Science Motivation Questionnaire II: Validation With Science Majors and Nonscience Majors

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Abstract: From the perspective of social cognitive theory, the motivation of students to learn science in college courses was examined. The students—367 science majors and 313 nonscience majors—responded to the Science Motivation Questionnaire II, which assessed five motivation components: intrinsic motivation, self-determination, self-efficacy, career motivation, and grade motivation. Exploratory and confirmatory factor analyses provided evidence of questionnaire construct validity. The motivation components, especially self-efficacy, were related to the students' college science grade point averages. The science majors scored higher than the nonscience majors on all of the motivation components. Among both science majors and nonscience majors, men had higher self-efficacy than women, and women had higher self-determination than men. The findings suggest that the questionnaire is a valid and efficient tool for assessing components of students' motivation to learn science in college courses, and that the components play a role in students' science achievement. © 2011 Wiley Periodicals, Inc. J Res Sci Teach 48: 1159–1176, 2011
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Accompanying the rapid pace of scientific discovery and growth of scientific knowledge is the need to make public-policy decisions about complex issues in areas such as health care, genetic engineering, and energy sources. In order to participate effectively in the decision-making process, citizens need to be *scientifically literate*, which means that they have the capability to understand scientific knowledge, identify important scientific questions, draw evidence-based conclusions, and make decisions about how human activity affects the natural world (Organisation for Economic Cooperation and Development, 2007).

Unfortunately, recent surveys reveal that many citizens in the United States lack scientific literacy: They cannot provide correct answers to basic questions about scientific facts and do not reason well about scientific issues (National Science Board, 2008). To address the critical need for scientific literacy, the American Association of Colleges and Universities (2011) has adopted a goal to build and sustain strong undergraduate education in science. The goal applies to both science majors and nonscience majors because it is essential that *all* students become scientifically literate citizens who are able to understand the complex issues that

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confront them. But it is difficult to achieve this goal because many students lack or lose the motivation to learn science—and these students include both science majors and nonscience majors.

By means of individual and group advisement sessions, science instructors can help students who lack motivation to learn science (Druger, 2006). But, at the beginning of courses, how can instructors know *which* students lack motivation? And *why* do they lack motivation? These are important questions for instructors, yet answering these questions is difficult, particularly at institutions with large-enrollment science courses where it is hard to know students personally. To help answer these questions, the Science Motivation Questionnaire was developed (Glynn & Koballa, 2006). The questionnaire provides instructors with a tool for efficiently gathering information that can increase the effectiveness of advisement sessions with students. The questionnaire also provides researchers with a tool for investigating students' motivation to learn science in college courses, the relationship of motivation to other student characteristics, and the interaction of motivation with instructional methods.

Validity is the most fundamental consideration in developing, evaluating, and revising a questionnaire. Validity is theoretically and practically important: It refers to the degree to which theory and evidence support the uses and interpretations of questionnaire scores (American Educational Research Association, 1999). Validity is a unitary concept, and many sources of evidence contribute to it. Traditionally, three of these sources are content validity, criterion-related validity, and construct validity (Osterlind, 2006). In earlier studies (Glynn, Taasoobshirazi, & Brickman, 2007, 2009), the Science Motivation Questionnaire was found to have good content validity and criterion-related validity, but the results of an exploratory factor analysis in the 2009 study suggested that the questionnaire should be revised to improve its construct validity, the extent to which the questionnaire assesses the latent motivational variables it targets. Thus, one purpose of the present study was to revise the questionnaire to improve its construct validity.

A related purpose of the present study was to evaluate the revised questionnaire with science majors and nonscience majors. Most studies of the motivation to learn science, including earlier studies with the questionnaire, focused on nonscience majors because instructors often find it challenging to motivate them (Druger, 2006). But the motivation of science majors also merits attention. Too many science majors are not making it through the academic "pipeline" leading to careers in science, and some groups of science majors are underrepresented in the pipeline, such as women in the physical sciences (National Science Foundation, 2002; Xie & Shauman, 2003). It is, therefore, important to assess the motivation of science majors and nonscience majors.

Theoretical Framework

Social cognitive theory, developed by Bandura (1986, 2001, 2006) and extended by others (e.g., Pajares & Schunk, 2001; Pintrich, 2003), construes human functioning as a series of reciprocal interactions among personal characteristics, environmental contexts, and behaviors. In social cognitive theory, students' learning is viewed as most effective when it is self-regulated, which occurs when students understand, monitor, and control their motivation and behavior, leading to desirable learning outcomes. Motivation is defined in this theory as an internal state that arouses, directs, and sustains goal-oriented behavior. By extension, the *motivation to learn science* can be defined as an internal state that arouses, directs, and sustains science-learning behavior. Motivated students achieve academically by engaging in behavior such as question asking, advice seeking, studying, and participating in classes, labs, and study groups (Schunk, Pintrich, & Meece, 2008).

Druger (2006) argues that one of the most important goals of an instructor of introductory college science courses is to help students become motivated self-learners. Like many science instructors, he evokes a variety of motivation components when expressing this goal: ''We want students to enjoy science, recognize its role in the world, gain greater self-confidence about learning science, and want to learn more about science'' (p. 39). It is noteworthy that no single component captures the essence of what instructors, such as Druger, mean when they describe students who are motivated to learn science. That is because the motivation to learn, as conceptualized in social cognitive theory, is a multicomponent construct: The components are types and attributes of motivation, which were reviewed by Glynn and Koballa (2006), Koballa and Glynn (2007), Eccles and Wigfield (2002), Pintrich (2003), and Schunk et al. (2008). Examples of these components are *intrinsic motivation*, which involves the inherent satisfaction in learning science for its own sake (e.g., Eccles, Simpkins, & Davis-Kean, 2006); *self-determination,* which refers to the control students believe they have over their learning of science (e.g., Black & Deci, 2000); *self-efficacy*, which refers to students' belief that they can achieve well in science (e.g., Lawson, Banks, & Logvin, 2007); and *extrinsic motivation*, which involves learning science as a means to a tangible end, such as a career or a grade (e.g., Mazlo et al., 2002). These mutually supporting components of motivation contribute positively to the arousal, direction, and sustainment of students' science-learning behavior. Together, these components constitute a componential model of motivation derived from social cognitive theory.

