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Investigating the Influence of Attribution Styles on the Development of Mathematical Talent

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Abstract: In this article, the authors examine the influence of attribution styles on the development of mathematical talent. The study employs a Self-Confidence Attitude Attribute Scale questionnaire, which measures ability and effort attributions. Participants are three groups of highly, moderately, or mildly mathematically gifted Finnish adolescents and adults ($N = 203$). The results of Bayesian classification modeling show that items attributing success to effort and failure to lack of effort are the best predictors for the level of mild mathematical giftedness and gender (females). The results of multivariate analysis of variance show that highly and moderately mathematically gifted students reported that ability was more important for success than effort, but mildly mathematically gifted tended to see effort as leading to success. Moderately and mildly mathematically gifted students attribute failure to lack of effort, whereas highly mathematically gifted students attribute failure to lack of ability.

Putting the Research to Use: It is essential that educators and parents understand the influence of different attribution styles on the development of mathematical talent. This study provides understanding of how highly, moderately, and mildly mathematically gifted adolescents and adults differ in their specific reasons for success and failure. Differences in attribution styles between the three groups of mathematically gifted, as measured with the Self-Confidence Attitude Attribute Scales questionnaire, indicate that it is important to know if the attributions for success or failure are stable or unstable, external or internal.

Knowledge of how learners or trainees use attributions to account for success and failure can help educators and parents gain a deeper awareness of the mathematically gifted and, thus, predict their expectancies and plan intervention strategies when needed. The information is also applicable to courses concerning the needs of the gifted. Furthermore, the information can be presented directly to mathematically gifted students to help them develop more insight into their own behavior.

Keywords: *attribution styles; self-regulation; mathematical talent; academic Olympians; vocational high school students*

In 2000, 180,000 students from 28 Organization for Economic Co-Operation and Development (OECD) member countries and 4 non-OECD countries (Brazil, Latvia, Liechtenstein, and the Russian Federation) participated in the first Programme for International Student Assessment (PISA). The results showed that students from Japan, Korea, New Zealand, and Finland scored highest in all tests measuring mathematics literacy (OECD, 2001). The Finnish students' ranking was even higher (i.e. third, when variation within country was taken into account; OECD, 2001). In 2003, the PISA follow-up study, focusing on mathematics literacy and involving 276,165 15-year-old students, was conducted in 41 countries (OECD, 2004). The results of overall student performance in different countries on the mathematics scale showed that

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Hong Kong students had the highest, and Finnish students had the second highest, mean student score (OECD, 2004). The finding of small within-country variance in the Finnish sample was repeated.

One logical reason for success in international comparison studies is the Finnish government's "equal opportunities and high-quality education for all" principle. The first practical consequence of the principle is that education is free for all students participating in these assessments. The second consequence is government's strong financial support for public sector educational institutions. This has led to the situation where there are no appreciable differences in teaching quality or premises between public and special schools. Partly for this reason, only a small minority of the schools in Finland are special schools with entrance examinations and financial support from private or corporate sources. There are no private universities or polytechnics in Finland.

The purpose of this study is to explore the attribution styles—that is, personal explanations for success and failure—in Finnish adolescents and adults (N = 203) with varying levels of mathematical giftedness to discover what attributions contribute to or impede the development of mathematical talent.

The first group, "Olympians," consists of highly mathematically gifted adults who have participated in the International Olympics for Mathematics. Tirri and Campbell (2002) reported that 80% of the Finnish Olympians apply their mathematical talent by choosing a career in science. The majority of them are researchers in academia or engineers in technical fields. The Olympians have been very successful in their graduate studies, and they have published articles and books related to their fields. Those Olympians who did not continue in academia chose a career as an engineer or as a CEO or a manager in leading Finnish companies, such as Nokia (Tirri, 2002; Tirri & Campbell, 2002).

The second group, "Prefinalists," consists of secondary school students who have taken part in national competitions in mathematics. The group represents the top level of Finnish 15-year-old students that participated in the international PISA 2000 study.

The third group, "Polytechnics," consists of adolescent students from a technical vocational high school who study mathematics as their major subject. In Finland, most of the vocational high schools are highly specialized regional institutions that train adolescents for the tasks of an expert. This particular institution is the top-rated technically oriented vocational high school in Finland.

Giftedness is not a monolithic construct. There are different levels of giftedness, and thus, the three groups representing mathematically gifted adolescents and adults in this study are not homogenous. Furthermore, we are not able to guarantee that the individuals within each group share the same level of mathematical ability. Intelligence quotient is, especially with children, a useful index of the discrepancy between mental and chronological age. As the participants of this study are adolescents and adults, we did not measure their IQ, but instead, we looked at their current or past achievements. Olympians are the most homogenous and mathematically gifted group in this study on the basis of their achievements as Academic Olympians and their traceable academic publication record (Nokelainen, Tirri, & Campbell, 2004; Nokelainen, Tirri, Campbell, & Walberg, 2004). We classify Olympians for the purpose of this study as highly mathematically gifted. Also, Prefinalists underwent a series of increasingly demanding mathematical tests to be included in the Academic Olympians training program. Their trainers are past Olympians—that is, members of the first group in this study. Prefinalists are classified as moderately mathematically gifted, as we do not yet know how many will be selected to participate as Academic Olympians in the future. Technical vocation high school students, who study mathematics as their major, represent mildly mathematically gifted students in this study. Group membership (1 = Olympians, 2 = Prefinalists, and 3 = Polytechnics) showed a strong positive correlation with secondary school mathematics grade average (from 1, the highest, to 7), with a correlation coefficient of $r(203) = .82$, $p < .001$.

Earlier studies of mathematical giftedness have mainly focused on within-group differences related to, for example, gender or attribution styles. There are very few between-group comparisons, except cross-cultural, reported. Socioeconomic differences do exist in Finland, but their impact on children's educational possibilities is minor because education is free at all levels. As the PISA results indicate (OECD, 2001, 2004), all individuals in Finland are provided with a uniformly high level of basic mathematical training, thus controlling, at least to some extent, individual-level educational differences. This allows us to interpret possible differences between the groups through differences in individuals' characteristics, such as mathematical giftedness and attribution styles.

All the participants completed the Self-Confidence Attitude Attribute Scales (SaaS) questionnaire (Campbell, 1996a). The instrument included 18 items based on Weiner's (1974, 1980, 1986, 1994, 2000) properties of attributional thinking, measuring ability and effort attributions on four dimensions: (a) success because of ability, (b) failure because of lack of ability, (c) success because of effort, and (d) failure because of lack of effort.

Our three research questions are as follows: (a) Are the four dimensions of the SaaS instrument present in the empirical sample? (b) What are the best predictors of the level of mathematical giftedness and gender among the SaaS variables? (c) Do the attribution styles differ by the level of mathematical giftedness or gender?

Theoretical Framework

Properties of Attributional Thinking

Reasons people give for an outcome, such as success or failure in a task, are called attributions (Heider, 1958). Factors involved in attributional thinking, such as specific reasons for success and failure, have been shown to be related in achievement settings (Weiner, 1974, 1980, 1986, 1994, 2000). In his studies, Weiner found that the four most frequent reasons for success and failure are ability, effort, task difficulty, and luck. Subsequent research identified learning strategies as a fifth possible reason for success and failure (Alderman, 2004): "It is no good thing trying harder if you do not know how to try."

