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ABSTRACT

This paper investigates computer literacy related cross-cultural factors that predict academic ability among mathematically gifted Olympians in Finland (N=72, 68 males and 4 females) and the United States (N=80, all males). The following research questions were formulated: (1) What is the nature of the connection between computer skills and development of the Olympians' mathematics skills (grade point average, or GPA)? (2) Does computer literacy contribute to the academic productivity? (3) What re the most culture-dependent components of computer literacy? The results for the first and second research questions indicate that computer literacy is more of a cross-culturally distinctive than a connective factor contributing to the development of the Olympians' mathematics skills and later academic productivity. In the Finnish data, the influence of computer literacy was positive for both GPA and productivity as opposed to the United States data where the influence was found to be negative. The third research question is investigated with dependence and classification modeling. The results indicate that the most culture-dependent variable measuring computer literacy is the use of the Internet. The components that predict the best culture-dependent computer literacy are programming skills, basic computing skills, and self evaluating computing skills. (Contains 24 references.) (Author/AEF)

CROSS-CULTURAL FINDINGS OF COMPUTER LITERACY AMONG THE ACADEMIC OLYMPIANS

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Abstract

This paper investigates computer literacy related cross-cultural factors that predict academic ability among mathematically gifted Olympians' in Finland (N=72, 68 males and 4 females) and United States (N=80, all males). Following research questions are formulated: (1) What is the nature of connection between computer skills and development of the Olympians' mathematic talent (GPA)? (2) Does computer literacy contribute to the academic productivity? (3) What are the most culture dependent components of computer literacy? The results for the first and second research questions are in parallel indicating that computer literacy is more cross-culturally distinctive than connective factor contributing to the development of the Mathematic Olympians' talent and later academic productivity. In the Finnish data the influence of computer literacy was positive for both GPA and productivity as opposite to the U.S. data where the influence was found negative. The third research question is investigated with dependence and classification modeling. The results indicate that the most culture dependent variable measuring computer literacy is the use of Internet. The components that predict best culture dependent computer literacy are programming skills, basic computing skills and self evaluated computing skills.

Keywords: Olympiad studies, Cross-cultural, Computer literacy, Mathematics talent, Academic ability

Introduction

Finland is known as a small Scandinavian country with advanced technological innovations. The national educational strategy in Finland has emphasized the importance of computer skills for every student and teacher (Ministry of Education 1995). Computer literacy is also a prerequisite in the advanced studies in mathematics, physics and chemistry in the Finnish Universities. Majority of the Finnish Olympians have chosen a career in science or are students in mathematics, computer science or physics (Tirri, 2001).

Finland has participated in Olympiad programs for several years. Separate programs exist for the Mathematics, Physics and Chemistry Olympiads. In the Mathematics Olympiad programs, series of increasingly difficult tests are administered. This testing concludes with the identification of the top national finalists (6-20 Olympians). These individuals are trained to compete in the International Olympiad programs.

Since 1995, the Americans have used three tests to identify Mathematics Olympians. In the first stage, 350.000 students participate in the American High Mathematical Examination (AHSME) test. After that, the top five percent of the participants take the American Invitation Mathematical Examination (AIME). The top six scorers (0.002%) are identified as Mathematics Olympians (Campbell, 1996b).

The major goal of this paper is to investigate computer literacy related cross-cultural factors that predict academic ability among the mathematically gifted population. The population is represented by those Finnish and American students who participated in the Mathematic Olympics during a period of some thirty years (Finnish 1965 – 1997, American 1972 - 1995). The study is part of an international research project that compares the opportunities for gifted people in different countries to actualize their giftedness (Campbell, 1996a). Germany (Heller & Lengfelder, 2000), Taiwan (Wu, 1996; Wu & Chen, 2001), Korea and China (Zha et al., 1996) are also involved in this project.

The research interests of this study are twofold: Firstly, we study the relation between basic computing skills and adacemic ability. Secondly, we build, based on item level analysis, the preliminary version of cross-cultural model for computer literacy of Academic Olympians.

Following research questions are formulated: (1) What is the nature of connection between computer skills and development of the Olympians' mathematic talent? (2) Does computer literacy contribute to the academic productivity? (3) What are the most culture dependent components of computer literacy?

When looking for an answer to the first two research questions a special interest is shown in the factors of education, both in homes and in schools, that have helped or hindered these people in the actualization of their giftedness. Furthermore, the self-perceptions of the Olympians regarding the attributions of ability and effort in their success are investigated within the theoretical framework of Weiner's theory (1980; 1994). The results of the Finnish study are compared to the earlier American study using the same instruments (Campbell, 1996b). The third research question is investigated with a Bayesian dependence (Silander & Tirri, 2000) and classification (Silander & Tirri, 1999) modeling.

