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Cultural Socialization to Computing in College

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Abstract — *Today many people have their first sustained encounter with computing on college campuses. In part this experience consists of learning to use a machine. But in larger part this experience consists of encountering an alien culture. A socialization model of that encounter and research based on that model are presented. Freshmen at two universities were surveyed and their responses about computer science courses were compared with their responses about other freshmen courses. Consistent with the model, students were more likely to report reality shock, confusion, control attempts, anger, and withdrawal in their computing courses than in other courses. This pattern was less typical of students in the teaching-oriented university than in the research-oriented one. In addition to the organizational difference, three factors were associated with fewer negative outcomes: being male, having taken a computing course in high school, and majoring in science or engineering in college. However, even male, experienced, engineering, and science students encountered computing as an alien culture.*

Powerful computing technology is changing how people do their jobs (Kraemer & Danziger, 1984; Palys, Boyanowsky, & Sutton, 1984), how people spend their leisure time (Vitalari, Venkatesh, & Gronhaug, 1985), and perhaps even how people think (Papert, 1980; Sheil, 1981; Turkle, 1984; Weizenbaum, 1976). As a consequence of these changes, our concept of what it means to be an educated citizen is also changing. Educational institutions are reflecting these changes in their resource allocation decisions and curricula. Elementary schools and high schools are buying computers and are incorporating computing into their curricula (Sheingold, Hawkins, & Char, 1984; Taylor, 1980). Many colleges now require their students to pass a programming course or to demonstrate their "computer literacy" in some other way before graduation. Some colleges even require their students to purchase computers at the beginning of their freshman year.

Computing as a general societal activity, however, is still relatively recent. Not much is known about novices' initial introduction to computing—what it is like or what it should be like. Initial encounters with computing on college campuses

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was the focus for this study. Colleges are particularly interesting encountering sites. As compared with elementary schools and high schools, colleges tend to have more computing resources available for students, and novices have the opportunity for more sustained interaction with computing. In colleges, computer experts from departments of computer science participate in the introduction of computing to novices. From the perspective of these experts and other faculty, computing is a discipline and a working environment, not just a talent, a sport, or a narrow skill tied directly to a weekly paycheck. Hence, in comparison with what is typical in other encountering sites, novices in colleges encounter more people who use computers, more computer experts, more kinds of computers and computing, higher standards of expertise, one or more computer "communities," and institutionalized expectations (in the form of courses, requirements, grades) that they will learn the fundamentals of computing.

Previous investigations of initial encounters with computing have typically employed one or more of three perspectives: technical capabilities, instructional practices, and individual abilities. A technical capabilities perspective focuses on the relative ease or difficulty with which new users learn particular computer operations as a function of hardware or software variations (e.g., Black & Moran, 1982). Often the people being studied are not new to computing itself, but rather are new to the particular operations being studied (e.g., DeYoung, Kampen, & Topolski, 1982; Schneider, Nudelman, & Hirsh-Pasek, 1982). An instructional perspective usually measures the accuracy with which people learn certain material, perhaps as a function of alternative instructional techniques (e.g., Anderson, Boyle, & Reiser, 1985). An individual abilities perspective investigates the extent to which more able students have better experiences (e.g., Arndt, Feltes & Hanak, 1983). Each of these perspectives focuses on an individual person interacting with a machine or a program in a social vacuum. In each case the focus is on how fast or how well the novice learns particular hardware or software operations and concepts. None of these perspectives investigates what a computing novice learns about such issues as: (a) the context in which computing occurs, (b) the kinds of people who compute, (c) the social organization of computing, and (d) the values associated with computing.

These are cultural issues. A cultural perspective assumes the existence of an ongoing culture in which particular hardware and software are artifacts. Members of the culture attach values to the artifacts, develop norms for their use, acquire status in relation to their expertise with the artifacts, develop attachment to others in the culture, etc. In colleges, the computer culture is often an adolescent one, which encourages pranks, idiosyncrasy, and irreverence.[1] Mild larceny, such as faking accounts, breaking codes, stealing time, and copying software, is admired if not rewarded explicitly. There is competition to write the best, fastest, biggest program or to build the best, fastest, and smallest hardware. True members of the culture are found at a terminal or computer at all hours of the day or night. Cultural values are revealed through a status hierarchy which assigns people to

[1]Although a cultural perspective on computing is not commonly found in the scientific literature, the popular press has provided some cultural descriptions. See Levy (1982) for a description of the undergraduate computer culture at Stanford University and Levy (1984) for a description of the early computer culture at MIT. See Kidder (1981) for a description of a similar culture in an industrial setting.

such categories as wizards, wheels, hackers, randoms, users, and losers (Steele, et al., 1983).

We assume that the culture of computing mediates novice experiences with computers. In this paper we investigate how novices—in this case, college freshmen—encounter the culture of computing, and what lessons they learn about it and themselves as a result. Hence, the lessons and experiences of interest are not those narrowly related to computing assignments or particular software but rather are those learned in the multipurpose social setting where computing is carried out by members of the campus computing community. Our concern is the nature of an initial socialization process and how variations in that experience affect students' readiness for further socialization. Readiness for further socialization is always an important educational outcome. Given the nature of computing technology—its power, variety, and the speed with which it is changing—it is particularly important in this case.

