has become almost mandatory to first figure out which of them is, or are utilized in each study in order to avoid any misunderstandings. A comparison of two studies that share the same theoretical background, both of which try to predict academic achievement from motivation illustrates this point.

Meece, Wigfield, and Eccles (1990) conducted a study within an expectancy-value framework that examined factors influencing junior high school
students’ math achievement. Constructs of primary interest were expectancy, value, anxiety, and achievement. Questions that asked about students’ performance expectancies in math comprised the expectancy construct whereas those that asked about their perceived importance of math constituted the value construct. The achievement measures encompassed math grades and enrollment intentions for future math courses. Self-efficacy measured as math ability perceptions was also included in the analysis. The investigators found that self-efficacy, expectancy, and value predicted math anxiety and that expectancy and value each predicted math grades and course enrollment intentions, respectively.

Berndt and Miller (1990) also examined the role of expectancy and value on junior high school students’ school achievement. The expectancy construct in this study was composed of perceived scholastic competence and causal attributions. An involvement scale that asked about students’ degree of participation in schoolwork and a school value scale that asked about their perceived importance of and interest in school learning constituted the value construct. Grades and school track comprised the achievement index. Berndt and Miller reported that although both expectancy and value positively influenced school achievement, expectancy related more strongly to achievement than did value. They also found that important indicators of expectancy were scholastic competence, ability attribution of success, and ability attribution of failure.

A major difference between the two studies is found from the sets of measures employed to represent the seemingly identical constructs. And this, in turn, might be able to explain why there is a discrepancy between results of the two studies conducted within a single theoretical framework. For instance, both expectancy and value demonstrated direct positive effects on grades and school track in Berndt and Miller’s study (1990), whereas only expectancy, but not value, was able to predict math grades in Meece et al.’s (1990). Here, value predicted enrollment intentions for future math courses but had no direct effect on math grades. In order to decide whether it is both expectancy and value that affect achievement as in Berndt and Miller or only expectancy as in Meece et al., it is necessary to compare what indicators characterized those constructs, expectancy and value, in these studies.

It is also noteworthy that each of the expectancy and value constructs in Meece et al.’s (1990) study was composed of a single subscale with two questions that asked students’ perceptions and beliefs in the respective area. Although this type of practice is not uncommon in the field, a question remains as to how well those two items could embody their target constructs such as expectancy and value. In some cases, substantive findings might be altered by utilizing different scales or by adding more indicators to portray the same construct.

Motivation across Time

Evidence points not only that the relationship between motivation and achievement fluctuates by measures included in studies but also that the nature
of academic motivation may not be uniform across different points in time. Several studies tested this hypothesis (e.g., Meece et al., 1990; Pokay & Blumenfeld, 1990).

Pokay and Blumenfeld (1990), for example, studied the relations among academic motivation, use of learning strategies, and achievement both early and late in the semester. The investigators were interested to see whether these relations would differ as a function of time. Academic motivation was represented by subscales measuring self-concept, value, and expectancy. Learning strategies were divided into metacognitive, general-cognitive, geometry-specific, and effort-management strategies. Prior algebra grade and two geometry test scores embodied achievement. It was found that value and expectancy predicted strategy use and that geometry-specific and metacognitive strategies predicted geometry test grade early in the semester. Although value retained its direct effect on strategy use later in the semester, only metacognitive strategy maintained its influence on later geometry test grade. In addition, self-concept was able to predict test grade only late in the semester.

Domain-Specificity of Academic Motivation

Weiner (1990) likewise suspected that there would be little generality of academic motivation across domains. The same child who enjoys reading history books and shows great interest in learning about history can detest studying mathematics and display anxiety when learning it. He or she is likely to adopt a learning goal in history but might pursue a performance goal in mathematics (Dweck, 1986, 1989), demonstrating a possibility that the nature of achievement goal orientation changes as a function of subject-matter areas.

Duda and Nicholls (1992) investigated this issue. They compared high school students’ goal orientations, beliefs about the causes of success, intrinsic satisfaction, and perceived ability in schoolwork and sport and obtained some interesting results. Specifically, they found that there was high cross-domain generality among goal orientations and beliefs about the causes of success. However, there was little generality for perceptions of ability and intrinsic satisfaction across schoolwork and sport. They thus concluded that it would be inappropriate to make broad statements about generality versus specificity of academic motivation due to this apparent discrepancy among motivational constructs.

In summary, it is clear that there is a need for diverse designs and methods in order to adequately address this complex nature of academic motivation.

Solution 1: Use of Multiple Indexes for a Single Construct

The previous comparison of Pokay and Blumenfeld’s (1990) and Meece et al.’s (1990) study demonstrated the difficulty of representing any motivational construct by a single measure and the potential consequences of such practice. The point is, it is extremely difficult and sometimes even unreasonable to try
to find a single measure that best represents any motivational construct. It is
more so when the potential fluctuation of motivation across time and domains
is considered. A scale that exhibits a sound and reliable performance in one
situation might not be the best measure in another.