Preliminary research

Campbell (1996b) investigated computer literacy of eighty United States Mathematics Olympians and found that those who spent the most time with computers had lower grades due to fact that computer literacy has no connection to their academic subjects. Recent findings of the study conducted by Feng, Campbell & Verna (2001) showed that computer literacy of fifty-five United States Physics Olympians had negative (-.10) effect on the SAT (math & verbal). Computer literacy has also been shown to be negatively associated with academic achievement of U.S. Mathematics Olympians (Campbell, 1996b).

Heller and Lengfelder (2000) investigated 100 German Olympians finalists and 135 prefinalists in mathematics, physics, and chemistry. They found that computers were used by 87 percent and 89 percent worked with at least one computer language. An e-mail address was provided by 54% of those surveyed. (Heller & Lengfelder, 2000.)

Wu and Chen (2001) investigated computer literacy of thirty-two Taiwan Physics and Chemistry Olympians. They found that most (94%) of the Olympians had an access to computer, with an average of 11 hours per week spent on personal computer. Seventy-two percent of Olympians were using e-mail and sixty-six percent had an access to Internet. They reported that self evaluated computer literacy was 2.39 in a 5-point scale. They concluded that in general the computer literacy in year 2000 among Physics and Chemistry Olympians was obviously better than that was found in Taiwan Mathemathics Olympians follow-up study two and four years earlier. (Wu & Chen, 2001.)

The previous studies concerning mathematics achievement have revealed that the home background of students, number of students in class and attitudes of students towards mathematics are student-level factors influencing achievement in mathematics over the last 30 years (Afrassa & Keeves, 1999).

Social values associated with cross-national differences in mathematics achievement are addressed in recent study by Shen (2001). The results suggest that economic development level, as measured by GNP per capita, has a positive but weak effect on mathematics achievement. Variables reflecting a society's value on education (i.e. students' perceived rigour of mathematics, students' school attendance and the number of parents living with the student) demonstrate strong effects on students' mathematical achievement (Shen, 2001, pp. 202-210).

Methods and procedures

The Olympians both in Finland and the U.S. were mailed a 14-page questionnaire and self-confidence attitude attribute scales (SaaS) (Campbell, 1996a). Their parents were mailed a shorter version of the same questionnaire and the inventory of parental influence (IPI) (Campbell, 1996a).

Four of the Finnish and two of the American Olympians were no longer living, and ten of Finnish and six of American Olympians kept their current addresses private or could not be located. The Finnish sample consisted of 72 Mathematics Olympians and 69 of their parents. The American sample was 80 Olympians and 55 parents. The Finnish Mathematics Olympians' data came from 68 males and four females. All the American Olympians were males. The total number of Finnish females who participated in the Olympics during the years 1965-1997 is fourteen. That is far more than the number of the American female participants (during years 1972-1995), a total of two. The Finnish data includes Olympians of different ages, ranging from 20 to 54 years of age. The American participants are far younger, the youngest being 15 and the oldest 41. (Table 1.) For more specific background mapping of the Olympic study, see Tirri (2001) and Campbell (1996a).

Table 1. Description of the Finnish and American Mathematics Olympians

	Finland (N=72)		U.S. (N=80)	
	(N)	(%)	(N)	(%)
Sex				
Male	68	94	80	100
Female	4	6	0	0
Age group				
- 22	6	8	18	23
23-29	15	21	28	35
30 -	49	68	30	37
Missing	2	3	4	5

Computer literacy and mathematical giftedness of the Olympians

The first research question (1) What is the nature of connection between computer skills and development of the Olympians' mathematic talent? is operationalized in this paper by dividing it into a series of subquestions: (1.1) Does computer literacy contribute to the development of mathematical talent?, (1.2) What is the role of socioeconomic factors (SES) in the development of mathematical talent?, (1.3) What factors in school hinder the development of mathematical talent?, (1.4) Do specific family processes inhibit or contribute to the development of math talent?, and (1.5) How confident are the Olympians in terms of their academic abilities?

Computer Literacy

The American (Campbell, 1996b) and Finnish Olympians reported extensive use of computers. Almost eighty percent of Finnish and over sixty percent of American Olympians owned a computer. About ninety percent of Finnish and over eighty percent of American Olympians worked daily on a computer. The Finnish Olympians used different software programs more extensively than did their American colleagues, the most distinctive difference being in the use of Internet, database and graphics applications that are usually closely related to Internet programming. Most Finnish (95.8%) and American (71.3%) Olympians have e-mail addresses and regularly use the Internet. The average number of computer languages known is almost the same for both countries. Finnish Olympians are more active programmers (M=10.24) than their American colleagues (M=0.64), but this great difference is largely explained with great dispersion in the Finnish data (SD=59.82). On a five-point scale, American Olympians rated their computer literacy as 4.08 and Finnish Olypians as 4.04. (Table 2.)

