

Stereotypical Descriptions of Computer Science Careers Are Not Representative of Most Computer Scientists

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Abstract

Using data from a large self-initiated online survey, we find that the career interests of many current and aspiring computer scientists diverge from the official profile of computer scientists established and promoted by the U.S. government – specifically that from the Department of Labor’s Occupational Information Network (O*NET). Five distinct profiles of career interests emerged from the data. Latent profile analysis suggests that many women in the profession value social and artistic expression in a way not currently recognized by official representations of computer scientists’ interests. Better admitting to a more nuanced and comprehensive picture of those interests has important implications for career guidance and workforce development and might help to address women’s underrepresentation in this STEM discipline.

Introduction

Accurate information about the characteristics of jobs and the workers who fill them is critical for career guidance, reemployment counseling, workforce development, and human resource management (1-2). To meet these needs, the U.S. Department of Labor maintains a publicly available database that provides official comprehensive descriptions for over 900 occupations (www.onetonline.org). Official descriptions of computer science (CS) related occupations create the impression that computer scientists are relatively uninterested in social tasks (working with, communicating with, and teaching other people; 2-3). This description is aligned with the “geek-programmer” stereotype, which casts computer scientists as socially awkward and unsociable (4).

Information that confirms the “geek-programmer” stereotype may lead women to “opt-out” of CS careers (5). It is widely acknowledged that people pursue careers they perceive to be aligned with their occupational interests, or preferences for work-related activities and contexts (6). A long history of research suggests that gendered socialization causes women to be more interested in social tasks that allow them to interact with and help others (5-9). To the extent women perceive their social interests to be mismatched with the work environment and those who occupy it, women may be reluctant to pursue careers in CS (4;5;9). However, the extent to which computer scientists are uninterested in social tasks is debatable.

Despite being presented as representative, the U.S. government’s official profiles of computer scientists’ interests are not informed by actual computer scientists but by the subjective judgement of graduate students in vocational psychology, who may not have any particular experience in the professions they characterize (2, 11). Relying entirely on the human judgment of psychology graduate students to create official interest profiles as it does (2,10-11), official statistics may inadvertently perpetuate biases about who should, and should not, pursue careers in CS. Such statistics are widely used by a wide array of private citizens, educational institutions, and other organizations promoting career and workforce development (2).

The present study is the first to test whether official depictions of the career interests of computer scientists reflect realities in the early 21st century. To do this, we describe the occupational interests of actual and aspiring computer scientists – known as interest profiles. We then compare these interest profiles to those assumed by the U.S. government. We find that actual profiles are not just more varied than assumed – but may also appeal to women more readily.

We used Latent Profile Analysis (LPA), a probabilistic and person-centered statistical technique (12), to identify groups of people (i.e., latent profiles) who share similar response patterns to the dominant framework of vocational interests: Holland's RIASEC model that characterizes interests as: Realistic (i.e., interest in practical tasks), Investigative (i.e., interests in analytic activities), Artistic (i.e., interests in creative work), Social (i.e., interests in working with others), Enterprising (i.e., interests in selling, leading), and Conventional (interests in working with numbers and machines; 3). These occupational interests are described further in the Methods section. Following best practices (13), we conducted two LPAs using samples of 500 people randomly selected from the following two groups: (1) interested but not employed in computer science and (2) actual computer scientists (see Method). This gave us a total sample size of 1,000.

Results

To examine the interest profiles for those interested and employed in computer science, we first conducted latent profile analyses (LPA) on each of the sub-samples: unemployed adults interested in computer science ($n = 500$) and adults employed in computer science ($n = 500$).

Profiles in this study are defined solely based on their variance on the occupational interests, allowing us to test what profiles naturally emerge for those interested in and employed in CS. Model fit indices were used to determine the optimal number of profiles. The number of profiles can differ between samples and analyses, with some models being more parsimonious (having fewer profiles) than others.

Aligned with previous research (13-16), we estimated models ranging from two to ten profiles, preferring solutions that did not have classes with a small number of individuals. We used Akogul and Erisoglu's (2017) analytic hierarchy process (AHP) to select the model with the optimal number of profiles. The AHP takes a holistic approach when considering information criteria, such as Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC), to select the best model.

