Computer Science Implementations:
A Study of Perceptions and Professional Development Needs

by

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Abstract

The goal of this research was to identify the perceived needs of teachers, evaluate the overall climate of the Computer Science classroom, and address strengths and weaknesses in support for Computer Science teachers. The purpose of this study was to determine Georgia K-12 Computer Science Educators' perceived level of knowledge and if there was a significant difference in perception of knowledge among demographic identifiers, perceived barriers to effective Computer Science instruction, and if a significant difference exists in the perceived level of satisfaction among demographic identifiers.

A survey research approach, quantitative design was chosen to describe the characteristics of the population sample. The survey instrument for this study was hosted in Qualtrics survey software and formatted as needed for the purpose of this paper. The survey instrument utilized was a mixed methods survey consisting of both quantitative and qualitative response options.

The results of the study showed that respondents have a higher perceived knowledge level for various Computer Science related topics as opposed to others. No statistical significance was found for the demographic identifiers of age or ethnicity for perceived knowledge. However, statistical differences were presented based on degree level earned. Male respondents were more likely to respond with a higher level of perceived knowledge than female respondents. Most respondents indicated the primary barriers were identified as lack of sample lesson plans, lack of computer software, and lack of industry partner contacts. A statistical difference in the perceived level of satisfaction based of gender was identified.

As a result of the findings additional analysis and research are needed to determine why males perceive higher knowledge levels than females and why females perceive more barriers

than males. A follow-up study should be conducted to clearly define barriers. Similar studies should be conducted in other states. The development of an aggressive Computer Science Teacher recruitment plan is needed to attract more entry-career teachers into the field, as well as ensuring demographic diversity.

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(Matthew 19:26) (Philippians 4:13)

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CTAE	Career Technical Agricultural Education
CTE	Career Technical Education
ESI	Essential Skills Inventory
GACTE	Georgia Association for Career Technical Education
GaDOE	Georgia Department of Education
GBEA	Georgia Business Education Association
GA SB 108	Georgia Senate Bill 108
CS4GA	Computer Science for Georgia
IT	Information Technology
NBEA	National Business Education Association
PAGE	Professional Association of Georgia Educators
SBEA	Southern Business Education Association
STEM	Science, Technology, Engineering, Math

Chapter 1 Nature of the Problem

Introduction and Background

The Computer Science field is growing rapidly and unfortunately, there is a deficit in the workforce to fill current vacancies and new positions that are expected to arise. Employment of Computer Science occupations is projected to grow 12 percent from 2014 to 2024, faster than the average for all occupations (U.S. Bureau of Labor Statistics, 2020). Because of the blistering pace at which Computer Science is growing, many corporations are backing a push for public schools to provide more access to the Computer Science content areas in public schools. In response to the demand for public schools to offer more Computer Science courses, many states have begun to push for the implementation of Computer Science standards across disciplines. The Georgia Legislature, for example, passed Senate Bill 108 (GA SB 108) during the 2019 legislative session. GA SB 108 will require all middle schools and high schools in Georgia to offer Computer Science courses by the 2024-2025 school year. Georgia has already approved standards for K-8 Computer Science education; for elementary grade levels, the standards will be worked into other courses in an effort to begin developing awareness. These embedded standards may be covered by media specialists and through instruction during connecting elective courses as well. Initiatives like Computer Science for Georgia (CS4GA) are a result of the recognized gap in graduates who can fill positions in this exponentially growing field. The extensive growth of the field, coupled with the introduction of Computer Science mandates in public schools, is at the heart of a new shift to transition teachers from content areas of math, science, and business education into computer-science-focused content areas. As of the time of this research, 33 states have expanded access to Computer Science education through legislation, funding, and initiatives similar to those in the state in Georgia (Code.org, 2019).

This primary education trend has featured consistent efforts by education reformers and policymakers to integrate computers and technology into education (Harper & Milman, 2016). Teachers who have transitioned from another content area into Computer Science may not have access to professional development, resources, and support needed to make the content shift confidently. Essentially following the framework of disruptive innovation (Christensen & Campbell, 2014), teachers who are at the top of their pedagogical area are moved into Computer Science as a way to bolster the content area and theoretically ensure its success. As enrollments in Computer Science courses are increasing, the growth is creating a shortage of qualified teachers to meet the demand (Shein, 2019). As a result of disruptive initiatives and new legislation for Computer Science education in public schools, many teachers are being transitioned into Computer Science education at the request of administrations, regardless of specific knowledge in Computer Science content. The teacher's effectiveness in these foreign positions is relative to the teacher's attitude or abilities that can impact the instructional environment (Roberts et al., 2007).

Purpose of the Study

The data collected will provide guidance in identifying knowledge gaps and resource deficiencies of current Computer Science educators. Data were analyzed to determine knowledge gaps by specific demographics. The identification of knowledge gaps led to recommendations for targeted professional development. By identifying the resource deficiencies, recommendations were made to advise the appropriate stakeholders. Therefore, the purpose of this study was to determine Georgia K-12 Computer Science Educators' perceived level of knowledge and if there was a significant difference in perception of knowledge among demographic identifiers, perceived barriers to effective Computer Science instruction, and if a significant difference exists in the perceived level of satisfaction among demographic identifiers.

Statement of the Problem

The extensive growth in the field of Computer Science coupled with recent Computer Science mandates in public schools is at the heart of a new shift to transition teachers from other content areas such as Math, Science, and Business Education, into Computer Science areas. Often high performing educators in various content areas have been transitioned into the new field of Computer Science (Dooley et al., 2018, p. 16). For some, the move to Computer Science was a choice, and for others, it was a decision made by administrators. These transitioned educators may have limited experience, education, and skills related to Computer Science (Hays & Kammer, 2021).

Successful implementation of Computer Science in public schools requires educators to have sufficient knowledge of Computer Science in addition to having the necessary resources. With the transition of educators from various other fields into Computer Science, it is important to ensure that these educators have the knowledge and resources needed to successfully teach Computer Science (Stanton et al., 2017). Therefore, the inherent problem is the lack of research related to the knowledge of Computer Science educators and the resources available to support the implementation of the curriculum.