Encountering Processes

Based in part on an earlier study of liberal arts freshmen (Sproull, Kiesler, & Zubrow, 1984) and in part on what is known about newcomers in foreign cultures (Church, 1982), a tentative model of individual encountering processes is proposed. If the encountered culture is an alien one, as is suggested below for computing, then socialization will occur under conditions of strangeness. Strangeness or unfamiliarity means that the novices' habitual and efficient strategies for learning will not be useful and appropriate. For instance, in familiar academic setting students know how to skim written material, attend to only the highlights of lectures, and rapidly infer "what is wanted" in assignments. Employing these heuristics in an unfamiliar environment is likely to produce errors, confusion, and misinterpretation. Therefore, novices must learn how to learn as well as what to learn. They must develop new ways of assimilating information and a new framework for it. They must learn how to recognize and interpret cues, and whom to rely upon as informants. In these processes, novices bring capabilities, prior experiences, and interests to the new setting. In that new setting, interactions between characteristics of the novices and characteristics of the culture will determine the nature of initial socialization into the culture. We suggest that the process of initial socialization has four major features: (a) reality shock, (b) confusion, (c) control attempts, and (d) initial socialization outcomes.

During the early days in a new culture, the novice experiences changes, contrasts, and surprises (Louis, 1980); we call this constellation of experiences, "reality shock." Reality shock includes anticipated objective and subjective differences from the novice's prior situation, for example, in title, social status, workload, customs, surroundings and language (Byrnes, 1966; Higbee, 1969; Smalley, 1963). It also includes unanticipated differences between expectations and reality. Students in our previous study said:

> I was surprised, really surprised at the people set up along the benches. There's no privacy. . . . It reminded me of a horse at a trough.

> I didn't think it was going to be something to learn how to program a computer. I thought it was going to be teaching us how to use the computer.

Reality shock signals that prior instrumental behaviors are no longer appropriate and new ones must be learned. It also colors the early lessons learned in the new culture, as these students illustrate:

I was almost finished with a program and it crashed. I didn't have a save. I didn't put save on. I had to start over. It was heartbreaking.

I mean, sometimes I feel like the computer is out after me. You know, everybody gets that feeling that the computer's after them sometimes.

How reality shock is interpreted and managed by the novice is key to the outcomes of socialization (David, 1971). Some people experience reality shock as a problem in the environment to be solved. Some people experience reality shock as confusion and lack of control in themselves (Oberg, 1966). Novices may feel overwhelmed and may question their own competence. These feelings can express themselves in thoughts such as, "I don't know what I'm doing" and "I must look foolish" or "Maybe I'm not the person I thought I was." One student told us how a "hacker" made him feel:

I was on the computer and something happened. I didn't know what was going on. I saw a guy sitting over there who looked like a real hacker. So I asked him, and he got up, and he started doing all of this stuff with my account without telling me what he was doing. He started messing around, You need this. Let's see. I'll give you this file. It's like, what are you doing? He wouldn't tell me.

These feelings also lead novices to question the capabilities of people they must depend upon:

I get the feeling from my computing teacher that he's just telling me half the story. That's all he is telling because when I get to the computer I still don't know what I'm doing. Even after listening to him in class.

In attempting to regain or assert control, novices try to reduce discrepancies between their expectations and the current state (e.g., Bandura, 1977; Carver & Scheier, 1982; Kanfer & Hagerman, 1981; Thompson, 1981). Control attempts can entail mental activity, such as constructing metaphors to explain what is happening, as well as physical activity such as talking with others and seeking help:

In the computation center they have these little gnomes and they sit down in the basement . . . in bug hot rooms, like the devil, and mess around with students and put errors in their programs.

If you stretch it a little, you can think of the user consultant as a librarian, someone who advises you when you don't know what to do.

You ask a hacker what to do and he tells you. You ask a friend what to do and if they've already done it, they tell you. You don't rely on lectures.

When control attempts succeed, positive outcomes follow. Positive outcomes are those in which the novice gains the skills and motivation needed to become further socialized as illustrated by this student:

I was glad that we were doing it on the computer. I don't know why. I just thought, Oh, neat, we get to use the computer again.

All novices learn cultural lessons. Here, it is assumed that novices normally have good self-esteem and abilities. But every culture specifies particular abilities that are important. Difficulty or anxiety attached to learning these abilities is neither unusual nor inconsistent with successful socialization. Mastering difficult situations can enhance positive socialization.

When the interaction of culture and individual attributes leads novices to feel not only confused, foolish, and unable to control consequences of their behavior, but also trapped in a situation where they must continue to experience these feelings, then negative socialization outcomes will ensue – anger or withdrawal (Brockner, 1979; Carver, Blaney, & Scheier, 1979). Anger leads to intransigence or active rejection of the values of the socializing agents (Goffman, 1961). The angry novice says, "These people are so crazy that only an idiot would want to act like them." Withdrawal also precludes positive socialization. As one withdrawn novice said:

Looking back, I'm really not afraid of computers, but I'm going to try to stay away from computers. I know I shouldn't because it's probably the thing of the future. But I'm really kind of leery to get into any type of computing again.

Most novices in college will ultimately come to terms with the culture of computing. They will learn to avoid or to work with computers, and some will become expert at computing. But if the above framework is meaningful, novices will also learn much more in their initial encounters with computing. They will develop an image of "the computer," of computer professionals, and of their own relationship to the computing culture. For educating students in meanings, uses, and organizational values of computing, these understandings are as important as the technical details of particular hardware or software that can be conveyed to novices in a first encounter.