The AHP has been tested on common real and synthetic datasets and found to produce more accurate results than relying on one type of information criteria alone (17). We found four distinct profiles for those employed in CS (AIC = 9827.48, BIC = 10029.78) and three profiles for those who are unemployed but interested in CS (AIC = 10045.42, BIC = 10218.22). Names and descriptions for each latent profile for both employed and aspiring computer scientists are provided in Table 1.

An official profile for CS was created by aggregating O*NET projected interest scores for each job included in the sub-samples. Latent interest profiles resembling the official profile were found in both

samples and these profiles are referred to as “Stereotypical”. However, only 30% of actual computer scientists sampled fit into the “Stereotypical” profile. The other 70% of computer scientists belonged to one of the three following groups: Artistic, Uninterested, and Multi-Interested. Figures 1 and 2 show how these distinct profiles compare to the official profile established by the US government. In corresponding colors, difference scores are provided for each latent profile, showing the distance from the latent profiles and O*NET projections for each interest type. Each of the four groups show higher social interests than the official profile.

Table 1
Descriptions of Latent Profiles Found

Sample	Group	Profile	N	% Sample	% Women	Interests	
						Higher	Lower
Employed in CS (N=500)	1	Artistic	99	20%	72%	Artistic	Realistic
	2	Uninterested	153	31%	52%	-	All Career Interests
	3	Stereotypical	152	30%	30%	Realistic Conventional	Artistic
	4	Multi-interested	96	19%	27%	All Career Interests	-
Interested in CS (N=500)	1	Artistic	204	41%	60%	Artistic	Realistic
	2	Uninterested	115	23%	44%	-	All Career Interests
	3	Stereotypical	182	36%	36%	Conventional Enterprising	Artistic

Note. Interests with scores equal or greater than 3.5 were labeled as “Higher”. Interests with scores lower than 3.5 were labeled as “Lower”.

Chi-square tests were then used to determine whether significant gender differences existed within each profile. Gender was significantly related to profile membership for both currently employed ($\chi^2(3) = 58.35, p < .001$) and aspiring ($\chi^2(2) = 21.65, p < .001$) computer scientists. Groups containing relatively larger proportions of women least resemble the official profile (see Fig. 1). Across samples, the Artistic group contained the largest proportion of women and differed the most from the official profile. Differing the least from the official profile, the Stereotypical groups are made up predominantly of men.

Discussion

The central finding of this investigation is that the occupational interest profiles of computer scientists are more diverse than previously assumed. The U.S. Department of Labor has portrayed computer scientists as relatively uninterested in social tasks (18). We found the interest profiles of actual computer scientists do not reflect this pattern and are generally much more varied. The social interests of actual and aspiring computer scientists appear to be widely underestimated. While computer scientists are generally portrayed as having very little interest in social tasks (4-5,14), we found they actually have moderate to high social interests.

Men and women also differed in their profile membership. Aligned with previous research (5, 7-9), we found women to be over-represented in profiles with high interest in social tasks. For example, the group that is most interested in helping others and creating things (i.e., Artistic) are over-represented by women in both samples. Therefore, the argument that women opt out of CS careers due to a lack of interest appears to be built on faulty premises, both about the actual interests of women and about the characteristics of CS jobs. All occupational profiles, regardless of gender, showed higher interest in social tasks than officially reported. Computer scientists appear to have a diverse set of interests, and many are interested in working with and helping others.

Women's lack of representation in CS careers not only denies society the advantage of their abilities and perspectives but also limits their participation in many well paid, high-growth professions (5). Displaying a more nuanced and comprehensive picture of computer scientists' interests might help address women's underrepresentation in CS. Unfortunately, that nuance is not often captured in the US government's standard recommendations. To the extent that current recommendations are internalized, and used in practice, by teachers, mentors, and others, people may be discouraged from CS careers who might otherwise be engaged and successful. Therefore, we urge guidance counselors, researchers, and policy makers to use these official profiles with caution until more resources are focused toward collecting and maintaining high quality data.

Methods

84,394 participants were passively recruited via an online survey posted to Time Magazine's website to create the largest database of occupational interests to date. At the time of writing, Time, an American weekly newsmagazine, reports a readership of 26 million, with about 80% of Time readers living in the United States. Time Magazine's digital audience is roughly split by gender, with slightly more women (56%) visiting their website than men (19). The survey was advertised on Time's website as a way for readers to "find out what job best matches [their] personality". As of July 2021, this survey can be found by going to <https://time.com/4343767/job-personality-work/>.