Research Questions

The research questions in this study were:

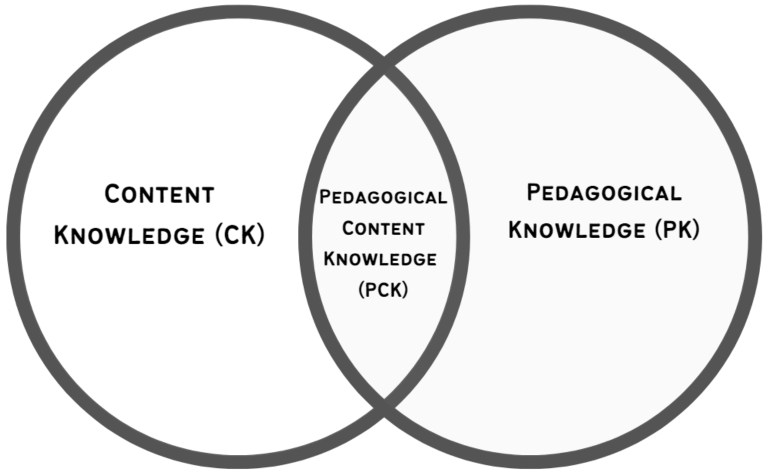
1) What is the perceived level of knowledge of specific Computer Science topics by Georgia K-12 Computer Science Educators?
2) Is there a significant difference in the perceived level of knowledge of specific Computer Science topics of Georgia K-12 Computer Science Educators among demographic identifiers?
3) What are the perceived barriers to effective Computer Science instruction?
4) Is there a significant difference in the perceived level of satisfaction of Georgia K-12 Computer Science Educators among demographic identifiers?

Theoretical Framework

Shulman (1987) suggests that there are seven categories of knowledge bases: content knowledge; general pedagogical knowledge; curriculum knowledge; pedagogical content knowledge; knowledge of learners and their characteristics; knowledge of educational contexts and knowledge of educational ends. These domains of knowledge are valuable in highlighting areas in which teachers may need to have knowledge. Shulman's theory implies that every educator needs a philosophical understanding of a subject to teach it successfully. Shulman (1987) identifies the assumption that most teachers have knowledge of the content in the subject area they are teaching. It is valid to note that assuming teachers have content knowledge in the subject they are teaching may not always be true. The knowledge of the content or subject matter is key in that you must know about the subject in order to teach the subject. He believed that the study of key knowledge bases could be used to understand the learning process of teachers and thus be used to redesign teacher-induction programs and professional development (Bowen, 2021). The concept of Pedagogical Content Knowledge (PCK) is used to describe the knowledge that teachers use to transform the subject matter into learning (1987). General pedagogical knowledge is the teacher's knowledge of and skill in the use of teaching methods and other pedagogical strategies that are not subject specific (Gudmundsdottir, 1987). General pedagogical content knowledge is knowledge that makes Computer Science teachers educators rather than other experts in the Computer Science field (1987). The combination or overlap of teachers' pedagogical knowledge and their content knowledge creates pedagogical content knowledge. Most simply put, teachers know the content matter (CK) of Computer Science and they know how to teach (PK), therefore they know how to teach Computer Science (PCK), as illustrated in Figure 1.

Figure 1

Pedagogical Content Knowledge



While this study brings to light the disruption of high performing educators and the transitioning of those educators into a new field with limited experience in Computer Science content area, the primary focus is on the perceived knowledge and motivation of Computer Science teachers. The Theory of Disruptive innovation will be discussed as a contextual supplement to the theoretical framework of this study. Throughout the last three decades, engagement and motivation have been identified as the primary contributors to success in educational practices. One of the critical limitations to research based on engagement and motivation is the lacking of a primarily accepted theory related to engagement and how it interconnects to motivation. Motivation is frequently thought to be an inner state of need or desire that activates an individual to do something for self-satisfaction (Li & Pan, 2009). The focus of this study relates to the self-perceived effectiveness of teachers in Computer Science related subject areas. It should be noted that the motivation and circumstances for each individual can vary greatly; thus, the motivation for each teacher may be different from those of his or her peers in the same field area.

Theories of achievement motivation are based on a person's feelings of personal competency; according to the competence motivation theory, motivation will increase when a person masters a task (Kent, 2006). Achievement Motivation Theory has also been referred to as the Acquired Needs Theory and the Learned Needs Theory (Lussier & Achua, 2007). The original motivation for each teacher entering a Computer Science classroom can vary considerably, creating widely differing experiences. To some, the move to Computer Science was a choice, and for others, it was a decision made by administrators or other building-level leaders. Each individual will have different experiences and skill sets. The number of variables and factors which can affect motivation are significant.

Robert White (1959) penned a well-known article in which he proposed the concept of effectance motivation defining effectance as the motivation to be both effective and competent. Hater (1978) later expanded on White's theory to include the internalization of self-regulated skills such as self-judgment, self-reinforcement, and self-set mastery goals. While Hater's elaboration primarily focuses on children and their need for praise and feedback from adults for positive emotional growth, the same basic concepts can be applied to Computer Science teachers transitioning in the classroom who seek positive reinforcement from administrators, coworkers, and through student achievement. A person's perceived level of achievement reflects the aim, purpose, or focus of the achievement behaviors in context to a particular moment. Achievement goals are not related to the level of aspired performance, but rather the reason a person attempts to achieve a specific task (*Achievement Goal Theory – IresearchNet,* 2016).

Achievement is not solely reliant on abilities alone, but also the collaboration of the individual's abilities with other crucial characteristics. One model of competencies is defined by five key elements: metacognitive skills, learning skills, thinking skills, knowledge, and motivation (Elliot et al., 2017). Motivation is thought to have an instrumental effect on achievement. The relationship between achievement and motivation identifies persons who are more highly motivated are also higher-achieving with consideration of the intrinsic and extrinsic motivation theory (Li & Pan, 2009). Arguably multiple types of motivation exist, but for the purpose of this research, we will consider achievement motivation and competence or self-efficacy motivation. Competence motivation or self-efficacy motivation can be derived from both intrinsic and extrinsic sources and refers to a person's beliefs in their own abilities (Elliot et al., 2017). Those who seek achievement motivation are attracted to tasks that are at a minimum of moderately challenging and are consistently seeking to better themselves or their accomplishments (2017). The assumption is made that teachers who have transitioned into a Computer Science classroom, no matter previous teaching experience or without consideration of previous knowledge or skill set, ultimately want to be successful and are therefore motivated by achievement. Elliot suggested two motivational orientations within performance goals, approach goals, and avoidance goals (Elliot & Harackiewicz, 1996). Performance-avoidance goals refer to the purposes of engagement in order to avoid failure, while performance-approach goals are oriented towards achieving success (Madjar et al., 2011).