Research Questions

The initial research by Sproull, Kiesler, & Zubrow (1984) was conducted within only one college at one point in time. The purpose of the current study was to determine whether that analysis was meaningful for other settings and whether novice characteristics affect the likelihood of a student's having a negative or positive socialization experience. The novice characteristics investigated were gender, experience with computing before college, and academic interests and abilities. Some analysts have observed that boys and girls behave differently toward computers (Linn, 1985; Turkle, 1984). Kiesler, Sproull, and Eccles (1985) have suggested that the culture of computing is less alien to boys than to girls. Students who have had experience with computers before attending college are likely to find the college computing culture different from any they have known before, but their prior experience should make coping easier than it is for students who have had no prior experience with computers. Finally, students who plan to study in engineering or science domains should be those whose initial competencies and interests match many of the competencies and interests associated with computing; these students might feel more at ease in the computer culture than liberal arts students.

The research reported in this paper addressed four questions. Is the difference between computing and other courses, discovered in our earlier study (Sproull, Kiesler, & Zubrow, 1984), reliable? Do females have more negative encounters than males? Do students with no computing experience prior to college have more negative encounters than do students with such experience? Do students with primarily non-technical interests and abilities have more negative encounters than do students with primarily science and engineering interests and abilities?

Parallel surveys of freshmen in two universities for two consecutive years were conducted to answer these questions. For each group, students' experiences with computing were compared to their experiences with their other courses. This comparison shed light on whether positive or negative experiences were particularly associated with computing apart from the more general experience of beginning college. The effects of gender, prior experience with computing, and college curriculum (as a proxy for academic interests and abilities) were then examined for each group.

METHOD

Setting

A comparative study of student encounters with computing was conducted in two universities in 1983 and 1984. As described in Table 1, both universities emphasized technical subjects, and in both, computing was highly valued. In fact, both institutions announced in 1982 a major expansion of computing for students and faculty. Both required freshmen to take a programming course. But the computer culture was much stronger at University A than at University B. University A was a research university where the computer science department had a world class reputation, and computer science was one of the most prestigious graduate programs. By contrast, University B was more professionally oriented with a strong reputation for excellent undergraduate education and a newly created computer science department.

Procedure

At University A freshmen filled out a questionnaire during their social science course, which was part of the required curriculum in the non-technical college and was recommended as an elective to many technical students. At University B a random sample of freshmen in a required humanities course filled out the same questionnaire. In 1983, the survey contained 61 attitudinal measures plus 7 questions on student background characteristics. Because of time constraints for administering the questionnaire in 1984, a shorter version was created. The 1984 survey contained only items from the 1983 questionnaire directly relevant to exploring the socialization process. There were nine such items: (a) three measures of socialization experience—reality shock, confusion, and control attempts; (b) three measures of initial socialization outcomes—pride, anger, withdrawal; and (c) three student characteristic items—gender, prior computing experience, and curriculum (as a proxy for academic interests). The results presented in this paper are based on the three student characteristics and answers to these six attitude items, as follows:

Table 1. General and Computing-Related Attributes of Two Universities in 1984.

Attribute	University: Research-oriented (A)	University: Teaching-oriented (B)
University Characteristics		
Total enrollment	5341	4107
Undergraduates	4027	3760
Male	2710	2899
Female	1317	861
% Female	32.7%	22.9%
Graduate students	1308	347
Male	1015	291
Female	293	56
% Female	22.4%	16.1%
% Graduates vs. all	24.5%	8.4%
Number of employees	1200	587
Number of faculty	481	251
Major academic divisions	Science Engineering Management (grad only) Humanities & Social Sciences Public Affairs (grad only) Fine Arts	Science Engineering Management Liberal Studies Graduate School
Libraries		
Number of libraries	3	4
Number of books	650,000	700,000
Computing Professionals		
Computer science department (teaching faculty)	approx. 20	9
First degrees in computer science	1965	1982
First computers on campus	1950's	1960's
Departments related to computer science e.g. Robotics	Yes	No
Values and Norms of Computing		
Presence of computer network/mail linking whole campus?	Yes	No
Any faculty may have an account on the network?	Yes	No
Top administrators with terminals or PC's in office?	All	Most
Telephone directory includes computer user-id's?	Yes	No
Administrators have PC's or terminals at home linked to mainframe?	Most	Few
Terminal room modeled after library reading rooms?	No	Yes
Computer education resources integrated with audio-visual and libraries?	No	Yes
Control over computer resources decentralized?	No	Yes, college controlled
Programming taught only by computer science faculty?	Yes	No, also by college faculty

continued

Table 1. continued

Attribute	University: Research-oriented (A)	Teaching-oriented (B)
Full Computerization of Campus		
Announce goal	1982	1982
PC's on campus	approx. 3500	approx. 2000
Terminals on campus	approx. 3000	approx. 400
Talking about Computing		
Size of description in student catalogue	102 lines	84 lines
Number of references to computing inputing in the president's annual report, 1983	14	6
Students debated over computerization	Yes	Yes

1. The course is very different from other courses. (Reality shock)
2. I feel I don't know what I am doing in this course. (Confusion)
3. In this course I talk to people who know more than I do. (Control attempts)
4. This course makes me angry. (Anger)
5. In this course I want to do just enough to get by. (Withdrawal)
6. I feel proud of my performance in this course. (Pride)

Students completed the items for each course that they took during the semester they were enrolled in computer science, answering (for each item) "true," "neither true nor false," or "false." Data analyses were based upon the proportion of students giving "true" responses. All students who answered all the items for computer science and for at least two other courses were included in the study.