The survey asked participants to identify their job if they self-identified as being currently employed and identify their aspirational ("dream") jobs if they self-identified as unemployed before responding to 20 questions about their interests in different types of work activities. At the end, participants were given a visual comparison of their interest in different tasks to the characteristics typical of their current or dream

job. We were granted approval to use this data by the Institutional Review Board (IRB) at North Carolina State University (IRB protocol #14112). Because data was collected passively on Time Magazine's website, informed consent was not collected for this portion of the study. However, all research was performed in accordance to the approved IRB protocol and relevant guidelines. No identifying information about study participants was shared with the researchers.

Sample

Any English-language reader of time.com was eligible to participate; however, only respondents from the United States and 18 years or older were included in this study. Consistent with the magazine's readership, those included in our final sample (N= 40,646) were mostly employed (76.58%) and women (64.6%). Most were educated and reported having either an undergraduate (43%) or postgraduate degree (36%). Different ages were well represented. Of those who disclosed their age (98%), 18% were between the ages of 18-25 years old, 22% between 26-33 years old, 25% between 34-45 years old, 17% between 46-55 years old, 12% between 56-65 years old, and 4% were over the age of 66.

From this larger sample, we randomly selected 500 participants from the following two groups: (1) employed in CS and (2) unemployed and interested in CS.

Employed in CS

From the larger sample described above, we randomly selected 500 participants who were employed in CS-related careers. The demographics of this group were similar to the group of aspiring computer scientists (described below). Of these 500 computer scientists, 56% were men and 44% were women. Most participants had either an undergraduate (49%) or postgraduate (33%) degree. This sample represented the ages typical of working Americans. Only 11% were between the ages of 18-25 years old, 28% between 26-33 years old, 32% between 34-45 years old, 17% between 46-55 years old, 11% between 56-65 years old, and only 2% were 66 years old or older.

Unemployed and Interested in CS

We also randomly selected 500 participants from the larger sample who identified themselves as being unemployed and interested in CS related careers. Of these 500 individuals, 52% were men and 48% were women. Like the larger sample they were selected from, most had either an undergraduate (43%) or postgraduate (29%) degree. Different ages were also well represented; 26% were between 18-25 years old, 17% between 26-33 years old, 19% between 34-45 years old, 12% between 46-55 years old, 13% between 56-65 years old, and 12% were 66 years old or older.

Individual-Level Occupational Interests

A shortened version of the popular Personal Globe Inventory (PGI; 20-21) was used to assess individuals' occupational interests. This shortened version was developed using item response theory (22) and has been validated (21-22). Participants were asked how much they enjoyed 20 different work activities on a scale from 1 ("Strongly dislike") to 7 ("Strongly like"). Each activity is tied to one of the following six

RIASEC career interest types: Realistic, Investigative, Artistic, Social, Enterprising, and Conventional. For each interest type, the corresponding definitions, reliability coefficients, and items are listed below. Reliability was calculated using the larger, overall sample as described in Glosenberg et al., 2019.

- **Realistic** (omega reliability coefficient = .78): Involves concrete practical activities and the use of machines, tools, and materials. Realistic interests were measured by asking participants how much they would enjoy the following tasks: (1) Install electrical wiring and (2) Oversee building construction.
- **Investigative** (omega reliability coefficient = .65): Involves analytical or intellectual activity aimed at troubleshooting, creative or knowledge use. Investigative interests were measured by asking participants how much they would enjoy the following tasks: (1) Categorize different types of wildlife and (2) Write a scientific article.
- **Artistic** (omega reliability coefficient = .92): Involves creating work in music, writing, performance, sculpture, or unstructured intellectual endeavors. Artistic interests were measured by asking participants how much they would enjoy the following tasks: (1) Sculpt a statue, (2) Paint a portrait.
- **Social** (omega reliability coefficient = .63): Involves working with others in a helpful or facilitative way. Social interests were measured by asking participants how much they would enjoy the following tasks: (1) Seat patrons at a restaurant, (2) Interview people for a survey, (3) Help children with learning problems, and (4) Teach people to dance.
- **Enterprising** (omega reliability coefficient = .70): Involves selling, leading, and manipulating others to attain personal or organizational goals. Enterprising interests were measured by asking participants how much they would enjoy the following tasks: (1) Oversee a hotel, (2) Manage an office, (3) Interview people for a survey, and (4) Seat patrons at a restaurant.
- **Conventional** (omega reliability coefficient = .85): Involves working with things, numbers, or machines to meet predictable organizational demands or standards. Conventional interests were measured by asking participants how much they would enjoy the following tasks: (1) Prepare financial reports, (2) Oversee a data analyst group, (3) Maintain office financial records, and (4) Manage an electrical power station.