The computer literacy factor used in the earlier American study (Campbell, 1996b) was constructed from the following variables: v27 "Use word processing software", v43 "Have an e-mail address", v30 "Use the Internet", v28 "Use math/statistics software", v45 "Self evaluated computer literacy", v20a "Own a computer", v29 "Use spread sheet software", v31 "Use database software", v21 "Use PC/MS DOS". We used this solution to store comparability to the earlier American study when looking for a solution to the first two research problems.

Socioeconomic Factors

A multi-item measure of socioeconomic status (SES) was calculated for each Olympian. We used the guide developed by Nam & Powers (1983) to code occupational and socioeconomic status scores. The Nam-Powers socioeconomic status scores combine education, income, and occupation in a multi-item index, which provides a direct and objective measurement of SES. The advantage of the Nam-Powers scale is that it provides combined scores for men and women.

Table 2. Finnish and U.S. Olympians Computer Utilization

			Country	
Variable code	**Variable description**		**Finland**	**U.S.**
V20a	*Own computer (%)*		79.0	65.0
US2	*Work on computer daily (%)*		92.0	82.5
V25	*Hours per week on personal computer*	*M (SD)*	17.14 (14.16)	11.20 (15.11)
V26	*Hours per week on main frame computer*	*M (SD)*	5.33 (8.38)	6.93 (10.82)
	Software programs used (%)			
V27	Word processing		97.2	67.5
V28	Mathematics/Statistics		55.6	33.8
V29	Spreadsheet		61.1	26.3
V30	Internet		95.8	42.5
V31	Database		31.9	11.3
V32	Games		52.8	37.5
V33	Graphics		52.8	6.3
V34	Desktop publishing		43.1	18.8
E2	Other		44.4	16.3
V43	*Have an e-mail address (%)*		95.8	71.3
V44	*Number of programming languages known*	*M (SD)*	4.24 (2.88)	4.16 (3.52)
COM1	*Number of computer softwares programmed*	*M (SD)*	10.24 (59.82)	0.64 (2.94)
V45	*Self evaluated computer literacy*			
	(Scale: highest 5; lowest 1)	M (SD)	4.04 (1.05)	4.08 (1.06)

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The Nam-Powers scale was developed from American census data. The scale values are useful internationally only in a relative sense. For example, university professors, medical doctors and teachers are considered high-scoring jobs in both countries. Similarly, farm labor positions are scaled as very low-level positions in both Finland and the US. But the Nam-Power averages for each country might not be precise enough for exact comparisons. This is especially true for developing countries. For highly developed countries like Finland and the US, the scores might be fairly comparable but even here it is important to use Nam-Powers only in a relative sense of status. This is not an absolute scale that can be used across the board in every country.

To calculate SES for each Olympian, we performed the following steps: Firstly we categorized both parents' educational level by giving equivalent points according to the scale, secondly we categorized parents' income information, and thirdly we produced a new variable, the Finnish adjusted "SES" value, by adding education, income and occupation and dividing the outcome by the number of factors.

The SES indices show that a majority of the Finnish (33%) and American (51%) Mathematics Olympians came from homes with a high-level socioeconomic status. The adjusted mean of the Finnish Olympians parents' income was rated in the highest class, as was the mean of the American Olympians' parents' income.

School Factors

Most of the Finnish Olympians did not take part in any kind of special educational arrangements for gifted children during their years at school. These arrangements include opportunities to study according to an advanced program or a special class for gifted students. In the U.S., 89% of the schools are public; 82.4% of the Olympians attended them. In contrast to Finland, over half of the U.S. Olympians were enrolled in gifted classes during their school career.

The Olympians and their parents were asked to rate the importance of school influences to the development of the academic talent of the Olympian (see Table 3). Parents rated school influences as being more important than did the Olympians. On the other hand, the Olympians, regardless of their socioeconomic status, viewed themselves as the most influential person in the development of their giftedness (Tirri, 2001).

Table 3. School Factors

	Finland		**U.S.**	
	(M)	**(SD)**	**(M)**	**(SD)**
School hindrances				
Parents' perceptions	2.04	0.91	2.49	0.99
Olympians' perceptions	1.53	1.08	2.03	0.87

Family processes

Both the Olympians and their parents in Finland and the U.S. rated the item "Home atmosphere was very conducive to learning" as the most influential factor in their talent development. It is also noteworthy that the parents' perceptions of the home atmosphere (see Table 4) were higher in both countries than were the Olympians'. This finding is expected because parents often report a "rosier" picture of reality. It is a difficult task to decide whose perception is the more accurate one.

Campbell (1996a) developed international factor scales that isolate five family processes: pressure, psychological support, parental help, press for intellectual development and monitoring/time management. Table 4 shows that the Olympians' families provided much more psychological support than pressure in both countries, but in Finland parents provide fewer intellectual resources (2.85) than in the U.S. (3.94). An explanation for this difference is the net wealth of the Americans or the greater availability of such intellectual resources.

