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Examining Rural Identity Among High School Computer Science Students

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Abstract

Students in geographically rural areas of the United States have less access to computer science education and are underrepresented in computer science majors and careers. At the same time, many rural occupations such as agriculture are becoming reliant on technology, and there is a need for skilled computer scientists with a rural background and skillset to develop effective tools and software that can be used in those occupations.

In addition, the values of grit, determination, self-sufficiency, and perseverance often studied in rural populations are also attributed to successful computer scientists. Given the need for rural students to participate in computer science careers, and the overlap in rural values and the qualities of good computer scientists, why do rural students not see themselves as future computer scientists, and why are they not interested in computer science majors and careers?

In this paper, we examine the geographical definition of "rural" as used by many researchers (based on the definition from the National Center for Education Statistics NCES) that is often applied homogenously across a school district or even entire county. We explore and validate a survey instrument used to measure "rural identity" of students at the individual level. In doing so, we discover a more broad and nuanced definition of "rural" that varies widely within individual schools.

By analyzing this rich dataset, we build the case that defining individual students as "rural" based on geographical location is insufficient to account for variances in their interest in computer science careers and their own self-identity as someone who could be a computer scientist. We use this information to inform future research and propose new avenues for engaging "rural" students in computer science.

1 Introduction

The Computer Science For All Initiative [1] set a goal of "offering every student the hands-on computer science and math classes that make them job ready on day one" [2]. Previous research has shown that rural students have less access and less participation in computer science education than their urban peers [3]. In fact, approximately one in five students in the United States who attend rural schools have been labeled "The Forgotten 20%" [4] due to the achievement gap compared to non-rural schools.

Although increasing *access* to computer science education in rural areas is one part of the solution, what is often overlooked in this discussion is the need to increase rural students' *interest* in learning computer science and pursuing further education or careers related to computer science. Rural middle and high school teachers in our professional development program [5] often report that they struggle to recruit enough students to enroll in their classes.

Previous work explored student identity, mindsets, and motivations related to studying computer science [6] and other STEM fields such as physics [7]. However, that research does not explicitly explore differences between rural and non-rural students, making it difficult to apply to a rural population.

Recently, researchers have identified a new phenomenon in rural areas that causes a strong *rural identity* that may play an important role in worldview and decision making. This rural identity remains largely unexamined in the realm of computer science education; however, understanding it may lead to better methods to increase rural student interest in computer science.

We propose a definition of and a scale to measure the strength of rural identity among middle and high school students studying computer science. We also examine correlations between rural identity and computer science interest and identity. We aim to provide rural identity questions to add to future surveys, enabling useful intersectional analysis of rural identity and other factors contributing to student interest in computer science.

Specifically, we pose the following research questions:

RQ1: To what extent does our measure of rural identity correlate with other measures of ruralness within this population

RQ2: Is rural identity homogenous within a school district?

RQ3: What correlations are there between rural identity and motivation toward or interest in computer science education or careers?

2 Literature Review

2.1 Rural Student Research Gap

Research on engaging rural students in computer science (CS) education is sparse but increasing. A search for the keyword "rural" among SIGCSE sponsored articles in the ACM Digital Library carried out in September 2024 yielded 147 research article results, 39 of which have been published only in the last two years.

Much of the previous research on the participation of rural students in computer science is focused on the lack thereof [8, 9, 10, 11]. For example, Warner et al. in Texas found that all racial and ethnic subgroups in their study had less access to computer science education and less participation in computer science in rural areas than the baseline across the entire state for each subgroup [3].

Other research focuses on specific interventions, such as the introduction of a particular tool (e.g., Alice [12]), device (e.g. robots [13, 14, 15, 16]), or concept (e.g., game design [16]) to increase student interest. Additional research on rural student access to CS is situated within the context of a particular country (e.g., El Salvador [14], Chile [17]).

A further area of emphasis is the introduction of CS to Native American students [18, 19, 20], who themselves are often located in rural areas. In addition, research has focused on embedding CS in other rural K-12 classes [21], such as language arts [15] or mathematics [22].