When measuring the motivation to learn science, science education researchers attempt to determine why students strive to learn science, what emotions they feel as they strive, how intensively they strive, and how long they strive. Measuring the motivation to learn science is challenging because a construct and its components are not directly observable variables. For this reason, they are called *latent* variables. Although latent variables cannot be directly observed, they can be measured by means of observed variables (items) that serve as empirical indicators. The items on the Science Motivation Questionnaire were designed to serve as empirical indicators of components of students' motivation to learn science in college courses. It is theoretically and practically important to ensure that these indicators are valid. Valid indicators can make a significant contribution to science education by providing researchers and instructors with the means of assessing students' motivation to learn science.

The Present Study

The Science Motivation Questionnaire was revised in the present study based on social cognitive theory and the results of an earlier exploratory factor analysis (Glynn et al., 2009). Exploratory factor analyses are used in the initial stages of questionnaire development to examine relationships among items and identify sets of items (factors) that have common characteristics. The factors represent latent variables—in this case, the motivation components. By providing information about the internal structure of a questionnaire, exploratory factor analyses are important steps toward establishing its construct validity, the extent to which it assesses the latent motivational variables it targets. In subsequent stages of questionnaire development, ''confirmatory factor analysis needs to be used to establish construct validity'' (Pett, Lackey, & Sullivan, 2003, p. 239).

The exploratory factor analysis by Glynn et al. (2009) provided insight into how students conceptualized their motivation to learn science. The psychometric factors indicated that the students conceptualized some components of motivation differently—broader in some respects and narrower in others—than researchers have done when discussing these components in the social cognitive literature. Broader conceptualizations were that intrinsic motivation involved personal relevance (e.g., Learning science makes my life more meaningful), and self-efficacy involved assessment anxiety (e.g., I worry about failing science tests). A narrower conceptualization was that extrinsic motivation was differentiated as grade motivation (e.g., Getting a good science grade is important to me) and career motivation (e.g., My career will involve science). The students' conceptualizations were reasonable: As they explained in interviews and essays in the 2009 study, what is intrinsically motivating to them is relevant; their low self-efficacy often leads to high anxiety; and, extrinsically, grades and careers primarily motivate them.

In light of the students' conceptualizations, the Science Motivation Questionnaire was revised to assess intrinsic motivation, self-determination, self-efficacy, career motivation, and grade motivation. The revised questionnaire targets positive, mutually supporting motivators and, therefore, includes items about self-efficacy but not anxiety, a negative motivator. In addition, one of the original scales—extrinsic motivation or "learning science as a means to a tangible end"—has been transformed into two scales, grade motivation and career motivation, that target more precisely the primary "ends" that college students focus on (Lin, McKeachie, & Kim, 2003). Grades are important short-term goals because they are measures of college success and part of the entry criteria for many careers. Careers are important long-term goals: In a series of nationwide student focus groups conducted by the American Association of Colleges and Universities, "professional success was identified. . .as the primary reason for pursuing a college degree, which students recognize as a basic requirement for success in today's competitive job marketplace" (Humphreys & Davenport, 2005, p. 36).

The revised questionnaire was evaluated with science majors and nonscience majors because it is important for researchers and instructors to assess *all* students' motivation to learn in their core curriculum science courses. Too many science majors are not making it through the academic programs that lead to science careers, and some groups of science majors are underrepresented in some programs, such as women in the physical sciences (National Science Foundation, 2002). And too many nonscience majors lack or lose the motivation to learn science (Druger, 2006). Science majors and nonscience majors are often in separate core-curriculum science courses in large colleges and in the same courses in small colleges. Regardless of how the core-curriculum science courses of a college are constituted, the revised questionnaire can be used to assess all students' motivation to learn science.

In conclusion, our goal in revising the questionnaire was to improve its construct validity. A related goal was to evaluate the revised questionnaire with science majors and nonscience majors. Associated with these goals were the following research questions:

- How valid is the revised questionnaire in terms of its scales, which are based on a componential model of motivation?
- What similarities and differences in motivation exist between students who are science majors and students who are nonscience majors?

Method

The assessment of personal characteristics such as motivation, attitudes, beliefs, and mood states encompasses a wide variety of constructs that are conceptualized on different theoretical levels (Embretson & Reise, 2000). Consequently, the development of these kinds of items poses complex challenges, which are discussed in detail by Boone, Townsend, and

Staver (2011), Bradburn, Sudman, and Wansink (2004), DeVellis (2003), Embretson and Reise (2000), Liu (2010), and Wilson (2005).

There are a number of measurement theories—e.g., classical test theory (CTT), item response theory (IRT), and generalizability theory (G theory)—that can be used to develop and revise questionnaire items. CTT has been used most often for this purpose, but IRT and G theory are being used increasingly because they can produce stronger results due to their stronger psychometric assumptions. Despite stronger assumptions, IRT and G theory "are not in opposition to CTT, nor do they supersede CTT. In fact their roots are firmly grounded in CTT. A more accurate view of modern theories is to hold that they extend CTT; they do not replace it" (Osterlind, 2006, p. 58). And, regarding the methodologies used to develop and revise questionnaire items, "no single methodology is considered universally best" (Osterlind, 2006, p. 102).