Such a dilemma can be nicely handled in structural equation modeling by
employing multiple indexes for constructs included in the analysis. Various
facets of each construct can be measured and incorporated as indicators of
the same construct. Whether or not the hypothesized facets are correlated
high enough to be considered as representing the same construct can also be
determined (e.g., Marsh, 1990; Marsh & Shavelson, 1985).

The need for utilizing multiple indexes also applies to dependent variables.
Most psychologists would agree that academic motivation increases the
amount of effort invested in a given learning task (e.g., Bandura & Schunk,
1981). How do researchers know when learners indeed express their enhanced
motivation by increasing their effort? Should they measure learners’ persis-
tence (e.g., Bandura & Schunk, 1981), strategy use (e.g., Pintrich & De Groot,
1990), or better yet, amount of mental effort invested (e.g., Salomon, 1984)?
All of them are valid indicators of effort with slightly different orientations.
Persistence puts emphasis on quantity of effort whereas strategy use does on
quality. Amount of mental effort invested (AIME) seems to stress both. A
proper representation of effort should be able to illustrate both quantity and
quality sides of it.

Employing multiple indexes helps alleviate this problem. It can provide
reliability and convergent validity for a given construct. If the researchers
can estimate students’ persistence, strategy use, as well as the amount of
mental effort invested in a given task and these three indicators of effort all
converge, they are in a far better position for claiming that they actually have
what they think they have. This approach also augments generalizability of
findings because the substantive conclusions are not likely to falter in subse-
cquent replications that utilize other indicators.

Despite all the advantages described above, it is not always the most practi-
cal way to measure a construct. In a study that involves numerous motivational
constructs and their interactions, the option of employing multiple scales for
each construct is just not feasible, if not impossible. In such cases, it may be
better to decide on a single scale that has been proven reliable and valid for
each construct.

**Solution 2: Self-Report Measures Supplemented with Behavioral Indexes**

A somewhat related solution comes from combining two different methods
of inquiry. As Blumenfeld (1992) pointed out, huge reliance of academic
motivation research on self-reporting questionnaires and their analyses tend
to isolate variables and their relationships. This approach, often characterized
as quantitative method, assumes that it is possible to select certain variables
for study without affecting other variables left in the context (Salomon, 1991). Recent findings based on a social–cognitive framework, however, attest to the difficulty or implausibility of isolating social and contextual factors that are closely intertwined with other variables of interest (e.g., Ames & Archer, 1987, 1988; Golub, Stipek, & Howes, 1984; Miller & Hom, 1990).

Thicker descriptions (Blumenfeld, 1992) of the nature of interconnectedness among variables can be provided by qualitative data or a systematic approach as Salomon (1991) called it. The growing interest in investigating causal impact of motivation on academic attainment in natural school settings also necessitates such approach. For example, three classroom structures suggested by Ames (1992)—task, authority, and evaluation and recognition—which are hypothesized to influence students’ goal orientations and motivational patterns undoubtedly affect each other. Although it is not impossible to delineate such mutual impact among variables by carefully specifying potential mediators and moderators in the process, systematic observations nonetheless help by bringing additional insights into learning the nature of the process.

Even without resorting to quantitative methods, one can supplement self-report data by other behavioral indexes. Overt behavioral data are immune to many of the problems inherent in self-report measures such as social desirability. They can thus act as a useful guideline for researchers in determining the validity of responses in self-reports.

A study on self-regulated learning conducted by Howard-Rose and Winne (1993) provides a good example. The researchers tested the existence of four different forms of cognitive engagement in self-regulated learning proposed by Corno and Mandinach (1983). They examined the component cognitive processes at two different levels of specificity: as relatively small-grained components (i.e., attending, rehearsing, monitoring, strategic planning, selecting, connecting, and tactical planning) and as two larger-grained sets of those small-grained component processes (i.e., acquisition and transformation). More important, the investigators collected their data using three different lines of inquiry. They administered the Self-Regulated Learning Rating Scale as a pretest, followed by the Metacognitive Questionnaire administered immediately after each of the six tasks students were asked to perform. They also collected what they called “traces” such as underlining and marks within a text and written notes in the margins of task materials as evidence of cognitive processes.

Results yielded by the three methods did not coincide with each other. When correlated with other aptitude variables, each of the small- as well as larger-grained cognitive components displayed rather conflicting results depending on the measurement tools utilized. Accordingly, Corno and Mandinach’s model of self-regulated learning failed to receive clear empirical support. Had the researchers employed only one mode of inquiry, a completely different conclusion might have been obtained.
Academic motivation research can greatly benefit by combining more than one measurement methods. Quantitative methods will arm motivation researchers with the kind of precision they need whereas qualitative ones will provide them with data that can lead to a deeper understanding of the situation at hand. Behavioral indexes obtained in the very context of performing cognitive tasks can provide valuable information on covert cognitive processes being applied in the setting. They can also help researchers determine the degree of authenticity in responses collected from self-report questionnaires.