Finally, a major area of emphasis in existing research is developing and examining training programs focused on K-12 teachers serving rural areas [17, 23, 16, 24, 25, 26, 27, 5]. This is an important piece of the puzzle, since quality CS education is based on the availability of teachers capable of teaching the material, especially in rural areas that struggle to recruit teachers at all.

Unfortunately, very little of the research found explores why rural students choose to study or not study computer science, whether they see themselves as a future computer scientist, and how a student's rural identity may impact that decision. In fact, students themselves are often not surveyed at all, most likely due to the difficulty in collecting consent and survey data from students spread across multiple schools.

Several notable papers examine rural student interest in CS. Qazi et al. discussed the introduction of the Exploring Computer Science (ECS) curriculum to many schools throughout Alabama, including several rural districts primarily serving African-American students. They measured student interest and confidence in CS, and most of the responses averaged 3.5 - 4.0 on a 5-point Likert scale [28]. Hu et al. described a similar project that brought ECS to students in Utah in 2016 and also included many rural schools [29]; unfortunately, no student data was presented in that article.

2.2 Rural

Much of the existing research regarding rural participation in CS uses a location-based approach to determine what constitutes rural vs. non-rural, but often definitions are not clearly defined. Alas, there are many competing definitions of what it means to be "rural" in education.

The United States Department of Agriculture (USDA) distinguishes metro counties by population size and nonmetro counties by degree of urbanization and adjacency to a metro area. This definition is often used in agricultural and economics research, but the granularity is at the *county* level. For states with fewer, large counties, it may not accurately depict how quickly an urban or suburban area can transition into a rural area, as those transitions largely do not follow county borders when applying a locale-based approach.

The National Center for Education Statistics (NCES) defines four different locale types (urban, suburban, town, rural), each with three different subtypes, and assigns each a unique two-digit locale code [30]:

- **City**
  - 11 Large: Inside principal city of 250,000 or more
  - 12 Midsize: Inside principal city of 100,000 to 250,000
  - 13 Small: Inside principal city of <100,000

- **Suburban**

  21 Large: Outside large city but in urbanized area

  22 Midsize: Outside midsize city but in urbanized area

  23 Small: Outside small city but in urbanized area

- **Town**

  31 Fringe: Inside urban cluster <10 miles from urbanized area

  32 Distant: Inside urban cluster 10 - 25 miles from urbanized area

  33 Remote: Inside urban cluster >35 miles from urbanized area

- **Rural**

  41 Fringe: <5 miles from urbanized area or <2.5 miles from urban cluster

  42 Distant: 5 - 25 miles from urbanized area or 2.5 - 10 miles from urban cluster

  43 Remote: >25 miles from urbanized area and >10 miles from urban cluster

This definition is a bit more granular than the one provided by the USDA, operating at the school district level instead of the county level. Under this scheme, more than 40% of the schools in the United States are situated in either **town** or **rural** locales [31].

This is the definition of "rural" most commonly used in education research, and it is sensible for any projects that discuss the lack of access to CS education in rural schools to use this definition as those concerns are mostly due to the school being situated in a *rural location*, often with fewer resources than a non-rural school.

However, we believe that defining "rural" in terms of a locale is not the appropriate definition to use when examining student interest and motivation to study CS, since decisions are not driven solely by location, but by the identity of the students themselves. Although it may be derived from that location, interest and motivation may also be impacted by other factors. Grouping an entire school of students together under a single heading ignores the individual nuances that we actually want to study and influence.

In our own experience, we have observed that students in rural schools possess a wide range of identities, both influenced by their rural locale but also by their own experiences and interests. In effect, we feel that rural identity is not homogeneous within a school district and should not be treated as such. So, in order to properly study "rural" as an identity, we must first develop a working definition of identity.