Definition and Terms

Career and Technical Education (CTE) - Career and Technical Education (including agriculture) will be courses offered to high school students which provide training and career preparation in various areas (*Career and Technical Education (CTE) Statistics-About CTE Statistics*, n.d.)

Career Technical Agricultural Education (CTAE) - Career and Technical Education (including agriculture) will be courses offered to high school students, which provide training and career preparation in various areas; used interchangeably with CTE (*CTE/CTAE Month*, 2011)

Coding - One or more commands or algorithm(s) designed to be carried out by a computer; interchangeable with the phrase computer programming (Code.org, 2016)

Computational Thinking - Mental processes and strategies (critical thinking) that include: decomposition, pattern matching, abstraction, algorithms; decomposing problems into smaller, more manageable problems, finding repeating patterns, abstracting specific differences to make one solution work for multiple problems, and creating step-by-step algorithms (Code.org, 2016)

Computer Literacy - Basic, nontechnical knowledge about computers and how to use them; familiarity and experience with computers, software, and computer systems (Merriam-Webster, 2016)

Computer Science (CS) - a. Using the power of computers to solve problems (Code.org, 2016) b. the study of computers, including their design (architecture) and their uses for computations, data processing, and systems control (Tucker, 2020)

Computing - An all-inclusive term that relates to and encompasses a wide range of activities related to the usage of computers and technology (*What Is Computing? - Definition From Techopedia*, n.d.) (*What Is Computing? - Definition From Techopedia*, n.d.)

Digital Divide - The economic, educational, and social inequalities between those who have computers and online access and those who do not (Merriam-Webster, 2016)

Discovery Learning Model - Inquiry-based, a constructivist learning theory that takes place in problem-solving situations where the learner draws on his or her own past experience and existing knowledge to discover facts and relationships and new truths to be learned (Burner, 2005)

Effectance - The state of having a causal effect on objects and events in the environment (White, 1959)

Information Technology (IT) - The development, implementation, and maintenance of computer hardware and software systems to organize and communicate information electronically (Random House, 2001)

Science, Technology, Engineering, Math (STEM) -An acronym that stands for science, technology, engineering and mathematics courses taught and correlated with Career and Technical Education with the intent of connecting academics with work readiness and real-life applications (Gustavsen, 2022)

Limitations

Limitations are the set of conditions outside the control of the researcher, which may create boundaries on the result of the study and applications to other situations (Price & Murnan, 2004, pp. 66-67). The limitations of this study included the response rate of individual educators, the use of a researcher designed survey, the demographic response rate, and the inability to clarify the content of the questionnaire. Additionally, this survey took place during a time period in which education was experiencing a major shift in multiple learning models due to a global pandemic.

Delimitations

Delimitations are the boundaries beyond which the study is concerned (Theofanidis & Fountouki, 2019). These boundaries included time, setting, and size of the sample population. This study is limited to educators that teach Computer Science related courses in a public school system in Georgia.

Summary

This research used a non-experimental research instrument to evaluate how Computer Science teachers perceive their knowledge level to teach Computer-Science-related content, perceived barriers to teaching Computer Science, level of satisfaction teaching Computer Science, and determine if correlations between demographic groups exists. The goal of this study was to identify the perceived needs of teachers, evaluate the overall climate of the Computer Science classroom, and address strengths and weaknesses in support for Computer Science teachers with hopes of bridging gaps in support and professional development opportunities.

The subsequent chapter will provide a review of literature examined to support the research study. The literature reviewed provided a cohesive summary of the existing knowledge in the field of Computer Science. The review provided the foundation for the research and guided the path for the framework for the study.

Chapter 2 Review of Literature

Introduction

The literature in this chapter examined the addition of Computer Science education in the K-12 classroom setting in Georgia, the factors that drove the push for Computer Science curriculum, and examples of how private corporations are working to help public schools and teachers. The research study is designed to measure the perceived level of knowledge, perceived barriers to effective CS instructions, and perceived level of satisfaction of Georgia educators in public K-12 classrooms which teach Computer Science and determine if professional development opportunities are crucial to helping maintain success in the classroom. This review will provide the foundation for the research and lay the framework for the study. Teachers' perception and comfort in the subject area may also provide understanding into the degree to which opportunities for continued professional development prepare them to teach (Lewis et al., 1999). Also, it may be worth noting that the subject field is known by other names in various countries; for example, European countries term the subject as Informatics (Diethelm et al., 2013). Additionally, it is crucial to understand that Computer Science is not Computer Literacy. Computer Literacy is the knowledge and awareness to use a computer sufficiently in order to function in society and the workplace, including nontechnical knowledge. Computer Science is having the knowledge to use the power of the computer to solve problems, understand their architecture, complete computations, process data, and control systems. Most simply stated Computer Science is distinct from Computer Literacy in that Computer Science is more concerned with computer design rather than computer use (Vegas & Fowler, 2020).

Computer Science in America

The Bureau of Labor and Statistics expects the field of Computer Science to grow at breakneck speeds, with 1.4 million Computer Science jobs available (Lockard & Wolf, 2012). However, less than one-third of those jobs will have qualified graduates to fill them (Forseman, 2018). Computer Science for All (CS4ALL) is an initiative backed by The White House and former President Obama. The initiative recognized Computer Science as a new necessary skill (Office of the Press Secretary, 2016). The initiative plans to provide over four billion dollars in funding to states in order to increase K-12 Computer Science trained educators and program implementation. The initiative is also a call to action to governors, mayors, education leaders, philanthropists, technology specialists, and more to get involved in the Computer Science movement (Office of the Press Secretary). During the 2015-16 regular session, the Georgia State Legislator reviewed and passed HB801 to include designated Computer Science courses to count as optional rigor requirements concerning the HOPE Scholarship (Georgia General Assembly, 2016). The University System of Georgia amended the Board of Regents Policy Manual section 4.2.1.1 to include Computer Science to count as a foreign language requirement as long as the courses are consecutive in nature and focus on a computer program language (Board of Regents Policy Manual, 2016). Computer Science courses are listed in the high school curriculum course requirements as an option for a fourth science (University System of Georgia, 2016). Although some high schools allow Computer Science courses to count as a math elective for graduation, it is not currently allowed as a course for entry with the University System of Georgia Board of Regents.