Official O*NET Occupational Interest Profiles

Occupational Interest Profiles (OIPs) were assessed using the RIASEC scores assigned to each job by the U.S. Department of Labor's detailed occupational database of incumbent workers, the Occupational Information Network (23-24).

To calculate Occupational Interest Profiles (OIPs), O*NET used two teams of three vocational psychology graduate students to establish interest scores for each occupation included in their database. These teams read information about each job's tasks, requirements, and generalized work activities to provide RIASEC ratings for over 900 jobs. Although the information provided to raters (e.g., job's tasks, requirements, work activities) is gathered by a stratified randomized sampling and surveying of actual job

incumbents across the United States (24), the teams of graduate students, and these teams of graduate students alone, decided the appropriate interest profiles for each job.

Participants of our survey identified their job title using a dynamic keyword search that matched their entered job title in lay terms (e.g., teacher, farmer) and the exact job titles used by O*NET (e.g., elementary school teachers, farmworkers). Through this system, we were able to match each participant to their current/dream job's interest scores projected by O*NET via occupational codes.

Occupations Categorized as CS

We recruited 442 participants from Amazon Mechanical Turk (Mturk) to categorize 80 job titles randomly selected from a bank of 707 into one of the following groups: (1) CS (i.e., those requiring some form of experience in computing), (2) STEM (i.e., those requiring some form of experience in science, technology, engineering, and/or mathematics), (3) Non-STEM (i.e., those requiring experience in neither STEM nor computing), or (4) Unsure (i.e., job titles they were unfamiliar with and did not know how to sort). This research was approved by the Institutional Review Board (IRB) at North Carolina State University (IRB protocol #14159). Informed consent was obtained from all participants. All research was performed in accordance with the approved protocol and relevant guidelines. No identifying information about study participants was shared with the researchers.

Each job was categorized by 5 to 26 raters, with most jobs assigned 14 raters. The average interrater agreement (25) for raters' individual categorization of job titles was strong ($rwg = .87$; 26). Of the 707 jobs classified, 46 were identified as CS and the remainder were classified as STEM or neither. These 46 job titles are provided in Table 2.

Table 2
Job Titles Characterized as CS and Included in the Final Samples

Job Titles	N
Market Research Analysts and Marketing Specialists	109
Software Developers, Applications	88
Graphic Designers	69
Information Technology Project Managers	62
Computer and Information Systems Managers	55
Computer Programmers	50
Operations Research Analysts	45
Computer Systems Analysts	45
Computer and Information Research Scientists	42
Web Developers	37
Computer User Support Specialists	35
Software Developers, Systems Software	31
Network and Computer Systems Administrators	27
Business Intelligence Analysts	25
Computer Hardware Engineers	24
Intelligence Analysts	24
Database Administrators	23
Information Security Analysts	22
Search Marketing Strategists	16
Securities and Commodities Traders	16
Software Quality Assurance Engineers and Testers	14
Database Architects	13
Desktop Publishers	12
Computer, Automated Teller, and Office Machine Repairers	11
Computer Network Architects	10
Data Entry Keyers	10
Quality Control Analysts	9

Job Titles	<i>N</i>
Video Game Designers	9
Logistics Managers	9
Air Traffic Controllers	9
Sound Engineering Technicians	8
Computer Systems Engineers/Architects	8
Computer Network Support Specialists	7
Audio-Visual and Multimedia Collections Specialists	4
Financial Quantitative Analysts	3
Logistics Analysts	3
Quality Control Systems Managers	3
Computer Science Teachers, Postsecondary	3
Clinical Data Managers	2
Computer Numerically Controlled Machine Tool Programmers, Metal and Plastic	2
Data Warehousing Specialists	1
Robotics Technicians	1
Web Administrators	1
Geographic Information Systems Technicians	1
Microsystems Engineers	1
Gaming Supervisors	1
Grand Total	1000

Note. *N* = number of people who categorized the corresponding job title as CS.