Solution 3: Repeated Measures and Longitudinal Designs

The best way to capture the changing nature of motivation across time is to implement repeated measures or longitudinal designs. As previously discussed, there is evidence that relations between motivation and achievement change as a function of time (e.g., Pokay & Blumenfeld, 1990). Conclusions drawn from a study that is carried out at the beginning of a semester might not hold up at the end of it. Studies that are based on measurements taken at a single point in time often overlook this possibility.

Another advantage of conducting longitudinal studies is that the direction of causality becomes clearer even without experimental manipulations which are not easy to realize outside laboratories. Self-efficacy, for instance, is frequently hypothesized to influence a variety of motivated thoughts and behaviors, such as persistence and intrinsic interest (e.g., Bandura & Schunk, 1981), expectancy and value (e.g., Meece et al., 1990), and strategy use and self-regulation (e.g., Pintrich & De Groot, 1990). What is implicit in these studies is the direction of causality such that heightened levels of self-efficacy brought about the changes observed in other variables. Without explicit provision of experimental manipulations and a control group, however, this assumption is only plausible at best. It is not transparent whether that inflated efficacy caused more strategy use and self-regulation or that increased use of strategies and improved self-regulation raised perceived competence. It is also possible that an increase in self-efficacy promoted strategy use and self-regulation which, in turn, enhanced efficacy perceptions.

The direction of causality among motivational variables is seldom unidirectional. More often than not, there exist reciprocal relations (Meece et al., 1990). Whether it is unidirectional or bidirectional, repeated measures and longitudinal designs can help uncover this potential complexity.

Such methods accompany rather obvious disadvantages, however. The time it takes to carry out a longitudinal study is too overwhelming for many researchers in the field. Analyses of data require more knowledge and skills than those dealing with cross-sectional ones. Although a longitudinal design itself does not preclude the possibility of experimental manipulations, it is unquestionably more difficult to manipulate variables at repeated points in time. When it does not involve deliberate manipulations, it is still difficult to
weed out influences from extraneous factors because data collection is more likely to take place in natural classroom settings. All these make the option of adopting cross-sectional designs more attractive and may be just part of the reasons why it is difficult to see many longitudinal studies in the current motivation literature.

**SUMMARY AND CONCLUSION**

Models of academic motivation that are primarily interested in cognitive aspects of it tend to make only implicit provisions for external factors that can also affect learner’s thought processes. More often than not, predictions concerning the nature and direction of influence from contextual variables are omitted from these set of models. On the contrary, social–cognitive theories of motivation represented by a goal theory specifically take into account factors in the learning environment that can augment or hamper students’ adaptive achievement orientations. Unfortunately, they seem to lack the precision witnessed in cognitive theories of motivation. What the field needs is a model with sufficient breadth that can capture the full dynamics underlying learners’ motivated behavior as well as depth and accuracy required in any good theoretical formulation.

Three problems are suggested that need to be resolved to this end. First, researchers in the field should be more careful when determining what variables or constructs to include in their models. Model specification is guided by researchers’ theoretical orientations that can easily overlook meaningful variables belonged to different research traditions. Without cautious and impartial consideration of potentially relevant variables and their relationships, it often results in rather arbitrary selection of model constituents. Constructs that lack discriminant validity exacerbates this problem. Researchers need to examine existing labels more mindfully and establish empirical support when necessary before inventing their own set of terms in order to avoid conceptual mess.

Although extensive research effort has been invested in disclosing the nature of relationship between learners’ academic motivation and their academic achievement, motivational influence on information-processing which is presumably responsible for different levels of learning and performance has been largely ignored. If we, as motivation researchers, are going to make suggestions on instructional strategies that are aimed at facilitating specific phases of learning, impact from motivational constructs on information-processing and its interaction with different types of knowledge will first have to be accounted for.

Practical considerations often hinder implementation of theoretically as well as methodologically sound research designs. Heavy reliance of motivation research on self-reporting questionnaires is once again criticized. However, by utilizing multiple indicators for each construct or by combining data
gathered from diverse modes of inquiry, richer descriptions can be obtained. Repeated measures and longitudinal designs provide a valuable means for studying motivational fluctuation across time which is not possible with one-shot self-reports. They can also make the direction of causality clearer without experimental manipulation. Domain-specificity or generality of motivational constructs is another area that needs a serious empirical investigation.

Path analysis and structural equation modeling are attractive solutions for many of the problems discussed above. Structural equation modeling, in particular, offers numerous advantages over other existing statistical methods. It allows researchers to correct for measurement error by employing multiple indicators for each construct, to test predictive and discriminant validity of constructs, and to test hypothesized causal relations in nonexperimental research.

It will be ideal that researchers demonstrate their investigative productivity with healthy studies. When quantity and quality compete with each other, it is often the quality side of the study that endures sacrifice. Conscious efforts to amend persisting problems in the current literature will bring the field steps closer to fully understanding and thus helping learners who do not have the will to learn.

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