Dai, Moon, and Feldhusen (1998) classify attribution constructs into three groups. First, *attribution appraisals* are explanations assessed following actual or manipulated success or failure in performing a specific task. Second, *attribution beliefs* are domain-specific or domain-general beliefs about the causes of success or failure. Third, *attribution styles* are generalized, stereotypical patterns of attributions and dispositional beliefs. Attribution styles are assessed in a similar way to attribution beliefs, except that a certain typology is imposed on the data using predetermined criteria. In this study, we examined attribution styles using Weiner's (1992) classification of reasons for success and failure: (a) internal and external attributions, referring to within or outside person causes; (b) stable and unstable attributions, referring to consistent or inconsistent causes over time; and (c) controllable and uncontrollable attributions, referring to the extent a person believes he or she has control over the cause of an outcome. In this study, we examined within-person factors (ability and effort) as they have typically been found to be the most frequently cited reasons for success and failure in achievement contexts. Those factors are classified as "internal" attributions. "External" attributions (luck, task difficulty) were omitted from the study design. Thus, our focus is on stable and unstable, controllable and uncontrollable, internal attributions. Most effort attributions tend to be unstable and controllable, as opposed to ability attributions, which are usually stable and uncontrollable. We will show later how the 18 SaaS items are related to these dimensions. We will also discuss in later stages of the analysis how the four SaaS factors describe dimensions of reasons for success and failure.

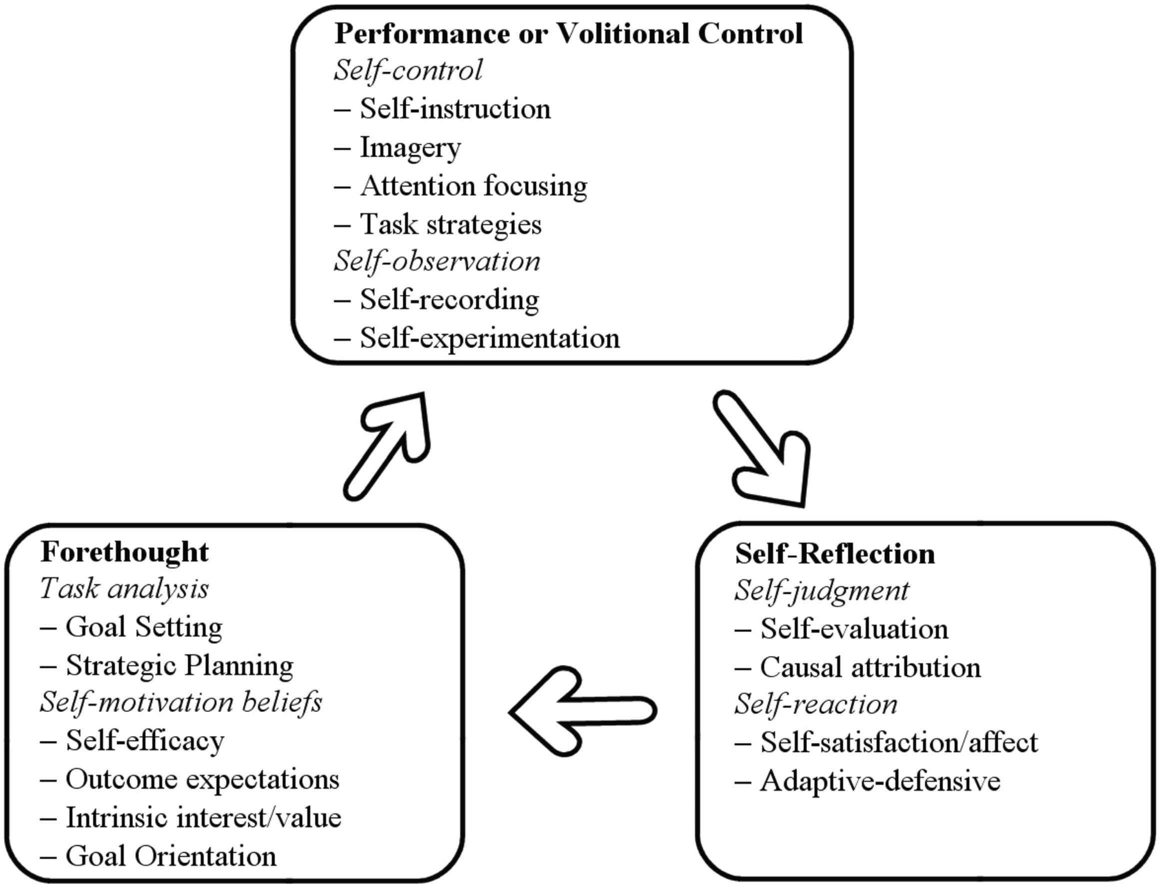
Self-Regulation and Attribution Styles

Self-regulation refers to the process through which self-generated thoughts, feelings, and actions are planned and systematically adapted as necessary to affect one's learning and motivation (Schunk & Ertmer, 2000; Zimmerman, 2000). According to social-cognitive theory, self-regulation is dependent on the situation. Therefore, self-regulation is not a general characteristic or a developmental level but rather is contextually dependent.

Zimmerman (2000) describes self-regulation as cyclical because the feedback from prior performance is used to make adjustments during current efforts. Personal, behavioral, and environmental factors are constantly changing, and therefore, an individual has to monitor these changes continuously to know whether any adjustments are required. Zimmerman describes the three feedback loops involved in monitoring one's internal state, one's behaviors, and one's environment as *the triadic forms of self-regulation*.

Figure 1 describes self-regulation of learning tasks as a cyclical, three-phase process (Zimmerman, 1998). The phases in this learning cycle are forethought, performance or volitional control, and self-reflection. Forethought, which creates the necessary conditions for learning, consists of task analysis and self-motivation beliefs. Performance or volitional control, which guides the learning process and regulates concentration and learning performance, consists of self-control and self-observation. Self-reflection, which refers to examining and making meaning of the learning experience, consists of self-judgment and self-reaction. Next, we examine more closely the last phase, which contains the focus of this article, attribution styles.

Figure 1
Cyclical Self-regulatory Phases



Source: Adapted from Zimmermann, 2000

Self-reflection begins with self-judgment, which is the process whereby an individual compares information attained through self-monitoring to extrinsic standards or goals. He or she wants to have fast and accurate feedback on his or her performance as compared to others. Self-judgment leads to attribution interpretations where the learner interprets the reasons for success or failure. Attribution interpretations can lead to positive self-reactions. The individual might interpret the failure of a strategy as the result of too little effort and then increase his or her efforts, but if he or she interprets the reason for failure as being a lack of ability, the reaction is liable to be negative. Attribution interpretations reveal the possible reasons for learning mistakes and help the learner to find those learning strategies that best suit the given situation. They also develop or promote the adaptation process. Self-regulated individuals are more adaptive and evaluate their performance appropriately. Positive reactions (e.g., self-satisfaction) reinforce positive interpretations of oneself as an individual and enhance intrinsic interest in the task.