CTT was chosen as an approach to developing and revising the Science Motivation Questionnaire items for this reason:

> In classical theory, items are assumed to be roughly parallel indicators of the underlying latent variable. Each item is assumed to be approximately equivalent in its sensitivity to the phenomenon of interest. These assumptions fit well when assessing many personal characteristics, such as attitudes, beliefs, and mood states (DeVellis, 2003, p. 150).

In CTT, items target features and qualities of the latent variable, as well as tasks and behaviors associated with it. In IRT, in comparison, items tend to target specific tasks or behaviors assumed to be hierarchical or progressive indicators of the latent variable. IRT fits well when assessing cognitive and physical variables, but "in personality assessment a wide variety of constructs are conceptualized on different theoretical levels...and not all of them are appropriately assessed by an IRT measurement framework" (Embretson & Reise, 2000, p. 324). CTT was also chosen because many widely used CTT-based questionnaires are available that served as exemplars for items assessing motivation, and CTT is frequently applied to multidimensional constructs as well as unidimensional ones.

Participants

At a public university with 25,335 undergraduate students in the southern United States, we studied 680 undergraduate students: 367 science majors and 313 nonscience majors. The science majors were enrolled fall semester ($n = 198$) or spring semester ($n = 169$) in *Principles of Biology* for science majors; the nonscience majors were enrolled fall semester ($n = 161$) or spring semester ($n = 152$) in *Basic Concepts in Biology* for nonscience majors. These courses are core-curriculum counterparts for science majors and nonscience majors, respectively. Both courses are 15-week semester courses with three 1-hour large-enrollment lectures (ns = 150 to 300) and a 2-hour lab (ns = 20) each week. The professor (second author) who taught *Basic Concepts in Biology* is a woman with a Ph.D. in genetics and 14 years of college teaching experience; the professor (third author) who taught *Principles of Biology* is a man with a Ph.D. in zoology and 14 years of college teaching experience.

The students had previously taken two or more science courses. They participated in the study between week 12 and week 14 of the 15-week semesters. All provided complete data. Voluntary participation, rather than compulsory, was specified by the university's guidelines for research with human participants. Informed consent forms were signed by the students, who volunteered "to help us better understand the goals of students in science courses" and to earn a small amount of extra credit. Some non-participants said later in the courses that they "didn't have time," "had a conflict," "lost the announcement," or "forgot."

The 367 science majors included 240 (65%) women and 127 (35%) men; the 313 nonscience majors included 215 (69%) women and 98 (31%) men. In studies of this kind (e.g., Lawson et al., 2007), women often outnumber men for three reasons, all of which apply here. First, women now earn more than 50% of the science undergraduate degrees in the U.S., with most of these degrees in the life sciences (Stine & Matthews, 2009). Second, women now earn more than 59% of all undergraduate degrees in the U.S., and more than 70% of the nonscience degrees in education, family and consumer sciences, the arts, and the humanities (Marsden, 2006; Toppo & DeBarros, 2007). And third, women volunteer more often than men for academic research studies of this kind (Porter & Whitcomb, 2005). In the present study, compared to the percentages of women and men in the courses, 12% more women than men volunteered.

Some of the participating students were from underrepresented groups, African American (7%), Hispanic or Latino (3.1%), Multiracial (0.6%), and Native American (0.2%). These percentages were similar to those of the university population. Minority status was not treated as a statistical variable because there were relatively small numbers in each underrepresented group and statistical inferences might be misleading.

Questionnaire Development and Revision

In an earlier study (Glynn & Koballa, 2006), following guidelines by DeVellis (2003) and Bradburn et al. (2004), the Science Motivation Questionnaire was developed to assess the *motivation to learn science*, a social cognitive construct defined as an internal state that arouses, directs, and sustains science-learning behavior. The results of an exploratory factor analysis (Glynn et al., 2009) indicated that construct validity could be improved by revising the questionnaire. These revisions were undertaken in the present study following procedures specified by Pett et al. (2003).

To revise the questionnaire, we used the 2009 results, the social cognitive research literature, focus groups of science majors (ns = 10 and 9) and nonscience majors (ns = 9 and 7), a table of specifications, evaluation by four science instructors (2 women and 2 men), and pilot testing. The instructors read transcripts of the students' focus-group comments as background information, discussed an initial pool of 44 candidate items in relation to the motivation to learn science, and concurred that 38 items were relevant. These items were pilot tested with samples of science majors ($n = 31$) and nonscience majors ($n = 34$). A set of preliminary analyses determined those items with characteristics—mean, variance, and intercorrelations—best suited for scales assessing the positive, mutually supporting motivation components.

In its final version, the Science Motivation Questionnaire II (see Table 1) included the following scales, each with 5 items: intrinsic motivation, self-determination, self-efficacy, career motivation, and grade motivation. These 25 items included 16 from the original questionnaire—identically worded or with syntactic changes to improve comprehensibility—and 9 new items. As DeVellis (2003) recommends, the items are randomly ordered, strongly worded, unambiguous declarative statements in the form of short, simple sentences without jargon. The statements are easy to read: The Flesch-Kincaid formula indicates readability at the sixth-grade level. The items are focused on the motivation to learn science in courses rather than a multitude of contexts, such as hobbies. Because of this focus, the scales are not long, and the entire questionnaire can be completed efficiently in about 15 minutes.