Sample

For University A, the sample was representative of the entire freshman class in terms of gender but underrepresented technical students. Responses were thus proportionally weighted to produce data representative of the university freshman population in terms of both academic interests and gender for the years studied.[2] Representativeness was not a problem at University B because a random sample was obtained there. Table 2 presents descriptive statistics for the two samples. The weighted data for University A were used only for cross-university comparisons. Unweighted data are appropriate and were used for cross-group comparisons within each university.

University differences were analyzed at the level of the entire student body. Group-level analyses were carried out separately for each university. In this way, any unmeasured differences that existed between the student groups at the two universities were controlled. For instance, technical students at the two universities may have differed in some unmeasured manner confounding interpretation

[2]The resulting weighted n's for University A in 1983 and 1984 are 73 technical men, 16 technical women, 39 nontechnical men and 35 nontechnical women.

Table 2. Number of Freshman Respondents Having Various Sample Characteristics.

	University					
	Research-oriented (A)			Teaching-oriented (B)		
	Technical Curriculum	Non-technical Curriculum	Total	Technical Curriculum	Non-technical Curriculum	Total
1983 Survey Sample						
Prior Computing			92			81
Male	29	29		48	7	
Female	9	25		19	7	
No Prior Computing			73			47
Male	14	17		29	6	
Female	9	33		10	2	
Total	61	104	165	106	22	128
1984 Survey Sample						
Prior Computing			108			122
Male	42	36		78	20	
Female	9	21		20	4	
No Prior Computing			57			38
Male	9	27		30	1	
Female	5	16		5	2	
Total	65	100	165	133	27	160

of the type of curriculum variable across universities. Although group-level differences between the universities could not be explored statistically, similarities and differences in the pattern of results for each university were noted.

RESULTS

Table 3 displays the percentage of students in 1983 and 1984 at each university who answered true to the questions about their computer science course, and the average percentage of students who answered true about their other courses. This average is used to simplify the presentation of data and to focus attention on the comparison between computing and other courses.[3] The data reported for University A are based on weighted responses. Inspection of the table shows computing was different from other freshmen courses in both years. The chief difference was the percentage of students reporting negative encounters. For instance in 1984 at University A, 46.9% of the students reported that their computer science course made them angry; only 20.5% said that their other courses made them angry ($t(163) = 5.75$, $p < .001$, 1984). At University A, more students reported more reality shock ($t(165 = 9.30$, $p < .001$, 1983; $t(163) = 9.41$, $p < .001$, 1984), control attempts ($t(165) = 11.48$, $p < .001$, 1983; $t(163) = 9.38$, $p < .001$, 1984), and

[3]The difference between computer science and each of the other courses was calculated and compared to the result with the averaged data. Of 72 cases, that is, 3 courses evaluated on six items at two universities in two years, the individual course comparison and the comparison of courses averaged were more than 10% apart in only 12 cases (which was not a significant difference).

Table 3. Percent of Freshmen at Each University Who Answered True to Socialization Items in 1984 and in (1983).

Items	Research-oriented university (A)		Teaching-oriented university (B)	
	Computer Science	Mean for Other Courses	Computer Science	Mean for Other Courses
Reality Shock				
Very different from other courses	67.2* (69.9)*	31.0 (32.9)	55.0* (63.3)*	37.4 (29.7)
Confusion				
I feel I don't know what I am doing	30.0* (40.5)	19.3 (33.0)	18.1 (35.9)*	13.4 (14.6)
Control Attempts				
I talk to people who know more than I do	56.9* (79.8)*	19.3 (33.0)	45.0 (70.3)*	40.7 (55.0)
Anger				
This course makes me angry	46.9* (48.6)*	20.5 (19.9)	36.3* (49.2)*	18.4 (21.4)
Withdrawal				
I want to do just enough to get by	23.7 (25.0)*	19.5 (16.5)	16.9 (28.9)*	12.9 (12.2)
Pride				
I feel proud of my performance	48.4 (44.9)	41.5 (37.1)	50.6* (39.1)	39.5 (44.0)

Note. University A *N*'s for the three courses used to obtain the "Mean for Other Courses" ranged from 118 to 165 in 1984 and from 113 to 165 in 1983. *N* for the computer science course was 165 for both years.
University B *N*'s for the three courses used to obtain the "Mean for Other Courses" ranged from 158 to 160 in 1984 and was 128 in 1983. *N* for the computer science course was 160 and 128 for 1984 and 1983, respectively.

*$p < .05$ for the comparison of computer science with the average of the other courses.

anger ($t(165) = 6.26$, $p < .001$, 1983) in computer science than they did for their other courses.[4] At University B, the same pattern held, but to a lesser degree. For example, in 1984, 36.3% of the University B freshmen reported computer science made them angry while only 18.4% said so about their other courses ($t(159) = 4.28$, $p < .001$, 1984) and the same pattern was found in 1983 ($t(127) = 5.96$, $p < .001$, 1983). Also, more students at University B experienced reality shock in computer science than in their other courses ($t(127) = 7.09$, $p < .001$, 1983; $t(159) = 4.41$, $p < .001$, 1984). The percentage of students reporting a positive outcome was the same across courses. At University A, about equal percentages of students reported pride in their computer science performance as reported pride in their other course ($t(165) = 1.84$, $p =$ n.s., 1983; $t(163) = 1.67$, $p =$ n.s., 1984). At Uni-

[4]A nominal alpha of .05 was used to assess significance. Since multiple dependent measures for each respondent were tested, some differences may have been found by chance. Fisher's lsd correction (Winer, 1971, p. 199), a rather conservative adjustment procedure, would set the critical alpha at approximately .01.

versity B, the percentage of students reporting pride was higher in the computer science course than in other courses in 1984 ($t(159) = 2.52$, $p < .02$, 1984); the percentage was about the same across courses in 1983 ($t(127) = -1.16$, $p =$ n.s., 1983).