Table 4. Family Factors

	Finland		U.S.	
	(M)	**(SD)**	**(M)**	**(SD)**
Conductive Home Atmosphere				
Parents' perceptions	2.85	0.70	3.52	0.77
Olympians' perceptions	2.10	0.97	3.10	0.80
Pressure				
Parents' perceptions	1.84	0.40	1.91	.55
Psychological support				
Parents' perceptions	3.94	0.35	4.15	.45
Parental help				
Parents' perceptions	1.76	0.42	2.71	.79
Press for Intellectual Development				
Parents' perceptions	2.85	0.33	3.94	.86
Monitoring				
Parents' perceptions	1.65	0.44	2.49	.91

Olympians' Attributions

The Finnish Olympians emphasized their own interests and efforts as key factors in their talent development. They mentioned "good memory," "self-discipline," "hating to lose," "desire to compete," "my own inner drive," and "my early learning in math and reading" as important factors influencing their development. The teachers are given credit, too. Ten of the Finnish Olympians reported "excellent teachers" and "teachers' active encouragement" as important factors in their talent development (Tirri, 2001). The U.S. Olympians attributed effort to be more important than ability in their success (Campbell, 1996b). This result equals the findings of Taiwan physics and chemistry Olympians (Effort: 3.35, Ability: 2.95) reported by Wu & Chen (2001). (Table 5.)

Table 5. Olympians' Self- Attributions

	Finland		U.S.	
	(M)	**(SD)**	**(M)**	**(SD)**
Effort attribution	3.18	0.45	3.21	0.62
Ability attribution	3.16	0.32	2.91	0.58

Path Analysis - GPA

Multivariate path analysis (see Simon, 1954; Jöreskog, 1969; Kaplan, 2000) is applied to one dependent variable, high school grade point average (GPA), and eight predictor variables. The term 'path analysis' is used here for modeling systems of structural relationships among a set of observed variables (Kaplan, 2000, pp. 13-39). When we concentrate on studying the causal relationships between variables in the model, we exclude the possibility of external causal relationships (i.e., latent variables) and thus avoid the criticism addressed to structural equation modeling in social sciences (Pearl, 2000, pp. 133-171).

The following predictor variables were used in the path analysis: Computer literacy factor (Table 2); two school hindrance factors, one from Olympians' and one from parents' perspective (Table 3); effort and ability attributions factors (Table 5); positive home influence factors including parents' factors of support, help, press for intellectual development and conducive home atmosphere (Table 4); negative home influence factors including parents' factors of pressure and monitoring (Table 4); and socioeconomic factors including parents' occupational status, educational levels and the family's income.

Table 6 shows that three of the American Olympians' variables and also three of the Finnish Olympians' variables had significant path coefficients with the GPA variable. In the U.S. data, there were significant negative influences for computer literacy (-0.30*, $p > 0.05$) and effort attributions (-0.27*, $p > 0.05$). American students with high computer literacy had lower grades (GPA) because there is no connection to academic courses (Campbell, 1996b). An interpretation of the fact that Finnish Olympians had a positive influence on their GPA from computer literacy and school hindrance factors experienced by their parents could be found in cultural differences. Campbell's' (1996a) conclusion regarding low GPAs is that the most computer literate Olympians were spending considerable amounts of time working on computers to pursue their own interests. Perhaps that is not the situation with their Finnish peers, because in Finland all kinds of (game) programming projects requiring mathematical skills are the most popular hobbies of young computer-oriented people. Findings of this study does not support Shen's (2001) results suggesting that economic development level has a positive but weak effect on mathematics achievement.

Table 6. High School Grade Point Average (GPA) – Path Coefficients and Correlations

Dependent variable	Predictor variables	Finland (U.S.) mathematicians Direct effect		Indirect effect		Total effect		r with GPA	
GPA									
	Computer literacy	0.34*	(-0.30*)	0.00	(-0.01)	0.34*	(-0.31*)	0.10	(-0.24)
	School hindrance (Olympians)	0.08	(0.15)	-0.24	(-0.07)	-0.16	(0.08)	-0.13	(0.06)
	School hindrance (Parents)	0.66*	(0.12)	-0.37*	(0.03)	0.29*	(0.15)	-0.11	(0.09)
	Effort attribution	-0.12	(-0.27*)	—	(—)	-0.12	(-0.27*)	-0.07	(-0.22)
	Ability attribution	0.01	(0.16)	0.00	(-0.02)	0.01	(0.14)	-0.03	(0.14)
	Positive home influence	0.20	(0.23*)	0.01	(-0.05)	0.21	(0.18)	0.12	(0.09)
	Negative home influence	-0.58*	(-0.11)	0.14	(-0.00)	-0.44*	(-0.11)	-0.13	(-0.11)
	SES	-0.22	(-0.14)	0.19	(0.06)	-0.03	(-0.08)	0.19	(-0.05)

* $p < 0.05$

$R^2 = 0.15$ (0.23)

Computer literacy and academic productivity

The second research question (2) Does computer literacy contribute to the academic productivity? is operationalized by raising one additional subquestion: (2.1) What is the role of school success (GPA) in the actualization of mathematical giftedness?