Table 1
Science Motivation Questionnaire II

In order to better understand what you think and how you feel about your college science courses, please respond to each of the following statements from the perspective of "When I am in a college science course..."

[Response scale: ○ Never ○ Rarely ○ Sometimes ○ Usually ○ Always]

01. The science I learn is relevant to my life
02. I like to do better than other students on science tests
03. Learning science is interesting
04. Getting a good science grade is important to me
05. I put enough effort into learning science
06. I use strategies to learn science well
07. Learning science will help me get a good job
08. It is important that I get an "A" in science
09. I am confident I will do well on science tests
10. Knowing science will give me a career advantage
11. I spend a lot of time learning science
12. Learning science makes my life more meaningful
13. Understanding science will benefit me in my career
14. I am confident I will do well on science labs and projects
15. I believe I can master science knowledge and skills
16. I prepare well for science tests and labs
17. I am curious about discoveries in science
18. I believe I can earn a grade of "A" in science
19. I enjoy learning science
20. I think about the grade I will get in science
21. I am sure I can understand science
22. I study hard to learn science
23. My career will involve science
24. Scoring high on science tests and labs matters to me
25. I will use science problem-solving skills in my career

End. Thank you

Students respond to each item on a rating scale of temporal frequency: never (0), rarely (1), sometimes (2), often (3), or always (4). The raw scores should be interpreted carefully because the scales are ordinal. The possible score range on each of the five 5-item scales is 0–20.

Procedures

We used a two-part (A and B) online procedure. In *Part A*, we asked about individual differences and academic background, after first explaining "Your responses will help science-education researchers to better understand and improve science instruction." To promote candid responses, we assured the students their identities would remain confidential as specified in the institutional review board documentation they received. Under such conditions, students' responses have been found to be reliable (Cassady, 2001; Kuh, 2005). Students' college science grade point averages (GPAs) were examined as an indicator of criterion-related validity. This variable was viewed as a correlate of motivation—not an equivalent of it—because many variables other than motivation can affect students' achievement. The college science GPAs were based on courses such as ecology, geography, geology, chemistry, astronomy, and physics. The grade scale (to one decimal place) was 4.0 = A, 3.0 = B, 2.0 = C, 1.0 = D, and 0 = F.

In *Part B* of the online procedure, we asked the students to respond to the items of the revised questionnaire. The items were presented without the questionnaire title and with the instructions: "In order to better understand what you think and how you feel about your college science courses, please respond to each of the following statements from the perspective of: When I am in a college science course..."

Results

First, with the *Statistical Program for the Social Sciences*, version 17.0 (SPSS, Inc., 2008), we computed descriptive statistics for students in the fall and spring sections and found no significant differences, so the sections were combined. Second, using a cross-validation approach (Byrne, 2001), the 680 students were randomly split into two samples of 340 students each. Third, the data of one sample were examined by means of an exploratory factor analysis (SPSS, Inc., 2008). Fourth, the data of the other sample were examined by means of a confirmatory factor analysis using the Analysis of Moment Structures (AMOS) program, version 7.0 (Arbuckle, 2006): This analysis was a test of the measurement model that examined relationships among items and scales (motivation components). Fifth, building on the measurement model, AMOS was used to test a structural model that examined relationships between the students' motivation components and college science GPAs. Finally, science majors and nonscience majors were compared on the motivation components and, within majors, women and men were compared.

Exploratory Factor Analysis

Exploratory factor analysis is designed for situations where the relationships between the observed and latent variables are uncertain. We used exploratory factor analysis to examine students' responses to the revised questionnaire because it included new items.

Adequacy of Correlation Matrix of Items. We computed correlations for all pair-wise combinations of the 25 items and determined that the resulting matrix of correlations was appropriate for factor analysis by means of a Bartlett's test of sphericity, $\chi^2 = 5{,}054.39$, $df = 300$, $p < 0.001$, and a Kaiser–Meyer–Olkin measure of sampling adequacy, KMO = 0.91. These tests of multivariate normality and sampling adequacy indicated that the matrix was of good quality.

Factor Extraction. To extract factors, we performed a *principal component analysis* on the items. A principal component analysis uses eigenvalues, which represent the proportion of variance accounted for by the factors. Eigenvalues are used to derive *factor loadings*, which indicate how strongly particular items are related to particular factors. Because with any factor extraction method there are advantages and disadvantages (reviewed by Fabrigar, Wegener, MacCallum, & Strahan, 1999), we also performed a *principal axis factoring*, with similar results.

Using the Kaiser–Guttman rule, we identified five factors that had eigenvalues greater than 1, indicating that they accounted for significant amounts of the total variance in the items. Together, these five factors accounted for 67.64% of that variance, which is considered good. We also used a *scree* plot: We examined potential factors by plotting them against their eigenvalues in descending order of magnitude to identify breaks in the slope of this plot. The scree plot supported the 5-factor solution obtained using the Kaiser–Guttman rule.

Factor Rotation. The five factors were rotated, turning their reference axes about their origin. Rotation is needed routinely because the original factor structure, while mathematically accurate, is difficult to interpret. We used a Varimax rotation to produce what is called a *simple structure* that facilitates interpretation; we also used a Direct Oblimin rotation with similar results.

Factor Loadings and Factor Interpretation. The factor loadings from the principal components analysis with the Varimax solution are in Table 2. All of the items (in boldface) met the criterion of loading at least 0.35 on their respective factor (Tabachnick & Fidell, 2000). The eigenvalue and percent of variance explained by each factor were: intrinsic motivation (8.83, 35.33%), career motivation (2.83, 11.31%), self-determination (2.21, 8.84%), self-efficacy (1.78, 7.13%), and grade motivation (1.26, 5.03%). The cumulative percent of variance explained by the factors was 67.64%.