The data in Table 3 suggest there might exist a bimodal distribution of students—a group whose experience was successful (about the same proportion in each course) and a group whose experience was unsuccessful (a high proportion of computer science students might be in this group). If so, the computer science course was producing as many potential "cultural recruits" as other courses were, but more "dropouts" than other courses were. This idea was examined by classifying students as potential cultural recruits or dropouts according to their answers to the three outcome questions. Potential recruits to a given field were defined as students who reported pride in their performance and no anger or withdrawal. Potential dropouts were defined as students who did not report pride but did report anger or withdrawal. This classification scheme was applied to the computer science outcomes and to the other course outcomes. Table 4 reports these findings.

For the sample from University A, computer science yielded more dropouts during both years ($t(165) = 2.86$, $p < .01$, 1983; $t(163) = 2.09$, $p < .04$, 1984). At University B, computer science appeared worse than other courses only in 1983: fewer recruits in 1983 ($t(127) = -2.17$, $p < .04$, 1983); and more dropouts ($t(127) = 5.4$; $p < .001$, 1983).

Differences Over Time

How stable were these findings? Responses to computer science minus the average response to other courses, were examined for both years. Then, the 1983 mean difference was subtracted from the 1984 mean difference. In this comparison, a positive score indicated that the gap between computer science and other courses increased, whereas a negative score indicated the gap decreased. (Data on "pride" frequently did not follow this rule since some students experienced greater success in their computer science course than in their other courses.) As can be seen by the negative signs in Table 5, the differences between computing and other courses diminished over time. To summarize the patterns shown in Table 5, we used the mean difference scores for reality shock, confusion, control attempts, anger and withdrawal for the two universities as data for T-tests. We excluded pride again from this comparison because it moved in the opposite direction from the other model components. On average, greater change occurred at University B in comparison with University A ($t(8) = 4.80$, $p < .01$). Compared with the student groups at University A, greater change occurred among the following student groups at University B: technical students ($t(7) = 2.59$, $p < .05$), those with precollege computing experience ($t(8) = 3.42$, $p < .01$), and males ($t(8) = 4.32$, $p < .01$).

Student Characteristics

Earlier it was suggested that the characteristics of novices interact with features of the setting to produce the cultural encounter. As such, gender, prior computing experience, and college curriculum (technical or nontechnical) were investigated as potentially relevant to the encountering process. The findings are presented in Table 6.

Table 4. Percent of Freshmen Classified by Socialization Outcome.

Student Characteristics	Recruits		Mixed		Dropouts	
	1984	1983	1984	1983	1984	1983
Research-oriented university (A)						
Entire Sample						
Computing	33.9	29.1	31.0	33.4	35.1*	37.5*
Average % Other Fields	36.9	33.2	37.1	41.8	26.0	25.0
	($n = 165$)	($n = 165$)				
Curriculum						
Technical						
Computing	47.7*	29.5	33.8	44.3	18.5	26.2
Average % Other Fields	33.3	28.7	38.2	40.4	28.5	30.9
	($n = 65$)	($n = 61$)				
Nontechnical						
Computing	17.0*	24.0*	29.0	24.1	54.0*	51.9*
Average % Other Fields	39.3	41.0	36.4	41.5	24.3	17.5
	($n = 100$)	($n = 104$)				
Gender						
Male						
Computing	29.8	30.9	36.9	32.0	33.3	37.1*
Average % Other Fields	33.0	31.1	38.6	45.2	28.4	23.7
	($n = 114$)	($n = 97$)				
Female						
Computing	27.5*	19.1*	17.6	30.9	54.9*	50.0*
Average % Other Fields	45.8	44.1	33.6	35.3	20.6	20.6
	($n = 51$)	($n = 68$)				
Prior Computing						
Yes						
Computing	34.3	29.8	29.6	36.9	36.1	33.3
Average % Other Fields	35.8	34.3	37.0	40.3	27.2	25.4
	($n = 108$)	($n = 84$)				
No						
Computing	19.3*	22.2	33.3	25.9	47.4*	51.9*
Average % Other Fields	39.2	38.7	37.1	42.0	23.7	19.3
	($n = 57$)	($n = 81$)				
Teaching-oriented university (B)						
Entire Sample						
Computing	38.8	27.3*	31.2	30.5	30.0	42.2*
Average % Other Fields	37.0	36.7	40.8	44.3	22.2	19.0
	($n = 160$)	($n = 128$)				
Curriculum						
Technical						
Computing	39.9	22.6*	32.3	30.2	27.8	47.2*
Average % Other Fields	36.0	38.7	42.3	41.5	21.7	19.8
	($n = 133$)	($n = 106$)				
Nontechnical						
Computing	33.3	50.0*	26.0	31.8	40.7	18.2
Average % Other Fields	42.0	27.3	33.3	57.5	24.7	15.2
	($n = 27$)	($n = 22$)				
Gender						
Male						
Computing	41.1	25.6*	32.5	27.7	26.4	46.7*
Average % Other Fields	34.5	36.7	43.4	44.4	22.1	18.9
	($n = 129$)	($n = 90$)				

continued

Table 4. continued

Student Characteristics	Recruits		Mixed		Dropouts	
	1984	1983	1984	1983	1984	1983
Female						
Computing	29.3	31.6	25.5	36.8	45.2*	31.6
Average % Other Fields	47.3	36.8	30.1	43.9	22.6	19.3
	($n = 31$)	($n = 38$)				
Prior Computing						
Yes						
Computing	42.6	27.2	32.8	35.8	24.6	37.0*
Average % Other Fields	37.8	36.6	38.0	43.2	24.2	20.2
	($n = 122$)	($n = 81$)				
No						
Computing	26.3	27.7	26.3	21.2	47.4*	51.1*
Average % Other Fields	34.2	36.9	50.0	46.1	15.8	17.0
	($n = 38$)	($n = 47$)				