School Success

Both the Finnish and American (Campbell, 1996b) Olympians were all very successful at school. Most of them ranked at least in the top ten among graduates of their high school class and over sixty percent in both countries (Finland 62.5%; U.S. 62.1%) were in the top three in their class. Olympians' Scholastic Aptitude Test (SAT) scores were also exceptionally high in both data sets. (Table 7.) An Emulated Scholastic Aptitude Test in the Finnish data was calculated from grade point averages and matriculation examination results by applying the following formula:

1 + ((size / rank) / 100) * top_ten

size = number of graduates [1, ... , n]

rank = ranking by school success [1, ... , n]

top_ten = top ten percent [3 = best, 2 = second best, 1 = in top ten, 0 = no value]

Table 7. Olympians in Finnish and U.S. High Schools

	Finland	U.S.
Rank in graduation class (%)		
1st	45.8	24.3
2nd	6.9	5.4
3rd	9.7	32.4
Grades in high school (Scale: highest 7; lowest 1)		
Mathematics	6.93	6.99
Science	6.79	6.90
Native language	6.14	6.50
Social studies	6.28	6.40

The academic success of the Finnish Olympians continued in their studies at universities. They reported that the transition to university studies was very easy (4.5 on a scale of 5). However, only 12% of the Olympians had had a chance to participate in a special program or individualized opportunities at their universities. The Olympians remained very independent in their studies; less than a half (40%) of them reported having mentors to aid their development. Compared to the American sample, the Finnish Olympians found the transition to university easier than did their American colleagues, and they had been provided fewer special programs and individualized opportunities as well as less mentoring during their university studies.

Productivity

Measures of productivity discussed here involve enrollment in colleges, completion of college/university degrees and academic productivity (including articles, books and patents published and research papers presented). The Olympians were successful in enrolling in the most selective colleges/universities in the United States and Finland. Eighty-six percent of Finnish Mathematics Olympians completed their undergraduate degrees; the analogous figure in the U.S. data is a full 100 percent. Thirty-one American (42%) and 29 (47%) Finnish Olympians completed their Ph.D or law degrees. Table 8 shows academic productivity among the U.S. and Finland Olympians in the form of publications and patents. It must be emphasized when comparing academic productivity that American Olympians are far younger than Finns and are therefore expected to publish later in their career.

Table 8 indicates that the typically American cultural habit of team work or mentoring is not very popular in Finland; only six Finnish Mathematics Olympians were mentored. Perhaps the effect of the sophisticated American mentoring culture is seen in the results that prove mentored Americans more productive than non-mentored in all productive areas. The same direction is observable, too, with Finnish Olympians but with smaller differences.

Table 8. Finnish and U.S. Olympians' Academic Productivity

	Finland			U.S.		
	Mentored Olympians (N=6) [M]	Non-mentored Olympians (N=57) [M]	Total (N=63) [M]	Mentored Olympians (N=46) [M]	Non-mentored Olympians (N=27) [M]	Total (N=73) [M]
Academic productivity						
Articles published	61 [10.2]	374 [6.6]	435 [6.9]	401 [8.7]	34 [1.3]	435 [5.9]
Books published	12 [2]	57 [1]	69 [1.1]	14 [0.3]	1 [0.0]	15 [0.2]
Research papers presented	70 [11.7]	494 [8.7]	569 [9.0]	252 [5.5]	22 [0.8]	274 [3.8]
Patents	3 [0.5]	5 [0.1]	8 [0.1]	12 [0.3]	3 [0.1]	15 [0.2]

Path Analysis - Productivity

The dependent variable in multivariate path analysis was "productivity" together with eleven predictor variables. The following predictor variables were used in the path analysis: Computer literacy factor (Table 2); mentoring (Table 8); two school hindrance factors, one from Olympians' and one from parents' perspective (Table 3); GPA (Table 7); effort and ability attributions factors (Table 5); positive home influence factors including parents' factors of support, help, press for intellectual development and conducive home atmosphere (Table 4), negative home influence factor including parents' factors of pressure and monitoring (Table 4), age (Table 1) and socioeconomic factor including parents' occupational status, educational levels and the family's income.

The results in Table 9 show that computer literacy was negatively related to productivity in the American data (-0.16), but quite strongly positively related in the Finnish data (0.26). The difference is explained by the fact that American computer literate individuals are employed outside academia (Campbell 1996b), but most Finnish Olympians have chosen academic careers (Tirri, 2001). It should be noted that GPA was not found to be an important variable for productivity. This observation is supported by two facts: (1) High dependency of age and productivity (Finnish: 0.52* and U.S.:0.51*, $p < 0.05$), and (2) biased age distribution (see Table 1), which leads us to conclusion that at the time of this study the Olympians were still "mainly knowledge consumers rather than knowledge producers" (Wu & Chen, 2001, p. 22).