2.3 Identity

Formation of identity is an important component of modern education [32]. In fact, previous research in CS education has examined the overlap between a student's own identity and the perceived identity of a computer scientist as a predictor of success [6]. In order to properly discuss rural identity, we must first determine how identity is defined.

Gee discusses four different ways to view identity [33]:

- Nature-Identity (e.g. "I am a twin")
- Institution-Identity (e.g. "I am a professor")
- Discourse-Identity (e.g. "I am charismatic")
- Affinity-Identity (e.g. "I am a Trekkie")

These identities are derived from a source of power, such as ones applied by an institution or developed within the discourse of a group, but are only applicable if they are recognized by both the person to whom they are applied and others.

Similarly to Gee's concept of a discourse-identity, Sfard & Prusak discuss the importance of defining identity through narrative. Specifically, they discuss a special type of identity that consists of stories a person tells to themselves about themselves, stating that these stories are "usually intended when the word identity is used unassisted by additional specifications... the first-person self-told identities are likely to have the most immediate impact on our actions" [34]. They also note the difference between an *actual identity*, which a person already has, and a *designated identity*, which is an identity that a person aspires to obtain. This concept of designated identity is therefore extremely important for educational research.

Noting the lack of a clear definition of identity in social science research, Abdelal et al. propose a framework to define and measure identity, with the stated goal of positioning "identity as a variable" in research [35]. Their proposed framework for measuring identity consists of understanding the *content*, or meaning, of the identity through the analysis of the constitutive norms, social purposes, relational comparisons, and cognitive models present within the identity. Their framework also includes the degree of *contestation*, or agreement, within the group that holds a shared identity, as each person may view the identity in a different way [35]

To measure identity, Abdelal et al. suggest many methods, including analysis of the discourse within a group, the content produced by the group, as well as various modeling techniques and surveys. Of particular note, they state that surveys "are fairly straightforward in the way they tap into the content of identities. Their questions often inquire directly into self-described attributes, attitudes, and practices that respondents believe that they should express as a member of X social group" [35].

2.4 Rural Identity

Researchers in social sciences have recently identified a complex, shared group identity dubbed *rural consciousness* [36, 37, 38, 39] that is seen as a powerful driving force behind the worldview and decision-making process of many people in rural areas. Walsh describes the influence of this identity as operating "as a lens through which people think about themselves, other people, and public affairs, among other things" [36]. We feel that the strength of this rural consciousness identity, as shown in much of the existing research on that identity's impact on political views, is further proof that the concept of an individual's rural identity should be clearly considered within an educational setting.

For the purposes of this work, we define rural identity primarily as an affinity identity as defined by Gee, as we see rural identity as a collective shared experience that builds upon common practices within a group [33]. We also see rural identity aligned with the concept of a self-told narrative identity and actual identity as defined by Sfard & Prusak, since we feel that those who have a strong rural identity would largely self-describe themselves as rural [34]. Finally, we follow the framework and methodology proposed by Abdelal et al. by examining the constitutive norms and social purposes of the shared rural identity through the use of surveys asking about self-described attitudes and practices that make up that identity [35]. Our definition of rural identity is given in Definition 1.

Definition 1 *Rural identity in this context is an affinity for other rural persons that is primarily experienced as a self-told narrative about one's own self and actions. It is characterized by shared experiences, common practices, and social norms found primarily in rural areas.*

To measure rural identity, Oser et al. developed the Rural Identity Scale (RIS) as part of their research on health outcomes within rural populations [40]. Their definition of identity largely matches our own, making it applicable to this project. The scale consists of 15 survey questions rated on a 4-point Likert scale, with each item asking about a particular attitude, practice, or social norm found in rural communities. Their initial work sought to provide initial validation of the scale, but was limited due to the populations used, located only within a single state and not representative of a larger rural populace.

In this work, we explore the use of the RIS questions as one way to measure the rural identity of middle and high school students studying computer science.

3 Methodology

We conducted student surveys distributed to middle and high schools using our Cyber Pipeline curriculum. Each teacher who registered to use our curriculum was asked to distribute and collect parental consent forms. Students were allowed to complete the surveys in the classroom or at home at the discretion of the teacher.