Note. University A *N*'s for the three courses used to obtain the "Average % Other Fields" ranged from 118 to 165 in 1984 and from 113 to 165 in 1983. *N* for the computer science course was 165 for both years.
University B *N*'s for the three courses used to obtain the "Average % Other Fields" ranged from 158 to 160 in 1984 and was 128 in 1983. *N* for the computer science course was 160 and 128 for 1984 and 1983, respectively.

*$p <= .05$ for the comparison of computer science with the average of the other courses.

At University A gender, prior computing experience, and type of curriculum made a difference in how students encountered computing. Women, in comparison with men, reported higher levels of reality shock ($t(162) = -2.83$, $p = .005$, 1983; $t(163) = -2.50$, $p = .014$, 1984), confusion ($t(163) = -3.96$, $p < .001$, 1983; $t(163) = -3.56$, $p < .001$, 1984), control attempts ($t(162) = -2.84$, $p = .005$, 1983; $t(163) = -2.48$, $p = .014$, 1984), and anger ($t(163) = -3.09$, $p = .002$, 1983; $t(163) = -3.00$, $p = .003$, 1984). Students with no prior computing experiences were more confused than were those with prior computing ($t(163) = -3.44$, $p = .001$, 1983; $t(163) = -3.06$, $p = .003$, 1984). Students in a non-technical curriculum, in comparison with those in a technical curriculum, were more confused ($t(163) = -4.25$, $p < .001$, 1983; $t(162) = -5.01$, $p < .001$, 1984), angry ($t(163) = -2.85$, $p = .005$, 1983; $t(163) = -4.92$, $p < .001$, 1984), and withdrawn ($t(155) = -3.44$, $p = .002$, 1983; $t(161) = -3.42$, $p = .001$, 1984).

Referring back to Table 4, observe that student characteristics were associated with the potential for further socialization. At University A in 1983 and 1984, the following significant differences were found: nontechnical students were more likely to be recruits in their other courses ($t(103) = -3.19$, $p = .01$, 1983; $t(99) = -4.58$, $p < .001$, 1984) and dropouts in computer science ($t(103) = 6.46$, $p < .001$, 1983; $t(99) = 4.68$, $p < .001$, 1984); women were more likely to be recruits in their other courses ($t(67) = -3.90$ $p < .001$, 1983; $t(50) = -2.24$, $p < .04$, 1984) and dropouts in computer science ($t(67) = 4.10$, $p < .001$, 1983; $t(50) = 3.96$, $p < .001$, 1984); and students with no prior computing experience were more likely to be recruits in their other courses ($t(80) = -2.69$, $p < .01$, 1983; $t(56) = -2.94$, $p < .01$, 1984) and dropouts in computer science ($t(80) = 4.88$, $p < .001$, 1983; $t(56) = 2.92$, $p < .01$, 1984). Equally interesting was the relative lack of significant differences

Table 5. Differences Between the 1984 and 1983 Mean Differences In Responses to Computer Science and to Other Courses.

	Curriculum			Prior Computing		Gender	
Items	Entire Sample	Technical	Non-Technical	Yes	No	Male	Female
University A							
Reality Shock	−0.8	4.4	−7.8	3.8	−8.6	−2.7	−0.9
Confusion	−4.0	−4.9	−10.5	−5.0	−6.7	−6.3	−5.7
Control	−9.1	−16.1	−2.6	−8.1	−3.5	−9.7	−1.0
Anger	−2.3	−11.4	0.6	1.8	−7.1	−3.1	0.0
Withdrawal	−4.4	−3.8	−5.9	−1.6	−5.8	−10.1	4.5
Pride	−0.8	8.4	−7.8	−2.7	−3.9	−6.2	3.8
University B							
Reality Shock	−16.0	−16.6	−13.2	−17.7	−5.7	−14.9	−18.8
Confusion	−16.7	−21.3	5.9	−9.3	−17.7	−19.1	−10.2
Control	−11.1	−12.7	−3.2	−5.8	−15.7	−10.3	−7.4
Anger	−10.1	−16.4	20.8	−13.2	4.2	−18.4	16.9
Withdrawal	−12.7	−14.0	−6.4	−14.4	−2.7	−18.1	2.9
Pride	16.1	24.1	−22.8	16.3	10.6	22.8	−10.3

Note. University A—*N*'s are 165 for both 1983 and 1984.
University B—*N*'s are 120 and 160 for 1983 and 1984 respectively.

between computer science and other courses for technical students, males, and those with prior computing experience.