Cross-cultural components of computer literacy

The third research question (3) What are the most culture dependent components of computer literacy? is divided into two sub-questions: (3.1) What is cross-cultural in the structure of variables measuring computer literacy?, and (3.2) Which components of computer literacy are the best predictors for the Mathematics Olympians country of origin?

We look for an answer to the first research question with the help of the Bayesian dependence modeling (Silander & Tirri, 2000; Nokelainen et al., 2001). The second research question is investigated with Bayesian classification modeling (Silander & Tirri, 1999; Tirri et al., 2002).

Table 9. Academic Productivity – Path Coefficients and Correlations

Dependent variable		**Finnish (U.S.) mathematicians**							
	Predictor variables	**Direct effect**		**Indirect effect**		**Total effect**		**r with Productivity**	
Productivity									
	Computer literacy	0.26	(-0.16)	-0.02	(0.01)	0.24	(-0.15)	0.12	(-0.11)
	Mentor	0.23	(0.07)	—	(—)	0.23	(0.07)	0.09	(0.32)
	School hindrance (Olympians)	0.31*	(-0.03)	-0.30*	(0.01)	0.01	(-0.02)	-0.22	(-0.19)
	School hindrance (Parents)	0.79*	(-0.09)	-0.45*	(0.00)	0.34*	(-0.09)	-0.20	(-0.19)
	GPA	0.10	(-0.03)	—	(—)	0.10	(-0.03)	0.20	(0.03)
	Effort attribution	0.44*	(0.17)	0.00	(0.01)	0.44*	(0.18)	0.29	(0.16)
	Ability attribution	-0.11	(0.01)	—	(—)	-0.11	(0.01)	-0.09	(0.17)
	Positive home influence	0.08	(0.02)	0.02	(0.03)	0.10	(0.05)	-0.03	(0.05)
	Negative home influence	-0.36*	(-0.09)	0.06	(0.02)	-0.30	(-0.07)	-0.14	(-0.20)
	Age	0.52*	(0.51*)	0.07	(0.02)	0.59*	(0.53*)	0.55	(0.52)
	SES	-0.08	(0.13)	0.13	(0.00)	0.05	(0.13)	-0.35	(0.07)

* $p < 0.05$

$R^2 = 0.27\ (0.38)$

Bayesian dependence modeling

We investigated probabilistic dependencies between all of the computer literacy variables (for variable description see Table 2). Bayesian search algorithm (Myllymäki et al., 2001) evaluated three data sets, Finnish, U.S., and combined (Finnish and U.S.) in order to find the model with the highest probability. During the extensive search, great number of models were evaluated: Finnish data, 3.657.122 models; U.S. data, 21.189.683 models; and combined data, 21.623.985 models.

Figure 1 presents causal model of the variables measuring computer literacy in Finnish, U.S., and combined data. Solid lines indicate direct causal relations and dashed lines indicate dependency where it is not sure if there is a direct causal influence or latent cause. In the Finnish data, core variables of the model measure extensive use (US2 "Work on computer daily") of basic computer software (V27 "Word processing", V33 "Graphics", V34 "Desktop publishing", V29 "Spreadsheet", and V28 "Mathematics/Statistics"). In the Finnish data there is only weak connection between the Internet (V30) and an e-mail address (V43). Working on computer daily is an important variable in the U.S data, too, but the strongest dependencies are found along two paths: First consisting of variables measuring use of mathematical software (V28) and programming (V44), and second measuring use of graphics (V33) and desktop publishing (V34) software. Analysis of the combined data reveals that the Internet (V30) is an important junction for two paths in the model: First path is publishing (V34, V33) oriented and second one is programming (V44, COM1, V28) oriented. The both U.S. and combined models show that working on computer daily (US2) is related to self evaluated computing skills (V45).