Ellström (2001) defines qualification as the competence that is actually required by a task and/or is implicitly or explicitly determined by individual qualities. In our study setting, the most interesting point is that competence may also be seen as an attribute of the individual, meaning, for example, a human resource that the person brings to mathematical problem-solving situations. Furthermore, attributions may emphasize formal competence as indicated by degree requirements and certificates or, the focus of this study, potential competence as indicated by the capacity of the individual to successfully complete tasks and face new challenges on the basis of demonstrated personal attributes and abilities (other than those obtained through formal training). Ellström (2001) has noticed that potential competence may vary greatly between individuals with the same formal qualifications, because they may possess very different levels of inherent ability and may have learned different things outside of school or studies through their working life and recreational activities. Thus, ability attributions affect later performance expectations and, in negative cases, the development or continuation of learned helplessness (Ruohotie & Nokelainen, 2000).

In this study, we concentrate on participants' self-evaluations on the basis of mathematics achievement and academic ability, because causal attributions (see phase "Self-Reflection" in Figure 1) play an important part in the self-regulatory process by being central elements of self-judgment and thus influencing, for example, goal setting and self-efficacy. We are interested to see if the attribution styles of highly mathematically gifted individuals differ from those of the mathematically able.

Our research questions are as follows: (a) Are the four dimensions of the SaaS instrument (success because of ability, failure because of lack of ability, success because of effort, and failure because of lack of effort) present in the empirical sample? (b) What are the best predictors of the level of mathematical giftedness (high = Olympians, moderate = Prefinalists, and mild = Polytechnics) and gender among the SaaS variables? (c) Do the attribution styles differ by the level of mathematical giftedness or gender?

Literature Review

Mathematical Giftedness and Attribution Styles

Campbell has conducted several cross-national studies on Mathematics Olympians (see, e.g., Campbell, 1994, 1996b; Nokelainen, Tirri, & Campbell, 2004). He made two interesting findings: First, the international data on mathematics self-concept verified the finding that their academic self-concepts fluctuate from grade school to high school and, second, that the Olympians attributed effort to be more important in their success than ability (Campbell, 1996b). The latter research finding has been verified by Chan (1996), who reported that adolescent gifted students were more likely to attribute failure to lack of effort than to attribute it to low ability. The American and Taiwanese Olympians have also attributed success and failure more to effort than to ability (Feng, Campbell, & Verna, 2001; Wu & Chen, 2001).

Heller and Lengfelder (2000) investigated 100 German Olympian finalists and 135 Prefinalists in mathematics, physics, and chemistry. In contrast to Campbell's findings, their results showed that participants in both groups valued ability significantly more highly than effort. Effort was estimated to be equally important in the case of failure as in the case of success (Heller & Lengfelder, 2000).

Marsh (1983) found, as he studied relationships between the dimensions of self-attribution, self-concept, and academic achievements, that those who attribute academic success to ability and who do not attribute failure to a lack of ability have better academic self-concepts and better academic achievement. Multon, Brown, and Lent (1991) have also shown a positive correlation between perceived ability and achievement.

Gender and Attribution Styles

In an American study by Verna and Campbell (2000), a small significant difference between males and females was found with regard to perceptions of ability. The female American Chemistry Olympians considered ability to be a more important factor for success than did the males. However, no difference was found for the effort factor.

Kerr (1994) and Reis (1998) have identified external barriers to gifted women as including the attitudes of parents and school, environmental options, and possible discrimination or harassment at school or at work. The possible internal barriers among gifted females included self-doubt, self-criticism, and low expectations. According to Siegle and Reis (1998), gifted girls tend to underestimate their abilities, especially in mathematics, social studies, and science.

Instrumentation of Attribution Theory

There is abundant literature and research on attribution theory, especially on attributional properties in achievement settings (Weiner, 1974, 1980, 1986, 1994, 2000), because the role of motivation in academic achievement has proven to be a popular topic. The principle of attribution theory is that students search for understanding, trying to discover why an event has occurred (Weiner, 1974). The interest is apparent as we examine the structure of existing measurement instruments: Biggs's (1985) 42-item Study Process Questionnaire consists of two scales (Motive and Strategy) with three approaches: (a) surface, (b) deep, and (c) achieving. The questionnaire contains six subscales (Surface Motive, Deep Motive, Achieving Motive, Surface Strategy, Deep Strategy, and Achieving Strategy). Ramsden and Entwistle's (1981) Approaches to Studying Inventory, which is one of the most widely used questionnaires on student learning in higher education, contains subscales including such factors as fear of failure, extrinsic motivation, and achieving orientation. Marsh (e.g., Marsh & O'Neill, 1984) has developed a set of scales (Self-Description Questionnaire I to III) for different age groups measuring self-concept with a multifaceted (e.g., mathematics, verbal, academic, physical) view. According to Strein (1995), research results during the past 15 years have strongly supported the multifaceted view emphasizing domain-specific self-concepts. In this study, we apply the SaaS questionnaire that was developed by Campbell (1996a) originally for cross-cultural Academic Olympiad studies.

Method

Sample

The Finnish education system includes comprehensive schools, postcomprehensive general and vocational education, higher education, and adult education. Comprehensive schools provide a 9-year compulsory educational program for all school-age children beginning at the age of 7. Postcomprehensive education is provided in upper secondary schools and vocational institutions. The Finnish higher education system includes 20 universities and 30 vocational high schools. The higher education system as a whole offers openings for 66% of the relevant age group (universities 29%, vocational high schools 37%).

Respondents in the first group, Olympians, are the Finnish students most gifted in mathematics. The group consists of individuals of different ages who participated in Olympiad Studies in Mathematics from 1965 through 1999. Separate programs exist for the Mathematics, Physics, and Chemistry Olympiads. In recent years, programs have been created for Biology and Computer Science Olympiads as well. Distinct studies have been undertaken in each of these academic areas. In the Mathematics, Physics, and Chemistry Olympiad programs, a series of increasingly difficult tests are administered. This testing concludes with the identification of the top national finalists (6 to 20 Olympians). These individuals are trained to compete in the International Olympiad programs.

The second group, Prefinalists, involved in this study consists of secondary school students who have taken part in the national competitions in mathematics from 2000 to 2001. Each year, schools all over Finland send their most talented students to this annual competition. The tests of this competition resemble the tests used in academic Olympians.

The third group, Polytechnics, consists of students of Espoo-Vantaa Institute of Technology. They need progressively advanced mathematical skills as they progress in their studies. However, compared to higher level mathematics studies in universities, technological mathematics studies in vocational high schools are more practically oriented.

In addition, respondents' parents were asked about their educational level. More than 60% of Olympians (62.2%) and Prefinalists (65.4%) parents had an academic degree. Only 23.9% of Polytechnics parents had the same educational level. Analysis of parental occupation in the three groups showed that Olympians and Prefinalists parents shared similar vocational interests, as they were, for example, doctors, teachers, and business managers. Polytechnics' parents were mainly middle-class (e.g., factory workers). However, in Finland, educational level is not a good predictor of socioeconomic status. Prefinalists' parents belong to the highest income class in Finland, with the average annual salary of US$83,597. Both Olympians' parents ($49,447) and Polytechnics' parents ($46,721) earn middle-level salaries in the Finnish context.