Whereas the results at University A showed a fair amount of stability across the years in the relationship between computer science and other courses, and the effects of student characteristics agreed with a priori expectations, the results at University B exhibited more instability and did not conform to these expectations. At University B, prior computing experience was the only measured characteristic that made a significant difference in how the students encountered computing in both 1983 and 1984. Students with no prior computing experience found computer science more confusing than did students who had prior computing experience ($t(126) = -4.08$, $p < .001$, 1983; $t(46) = -3.66$ $p < .005$, 1984). No other differences persisted during the two years at University B for any of the other student groups.

Multivariate Analyses

Multivariate logit analyses were performed in order to test the explanatory power of the independent variables (gender, prior computing experience, and curriculum) in a multivariate context. A dichotomized version (median split) of the average response was used for each student's noncomputing courses to control for effects attributable to first year college course work (Knoke & Burke, 1980). This variable was constructed by taking the mean of the sum of the true responses for non-computing courses for each student and then assigning a value of high or low to those scores, based on a split at the median of total scores.

The analysis was carried out in a stepwise fashion with the non-computing course value entered into the equation prior to the other variables. Gender, prior com-

Table 6. Effect of Student Characteristics on Percent of Freshmen Responding True to Socialization Items in 1984 and in (1983).

Items	Gender		Prior computing		Curriculum	
	Male	Female	Yes	No	Tech	Non-Tech
Student Characteristics, University A Freshmen						
Reality Shock						
Very different from other courses	63.2* (67.0)*	82.4 (85.3)	65.7 (64.3)*	75.4 (85.2)	61.5 (63.9)*	74.0 (80.8)
Confusion						
I feel I don't know what I am doing	25.4* (36.1)*	52.9 (66.2)	25.9* (35.7)*	49.1 (61.7)	13.8* (27.9)*	47.0 (60.6)
Control Attempts						
I talk to people who know more than I do	54.4* (75.3)*	74.5 (91.2)	53.7* (76.2)	73.7 (87.7)	47.7* (78.7)	69.0 (83.7)
Anger						
This course makes me angry	43.9* (45.4)*	68.6 (69.1)	46.3 (44.0)*	61.4 (66.7)	29.2* (41.0)*	66.0 (63.5)
Withdrawal						
I want to do just enough to get by	25.4 (26.8)	31.4 (32.4)	24.1 (22.6)	33.3 (35.8)	13.8* (14.8)*	36.0 (37.5)
Pride						
I feel proud of my performance	43.0 (45.4)	43.1 (39.7)	47.2 (47.6)	35.1 (38.3)	63.1* (49.2)	20.0 (39.4)
Recruits	29.8 (30.9)*	27.5 (19.1)	34.3* (29.8)	19.3 (22.2)	47.7* (29.5)	17.0 (24.0)
Student Characteristics, University B Freshmen						
Reality Shock						
Very different from other courses	52.7 (62.2)	64.5 (65.8)	49.2* (60.5)	73.7 (68.1)	55.6 (64.2)	51.9 (59.1)
Confusion						
I feel I don't know what I am doing	17.1 (35.6)	22.6 (36.8)	10.7* (23.5)*	42.1 (57.4)	18.8 (40.6)*	14.8 (13.6)
Control Attempts						
I talk to people who know more than I do	40.3* (70.0)	64.5 (71.1)	41.8 (64.2)*	55.3 (80.9)	45.9 70.8)	40.7 (68.2)
Anger						
This course makes me angry	32.6* (51.1)	51.6 (44.7)	30.3* (46.9)	55.3 (53.2)	33.8 (52.8)	48.1 (31.8)
Withdrawal						
I want to do just enough to get by	15.5 (33.3)	22.6 (18.4)	13.9 (27.2)	26.3 (31.9)	15.8 (31.1)	22.2 (18.2)
Pride						
I feel proud of my performance	54.3 (35.6)	35.5 (47.4)	54.1 (42.0)	39.5 (34.0)	51.1 (34.0)*	48.1 (63.6)
Recruits	41.1 (25.6)	29.0 (31.6)	42.6 (27.2)	26.3 (27.7)	39.8 (22.6)*	33.3 (50.0)

Note. University A *N*'s are 165 for both 1983 and 1984. University B *N*'s are 128 and 160 for 1983 and 1984 respectively.

*$p < .05$ for the comparison between individual student groups, eg. males and females.

Table 7. Effects of Student Characteristics on Socialization Variables for University A, 1984 and 1983 Combined.

Socialization variables	Constant	Average of Non-computing Courses	Prior Computing Experience	Curriculum	Gender	Chi-Sq	df	p
	Coefficients of explanatory variables					Goodness of fit		
Process Measures								
Reality Shock	0.595*	0.154*	−0.164*	−0.159*	−0.216*	14.10	11	0.228
Confusion	−0.104	0.152	−0.204*	−0.331*	−0.268*	17.38	11	0.097
Control Attempts	0.633*	0.246*	−0.196*	−0.094	−0.223*	7.76	11	0.734
Outcomes								
Anger	0.076	−0.151*	−0.137*	−0.259*	−0.202*	13.37	11	0.270
Withdrawal	−0.508*	0.204*	−0.108	−0.309*	−0.015	11.10	11	0.435
Academic Pride	−0.119	0.196*	0.078	0.200*	0.014	15.34	11	0.167
Recruits	−0.475*	0.024	0.101	0.199*	0.049	13.73	11	0.249

*$p < .05$ for the coefficient.

puting experience, and type of curriculum were entered into the equation simultaneously. These three variables were treated as a set because there was no theory to give precedence to one over the other and because they were somewhat statistically interdependent. Interactions were included only if an independence model proved a poor fit. Because of small cell sizes, the data for 1983 and 1984 were combined. This strategy worked quite well for University A due to the stability of relationships across the years, but did little to reveal systematic relationships in the data for University B. Therefore, the results presented next apply to University A only.