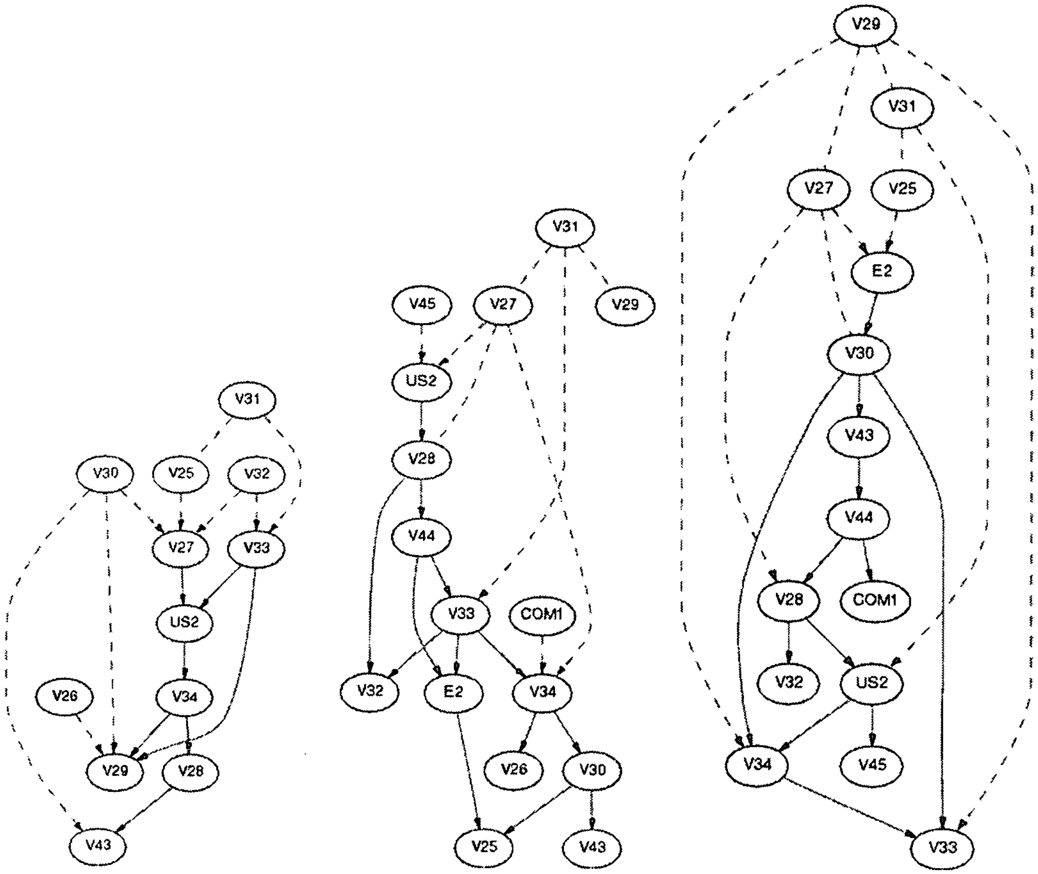

Figure 1. Causal model of the variables measuring computer literacy in Finnish (left), U.S. (middle) and combined (right) data

Table 10 presents the most dependent and independent variables of computer literacy in all three data sets (Finnish, U.S. and combined). The number of independent variables is highest in the Finnish model (4) while all the variables in the U.S. model seem to have statistical dependencies. The dependent variables list of both Finnish and U.S data set show that country-spesific structures do exist among variables measuring the computer literacy of Mathematics Olympians. The dependent variables list of combined data indicate that we are able to construct a cross-cultural structure of computer literacy variables.

Table 10. The most dependent and independent variables of computer literacy

Country	Dependent variables	Independent variables
Finland	V27, V33, US2, V34, V29, V28, V43	E2, V44, V45, COM1
U.S.	US2, V28, V44, V33, V32, E2, V34, V26, V30, V25, V43	–
Combined	E2, V30, V43, V44,V28, COM1, V32, US2, V34, V45, V33	V26

Bayesian classification modeling

We conducted the Bayesian classification analysis (Silander & Tirri, 1999) in order to find out which variables measuring computer literacy are the best predictors for the Mathematics Olympians country of origin. We derived the model for classifying data items according to the class variable "CON" ("U.S.", "Finland") with the 17 variables of computer literacy (see Table 2) as predictors. The estimated classification accuracy for the model was 82.64%.

Table 11 lists the variables ordered by their estimated classification performance in the model. The strongest variables, i.e. those that discriminate the two countries best, are listed first. The percentual value attached for each variable in Table 11 indicate the predicted decrease in the classification performance if the variable is dropped from the model.

Table 11. Importance ranking of the variables in the Bayesian classification model

Variable name		Decrease in predictive classification if variable is dropped (%)
V30	*Internet*	13.89
V33	*Graphics software*	7.64
V27	*Word processing software*	5.56
V45	*Self evaluated computer literacy*	4.17
E2	*Other software*	1.39
V31	*Database software*	0.69

Table 11 indicates that variables in the model spread into three categories: Top (one variable), middle (three variables), and lower class (two variables). The most important variable is V30 "I use the Internet". Removal of that variable would weaken the performance of the whole model from 82.64% to 68.75%. In addition, middle group variables, variable V33 "I use graphics software", variable V27 "I use word processing software", and variable V45 "Self-evaluated computer literacy", have total effect of 17.37 percent (Table 11).

The weakest predictors of our model were variable E2 "I use other software", and variable V31 "I use database software". Those variables were thus the most common computer literature variables among Finland and U.S. Mathematics Olympians (Table 11).

In the classification process the automatic search tried to find the best set of variables that predict the country for each data item. This procedure is akin to the stepwise selection procedure in the traditional linear discriminant analysis (Huberty, 1994, 118-126). The variables that were not selected for any subset are not good ones to predict cross-cultural attitudes in our data. These variables are presented in Table 12.