Reliabilities. The items associated with the factors comprised the scales of the revised questionnaire. The reliabilities (internal consistencies) of the scales, assessed by Cronbach's alphas, were: career motivation (0.92), intrinsic motivation (0.89), self-determination (0.88),

Table 2
Exploratory factor analysis of sample 1: Factor loadings of items

	F_1	F_2	F_3	F_4	F_5
Factor 1. Intrinsic motivation					
Learning science is interesting	**0.80**	0.23	0.14	0.17	0.08
I am curious about discoveries in science	**0.80**	0.27	0.13	0.12	0.11
The science I learn is relevant to my life	**0.78**	0.21	0.03	0.21	0.12
Learning science makes my life more meaningful	**0.78**	0.23	0.10	0.11	0.04
I enjoy learning science	**0.75**	0.25	0.21	0.26	0.03
Factor 2. Career motivation					
Learning science will help me get a good job	0.18	**0.84**	0.24	0.12	0.15
Understanding science will benefit me in my career	0.27	**0.84**	0.13	0.13	0.20
Knowing science will give me a career advantage	0.33	**0.82**	0.11	0.11	0.18
I will use science problem-solving skills in my career	0.35	**0.76**	0.12	0.18	0.07
My career will involve science	0.41	**0.57**	0.08	0.13	0.06
Factor 3. Self-determination					
I study hard to learn science	−0.01	0.11	**0.82**	0.02	0.24
I prepare well for science tests and labs	0.12	0.02	**0.81**	0.23	0.15
I put enough effort into learning science	0.16	0.07	**0.77**	0.11	0.15
I spend a lot of time learning science	0.16	0.26	**0.74**	0.02	0.15
I use strategies to learn science well	0.13	0.17	**0.72**	0.29	0.07
Factor 4. Self-efficacy					
I believe I can earn a grade of "A" in science	0.10	−0.08	0.03	**0.82**	0.14
I am confident I will do well on science tests	0.14	0.11	0.16	**0.81**	0.06
I believe I can master science knowledge and skills	0.30	0.16	0.22	**0.68**	0.08
I am sure I can understand science	0.33	0.19	0.16	**0.68**	−0.03
I am confident I will do well on science labs and projects	0.08	0.33	0.11	**0.56**	0.05
Factor 5. Grade motivation					
Scoring high on science tests and labs matters to me	0.05	0.06	0.19	0.05	**0.84**
It is important that I get an "A" in science	0.06	0.05	0.11	0.24	**0.77**
I think about the grade I will get in science	0.08	0.12	0.15	−0.14	**0.77**
Getting a good science grade is important to me	0.09	0.24	0.22	0.04	**0.73**
I like to do better than other students on science tests	0.06	0.11	0.10	0.36	**0.47**

The factor loadings of the items in boldface all exceeded a criterion of 0.35 on their targeted factor. The $n = 340$.

self-efficacy (0.83), and grade motivation (0.81). According to DeVellis (2003), a coefficient above 0.80 is "very good," 0.70 to 0.80 is "respectable," 0.60 to 0.69 is "undesirable to minimally acceptable," and below 0.60 is "unacceptable." The Cronbach's alpha of all 25 items was 0.92.

Confirmatory Factor Analysis

In the first step of a two-step model building approach, following procedures specified by Byrne (2001) and Schumacker and Lomax (2004), we performed a confirmatory factor analysis to test our measurement model (see Figure 1). The factors in the model corresponded to sets (scales) of related items, identified by the exploratory factor analysis, that were assumed to represent the components of the construct, the motivation to learn science. In the second step, we built a structural model on the measurement model that examined relationships between the students' motivation components and college science GPAs. We used a two-step approach because "once it is known that the measurement model is operating adequately, one can then have more confidence in findings related to the assessment of a hypothesized structural model" (Byrne, 2001, p. 147). Based on a componential model of motivation derived from social cognitive theory, we hypothesized that: (1) the students' questionnaire responses can be explained by the five specified factors, (2) the factors are related because they measure positive, mutually supporting components of the construct, and (3) the factors are related to students' college science GPAs.

We used well-established indices and criteria to assess the goodness of fit of the measurement model (Byrne, 2001; Kline, 2005; Schumacker & Lomax, 2004). Because any given index evaluates only particular aspects of model fit, we used multiple indices. Our first index was a normed chi-square. The chi-square statistic assesses a model's "badness of fit" or the extent that a proposed model varies from the data. Nonsignificant p values are ideal, but unrealistic because the statistic is very dependent on sample size: Larger samples yield larger chi-squares. Consequently, to reduce the effect of sample size on the chi-square statistic, it is recommended that the obtained chi-square be divided by the degrees of freedom (χ^2/df), producing a normed chi-square, with a value in a recommended range of 1.0–3.0 and in some circumstances "even as high as 5.0" (Kline, 2005, p. 137).

Our second index was a standardized root mean square residual (SRMR), which represents the average value, ranging from 0 to 1, across all standardized residuals. This value will be 0.05 or less in a well fitting model. Our third index was a goodness-of-fit (GFI) index, which estimates the proportion of variability in the sample covariance matrix explained by the model. The GFI ranges from 0 to 1, with a value of 0.90 or higher indicating a good model fit. Our fourth index, the Bentler comparative fit (CFI) index, compares our model with the standard "null" (independence) model that assumes zero population covariances among the observed variables. The CFI ranges from 0 to 1, with a value of 0.90 or higher indicating a good fit. Our fifth index, the Steiger–Lind root-mean-square error of approximation (RMSEA), assesses a lack of fit of the population data to the estimated model; a value of less than 0.10 indicates a good model fit.