Procedure

All the participants completed the SaaS questionnaire (Campbell, 1996a) based on Weiner's (1974) self-attribution theory. The Mathematics Olympians' data (n = 77) included 68 male and 9 female respondents. The sample is quite representative, as the total number of Finnish Mathematics Olympians is 84 (70 males and 14 females). The second group (n = 52) is a sample from about 200 secondary school national competitors in mathematics. The polytechnic student data (n = 74) is a fully representative sample of an advanced mathematics course held at Espoo-Vantaa Institute of Technology in Autumn 2001, the total number of participants in which is approximately 3,000. Olympiad data was collected between 1997 and 2002, the Polytechnic data in 2001, and the Prefinalists data between 2001 and 2002.

Table 1 shows that, except for the Polytechnics, gender is biased toward males. This finding is related to the well-documented tendency of females not to pursue careers in science even though they are as equally capable as males (e.g., Enman & Lupart, 2000), unless one or both of their parents are in the same field (Tirri,

Table 1
Description of Mathematics Olympians, Prefinalists, and Polytechnics Data

	Olympians (n = 77)		Prefinalists (n = 52)		Polytechnics (n = 74)	
	n	%	n	%	n	%
Gender						
Male	68	88	43	83	40	54
Female	9	12	9	17	34	46
Age						
Median	37		17		24	
Range	20 to 55		15 to 20		20 to 34	

Note: Total N of the data is 203.

2002). The student's age is a good predictor for group membership.

Measurement Instrument

The SaaS instrument was mailed to respondents in a traditional paper-and-pen form (see Table 2). The instrument used a 6-point Likert-type scale ranging from 1 = *strongly disagree* to 6 = *strongly agree*. The SaaS questionnaire included 18 items measuring the students' attributions based on self-attribution theory (Weiner, 1974). Although Weiner's original conceptualization contained four attributions (ability, effort, difficulty, and luck), the statistical analysis based on numerous empirical samples produced only two distinct scales: Effort and Ability (Campbell, 1996a, 1996b; Feng et al., 2001; Heller & Lengfelder, 2000; Tirri, 2001). In each of these studies, a consistent factor structure was found for the Ability and Effort scales. Statements linking success and effort produced high scores on the Effort scale. Statements on the Ability scale expressed the view that ability is more important than hard work.

In addition to SaaS, we asked for the following background information from the respondents: gender, age, number of programming languages known, and average of mathematics, physics, and chemistry secondary school grades.

Statistical Analysis

The data analysis began by examining all the items to see if they were technically applicable for linear statistic computations based on multivariate normality assumptions, such as exploratory factor analysis (EFA) and multivariate analysis of variance (MANOVA).

In the second stage, we conducted an explorative factor analysis to answer the first research question: Are the four dimensions of the SaaS instrument (success because of ability, failure because of lack of ability, success because of effort, and failure because of lack of effort) present in the empirical sample?

Bayesian classification modeling (Silander & Tirri, 1999, 2000) was conducted in the third stage of the analysis to answer the second research question: What are the best predictors for the level of mathematical giftedness (high = Olympians, moderate = Prefinalists, and mild = Polytechnics) and gender among the SaaS variables? Bayesian classification modeling resembles linear discriminant analysis (LDA; Huberty, 1994), but it is free of most of the assumptions of Gaussian modeling (Nokelainen, Ruohotie, & Tirri, 1999; Nokelainen & Tirri, 2004).

In the fourth stage, we conducted MANOVA (with the Roy-Bargman step-down analysis and Bonferroni post hoc test) to see if the attribution styles differ by the level of mathematical giftedness or gender. When investigating more than one dependent variable, we applied factorial MANOVA instead of a series of ANOVAs, as it controls for increasing risk of Type I error (falsely rejecting null hypothesis when it is true).

Results

Investigating Variables Statistical Properties

In the first stage, a frequency analysis was carried out for all the variables. Results show that the respondents used the whole scale from 1 (*totally disagree*) to 6 (*totally agree*) for all items. According to Kerlinger (1986), before constructing one's own questionnaire, "one should first ask the question: Is there a better way to measure my variables?" (p. 495). He classifies weaknesses of rating scales into extrinsic and intrinsic.

Table 2
Descriptive Statistics and Attribution Dimensions of the Self-Confidence Attribute Attitude Scale

Item	Olympians (n = 77)		Prefinalists (n = 52)		Polytechnics (n = 74)		Stable – Unstable[a]	Controllable – Uncontrollable[b]
	M	*SD*	*M*	*SD*	*M*	*SD*		
Effort (12 items)								
1. I did poorly only when I did not work hard enough.	3.79	0.97	3.56	1.15	3.46	1.15	U	C
2. You can be successful in anything if you work hard enough at it.	3.27	1.23	3.78	1.03	3.99	0.85	U	C
6. When I scored low on a test, it was because I didn't study hard enough.	3.92	0.79	3.63	0.97	3.53	0.95	U	C
8. My achievement would have been better if I tried harder.	3.29	1.25	3.83	0.96	4.09	0.69	U	C
9. Self-discipline is the key to school success.	3.27	0.91	3.47	0.92	3.41	1.06	S	C
10. The smart kids tried the hardest.	2.43	0.93	2.81	0.95	2.22	0.93	S	C
11. Poor study habits are the main cause of low grades.	3.32	0.91	3.44	0.98	3.54	1.04	U	C
12. I had to work hard to get good grades.	2.11	0.95	2.08	0.95	2.74	1.03	S	C
15. When I didn't understand something, it meant I didn't put in enough time.	3.69	0.87	3.58	1.07	3.51	0.94	U	C
16. I could have done better in mathematics if I had worked harder.	3.11	1.17	3.81	1.05	4.01	0.85	U	C
17. Hard work is the key to get good grades.	2.83	1.05	2.77	1.13	3.00	0.89	S	C
18. I let people down when I don't work hard enough.	2.64	1.05	2.62	1.14	2.45	1.09	U	C
Ability (6 items)								
3. There are some things you cannot do no matter how hard you try.	3.68	1.19	3.29	1.17	2.97	1.19	S	U
4. I worked harder if I liked the teacher.	3.16	1.22	3.57	1.24	3.77	0.99	U	C
5. Being smart is more important than working hard.	2.99	1.03	3.23	0.92	2.64	1.03	S	U
7. You have to have the ability in order to succeed in most things.	3.92	0.74	3.90	0.69	3.86	0.75	S	U
13. When I did poorly in school it was because I did not have the needed ability.	2.46	1.04	2.37	0.98	2.09	0.80	S	U
14. Why work in an area where your ability is low?	2.81	1.03	2.75	1.23	2.58	1.16	S	U

a. Stable and unstable attributions refer to consistent or inconsistent cause over time.
b. Controllable and uncontrollable attributions refer to extent person believes he or she has control over the cause of an outcome.