Currently 29 states allow for Computer Science courses to count as a science course and 47 states and the District of Columbia allow Computer Science courses to count as a math class (Orban, 2019). In Michigan's plan to be in the top 10 states in respect to student achievement, they incorporated technology competencies for students. Michigan Integrated Technology Competencies for Students (MITECS) were complemented with the adoption to the K-12 Computer Science Standards, which incorporate the K-12 Computer Science Framework (Norris & Soloway, 2019).

House Resolution 1560 was sponsored by Representative Vernon Ehlers with the official title “Supporting the increased understanding of, and interest in, Computer Science and computing careers among the public and in schools, and to ensure an ample and diverse future technology workforce through the designation of National Computer Science Education Week” (2010). Representative Ehlers worked with Representatives Jared Polis and Betty McCollum to draft the resolution after being made aware of the declining enrollments in Computer Science related degrees by Professor Joel Adams of the Department of Computer Science at Calvin College (Code.org, 2015). House Resolution 1560 was introduced July 27, 2010, and passed unopposed by the 111th Congress (Ehlers, 2010). The bill designates the week of December 5 as National Computer Science Education Week to encourage mechanisms for teachers to receive innovative professional development so that they can provide sustainable learning experiences in Computer Science, provide the opportunity for students to experience Computer Science concepts, and provide opportunities for females and underrepresented minorities in Computer Science (GovTrack.us, 2023).

Computer Science Job Families

The Bureau of Labor and Statistics (2022) groups computer-related jobs under the occupation group of computer and information systems. The following includes the occupation titles and career profiles within the occupation group.

- Computer and Information Research Scientists
    - Data science (algorithms, data visualization, patterns, and model development)
    - Robotics (human/machine interaction, programming)
    - Programming (develop new languages, image processing)
- Computer Network Architects
    - Data and network topology
    - Hardware and software
    - Information security
- Computer Programmers
    - Write programs
        - Design
        - Innovation
    - Knowledge of multiple languages
    - Test refine errors in code
    - Organization, flowchart, textual design
- Computer Support Specialists
    - Test and evaluate network systems
    - Maintenance of networks
    - Troubleshooting
    - Diagnostics
    - Set up and repair
- Computer Systems Analysts
    - Software quality assurance (knowledge of emerging technology, infrastructure and cost, functionality of computing systems, design and implement systems, configure software and hardware, flowcharts and diagrams)
    - Programming analysts (Coding, debugging, data flow, problem-solving)
- Database Administrators
    - System DBA (data security, physical and technical aspects of database, program patches and debugging, upgrades)
    - Application DBA (software support, write and debug programs, application management)
    - Identify user needs, create databases, modify and test structures
- Information Security Analysts
    - Monitor and investigate security breaches

    - Install and use software (encryption, firewall, protect information)
    - Simulate attacks to discover vulnerabilities
    - Research IT trends
    - Develop security standards and best practices
    - Help end-users
- Network and Computer Systems Administrators
    - Identify organizational needs
    - Upgrades and Repairs
    - Computer and network security
    - Add users and user permissions
    - Train users
    - Interpret and solve problems
    - Automation systems and alerts
    - Design and Topology
- Software Developers
    - Analyze user needs
    - Design, test, develop software
    - Innovation
    - Create models, diagrams, flowcharts
    - Functionality and maintenance during testing
    - Documentation
    - Collaboration
    - Augmented Reality
    - Language: Python, Java, etc
- Web Developers
    - Innovate, Create, and test applications
    - Code/ programming of websites
    - Collaboration
    - Graphics, animation, design, video
    - Language: CSS, HTML etc
- General Topics
    - Ethics and legal issues
    - Flow Charts
    - Computational thinking
    - Innovation

Skills Sought by American Employers

Employers often report that new hires typically do not know how to communicate and that they have insufficient experience and preparation for working as part of a team (Lingard, 2010). The gap in communication skills generally is addressed in CTAE standards and referred to as a soft skill. Soft skills are those personal attributes which make someone more likely to be employable.

The value of communication skills is more than simply maintaining a conversation. For example, the skill set is also essential to problem solving. Computational thinking refers to the thought processes involved in expressing solutions as computational steps or algorithms in order to solve problems (Wing, 2010). Employers understand and value the need for teaching teamwork skills in engineering and Computer Science education (2010). Interpersonal skills and communication skills rank among the top of the employer requested skills. Employers also seek individuals with computational thinking skills and problem-solving abilities (Sartore et al., 2020). Additional skills include analytical skills, innovation, math skills, reasoning skills, creativity, and knowledge of programming languages (Bureau of Labor Statistics, U.S. Department of Labor, 2020). With more career fields and opportunities arising and the need for Computer Science skills by employers, giving K-12 students an educational start in Computer Science became imperative.

K-12 Computer Science Framework

The foundation of K-12 Computer Science education in Georgia and thirteen other states is the K-12 Computer Science Framework. This framework was designed with the intent to define the most basic expectations of what all K-12 students should have the opportunity to learn in K-12 Computer Science classrooms. The K-12 Computer Science Framework was developed by a steering committee headed by the Association for Computing Machinery, Computer Science Teachers Association, Code.org, Cyber Innovation Center, and National Math and Science Initiative in partnership with states and school districts (K-12 Computer Science Framework, 2016).

The cooperative work defined and acknowledged the misconceptions of Computer Science, addressed the gaps in the opportunity to learn Computer Science in K-12 classrooms versus the demand, guided standards and professional development, and created a blueprint for Computer Science pathway implementation. The K-12 Computer Science Framework (2016) gave guidance as to what students should be able to do and learn in a K-12 Computer Science pathway and what Computer Science should look like in the various levels of K-12 education. The goal is to provide guidance to states who wish to develop state-specific K-12 Computer Science standards based on a national consensus without creating a national set of education standards such as those in core academic subjects. This framework builds upon other publications that detailed expectations for K-12 Computer Science classrooms (K-12 Computer Science Framework, 2016).