Declarations

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Author contributions:

Conceptualization: JEM, TSB, AG

Methodology: TSB, AG

Formal Analysis: JEM

Investigation: JEM, TSB, AG

Visualization: JEM

Project administration: JEM

Supervision: TSB, AG

Writing – original draft: JEM

Writing – review & editing: TSB, AG

Competing interests: The authors declare no competing interest.

Data and materials availability: The sample of 84,394 employed and unemployed adults who took our occupational interest survey posted on an internationally popular English-language news website are available at <https://osf.io/be5ja/>. This data is further described in doi:10.1016/j.jvb.2019.01.002. The sample of 442 adults who categorized 47 job titles as CS (which are listed in *Table 2*) are available at https://osf.io/f5nm/?view_only=7b9360268ba14b40a0e051cf3a5020ef.

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Figures

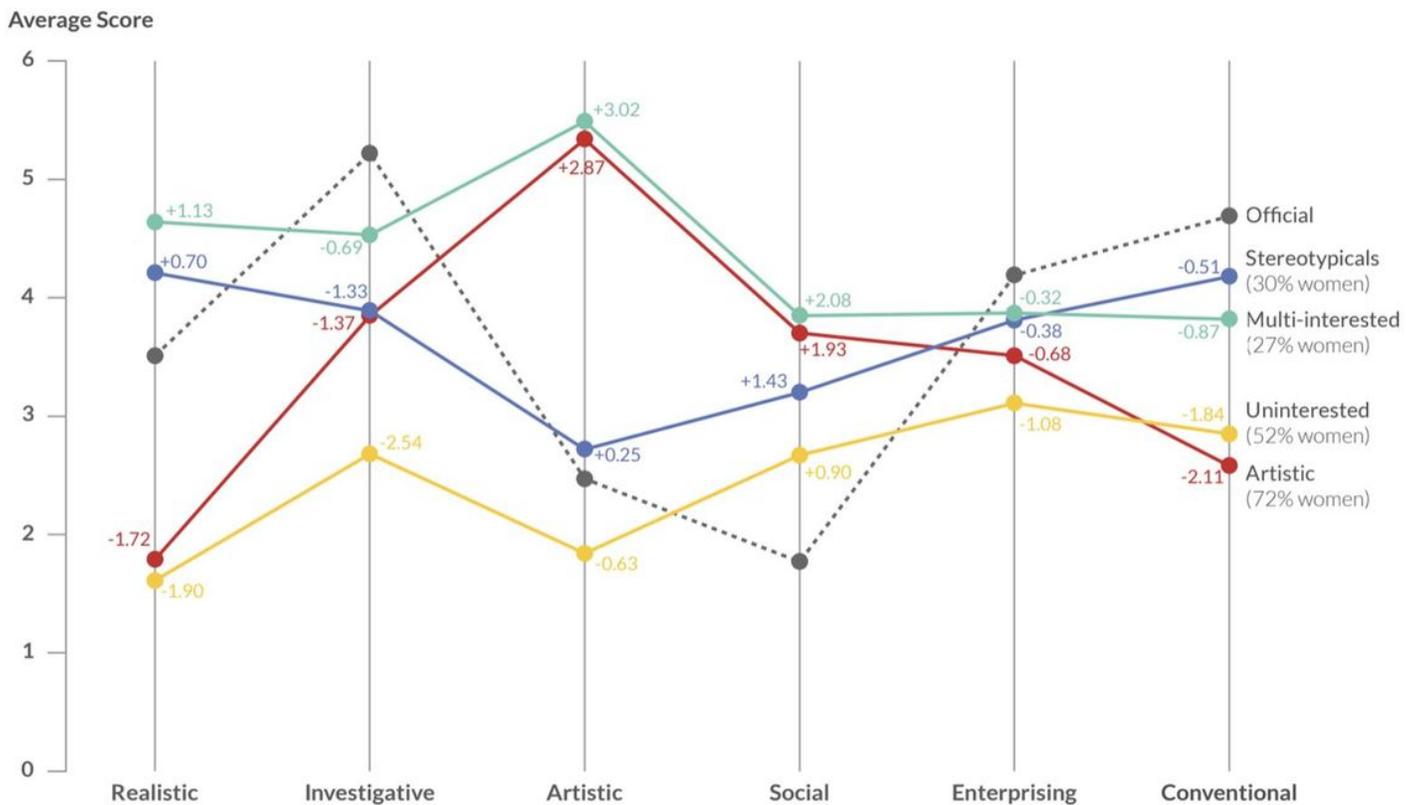


Figure 1

Interest Profiles of Employed Computer Scientists Compared to the Official Profile.