The extrinsic defect is that scales are much too easy to construct and use. Sometimes a scale is used to measure things for which it is not appropriate. Kerlinger defines the intrinsic defect of rating scales as their proneness to constant error. He lists four main sources: halo effect, the error of severity (to rate all items too low), error of leniency (to rate all items too high), and error of central tendency (to avoid all extreme judgments). To address this issue, we analyzed the overall response tendency. We found that distribution of the modes on a 6-point Likert-type scale was multimodal and slightly biased toward positive values: (a) $n = 0$, (b) $n = 5$, (c) $n = 0$, (d) $n = 11$, (e) $n = 0$, and (f) $n = 0$.

Numerous publications declare that certain attributes belong to data appropriate for multivariate analysis (e.g., Bradley & Schaefer, 1998; Tabachnick & Fidell, 1996). The most commonly used criteria for accepting variables for multivariate analysis are as follows: (a) a standard deviation of no more than half the mean, (b) skewness less than +/– .3, and (c) correlation between +/– .3 and .7. When we examined the 18 items using the first two criteria, we noticed that all the items passed the first criteria, but only 4 items passed the second criteria. As it seemed impossible to take the second criteria literally because of a high rejection rate at the .03 level, we examined the skewness of items in three additional levels (.05, .07, and .08). The .07 level proved to be suitable for this data set, suggesting rejection of three items (#4, #6, and #7). A nonparametric interitem correlation matrix was produced to examine the third criteria. Thirteen items reached the desired level, as the values ranged from –.48 to .71 ($M = .05$, $SD = .16$). The rejected items were #4, #7, #10, #14, and #18. We examined multivariate normality with Mahalanobis distances. The maximum values for the two SaaS scales were below critical values obtained from the chi-square table (alpha = .001), thus not indicating the presence of outliers.

Finally, when we combine the results of the variable selection phase, it seems obvious that at least two items (#4, "I worked harder if I liked the teacher," and #7, "You have to have the ability in order to succeed in most things") should be omitted from further analysis.

Explorative Factor Analysis

Our next task, according to the first research question, was to see if the combined sample and three subsamples contained the following four dimensions: (a) success because of ability, (b) failure because of lack of ability, (c) success because of effort, and (d) failure because of lack of effort. We performed the analysis with 16 items, as the variable rejection based on communalities of two-dimensional principal components analysis structure did not appear to provide a feasible solution. Factor analysis with the maximum likelihood extraction method and direct oblimin rotation (delta value was set to zero, i.e., letting factors correlate) was conducted for the combined sample ($N = 203$) and for each sample separately (Olympians $n = 77$, Prefinalists $n = 52$, and Polytechnics $n = 74$).

A four-factor solution with eight items grouped the variables in all three subsamples and the combined sample as expected. Next, we present the eight items operationalizing the four SaaS factors. Factor 1, success because of ability, included only one variable: #5, "Being smart is more important than working hard." The logic behind this solution was that the other two related items (#4, "I worked harder if I liked the teacher," and #7, "You have to have the ability in order to succeed in most things") were omitted from further analysis because they did not meet the assumptions of multivariate analysis. Factor 2, failure because of a lack of ability, included Items 3, "There are some things you cannot do no matter how hard you try," and 13, "When I did poorly in school it was because I did not have the needed ability" (alpha = .62). Factor 3, success because of effort, included Item 9, "Self-discipline is the key to school success"; Item 12, "I had to work hard to get good grades"; and Item 17, "Hard work is the key to get good grades" (alpha = .63). Factor 4, failure because of a lack of effort, included Items 8, "My achievement would have been better if I tried harder," and 16, "I could have done better in mathematics if I had tried harder" (alpha = .82). The Cronbach's alpha values for the four factors within the three groups varied as follows: Olympist data (Factor 1 = not calculated, Factor 2 = .56, Factor 3 = .75, and Factor 4 = .76), Prefinalists data (Factor 1 = not calculated, Factor 2 = .60, Factor 3 = .67, and Factor 4 = .84), and Polytechnics data (Factor 1 = not calculated, Factor 2 = .59, Factor 3 = .42, and Factor 4 = .80).

Although we found only one item measuring the first SaaS dimension, success because of ability, correlations between factors behaved as expected (see Table 3). Ability and effort factors correlated negatively with each other, and both effort factors, as well as both ability factors, correlated positively.

Table 4 shows how four SaaS factors are related to internal, stable-unstable, and controllable-uncontrollable

Table 3
Correlations Between the Self-Confidence Attribute Attitude Scale Factors

	1	2	3	4
1. Success because of ability (Item 5)	1.000			
2. Failure because of lack of ability (Items 3, 13)	0.135	1.000		
3. Success because of effort (Items 9, 12, 17)	–0.194**	–0.052	1.000	
4. Failure because of lack of effort (Items 8, 16)	0.151*	–0.286**	0.171*	1.000

Note: Item descriptions can be found in Table 2.
*$p < .05$. **$p < .01$ (two-tailed).

Table 4
Self-Confidence Attribute Attitude Scale Factors by Attribution Dimensions

	Internal			
	Controllable		Uncontrollable	
	Items	Factors	Items	Factors
Stable	9, 12, 17	Success because of effort	5	Success because of ability
Unstable	8, 16	Failure because of lack of effort	3, 13	Failure because of lack of ability

attribution dimensions. The stable-unstable dimension is important, as research has typically found that learners view ability as relatively stable (Alderman, 2004). For example, if a mathematically gifted person is convinced that he or she is not able to solve certain types of problems, it is an indication of an internal-stable attribution, and his or her failure appears to be fixed. This belief pattern is known as learned helplessness. However, there is also a third dimension: controllable-uncontrollable. As seen in Table 4, both ability factors represent uncontrollable attributions, and both effort factors represent controllable attributions. If the mathematically gifted person decides to continue solving problems related to areas he or she finds difficult, he or she has changed an uncontrollable attribution (ability) to one that he or she can control (effort). The least serious dimension for the learner's self-esteem is unstable-controllable, because the first component refers to a situation that is temporary by nature and the second refers to an effort level that is adjustable. For example, a learner explains his or her failure in integral calculations by saying that certain routine procedures need more practice. No single SaaS item (see Table 2) or factor represents the last quarter of Table 4, unstable-uncontrollable, as it describes, for example, a situation in which a mathematically gifted person guesses correctly the answers to those competition exercises that he or she is unable to solve. Although we did not include external attributions in our design, we will demonstrate it by converting the latest internal-unstable-uncontrollable example to the form of external-unstable-uncontrollable. This is accomplished by replacing "guessing" (internal attribution) with an "easy test" (external attribution).