Innovation and Disruptive Leadership

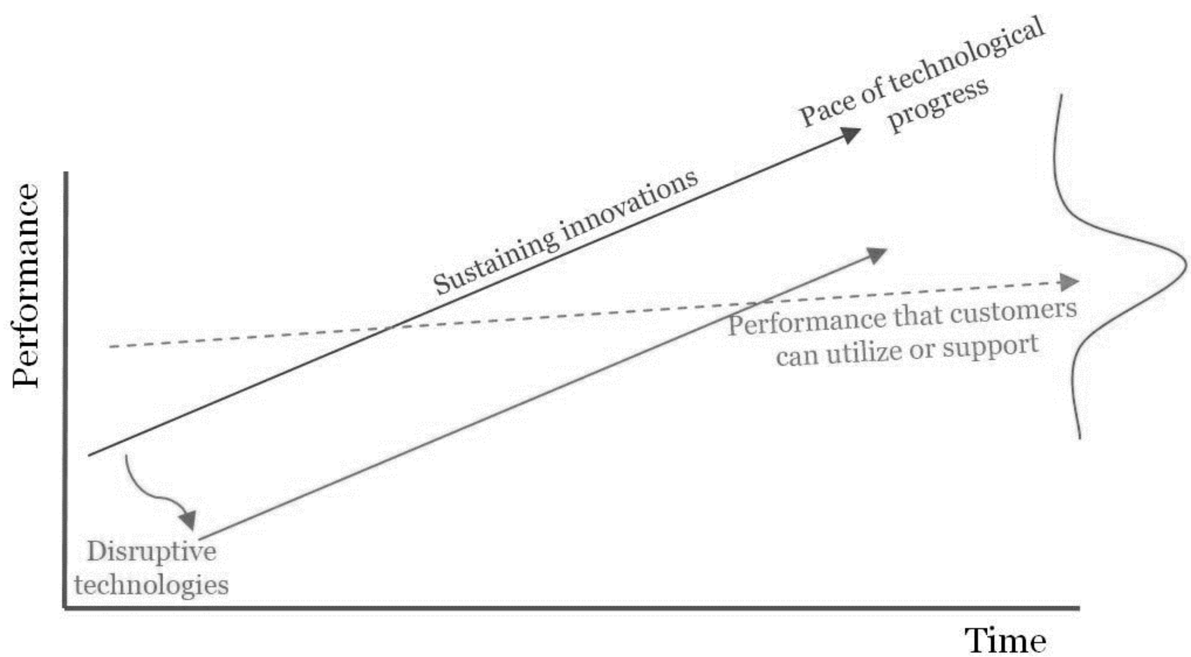
Organizational leaders often look for innovative people to add to their organization and, in turn, seek ways to become more innovative themselves. Defined are five discovery skills that disruptive innovators possess and become key to their ability to break the status quo. By practicing the discovery skills of associating, questioning, observing, experimenting, and networking, innovators are able to think and act differently than those around them (Horn, 2017). The mastery of the five discovery skills gives the innovator the power to spark creativity in others, usually resulting in a disruptive innovation that leads to a more refined way of accomplishing a task, a ground-breaking product, or solves a long-standing problem. Innovative companies follow philosophies that create a culture of creativity. The philosophical practices followed include innovation as part of everyone's job, allowing disruption to be part of the company's innovation portfolio, designing small project teams to take innovative products to the market, and willingness to take smart risks in the pursuit of innovation. When these philosophies are followed and combined with leaders who invoke the five discovery skills, they illustrate the courage to innovate and challenge the status quo (Dyer et al., 2011).

Disruptive innovation also entered Georgia education systems. In the early 2000's, The Professional Association of Georgia Educators (PAGE) began coaching schools to follow the Schlechty (2002) model for school design teams. After years of rigid and restrictive teaching models as the dominant classroom pedagogy, the new design model created a paradigm shift where teachers create original customized work that meets the needs, motives, and values of their students, a clear example of disruptive innovation (Schlechty Center, 2017). In terms of education, the word disruption is used to define a disturbance or event that stops the standard flow of the classroom. Disruption is generally an adverse event that inhibits the learning process of students. Disruption is derived from the prefix *dis*- meaning apart and the root **runp*- meaning to break, first noted in the early 15th century as a medical term for laceration of tissue (Harper, 2001). Use of the term innovation, derived from the Latin term *innovates,* meaning to renew or alter (Random House Webster's Unabridged Dictionary, 2001), in education is much more acceptable. Disruptive Innovations in businesses are new methods or procedures that make products and services more accessible and affordable (Horn, 2017). Disruptive technologies are part of a cycle where companies develop and improve upon products in order to utilize the full potential of the technology (Bower & Christensen, 1995). Arnett (2019) stated that teachers could use disruptive innovation as a powerful force for improving the learning experiences of students. Therefore, this disruptive innovation allowed all Georgia educators a chance to personalize lessons within their educational area that were more effective and suited for their classes; however, it became a necessity for Computer Science teachers.

The transformation of K-12 teachers to Computer Science educators from their roles in a prior content area created a pattern of the classroom, content, and professional development disruption. The Theory of Disruptive Innovation could be used to explain the process of moving high performing teachers into new content areas while expecting the teachers to not only increase performance but, also, increase the motivation of others to participate in the new content area (Arnett, 2019). Administrators who allow teachers at the top of their field to move into Computer Science are applying disruptive innovation by breaking the norm to create a better product and achieve more accessibility. Essential to disruptive innovation is strategically managing skill sets to create energy for the growth of the new product (Bower, J. L., & Christensen, C. M., 1996). Schools benefit from disruptive innovation as it amplifies the capacity of teachers to provide learning experiences to students who would traditionally miss out on the opportunity (Arnett, 2017). This amplification is a part of the disruptive innovation model.