A total of five surveys were distributed. All surveys and procedures were reviewed and approved by our university's Institutional Review Board (IRB):

- Rural Identity Survey
- Rural Identity Addendum
- Careers Survey (adapted from [6])
- Mindsets & Motivations Survey (adapted from [7])
- Demographics Survey

The first section of the rural identity survey was adapted from the 15 RIS items [40], replacing "county" with "community" in most of the items. Two items regarding local politics and history in the RIS were omitted as we felt they would not be as relevant to a school-age audience. All items were presented as a 5-point Likert scale, ranging from "Strongly Disagree" to "Strongly Agree." The items included from the RIS in this survey are listed below:

Q1: I feel a sense of belonging with people who live in my community

Q2: Everyone knows one another's business in my community

Q3: I exchange good or services with my neighbors (e.g., food, farm equipment, and assistance)

Q4: I go to local town hall or community meetings

Q5: I talk with a country accent

Q6: I have weekly dinners with my extended family

Q7: I plan to live in this community all my life

Q8: I follow local high school athletics

Q9: My immediate family works in land-related production and/or extraction, such as farming, raising livestock, cutting lumber, and mining

Q10: I or my family cans or preserves vegetables, fruits, and/or herbs

Q11: I go to family reunions

Q12: I go to the annual community festival or fair

Q13: My family members have lived in this community for generations

The second section of the rural identity survey inquired about a student's inspirations, mentors, experiences mentoring others, and access to computing resources. These questions were adapted from [6].

The rural identity addendum survey was distributed later in the semester to collect additional data based on initial feedback. There are three direct questions regarding rural identity on a 5-point Likert scale:

AQ1: I am a rural person

AQ2: My classmates would say I am a rural person

AQ3: I live in a rural area

It also includes a question asking the student if they live within the city limits of a city or town (yes, no, not sure) and another asking approximately how many minutes it takes to drive from home to school (integer response). Our goal is to correlate these direct measures of identity with the RIS results to see if a simpler demographic question can be used in the future.

4 Data Collection

We partnered with 25 schools, with a total anticipated enrollment of 416 students across 38 unique courses. Of these, we received parental consent forms from 13 schools, and 11 of those schools had at least one student complete the surveys.

Table 1: Survey Responses

School	NCES Locale	Responses
U1	12: Urban Midsize	9
S1	21: Suburban Midsize	8
S2	21: Suburban Midsize	20
T1	31: Town Fringe	1
T2	32: Town Distant	5
T3	33: Town Remote	26
T4	33: Town Remote	5
R1	42: Rural Distant	6
R2	42: Rural Distant	11
R3	43: Rural Remote	3
R4	43: Rural Remote	12
		$N = 106$

Since this work relies primarily on the results of the rural identity survey, responses to that survey were collected first. We received 192 total responses. Of that number, five student responses were removed due to students opting out. In the case of duplicate but complete responses, the earliest response for each student was kept. A response was considered complete as long as all questions on the rural identity scale were completed, even if later questions were omitted. An additional 81 responses were removed as duplicate responses, incomplete responses, or due to lack of parental consent, leaving a total of 106 valid responses. A list of anonymized school districts, locales, and the number of valid responses received can be found in Table 1.

The responses to the other surveys were collected and matched with the valid responses from the same student to the rural identity survey. A total of 72 responses were matched from the careers survey, 76 responses from the mindsets & motivations survey, 70 responses from the demographic survey, and 11 responses from the rural identity addendum. Once all data was matched and verified, all identification information was removed from the data and the school districts were randomly named according to the NCES locale codes.