Bayesian Classification Modeling

We conducted the Bayesian classification modeling with the B-Course program (Myllymäki, Silander, Tirri, & Uronen, 2002) to find out which variables measuring attribution styles are the best predictors for the level of mathematical giftedness (high = Olympians, moderate = Prefinalists, and mild = Polytechnics) and gender (Research Question 2). In the classification process, the automatic search tried to find the best set of variables to predict the class variable for each data item. This procedure resembles the traditional LDA (Huberty, 1994), but the implementation is totally different. For example, a variable selection problem that is addressed with forward, backward, or stepwise selection procedure in LDA is replaced with a genetic algorithm approach (e.g., Hilario, Kalousisa, Pradosa, & Binzb, 2004; Hsu, 2004) in the Bayesian classification modeling. The genetic algorithm approach means that variable selection is not limited to one (or two or three) specific approach; instead, many approaches and their combinations are exploited. One possible approach is to begin with the presumption that the models (i.e., possible

Table 5
Importance Ranking of the Self-Confidence Attribute Attitude Scale Items by the Level of Giftedness and Gender

		The Level of Giftedness						Gender			
	Drop[a]	Olympians (n = 77)		Prefinalists (n = 52)		Polytechnics (n = 74)		Male (n = 149)		Female (n = 52)	
Class and Predictor Variables	%	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
The level of giftedness[b]											
10. The smart kids tried the hardest.	14.36	2.43	0.93	2.81	0.95	2.22	0.93				
16. I could have done better in mathematics if I had worked harder.	7.92	3.11	1.17	3.81	1.05	4.01	0.85				
12. I had to work hard to get good grades.	6.93	2.11	0.95	2.08	0.95	2.74	1.03				
5. Being smart is more important than working hard.	4.95	2.99	1.03	3.23	0.92	2.64	1.03				
3. There are some things you cannot do no matter how hard you try.	3.96	3.68	1.19	3.29	1.17	2.97	1.19				
4. I worked harder if I liked the teacher.	2.48	3.16	1.22	3.57	1.24	3.77	0.99				
8. My achievement would have been better if I tried harder.	1.98	3.29	1.25	3.83	0.96	4.09	0.69				
Gender[c]											
12. I had to work hard to get good grades.	6.93							2.23	0.96	2.67	1.10
8. My achievement would have been better if I tried harder.	6.44							3.68	1.13	3.85	0.87
2. You can be successful in anything if you work hard enough at it.	3.96							3.65	1.14	3.71	0.98
1. I did poorly only when I did not work hard enough.	3.47							3.67	1.11	3.43	1.03
14. Why work in an area where your ability is low?	2.97							2.78	1.13	2.61	1.02
5. Being smart is more important than working hard.	1.98							2.96	0.99	2.86	1.06

a. Decrease in predictive classification if item is dropped from the classification model.
b. Classification accuracy is 65.35%.
c. Classification accuracy is 79.70%.

predictor variable combinations) that resemble each other a lot (i.e., have almost same variables and discretizations) are likely to be almost equally good. This leads to a search strategy in which models that resemble the current best model are selected for comparison, instead of picking models randomly. Another approach is to abandon the habit of always rejecting the weakest model and instead collect a set of relatively good models. The next step is to combine the best parts of these models so that the resulting combined model is better than any of the original models. B-Course is capable of mobilizing many more viable approaches, for example, rejecting the better model (algorithms such as hill climbing, simulated annealing) or trying to avoid picking similar model twice (tabu search).

First, we derived the model for classifying data items according to the class variable level of mathematical giftedness (Olympians, Prefinalists, and Polytechnics) with 18 variables of the SaaS scale as predictors (items are listed in Table 2). The estimated classification accuracy for the model was 65.4%. Second, we derived the model for classifying data items according to the class variable gender. The estimated classification accuracy for the model was 79.7%.

Table 5 lists the variables ordered by their estimated classification performance in the model. The strongest variables—that is, those that discriminate the independent variables best—are listed first. The percentage value attached to each variable indicates the predicted decrease in the classification performance if the variable were to be dropped from the model. The table shows that the variables in the first two models, level of giftedness and gender, have a clear order of importance. The most important variable for both models is Item 12, “I had to work hard to get good grades.” If we remove that variable from the first model, it would weaken the performance from 65.4% to 58.4%. Removal of the variable from the second model would weaken the performance from 79.7% to 72.8%.

Differences in the group means in Table 5 show that the first classification between three groups of the mathematically gifted is based on effort attributions as five items out of seven measure success or failure because of effort. The first item, 10, “The smart kids tried the hardest,” is the best overall predictor variable. However, the other items are more interesting, as they show that both mildly (Polytechnics) and moderately (Prefinalists) mathematically gifted individuals attribute failure to lack of effort, but only mildly mathematically gifted individuals attribute success to effort. Highly (Olympians) and moderately (Prefinalists) mathematically gifted individuals prefer ability as an explanation for their success.

Females in this sample tend to attribute success to effort more than males. Furthermore, they are also more likely to attribute failure to lack of ability than males. Both findings are consistent with existing research (e.g., Alderman, 2004; Vermeer, Boekaerts, & Seegers, 2000). However, we note that “female voice” in this study belongs to mostly those who are mathematically mildly gifted as they are members of the Polytechnics group. This explains at least to some extent why items measuring effort have such an important role in the first two classification models.

Multivariate Analysis of Variance

We investigated the third research question, “Do the attribution styles differ by the level of mathematical giftedness) and gender?” with a 3×2 factorial multivariate analysis of variance. The four dependent variables were SaaS factors based on both theoretical assumptions (Weiner, 1974) and the results of preceding EFA: success because of ability, failure because of lack of ability, success because of effort, and failure because of lack of effort. The independent variables were the level of mathematical giftedness and gender. Preliminary assumption testing was conducted to check for normality, linearity, univariate, and multivariate outliers; homogeneity of variance-covariance matrices; and multicollinearity. No violations were discovered except for the fourth factor, failure because of lack of effort, for which the test of homogeneity of variance was not met (Levene’s $p < .001$, Cochran’s $p = .014$, Bartlett-Box’s $p = .002$). Larger variances indicate that a .05 alpha level is overstated and the differences should be assessed using a lower value (e.g., .03; Hair, Anderson, Tatham, & Black, 1998). For such dependent variables, Tabachnick and Fidell (1996) suggest using Pillai’s criterion instead of Wilks’s lambda.

With the use of Pillai’s criterion, the level of mathematical giftedness multivariate main effect on the SaaS factors was found to be significant, $F(8, 384) = 4.33$, $p < .001$. The gender multivariate main effect on the SaaS factors was not found to be significant, $F(4, 191) = 0.23$, $p = .992$. The level of mathematical giftedness and gender multivariate interaction was not found to be significant, $F(8, 384) = 0.45$, $p = .893$. The results reflected a modest association between three groups of mathematically gifted and the SaaS factors, partial $\eta^2 = .08$ (Pillai’s trace) – .16 (Roy’s Largest Root). This

Table 6
Tests of the Level of Giftedness, Gender, and Their Interaction

IV	DV	Univariate *F*	*df*	Step-down *F*[a]	*df*	α	η^2
The level of giftedness	SUC_ABI	3.28*	2,194	3.28*	2,194	.01	.03
	FAI_ABI	11.99***	2,194	11.20***	2,193	.01	.10
	SUC_EFF	4.12*	2,194	3.05*	2,192	.01	.03
	FAI_EFF	17.80***	2,194	11.43***	2,191	.01	.11
Gender	SUC_ABI	0.00	1,194	0.00	1,194	.01	.00
	FAI_ABI	0.91	1,194	0.92	1,193	.01	.00
	SUC_EFF	0.13	1,194	0.11	1,192	.01	.00
	FAI_EFF	0.18	1,194	0.09	1,191	.01	.00
Group by gender	SUC_ABI	1.00	2,194	1.00	2,194	.01	.01
	FAI_ABI	0.09	2,194	0.16	2,193	.01	.00
	SUC_EFF	0.23	2,194	0.38	2,192	.01	.00
	FAI_EFF	0.73	2,194	0.26	2,191	.01	.00

Note: α = adjusted alpha level. η^2 = effect size for the step-down *F*. SUC_ABI = success because of ability; FAI_ABI = failure because of lack of ability; SUC_EFF = success because of effort; FAI_EFF = failure because of lack of effort.
a. Roy-Bargman step-down *F*.
$*p < .05$. $**p < .01$. $***p < .001$.

finding suggests that group membership explains attribution styles from 8% to 16%. The achieved statistical power for this main effect was 1.0.