Inspection of Table 7 demonstrates the importance of general adaptation to college, gender, prior computing experience, and type of curriculum as explanatory variables in understanding the socialization of freshmen to computing. The coefficients reported reflect the change in the log of the odds ratio for those answering true over those not answering true. If the χ^2 statistic is roughly equal to the number of degrees of freedom, then the model is accounting for a significant proportion of the systematic variation in the data. A p-value of greater than .1 indicates random variation in the residuals. In general, positive encounters with other courses, being male, having prior computing experience, and being in a technical curriculum all made separate contributions toward the likelihood of a positive encounter—or unlikelihood of a negative encounter—with computing at University A.

DISCUSSION

This research has used a cultural socialization approach to explain why computer science can be relatively alienating to college freshmen in comparison to other courses. Within this framework the students most likely to become cultural dropouts are female liberal-arts students with no computing experience prior to college. The students most likely to become cultural recruits are male science and engineering students with computing experience prior to college. These effects were much stronger and more stable over time at the research-oriented university. The findings suggest that introducing computing is not simply imparting technical skills. The cultural experience is also important.

This study has several limitations. Among them, the measures were based on self-report and were collected only once. The study could be strengthened by measuring experience at more than one point in time and by collecting behavioral data on the long-term impact of early cultural experiences.

Given the data at hand, we believe that differences in the pattern of results across the two universities can be explained by differences in the strength of the computing culture at the two universities. At University A where the culture is stronger, the results are strong, internally consistent, and stable over time. The introductory computing courses were taught by computer science faculty members who might have been perceived as hostile gatekeepers by many students.

At University B, by contrast, the culture and environment were not stable during the period under investigation. In 1983 nontechnical students took introductory programming courses taught by nontechnical faculty while technical students took their courses from the computer science faculty. A cultural perspective would interpret these differences this way: gatekeepers for the "true" culture would provide stringent tests of competence and harsh initiation rites while "tour guides" for visitors would provide pleasant and welcoming experiences. A cultural perspective would suggest that in this situation technical students would be more alienated than nontechnical students. In fact, the outcome results presented in Table 4 suggest this: nontechnical students were more positive than technical students towards computing in 1983. By 1984, the computer science department at University B was exerting more influence over initial encounters. In this year both technical and nontechnical students took their introductory programming courses from computer science faculty. The proportion of recruits among technical students rose from the previous year while the same proportion for nontechnical students decreased.

The data suggest that individual ability is insufficient to explain differences in reactions to computing. Although this possibility was not examined directly through such variables as IQ, SAT scores, or GPA, the "average of non-computing courses" variable (see the logit analyses reported in Table 7) serves as a weak proxy for generalized ability. If only ability were operating, then that variable alone should have produced a good fit to the data. It did not. Being male, previous experience with computing, and interest in technical subjects (as evidenced by enrollment in a technical curriculum) all contributed to the probability of positive computing experiences, in addition to the contribution made by generalized ability.

Several implications can be suggested for altering learning experiences to ameliorate some of the negative reactions found in this study. One is to provide a competence-based introduction to computers and computing prior to introducing programming. Most university computing environments are varied enough that simply giving students familiarity with different machines should be helpful. Another is to insure that students have positive and successful experiences with computing early on in order to bolster their confidence. At some universities these experiences center on using word processing and document formatting programs to produce papers in freshman writing courses. A third suggestion centers on providing helpful peer tutoring and consulting. Recognizing the power of the computing culture however, it is insufficient simply to hire students with technical skills and expect them to be good consultants. (Several years ago the student consultants in one university were called "user confusers.") They must be trained in how to help in a way that is useful to the client. They should also have incentives to be helpful, rather than, for instance, to be impressive or superior. Such incentives might include bonus pay for positive evaluations from clients.

In one sense, the topic of this paper is transitory. Ten years from now very few people will have their first encounters with computing in college—everyone will have had experience with computing in elementary and high schools or at home. Because the nature of students' pre-college experiences with computing were not examined in this study, it is not possible to determine exactly why earlier experience for students in our sample helped them in college. Skills learned by most students in the lower grades are different from those learned in college, and the culture of computing is only faintly represented in schools. But skills learned in school probably include familiarity with computer keyboards and computer algorithms. Using a computer in school or at home entails exposure to the language and conventions of computing, and even to young computer hackers. These various exposures might inoculate students against experiencing computing as alien, just as travel in childhood, learning a foreign language, and the study of cultural variation inoculates people against culture shock when they visit or live abroad. Alternately, if students have negative experiences in the early grades, these may well have particularly serious consequences in reducing students' interests in technical fields and affecting their self-images of technical ability.

The effects of gender and specialized interests on socialization to computing may not be transient, however. In our research, these characteristics contributed to socialization outcomes even controlling for prior experience with computing in University A (Table 7) and they show strong univariate effects in University B (Table 6). Of course, it is probably not important that everyone pursue computing skills. But if gender is associated with skills or affective orientations that are strongly associated with later economic rewards or the paths to pursue them, then structural discrimination can result (Hearn, 1980). The case of mathematics is illustrative. Women are less likely than men to be interested in and take college level courses in mathematics. This pattern effectively closes women out of many career options (Ernest, 1976; Randour, Strasburg, & Lipman-Blumen, 1982; Sells, 1973). A similar pattern could emerge for computer science.

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