5 Data Analysis

5.1 Principal Axis Factoring

We first performed an Exploratory Factor Analysis (EFA) procedure on the 13 questions included from the RIS to determine whether all measured variables loaded onto a single factor or multiple factors [41]. Given that we believe that rural identity data may not be normally distributed (e.g., bimodal, with students either strongly or not strongly feeling connected to a rural identity), we performed the Principal Axis Factoring (PAF) technique since it is appropriate for such data [41]. This assumption was confirmed using the Shapiro-Wilk normality test on each individual item, where observed p values were much less than the

$p > 0.05$ standard for a normally distributed variable; therefore, the responses to individual items of the RIS were not normally distributed. This follows the framework used by Oser et al. in the original analysis of the RIS [40].

Cronbach's alpha α was used as a measure of the internal consistency of our survey. Our data produced $\alpha = 0.81$, which is considered good. Removing any single item did not increase reliability ($\alpha = [0.79, 0.81]$). Therefore, we believe that the survey is internally reliable and consistently measures a single characteristic.

To perform PAF, we followed the process described in [42] using R version 4.4.2. We started by determining whether the data were suitable for PAF. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy determined if enough data had been collected to perform factor analysis. The KMO value for our data was 0.8, which is considered good. Next, we used Bartlett's Test of Sphericity to verify the null hypothesis that variables are unrelated. Our data yielded $\chi^2(78) = 317.318, p < 1e - 29$, with a p value less than 0.05 indicating that the correlations are large enough for factoring. Finally, checking the determinant of the correlation matrix tests if the variables are too highly correlated. The determinant of our dataset was 0.041, which is greater than 0.00001, which indicates that it is suitable for analysis [43].

Several criteria were considered when determining the number of factors to analyze. First, Kaiser's criteria of eigenvalues greater than 1 led to a single factor solution, though it is worth noting that one of the eigenvalues was exactly 1 so a two factor solution is also supported. Analysis of the scree plot of eigenvalues also suggested a two-factor solution. Finally, prior work on the RIS would indicate that a one-factor solution is expected. We chose to analyze models extracting both one and two factors. Each model was explored using orthogonal (varimax) and oblique (oblimin) rotation. The oblimin rotation was chosen as the preferred model as we believe that the factors present in the data are correlated.

We considered items with a factor loading of 0.40 significant. A single factor solution yielded 11 items with significant loading. This accounted for 26% of the total variance. The two-factor solution had five items loaded in the first factor and three items in the second factor, which is a total of 31% of the total variance. An item that was loaded on both factors was omitted. The items and significant factor loadings greater than 0.40 are shown in Table 2.

While the two-factor solution does produce some interesting results and may provide the basis for future work, we will use the single-factor solution for the rest of this analysis as it fits most closely with the prior work already performed on this scale by the original authors.

5.2 Correlations

Using the factor loadings of the single-factor solution above, we computed a weighted rural identity (WRI) measure based on responses to the RIS survey for each student. The Shapiro-Wilk normality test on the resulting data produced $p = 0.80$, much larger than the $p > 0.05$ standard; therefore the new WRI measure is normally distributed. The mean WRI value was 1.40 with a standard deviation of 0.38. Larger WRI values indicate a stronger rural identity.

Table 2: Significant Factor Loadings

Item	**1 Factor**	**2 Factor A**	**2 Factor B**
Q1	0.46	0.61	
Q2			
Q3	0.65		
Q4	0.48		0.63
Q5	0.47		0.58
Q6	0.45		0.56
Q7	0.50		
Q8	0.49	0.66	
Q9	0.66	0.44	
Q10	0.55		
Q11	0.44		
Q12		0.45	
Q13	0.63	0.53	

Next, we performed an exploratory analysis in Excel by computing the Pearson's correlation coefficient ρ between the WRI and other measured items from the various surveys, examining any interesting results. All survey items were presented as a 5-point Likert scale. In our review, Pearson's correlations $\rho > 0.30$ were considered interesting and $p < 0.01$ significant. The results of this analysis are presented in Table 3.