To further investigate the impact of the level of mathematical giftedness main effect on the SaaS, a Roy-Bargman step-down analysis was performed. Step-down analysis resolves the problem of correlated univariate *F* tests with correlated dependent variables (Tabachnick & Fidell, 1996). The following priority order of SaaS factors from most to least important was developed on the basis of theoretical assumptions, instead of assigning priority on the basis of univariate *F*, to avoid problems inherent in stepwise regression: (a) success because of ability, (b) failure because of lack of ability, (c) success because of effort, and (d) failure because of lack of effort. In step-down analysis, each SaaS factor was analyzed, in turn, with higher priority factors treated as covariates and with the highest priority SaaS factor (success because of ability) tested in a univariate ANOVA. In addition, univariate *F* values were calculated to allow correct interpretation of the step-down analysis. Results of the analysis are summarized in Table 6. An experiment-wise error rate of 5% was achieved by the apportionment of alpha, as shown in the last column of Table 6, for each of the SaaS factors.

A unique contribution to predicting differences between the three groups of mathematically gifted was made by the success because of ability factor, step-down $F(2, 194) = 3.28$, $p = .040$, $\eta^2 = .03$. According to Cohen (1988), the effect size is small, indicating that only 3% of the variance in the dependent variable is attributable to differences in mathematical giftedness. Highly (mean success because of ability = 3.45, $SE = .07$) and moderately (mean success because of ability = 3.56, $SE = .09$) mathematically gifted individuals evaluated the role of ability to be higher than the mildly mathematically gifted did (mean success because of ability = 3.28, $SE = .07$). The mean difference between the moderately and mildly gifted reached statistical significance using Bonferroni adjusted alpha level of .013, $p = .040$. This result is consistent with both Weiner's (1986) findings showing high-achieving students' tendency to use internal-stable-uncontrollable causal attributions for success and Heller and Lengfelder's (2000) findings for German Olympians and Prefinalists. However, studies of American and Taiwanese Olympians showed opposite results, as participants referred more to effort than ability attributions (Campbell, 1996b; Feng et al., 2001; Wu & Chen, 2001).

After the pattern of differences measured by the first SaaS factor was entered, a difference was also found on failure because of lack of ability, step-down $F(2, 193) = 11.20$, $p < .001$, $\eta^2 = .10$. The effect size of this finding is moderate, indicating that 10% of variance in the dependent variable is attributable to differences in mathematical giftedness. Mathematically highly gifted (adjusted mean failure because of lack of ability = 3.00, $SE = .09$) students attributed failure to lack of ability more than moderately (adjusted mean failure because of lack of ability = 2.60, $SE = .11$) and mildly (adjusted mean failure because of lack of ability = 2.38, $SE = .09$) mathematically gifted. The mean difference between highly and moderately mathematically gifted students reached statistical significance using Bonferroni adjusted alpha level of .013, $p = .028$. Also, the mean difference between the highly and mildly mathematically gifted reached statistical significance using Bonferroni adjusted alpha level of .013, $p < .001$. This internal-stable-uncontrollable finding, which according to Marsh (1983) may lead to low academic self-concept and achievement, is against Weiner's internal-unstable-controllable expectation for high achievers who have failed.

The third step in the analysis was to enter the success because of effort factor. This step-down reached statistical significance, however, with a small effect size, $F(2, 192) = 3.05$, $p < .05$, $\eta^2 = .03$. Mildly mathematically gifted individuals valued success because of effort higher (adjusted mean success because of effort = 3.04, $SE = .09$) than those who were highly (adjusted mean success because of effort = 2.74, $SE = .09$) and moderately gifted (adjusted mean success because of effort = 2.79, $SE = .10$). The mean difference between mildly and highly gifted students reached statistical significance using Bonferroni adjusted alpha level of .013, $p = .029$. This result showing mildly mathematically gifted Polytechnics preferring internal-unstable-controllable attributions was expected.

After the pattern of differences measured by success because of ability, failure because of lack of ability, and success because of effort was entered, a difference was also found on the attitude toward failure because of lack of effort, step-down $F(2, 191) = 11.43$, $p < .001$, $\eta^2 = .11$. According to Cohen (1988), the effect size for this finding is classified as large. Mildly (adjusted mean failure because of lack of effort = 3.99, $SE = .11$) and moderately (adjusted mean failure because of lack of effort = 3.77, $SE = .12$) mathematically gifted students attributed failure to lack of effort more than the highly gifted did (adjusted mean failure because of lack of effort = 3.27, $SE = .11$). The mean difference between mildly gifted Polytechnics and highly gifted Olympians reached statistical significance using Bonferroni adjusted alpha level of .013, $p < .001$. In addition, the mean difference between moderately gifted Prefinalists and highly gifted Olympians reached statistical significance using Bonferroni adjusted alpha level of .013, $p < .001$. The group-level results of this second SaaS failure factor were not congruent with theoretical expectations. We expected to see mildly gifted individuals prefer internal-stable-uncontrollable attributions—that is, failure because of lack of ability—instead of internal-unstable-controllable.

Summary of Results

In this article, we have examined the influence of attribution styles on the development of mathematical talent in three groups of mathematically gifted Finnish adolescents and adults ($N = 203$).

All the participants completed the SaaS questionnaire (Campbell, 1996a). The instrument included 18 items, based on Weiner's (1974) attribution theory, measuring the students' ability and effort attributions on four dimensions: (a) success because of ability, (b) failure because of lack of ability, (c) success because of effort, and (d) failure because of lack of effort.

The research questions in this study were as follows: (a) Are the four dimensions of the SaaS instrument (success because of ability, failure because of lack of ability, success because of effort, and failure because of lack of effort) present in the empirical sample? (b) What are the best predictors for the level of mathematical giftedness and gender among the SaaS scale variables? and (c) Do the attribution styles differ by the level of mathematical giftedness (Olympians, Prefinalists, and Polytechnics) or gender?

The first research question was addressed with EFA. The results showed that the four dimensions of the SaaS were present in all samples. The overall alpha values ranged from .62 to .82. Three alpha values were less than .60 in the group level (Olympians, Factor 2 alpha = .56; Polytechnics, Factor 2 alpha = .59 and Factor 3 alpha = .42).