The analysis of the second sample data ($n = 340$) yielded fit indices of $\chi^2/df = 2.77$, SRMR $= 0.04$, GFI $= 0.93$, CFI $= 0.91$, RMSEA $= 0.07$, indicating that the measurement model fits the data well, providing evidence of questionnaire construct validity. The unstandardized estimates of parameters—the item regression weights, covariances of factors, and variances of factors and errors—were all reasonable and statistically significant; all standard errors were also in good order. The standardized factor loadings and correlations among the factors provided by AMOS are in Figure 1. The factor loadings are estimated correlations,

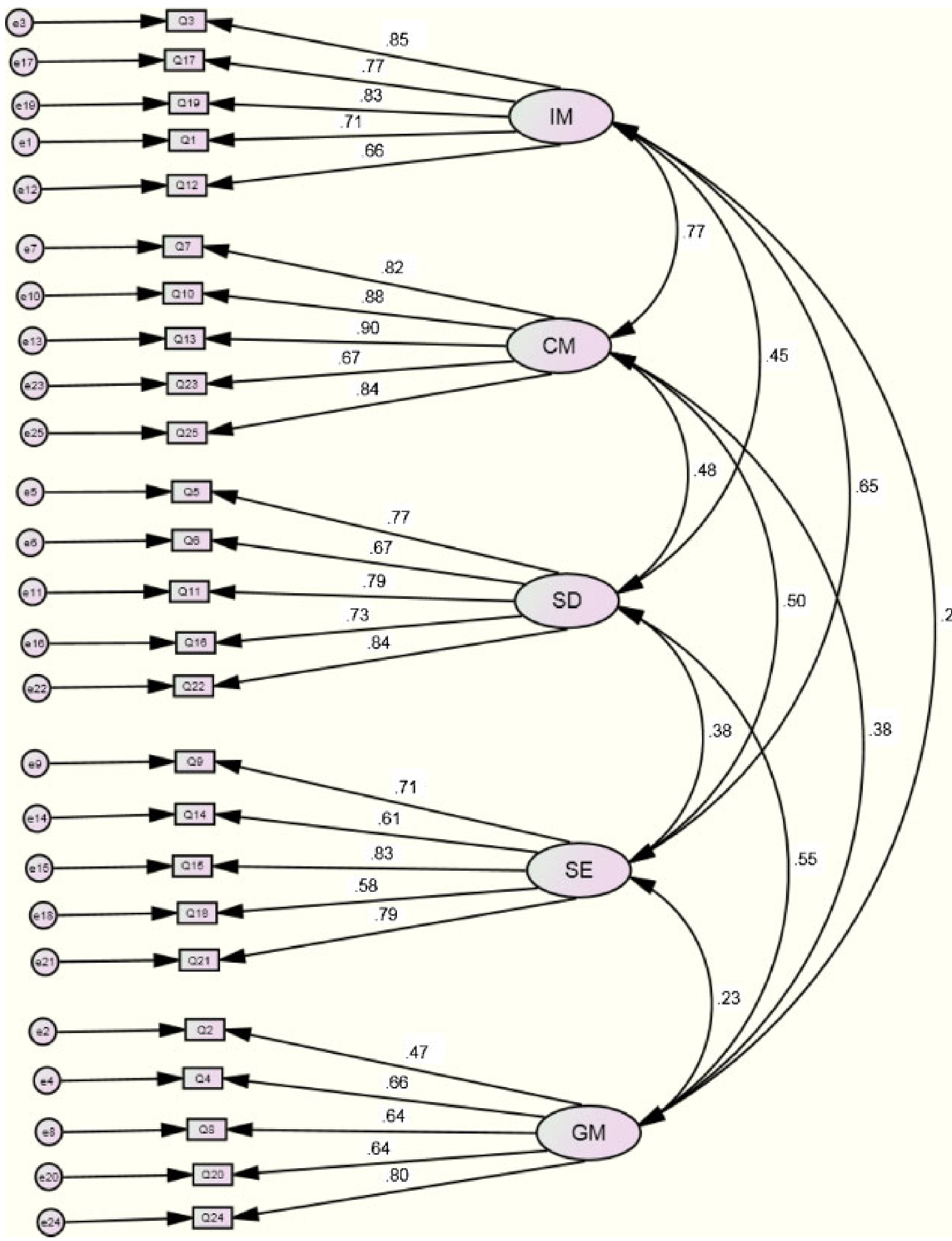

Figure 1. Confirmatory factor analysis of sample 2: Standardized factor loadings and correlations. IM, intrinsic motivation; CM, career motivation; SD, self-determination; SE, self-efficacy; GM, grade motivation; Q, questionnaire item; e, error term; the n = 340.

often referred to as validity coefficients, which indicate how well a given item measures its corresponding factor. The loadings ranged from high to moderate—the lowest was 0.47, exceeding the factor-loading criterion of 0.35 (Tabachnick & Fidell, 2000).

The correlations among the factors in Figure 1 are considered corrected (i.e., disattenuated) for measurement error and thus may be viewed as representing the true associations among the motivation components represented by the factors. (These corrected correlations were similar to the uncorrected ones, but the latter were smaller, ranging from $r = 0.20$ for intrinsic motivation and grade motivation to $r = 0.71$ for intrinsic motivation and career motivation.) Consistent with social cognitive theory, these positive correlations, all ps < 0.001, suggest the motivation components were mutually supportive: in particular, intrinsic motivation to learn science strongly oriented students towards careers that involve science.