Figure 2

Disruptive Innovation Model



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In Figure 2, the first trait of the Disruptive Innovation model, represented by a dotted line, is the rate of improvement that customers can utilize or absorb. The technologies are present, but not usable, due to outside factors. The sustaining innovations and pace of technology are often the progress of innovation and improvement. This pace usually is faster than the ability of customers in any market to use the technology (Christensen, 2014). Lastly, the element between sustaining innovation and disruptive innovation illustrates the growth and incremental improvement gains achieved by those with higher-end performance (Figure 2). Application of this model can be applied to education and transitioning teachers. By representing current K-12 teacher graduates and the current Computer Science course offerings by the rate of improvement and comparing the pace of technology to the growth expected in Computer Science along with legislation related to Computer Science, a comparison of disruption can then be identified as teachers who excel in his or her given field. Innovative leaders are not trapped by the “status quo bias” or the tendency to leave procedures in place without attempting to make them better (Dyer et al., 2011). Although high-quality teachers are successfully teaching students in their current content area, an innovative leader is willing to disrupt the norm in order to foster disruptive innovation, creating a better product. For many schools, this type of teacher leadership is their only way to offer the expanding field of Computer Science to students.

Trends and Barriers in Computer Science

With the exponential growth in Computer Science and related fields, many stakeholders are stepping up to push Computer Science courses to be taught in primary school through high school. Learning opportunities are not universally accessible in all areas; however, there is a notable increase in availability (Google Inc. & Gallup Inc., 2016). Leading technology companies have pledged millions of dollars to help fund Computer Science education. Amazon, Facebook, Google, Microsoft, and Salesforce forged a partnership with the Trump administration in order to increase computer and technology training in schools to bolster the United States in areas that other nations are gaining an advantage (Kang, 2017).

Included in the barriers to offering Computer Science education in more schools is the lack of qualified teachers. Sixty-three percent of K-12 principals and seventy-four percent of superintendents of schools, which do not offer Computer Science in their school or school district, cite the lack of available teachers as the reason they do not offer the courses (Google Inc. & Gallup Inc., 2016). Secondary to the lack of teachers is the lack of student demand. High school principals of schools that do not offer Computer Science courses are likely to cite a lack of qualified teachers as the number one reason for not offering the content area and a lack of student demand as the secondary deciding factor (2016). Parents and guardians see the need for Computer Science, but at the same time, administrators do not conceptualize the demand for the courses. Ninety percent of parents and guardians feel providing opportunities to learn Computer Science is a good use of school resources (2016), but less than ten percent of principals and superintendents noted a demand for the course as being high among parents and students (Google, 2015).

Curriculum Insufficiency

As large financial commitments are made to Computer Science, such as the $300,000,000 pledge from the Internet Association Members and other businesses (Internet Association, 2017), a need has arisen to review the components that make Computer Science education successful. Merely providing access to Computer Science is not enough; teacher practice, pedagogy, and classroom norms that bring purpose and engagement to the instruction are critical to success in a Computer Science classroom. Observations and research have brought attention to merely adopting a curriculum without substantial professional development that does not sufficiently develop the instructional practices that are needed for a successful classroom. Computer science instruction is full of complex theories, practices, and concepts that teachers must receive instruction on how to teach students (Lewis et al., 1999). Professional development must be authentic and move beyond the static events where presenters talk at teachers and expect them to obtain new teaching strategies to apply in the classroom (1999). Research suggested that teachers must spend more than a day in professional development in order to achieve confidence and preparedness in the relative content areas (1999). Immersive Computer Science professional development allows educators to see Computer Science from the role of the student following the Teacher-Learner-Observer-Model (Goode et al., 2014).

To maximize the fruitfulness of professional development, the Teacher-Learner-Observer-Model makes use of the idea that teachers learn more about teaching by teaching. Thus, during professional development using this model of instruction, participating teachers are divided into groups and assigned a specific topic relevant to the purpose of the professional development. The group designated as teachers prepares a lesson based on the topic and then teaches it to a group of teachers designated as learners while the remaining members of the professional development cohort are identified as observers (Goode et al., 2014). Each group fulfills its role while making notes for discussion. At the end of the lesson, the learners and observers provide feedback to the teachers. After a lesson revision period, the roles are swapped between members, a new group assumes the role of teacher, and the process begins again with a new lesson. It is relevant to recognize that teacher learning is dynamic and occurs over time; the establishment of professional learning communities is essential in the success of new or transitioning Computer Science teachers. Failure to properly train teachers to correctly and enthusiastically teach Computer Science can result in students deciding Computer Science is not a career field for them (2014).

Summary

Computer Science is in high demand and can be found in every employment field. Forty-two percent of principals and seventy-three percent of superintendents do not feel they have a currently employed teacher who encompasses the needed skills to teach Computer Science (Google, 2015). Approximately half of principals and superintendents point to a lack of funding for professional development as the reason for not offering courses in Computer Science (Google, Inc. & Gallup, Inc., 2016). Many organizations have stepped up to the plate to combat the cost and lack of training for educators in Computer Science teaching methods. Code.org hosted multiple training events coined TeacherCon. TeacherCon was held in multiple states and various dates at no cost to the teachers participating or the districts from which the teachers were employed. Through the efforts of Code.org, almost 44,000 teachers have been trained (Code.org Advocacy Coalition, 2018). Multiple other organizations have also offered cost-free training throughout the United States and across the world.

It is estimated that the teaching profession will experience a shortage of teachers with the increase continuing for the next several years. Research suggested that the field could experience a shortage of 200,000 teachers in the next five years (Boyce, 2019). The shortage of new graduates wanting to enter the profession, teachers are retiring at a fast pace, and educators are leaving the field for other careers before retirement has created a strain on the education system. Educational research and journalists cite several indicators for the shortage, including declining enrollment in teacher preparation programs (García & Weiss, 2019). With more and more schools offering Computer Science and an already growing teacher shortage, a lack of teacher induction programs with concentrations related to Computer Science education, and the competing high wage potential in private industry, Computer Science is experiencing the largest shortage of K-12 teachers than many other content areas. Currently, 33 states offer Computer Science programs, yet only 36 teachers graduated with Computer Science degrees in 2017 (Shein, 2019). Schools in high poverty areas often see greater struggles in finding qualified staff to fill positions. Additionally, schools in high poverty areas are likely to have more diverse populations and serve more minority and low-income students. Schools with a large number of low-income students and large subgroups of minority students, students with disabilities, and English Language Learners (ELL) are generally referred to as high-needs schools (García & Weiss, 2019). Students served in high-needs schools are often taught by less-experienced teachers, have less access to high-level science, math, and advanced placement courses, and receive less financial support at the state and local level for teachers and instructional materials (Duncombe, 2017). By increasing the appeal of Computer Science as a major to women and underrepresented minorities, it is possible to reduce the growing gap in the field (Shein, 2019). The reduction of the teacher shortage in Computer Science and the impending shortage of Computer Science professionals can likely be solved by providing better professional development for teachers transitioning to Computer Science content.