The second research question was analyzed using Bayesian classification modeling. The classification variables were the level of mathematical giftedness (high = Olympians, moderate = Prefinalists, and mild = Polytechnics) and gender. Eighteen SaaS items were predictors in all the analyses. The results showed that both Polytechnic students and females think that they "had to work hard to get good grades." When we further examined the females' preference for effort as a cause for success, we learned that the result was true only for the Polytechnics and Prefinalists samples, as there was no difference between female and male Olympians' responses. Thus, Verna and Campbell's (2000) earlier finding that female Chemistry Olympians considered ability to be a more important factor for success was not repeated in this study. Failure because of lack of ability was the only self-attribute scale that was able to predict respondent's age. The youngest students (15 to 28 years old) believed more in their abilities than the older ones (29 to 41 and 42 to 55 years old). We explain this finding with the fact that the younger individuals have not yet reached as high a level in their mathematical studies as the older ones and thus realized that "the more you know, the more you know you ought to know."

The third research question was analyzed with a 3 × 2 factorial design MANOVA. Dependent variables were four SaaS factors (success because of ability, failure because of lack of ability, success because of effort, and failure because of lack of effort). Independent variables were the level of mathematical giftedness (high = Olympians, moderate = Prefinalists, and mild = Polytechnics) and gender. Results showed that the level of mathematical giftedness multivariate main effect on the SaaS factors was found to be significant. The gender multivariate main effect on the SaaS factors and the level of mathematical giftedness and gender multivariate interaction were not found to be significant. Highly and moderately mathematically gifted individuals felt that ability is more important to success than effort. According to Dai et al. (1998), such attributions represent self-awareness of high potentialities that constitute a necessary but not sufficient condition for high levels of performance. Mildly mathematically gifted individuals tended to see effort leading to success. Mildly and moderately mathematically gifted students attributed failure to lack of effort. The highly gifted attributed failure to lack of ability. This finding is related to self-concept, as mildly and moderately mathematically gifted individuals tend to judge their efficacy favorably, whereas the highly gifted are likely to base their appraisals of self-efficacy on the actual difficulty levels of the tasks in question (see Dai et al., 1998, for discussion).

Limitations of the Study

In this study, we measured attribution styles with a questionnaire. Such self-reporting allows us to study, as opposed to attribution appraisals or causal beliefs, hypothetical success and failure situations without clear reference to who is the performer. The first possible source of error is the SaaS instrument translation from English to Finnish. To control the error variance because of translation, all the items were retranslated back to English and compared with the original items. However, no pilot study with correlational analyses was conducted. A second possible source of error is cross-cultural differences between U.S. and Finnish mathematicians, as the original instrument was developed for studies among the U.S. mathematics Olympians. Fortunately, the language of the SaaS items is free of cultural references. A third possible source of error is the psychometric properties of the SaaS instrument itself, as no alpha values were reported in the original study (Campbell, 1996a).

Discussion

The theoretical idea of Ellström (2001) essential to this study is that attributions for success or failure affect potential competence, which is a human resource each individual brings to the mathematical problem-solving situation. So what are the "good" attributions that give rise to individual's potential competence? The previous research body shows two trends: The first is seeing ability as a more important explanation for success than effort (e.g., "ability is everything"; e.g., Heller & Lengfelder, 2000), and another is claiming that "ability without effort goes nowhere" (e.g., Campbell, 1996b; Chan, 1996; Feng et al., 2001; Wu & Chen, 2001).

Why do several international Academic Olympian research teams end up with contradictory results? The first natural explanation is cultural differences (Campbell, Tirri, Ruohotie, & Walberg, 2004). We suggest here that the second natural explanation is statistical. In all of the aforementioned studies, effort and ability attributions were calculated as mean scores of 18 SaaS items: the Effort scale was measured with 12 items and the Ability scale with 6 items (see Table 2). The results of variable selection and EFA indicated that, in the Finnish sample, keeping all 18 SaaS items on the model does not lead to a psychometrically justified solution (α_{effort} = .63 and $\alpha_{ability}$ = .27). We forced the two-factor solution and calculated internationally comparable mean scores for the Finnish Olympian sample (n = 77) but found no difference between ability (M = 3.16, SD = 0.32) and effort attributions (M = 3.18, SD = 0.45). It should also be noted that the reported mean difference between Ability (M = 2.91, SD = 0.58) and Effort (M = 3.21, SD = 0.62) scales in the American study (Campbell, 1996b) is quite small.

The third trend in research (e.g., Schunk & Ertmer, 2000; Zimmermann, 2000) says that ability and effort without self-regulation goes nowhere. Figure 1 shows that ability is present in the "Self-Reflection" phase that precedes the "Forethought" phase, where individuals set goals and plan actions. At this point, it is important to make a distinction between an individuals' real and self-perceived ability level. The real ability level is what the first research trend is speaking about, but according to the concept of self-regulation, it is undistinguishable from the self-perceived ability. This notion comes from the fact that effort is represented in the preceding phase, "Performance or Volitional Control," in the cyclical self-regulation process described in Figure 1 via self-control. It is therefore sending adjusting signals via self-observation to the individual's self-perceived ability. Our results that show highly mathematically gifted preferring ability over effort as an explanation for success or failure might indicate that their perceived ability level is so high that they are able to meet the most demanding challenges by adjusting their efforts. According to the "attribution asymmetry" phenomenon (Dai et al., 1998), high-ability students tend to attribute their success to both ability and effort. According to them, attributing success to ability represents self-awareness of high potentialities that constitute a necessary but not sufficient condition for success. Attributing success to effort has a self-enhancing and motivating effect, as one feels in control of one's own development.

It is not our primary purpose to compare ability and effort only with questions that ask "Which is a better explanation for success?" but rather to continue with further questions, such as "What are the best developmental practices for those individuals who mostly prefer effort over ability as an explanation for success in a given task?" As Campbell (1995) says, "achievers need four qualities: ability, discipline, confidence and good working habits" (p. 186). Thus, a high effort level as a cause for success may indicate that tasks are too demanding and thus individuals feel that too much effort is needed to accomplish the task. Furthermore, this might indicate that an individual needs more support to be convinced that he or she has the ability to succeed. Research has shown that ability is often viewed as a stable and uncontrollable attribution (e.g., SaaS Item 7, "You have to have the ability in order to succeed in most things"). The worst scenario for a mathematician according to some of the self-attribution theorists (e.g., Dweck, 1999) is to blame personal ability for failure, as it is believed to be something that you either do or do not have, an internal and stable attribution. It is interesting that the most highly mathematically gifted in this study scored highest in this respect when compared to those who were moderately and mildly gifted. This finding makes sense if we agree that Olympians represent the highest mathematical giftedness level in this study and thus have probably faced a lot more demanding mathematical tasks during their lifetime than the other two group members.

Kay Alderman (2004) suggests that it is up to the teacher or trainer to convince a learner or trainee that mathematical thinking ability as a skill or knowledge is a learnable, unstable quality. Thus, knowledge of how learners or trainees use attributions to account for success and failure can help teachers or trainers predict their expectancies and plan intervention strategies when needed.

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