In the second step of the model building approach, we examined the relationships between the students' motivation components and college science GPAs. The GPAs were related to self-efficacy (0.58), self-determination (0.41), grade motivation (0.35), career motivation (0.34), and intrinsic motivation (0.29), all ps < 0.001. For visual clarity, the GPA paths are not shown in Figure 1.

Science Majors and Nonscience Majors

The science majors and nonscience majors from both samples ($n = 680$) were compared on the motivation components using both estimated factor scores and factor-based scale scores, with similar results. In Table 3 we report the latter because "these scores are more easily interpreted than estimated factor scores and can also be compared from one study to another. The correlations between estimated factor scores and factor-based scales are also high" (Pett et al., 2003, p. 223). The means were compared using independent samples t-tests. When the comparisons were statistically significant, Cohen's d effect size (Cohen, 1992) was computed, interpreting effects as negligible (0–0.19), small (0.20–0.49), medium (0.50–0.79), or large (0.80 and above).

Table 3
A comparison of science majors and nonscience majors on the motivation components

	Science Majors			Nonscience Majors		
	Men ($n = 127$)	Women ($n = 240$)	Total ($n = 367$)	Men ($n = 98$)	Women ($n = 215$)	Total ($n = 313$)
Intrinsic motivation						
M	14.38	13.98	14.12	11.61	11.32	11.41
sd	3.20	3.08	3.12	3.98	3.56	3.69
Career motivation						
M	15.77	16.04	15.95	10.74	11.31	11.13
sd	3.19	3.13	3.15	4.78	4.96	4.90
Self-determination						
M	14.50	15.20	14.95	12.38	14.17	13.61
sd	3.29	2.98	3.10	2.99	3.00	3.11
Self-efficacy						
M	14.30	12.40	13.06	12.13	10.85	11.25
sd	2.93	3.19	3.23	3.10	3.37	3.34
Grade motivation						
M	16.72	17.09	16.96	15.59	16.34	16.11
sd	2.74	2.16	2.38	3.02	2.50	2.69

The scores on each component can range from 0 to 20.

An indication of construct validity was that science majors scored significantly ($p < 0.001$) higher than the nonscience majors on all scales: intrinsic motivation, $t(678) = 10.36$, Cohen's $d = 0.79$; career motivation, $t(678) = 15.43$, Cohen's $d = 1.17$, self-determination, $t(678) = 5.62$, Cohen's $d = 0.43$, self-efficacy $t(678) = 7.17$, Cohen's $d = 0.55$, and grade motivation $t(678) = 4.39$, Cohen's $d = 0.33$. Among the science majors, the men had higher self-efficacy than the women, $t(365) = 5.58$, $p < 0.001$, Cohen's $d = 0.62$, and the women had higher self-determination than the men, $t(365) = 2.06$, $p < 0.05$, Cohen's $d = 0.22$. Among the nonscience majors, too, the men had higher self-efficacy than the women, $t(311) = 3.21$, $p < 0.001$; Cohen's $d = 0.40$, and the women again had higher self-determination than the men, $t(311) = 4.91$, $p < 0.001$, Cohen's $d = 0.60$.

Discussion

Based on social cognitive theory and previous findings, we revised the Science Motivation Questionnaire to improve its construct validity and evaluate it with science majors and nonscience majors in core-curriculum college courses. The present findings indicate that the revised questionnaire is valid and provides a profile of the components that contribute to a student's motivation. Researchers, instructors, and academic advisors can track changes in a student's profile during a course or a series of courses. This profile—shared with the student and explained—can serve as a blueprint for the student to build on areas of strength and improve areas of relative weakness.

Components of Students' Motivation to Learn Science

A componential model of motivation was implemented in the questionnaire by means of scales assessing intrinsic motivation, self-determination, self-efficacy, career motivation, and grade motivation. Exploratory and confirmatory factor analyses provided evidence supporting the construct validity of these scales. The scales were positively related, consistent with the view that the components were mutually supporting. In particular, intrinsic motivation and career motivation were strongly related, suggesting that intrinsic motivation oriented students to careers that involve science.

The scales were also related to students' college science GPAs, providing evidence of criterion-related validity. It is noteworthy that self-efficacy was the scale most related to science GPAs. Self-efficacy affects achievement by predisposing students to work harder, persist longer, and overcome barriers when pursuing academic goals (Britner, 2008). The self-efficacy finding is consistent with the emphasis placed upon it in social cognitive theory:

> Among the mechanisms of human agency, none is more central or pervasive than beliefs of personal efficacy. Whatever other factors serve as guides and motivators, they are rooted in the core belief that one has the power to produce desired effects; otherwise one has little incentive to act or to persevere in the face of difficulties. (Bandura & Locke, 2003, p. 87)

The scales were found to be useful in assessing the motivation of both science majors and nonscience majors. The science majors scored higher than the nonscience majors on all scales, providing additional evidence of construct validity. Among both science majors and nonscience majors, men had higher self-efficacy than women, and women had higher self-determination than men (see also Cavallo, Potter, & Rozman, 2004; Glynn et al., 2009). Self-determination is manifested in a variety of ways: Not only do women have higher college enrollment and completion than men, but women are more likely than men to engage in behavior such as attending class on time, sitting in the front of the class, taking notes, studying the textbook, and studying in an organized way (Zusman, Knox, & Lieberman, 2005). Although not well understood, gender differences in the motivation to learn science are attributed to socialization by parents, teachers, peers, media, and role modeling rather than to "innate or natural differences" between women and men (Xie & Shauman, 2003, p. 215).