Table 12. The variables excluded from the Bayesian discriminant analysis

V20a	*Own computer (%)*
US2	*Work on computer daily*
V25	*Hours per week on personal computer*
V26	*Hours per week on main frame computer*
	Software programs used
V28	Mathematics/Statistics
V29	Spreadsheet
V32	Games
V34	Desktop publishing
V43	*Have an e-mail address*
V44	*Number of programming languages known*
COM1	*Number of computer softwares programmed*

The overall result of 82.64% is just an average performance rate of the classification model. Table 13 presents classification performance by groups. The second column in Table 13 ("Success for different predictions") presents the estimated correctness of classification performance and its reliability by groups. The figure is this colum show the probability for

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correct classification for each country in percentages. Next to each estimate there is a figure indicating the percentage of the sample size used to calculate this estimate. The third column in Table 13 ("Success in different classes") presents the group difficulty, i.e. how well the data items of different classes can be predicted. The fourth column of Table 13 ("Predicted group membership") shows how many of the members of certain class were predicted to be members of certain other class. The entries denoting numbers of correct classifications are denoted by printing them **strong**. The Finland data was a slightly more coherent compared to U.S. yielding the predictive classification results with 10 misclassifications compared to 15 misclassifications of U.S. data. (Table 13.)

Table 13. Classification performance by groups

	Success for different predictions (%, N)	Success in different classes (%, N)	Predicted group membership (N)	
			U.S.	Finland
U.S.	85 (68)	79 (73)	58	15
Finland	80 (76)	85 (71)	10	61

Preliminary model for computer literacy

Based on the dependency and classification modeling results, a preliminary five component model for computer literacy of Mathematics Olympians was constructed (Table 14).

We derived a model for classifying the data items according to the class variable "CON" (Finland, U.S.) with the five components as predictors. The estimated classification accuracy for the five component model was 77.08%.

Table 14. The five component model for computer literacy of Academic Olympians

1. Basic computing skills (c_skill)	
	Software programs used
V27	Word processing
V28	Mathematics/Statistics
V29	Spreadsheet
V30	Internet
V31	Database
V32	Games
V33	Graphics
V34	Desktop publishing
E2	Other
V43	*Have an e-mail address*
2. Hours spent with computer per day (c_hours)	
V25	*Hours per week on personal computer*
V26	*Hours per week on main frame computer*
3. Number of computer languages (c_lang)	
V44	*Number of programming languages known*
4. Programming skills (c_prog)	
COM1	*Number of computer softwares programmed*
5. Self evaluation of computer literacy (self_ev)	
V45	*Self evaluated computer literacy*

Table 15 lists the variables ordered by their estimated classification performance in the model. The strongest variables, i.e. those that discriminate the two countries best, are listed first. The percentual value attached for each variable in Table 15 indicate the predicted decrease in the classification performance if the variable is dropped from the model.

Table 15. Importance ranking of the variables in the five component model

Variable name		Decrease in predictive classification if variable is dropped (%)
C_PROG	*Programming skills*	19.44
C_SKILL	*Basic computing skills*	13.19
SELF_EV	*Self evaluation of computer literacy*	4.86

We also evaluated the four component version (programming skills omitted) of the model to the U.S., Taiwan, China and Finland Mathematics Olympists' computer literacy data (N=238). The estimated classification accuracy for the four component model was 67.09%. Self evaluation of computer literacy was found to be common predictive component in both models.

Concluding remarks

In this paper we have discussed computer literacy related cross-cultural factors that predict mathematical talent and academic productivity in adulthood. Our sample included 152 Olympians from the United States and Finland. This group represents the most highly performing high school students in mathematics in both countries.

The empirical findings reported in this paper indicate that Olympians from both countries reported extensive use of computers. However, the Finnish Olympians used more extensively different software programs than their American colleagues. The Finnish Olympians were especially more advanced in the use of Internet and database applications. Computer literacy was used as one of the predictor variables in the path analysis predicting the academic success of the Olympians. In the Finnish data there were significant positive influence to GPA from computer literacy.

In the U.S. data there were significant negative influences for computer literacy and effort attributions. This finding can be explained by the lack of connection between high computer literacy and academic courses among American Olympians. In Finland computer literacy is more connected to academic studies. Another interesting finding was that in Finland computer literacy was positively related to Olympians' productivity (0.26). In the American data computer literacy was negatively related to productivity (-0.16). The difference is explained with the fact that American computer literate individuals are employed outside academia (Campbell 1996), but most Finnish Olympians have chosen academic careers (Tirri 2001).

The dependence and classification modeling showed that the most culture dependent variable measuring computer literacy is the use of Internet. The components that predict best culture dependent computer literacy are programming skills, basic computing skills and self evaluated computing skills.

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