5.3 Homogeneity Of Rural Identity

We also examined the homogeneity of rural identity within each school district using a scatter plot. That data is presented in Figure 1

6 Results

6.1 RQ1 - Rural Identity Correlation To Ruralness

We examined how well the WRI (calculated from the RIS after factor analysis) correlated with other ways to measure rural identity. We first grouped students by the major category (urban, suburban, town, rural) of the NCES locale assigned to their school district. We observed a mean WRI of 1.50 for students in rural schools, 1.48 for town, 1.17 for suburban, and 1.19 for urban. To determine significance, we performed a pairwise t-test of the WRI between each of these student populations. We observed significant differences between suburban and town, and suburban and rural populations, with $p < 0.02$ for each. This provides clear evidence that the WRI measured in suburban populations is statistically different from town and rural populations. We did not expect to find a difference between town and rural populations, and our urban population sample was small enough ($N = 9$) that we did not expect to reach significance. Overall, this provides strong evidence that the WRI correlates well with NCES locales.

Table 3: Interesting & Significant Correlations

Item	ρ	N	p
How important have the following people been in your learning how to use computers?			
c. My mother	0.57	100	<.001
e. My guardian	0.47	100	<.001
f. My sister	0.31	100	<.005
h. Another relative (uncle, aunt, cousin, etc.)	0.42	100	<.001
j. Other adult in my community	0.42	100	<.001
In the future, can you see yourself...			
b. Becoming a computer programmer or engineer of some sort?	-.31	72	<0.01
j. Becoming a doctor or nurse?	0.30	72	<0.01
r. Taking a computer programming class in high school?	-0.36	72	<0.005
w. Learning more about programming?	-0.31	72	<0.01
y. Majoring in computer science in college?	-0.3	72	<0.005
How much do you agree with each statement?			
a. I would like to learn more about computers	-0.36	72	<0.005
d. Learning about what computers can do is fun	-0.30	72	<0.01
e. I am NOT the kind of person who works well with computers	0.32	72	<0.01
h. I like the idea of taking computer classes	-0.32	72	<0.005

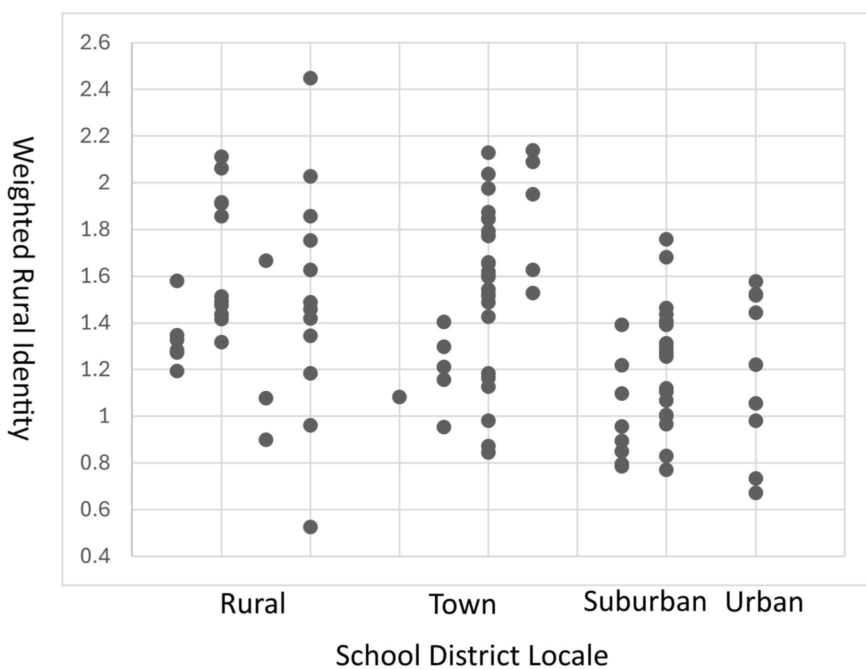

Figure 1: Scatter Plot of Rural Identity by School District

We also calculated Pearson's correlation coefficient ρ between the WRI and responses to the rural identity addendum survey. Although a high degree of correlation was observed ($\rho = 0.50$) between the WRI and the clearly stated identity question "I am a rural person," we only received $N = 11$ valid responses to that survey; therefore, with $p = 0.11$ it was not significant. We still feel very strongly that a such a clear identity question in a demographic survey may be sufficient for measuring rural identity, and plan to continue to collect data in order to test that claim.