The next chapter will identify the methods and procedures of the study. The population of the study and the details of the statistical analysis utilized for each research question will be discussed.

Chapter 3 Methods and Procedures

Introduction

Computer Science education is becoming more widespread in K-12 classrooms due to its profound impact on our day to day lives and lack of qualified persons to fill positions; as a result, K-12 teachers are being transitioned from various content areas into Computer Science resulting in a feelings of being overwhelmed, under supported, and under-qualified to prepared students in Computer Science related content. With the growth of Computer Science and initiatives to increase educational opportunities to learners, a resulting lack of certified educators has emerged. The Georgia Professional Standards Committee (GaPSC), the certifying entity for the state of Georgia, reports just over 260 teachers in the state hold certification in Computer Science (Dalton, 2019). The state currently has 181 school districts with multiple schools within districts that will fall under GA SB 108.

Computer Science teachers express disappointment with the perceived lack of support from administration combined with the reluctance of information technology staff to support software and technology needs they feel could compromise the integrity and security of the school's computer network (Sentance & Csizmadia, 2017). Teachers implementing Computer Science education topics and theories are key to the success of the discipline in K-12 schools. As with any innovation, Computer Science's successful integration into the education institution considerably depends on the perceptions, beliefs, and attitudes of the teachers who are charged with implementing it (Fessakis & Prantsoudi, 2019).

The K-12 Computer Science Framework identifies the following five core concepts Computing Systems, Networks and Internet, Data and Analysis, Algorithms and Programming, and

Impacts of Computing as major content areas in the field of Computer Science (K-12 Computer Science Framework, 2016). Computing Systems is explained as the computing devices and ways that humans interact with those devices specifically hardware, software, and identifying and correcting problems with devices (2016). The researcher reviewed of the K-12 Computer Science Framework, identified the Computer Science Topics of Clients, Debugging programs, Development environments, Operating systems, Project management, and Servers from the survey instrument as most aligned with the core topic of Computing Systems.

Networks and Internet is explained as the connected computing devices that share information and resources and provided connectivity in the computing world by providing fast, secure communications and facilitating innovation (K-12 Computer Science Framework, 2016). The researcher reviewed of the K-12 Computer Science Framework, identified the Computer Science Topics of Bandwidth, Cloud based computing, Cybersecurity, Domain Name Systems, Encryption, Mobile computing, Networks, Parts of a URL, Website development and design, and wireless communication from the survey instrument as most aligned with the core topic of Networks and the Internet.

Data and Analysis can be identified as the need for computing systems to process data effectively, store data, and analyze data to provide understanding and make accurate predictions. (K-12 Computer Science Framework, 2016). The researcher reviewed of the K-12 Computer Science Framework, identified the Computer Science Topics of Computational thinking, Data analyzation using computational tools, Manipulations of data, Modeling to solve real-world problems, and Simulations to solve real world problems from the survey instrument as most aligned with the core topic of Data and Analysis.

Impacts of Computing was identified as the way computing affects many aspects of the world in both positive and negative ways including behaviors, cultural, and social interaction and various levels and calls for understanding of social implications in the digital world (K-12 Computer Science Framework, 2016). The researcher reviewed of the K-12 Computer Science Framework, identified the Computer Science Topics of Augmented reality, Automations and Animations, Copyright and intellectual property, Crowd sourcing, Ethical, social, and legal issues, and Virtual reality from the survey instrument as most aligned with the core topic of Impacts of Computing.

Algorithms and Programming was identified as the process of controlling all computing systems, empowering people to communicate and solve compelling problems (K-12 Computer Science Framework, 2016). The researcher reviewed of the K-12 Computer Science Framework, identified the Computer Science Topics of Analyze algorithms, APIs, C, C++, Develop algorithms, Flow charts, HTML, Java, Java Scripts, Python, Story boards, and Visual (block) programming from the survey instrument as most aligned with the core topic of Algorithms and Programming.

Purpose of the Study

This study aimed to provide guidance in identifying knowledge gaps and resource deficiencies related to Computer Science educators. The goal was to identify the perceived needs of teachers, evaluate the overall climate of the Computer Science classroom, and address strengths and weaknesses in support for Computer Science teachers.

Therefore, the purpose of this study was to determine Georgia K-12 Computer Science Educators' perceived level of knowledge and if there was a significant difference in perception of knowledge among demographic identifiers, perceived barriers to effective Computer Science instruction, and if a significant difference exists in the perceived level of satisfaction among demographic identifiers.

Research Questions

1) What is the perceived level of knowledge of specific Computer Science topics by Georgia K-12 Computer Science Educators?

2) Is there a significant difference in the perceived level of knowledge of specific Computer Science topics of Georgia K-12 Computer Science Educators among demographic identifiers?

3) What are the perceived barriers to effective Computer Science instruction?

4) Is there a significant difference in the perceived level of satisfaction of Georgia K-12 Computer Science Educators among demographic identifiers?