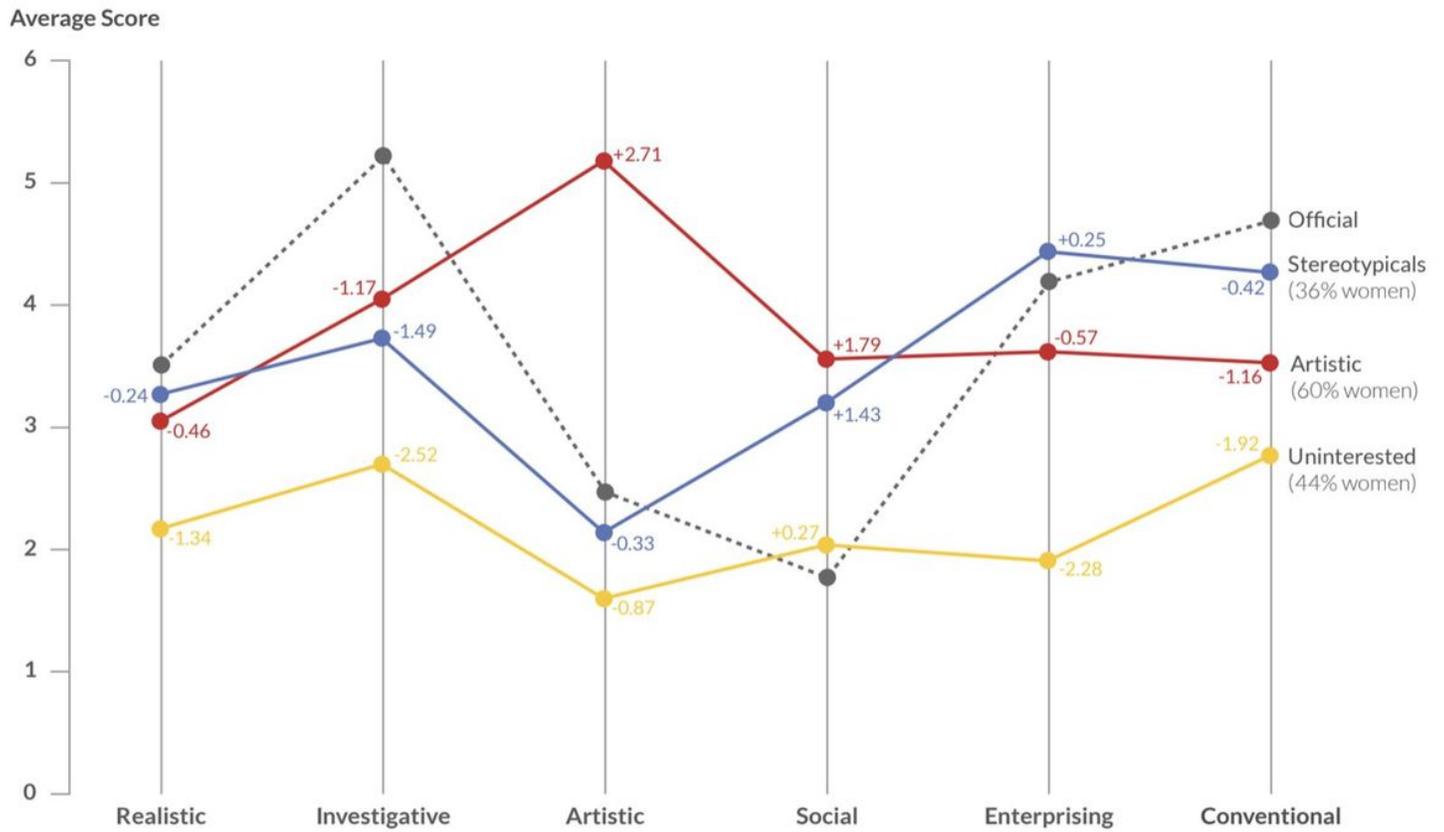


Figure 2

Interest Profiles of Those Interested in CS Compared to the Official Profile.