Use of the Questionnaire in Research and Instruction

The findings suggest that the Science Motivation Questionnaire II is a good tool that researchers, instructors, and academic advisors can use to efficiently assess students' motivation to learn science in college courses. As a research tool, the questionnaire can be used to examine relationships between students' motivation and student characteristics such as cultural background (Lee, 2001), teacher characteristics such as beliefs about science (Lumpe, Haney, & Czerniak, 2000), and learning methods such as project-based learning (Krajcik & Blumenfeld, 2006). The questionnaire can also be used with essays, interviews, case studies, and other qualitative methods to provide comprehensive insight into students' motivation to learn science (see Glynn et al., 2009).

As an instructional tool, the questionnaire can be administered at the beginning of a course to assess students' motivation to learn science. Students who are metacognitively aware of their motivation are better equipped to self-regulate their science-learning behavior (Bandura, 2006; Schunk, Pintrich, & Meece, 2008; Zimmerman, 2008). For this reason, the instructor should explain the purpose of the questionnaire. The instructor should also help students to understand their questionnaire scores and provide advisement sessions for low-motivation students, emphasizing the importance of motivation and recommending strategies (Slater, Prather, & Zeilik, 2006) to increase their motivation and science-learning behavior.

The questionnaire also can identify high-motivation students: This is important information for an instructor who wishes to organize collaborative-learning groups of students and ensure that each group includes at least some highly motivated students. The instructor can request that these students act as group leaders, who encourage all students to engage fully in the work of the group.

Academic advisors can administer the questionnaire to students before they begin their core-curriculum science courses. The questionnaire can be one tool in a set of psychometric tools that advisors use to help students monitor their motivation to learn science in their courses and think about career possibilities. The questionnaire can be periodically administered to both science majors and nonscience majors as they proceed through their program of coursework to help assess changes in their motivation to learn science. Students with high motivation are likely to achieve well in science courses. Students with low motivation run the risk of underachieving and limiting their career options, since science plays an increasingly important role in most careers.

When using the questionnaire, the students' raw scores on each scale should be converted to standard scores, establishing a derived scale consistent with the nature of the items. Generally, standard scores provide more practical information for decision making than raw scores (Osterlind, 2006). A commonly used standard score is the z-score: the units are *located* (i.e., mean) at 0 with a *scale* (i.e., standard deviation) of 1. Percentiles can also be calculated, in conjunction with norming, the process by which the scales are interpreted in context for representative groups. The assumptions and limitations of CTT should also be kept in mind, such as, "items are assumed to be roughly parallel indicators of the underlying latent variable" (DeVellis, 2003, p. 150) and ordinal scales are analyzed *as if* they are interval.

Directions for Future Research

One direction for future research is continued improvement of the questionnaire because "construct validity is a never-ending, ongoing, complex process over a series of studies in a number of different ways" (Pett et al., 2003, p. 239). If motivation items can be developed based on specific tasks or behaviors in a hierarchy or progression, and IRT assumptions met, then advantages can be gained, such as justified interval scales in logit units (Embretson & Reise, 2000). There are many widely used tests of cognitive and physical capabilities based on IRT that serve as exemplars for the construction of items in those domains. An analogous body of motivation questionnaires based on IRT does not yet exist, so constructing good items is a challenge, but the challenge provides a rich opportunity for future research. Boone et al. (2011), Embretson and Reise (2000), Liu (2010), and Wilson (2005) provide guidance for the development of questionnaire items based on IRT and the Rasch Model.

A second direction for future research is to use the questionnaire—in conjunction with qualitative methods—to further examine the motivation of science majors. Because lack of motivation has historically been a serious issue with many nonscience majors, more research has been conducted with them than science majors. But science majors also merit research attention to answer important questions. For example, more women than men earn degrees in the life sciences, but fewer women than men earn degrees in the physical sciences (Ceci & Williams, 2007). What role does motivation play in these differences? If the motivation to learn physical sciences is less in women than in men, then how can it be nurtured in women?

A third direction for future research is to examine how students' motivation changes during their core-curriculum science courses. If nonscience majors begin college with low motivation, to what extent can instructional methods foster their motivation? Longitudinal studies are needed to address questions such as these and suggest how students' motivation can be fostered. Ideally, students will retain their motivation to learn science after their core-curriculum courses are completed. One indicator of this will be students electing to enroll in science courses that are not required by their programs.

A fourth direction for future research is to use discipline-specific versions of the questionnaire. The items of the revised questionnaire, like the items of the original questionnaire, were designed so that the word *science* in each item can be replaced with the word *biology*, *chemistry*, or *physics*, creating a Biology Motivation Questionnaire, Chemistry Motivation Questionnaire, or Physics Motivation Questionnaire, respectively (e.g., Taasoobshirazi & Carr, 2009; Taasoobshirazi & Glynn, 2009). By this means it is possible to create discipline-specific questionnaire versions for these and other science disciplines, but researchers should examine each item to ensure it is representative of their target discipline and, when using any version of the questionnaire, establish its validity.

Conclusion

The exponential growth of scientific knowledge is accompanied by the need to make public-policy decisions about complex issues. In order to participate effectively in the decision-making process, it is essential that *all* students—science majors and nonscience majors—become scientifically literate citizens. Science-education researchers, science instructors, and academic advisors can support students' scientific literacy by fostering their motivation to learn science. This task requires a set of good assessment tools, one of which can be the Science Motivation Questionnaire II: It is reliable, valid, and efficient. For science-education researchers, this tool—used in conjunction with qualitative methods—can help provide a comprehensive understanding of students' motivation to learn science. For science instructors and academic advisors, this tool—used in conjunction with individual and group advisement sessions—can help nurture students' motivation to learn science.

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