6.2 RQ2 - Rural Identity Homogeneity

We examine the data shown in Figure 1. A clear example can be found in the data for school R4, a rural school with $N = 12$ responses. In that single rurally located school district, we observe both our smallest (0.52) and largest (2.44) WRI values. We see similar results in school district T3, with a wide range from 0.87 to 2.13. Even suburban district S2 and urban district U1 include multiple WRI values above the global average of 1.40. We believe that this provides clear evidence that our measure of rural identity is not homogeneous among students within a school district.

6.3 RQ3 - Correlations Between RIS And Computing Interest

We observed significant correlations in three broad areas. First, we observed that a higher WRI was correlated with a higher agreement that female figures, such as a mother or sister, were important in learning how to use computers. The survey included similar questions asking about fathers and brothers, which did not show significant correlations. We also observed similar high correlations between WRI and the importance of a guardian, another relative, or another adult in the community in learning how to use computers. We believe this may be evidence of the importance of having a mentor encouraging rural students to pursue taking classes in computing in school, and also the diverse nature of those mentors.

We also observed significant negative correlations between higher WRI (and, therefore, stronger rural identity) and students viewing themselves as a future computer programmer or taking future computing courses. Although this was not unexpected, it is still very powerful to find such strong evidence of our belief that students with a rural identity do not view themselves as compatible with careers or future study in computer science. We believe that this result alone underscores the importance of identifying rural students as underrepresented in computer science and focusing our Broadening Participation in Computing (BPC) efforts in that direction.

Finally, we observed similarly strong correlations between higher WRI and overall lack of interest and excitement in learning more about computers, taking computer classes, or generally working well with computers at all. Again, this underscores the importance of future work to understand how rural identity interacts with the mindsets and motivations to study computer science, and the development of targeted interventions to help encourage more rural students to explore CS.

Another interesting result was an observed significant correlation between WRI and the number of people sharing a primary computer at home. Although that question was presented as a numerical response and not a 5-point Likert scale, it correlated with the weighted rural identity with Pearson's $\rho = 0.35 (p < 0.001; N = 97)$.

None of the items in the mindsets & motivation survey showed interesting or significant correlations to the weighted rural identity.

7 Limitations

Data for this project were collected from schools within a single state in the United States. The students who participated in the study had already enrolled in at least one computer science course (equivalent to CS0/AP CS P or CS1/AP CS A) using curriculum provided by the authors. Therefore, the student sample is not wholly representative of all students or all rural students, and our analysis should not be generalized in that way.

Several authors of this paper identify as rural and are dedicated to improving the access and quality of CS courses in rural schools. Therefore, we may bring our own biases based on our prior experience and ongoing outreach work to this analysis.

8 Conclusion & Future Work

In this project, we proposed a definition of rural identity for use in educational research. We then explored using the Rural Identity Scale (RIS) to measure the rural identity of middle and high school computer science students. We used principal factor analysis to calculate a single factor solution that created a weighted rural identity measure (WRI) for each student. We showed that the measure correlated well with the rural locale and was significantly different between suburban populations and those in towns or rural areas. We then explored correlations between the WRI and various other survey measures of interest in and motivation to study computer science. We found positive correlations between WRI and several types of mentors helping students learn to use computers, but many negative correlations between WRI and interest in computer science as a future area of study or a career.

We plan to extend this work to develop a simple, reliable measure of a student's rural identity, which we hope to include in future demographic surveys. We also plan to continue to collect and analyze data as part of our ongoing work to increase access to computer science courses in rural areas. We also plan to explore targeted interventions to increase rural student interest in computer science as a future area of study or career path.

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