Table 1

Research Question Statistical Analysis

Research Question	Survey Question	Statistical Analysis
What is the perceived level of knowledge of specific Computer Science topics by Georgia K-12 Computer Science Educators?	Q4	Descriptive statistics, including frequencies and percentages to summarize, analyze, and describe the data and to provide an indication of the relationships between variables.
Is there a significant difference in the perceived level of knowledge of specific Computer Science topics of Georgia K-12 Computer Science Educators among demographic identifiers?	Q1, Q2, Q3, Q4, Q6, Q7, Q8, Q9, Q10, Q11, Q12, Q13, Q14, Q17	The method of analysis to test the research question utilizes the non-parametric equivalent of the parametric One-Way ANOVA. Specifically, a series of non-parametric Kruskal-Wallis tests were conducted on each D.V. (Computer Science Topics) to determine statistically significant differences in mean ranks among the demographic groups. Where statistically significant differences were found, a post-hoc analysis utilizing the Mann-Whitney U test was conducted by comparing each demographic with another category to determine the source of overall statistical significance.
What are the perceived barriers to effective Computer Science instruction?	Q5, Q17	Descriptive statistics, including frequencies and percentages to summarize, analyze, and describe the data and to provide an indication of the relationships between variables.
Is there a significant difference in the perceived level of satisfaction of Georgia K-12 Computer Science Educators among demographic identifiers?	Q2, Q3, Q6, Q7, Q8, Q9, Q10, Q11, Q12, Q13, Q14, Q15, Q16, Q17	Non-parametric equivalent of the parametric One-Way ANOVA. Specifically, the non-parametric Kruskal-Wallis tests to determine statistically significant differences in mean ranks among the demographic variables. Where statistically significant differences were found, a post-hoc analysis utilizing the Mann-Whitney U test was conducted by comparing each demographic category with another demographic category to determine the source of overall statistical significance

Research Design

A survey research approach, quantitative design was chosen in order to describe the characteristics of the population sample. The general purpose of quantitative research is to investigate a particular topic or activity through the measurement of variables in quantifiable terms (Mertler, 2018, p. 109). Babbie and Wagennar (2010) defined quantitative methods as emphasizing objective measurements and the statistical, mathematical, or numerical analysis of data collected through polls, questionnaires, and surveys. The survey instrument for this study was hosted in Qualtrics survey software and formatted as needed for the purpose of this paper. A total of 17 questions were captured. The survey instrument (Appendix 1) utilized was a mixed methods survey consisting of both quantitative and qualitative response options.

Survey research can be used in a descriptive manner in a combination with correlational research (Mertler, 2018, p. 112). The purpose of correlational research is to discover, and then possibly measure, relationships between two or more variables (Mertler, 2018, p. 119). The relationship between the specific demographic groups of Computer Science teachers in Georgia [the various educational experiences (i.e., teacher induction programs, professional development, or other coursework), the factors related to years of experience in the classroom] and their perceptions of Computer Science content and knowledge and the degree to which they feel satisfied teaching Computer Science were analyzed.

The largest advantage of survey research is the potential to receive more information obtained from the sample of individuals (Wallen et al., 2012, p. 13). In addition to allowing for a large number of responses, survey research allows for this to be done more efficiently than other methodologies (Mertler, 2018, p. 118). Other advantages include the capability to apply generalizability of results to large populations, versatile in terms of topics investigated, and various models of data collection (2018, p. 118). The independent variables in the case of this study were specific demographics of the Computer Science teachers in the state of Georgia as well as the various educational experiences. The dependent variable of this study is the perceptions of content knowledge, perceived barriers to Computer Science instruction, and perceived satisfaction in Computer Science content area.

There are multiple difficulties involved in survey research such as ensuring the questions are clear and not misleading (Wallen et al., 2012, p. 13). Additional disadvantages or difficulties include getting respondents to answer thoughtfully and honestly, along with the possibility of not receiving a sufficient number of completed questionnaires to enable meaningful analyses (2012, p. 13). Another concern with the use of survey research is that response rates may be slow (2012, p. 118). Lastly, and possibly the most notable limitation, is the self-reporting nature of surveys with responses being based on what respondents perceive to be true (2012, p. 118).

Population

The population included teachers in Georgia public schools who teach at least one course that incorporates standards for Computer Science education. Grade levels were concentrated into grade bands based on the rationale of the K-12 Computer Science Standards, which are the most widely adopted throughout the United States. The standards are organized in grade bands rather than grade levels to afford schools flexibility in presenting the content while maintaining a structured, developmental progression from one band to another (Georgia Department of Education, 2019). Additionally, participants did not have to hold valid Computer Science certification and may be considered out of field. The population sampling allowed for the study to include K-12 Computer

Science and STEM teachers. Surveys were distributed to Regional Education Service Agencies (RESA), Columbus State University, Georgia State University, and Augusta University via email request for distribution to in-service teachers who are participating in endorsement programs and state endorsed professional development programs. Members of the Georgia Department of Education (GaDOE) Computer Science EdWeb community were asked to participate through distribution of the survey via posting on the community discussion boards.

Utilizing convenience sampling the researcher distributed the survey to possible participants. Convenience sampling is a type of nonprobability sampling in which people are sampled because they are convenient sources of data for the researcher (Lavrakas, 2008). The researcher obtained a list of emails of potential Computer Science teachers through a list-serv email concerning public input for future Computer Science Pathways. Approximately 407 emails were sent. A request for survey responses was posted on the researcher's personal Twitter page with tags for Georgia Computer Science Teacher Association, Georgia Department of Education Computer Science Group, Georgia Virtual Learning, Georgia Computer Science for All, Georgia CTAE, and Computer Science Education Research. Additionally, Georgia Computer Science Teacher Association posted a call to action on its discussion boards asking for members to complete the survey. As of December 2020, there were 403 credentialed Computer Science teachers in Georgia (Georgia Department of Education, 2020). A total of 106 (N = 106) respondents submitted a completed survey which translates into a 26% response rate.

Instrument Design

The instrument used for collection of data in this research study was a researcher-developed questionnaire that was delivered online via Qualtrics. The instrument was used to gather information from public school teachers who teach Computer Science related courses and standards in the state of Georgia. The survey instrument distributed and used for the purpose of this research was titled, Computer Science Perceptions. The researcher developed the survey after being unable to locate an existing survey instrument that would serve the research purpose. The online survey instrument was deployed to determine if a correlation relationship exists between various demographics of public school Computer Science teachers the various educational experiences (i.e., teacher induction programs, professional development, or other coursework), the factors related to years of experience in the classroom, their perceptions of Computer Science content and knowledge, and the degree to which they feel satisfied teaching Computer Science. Included are detailed sections defining the research design, overview of research methods, participant population sampling, and instrument design.

The survey instrument in this research included an introduction section defining and explaining the purpose of the survey. This survey was designed to provide insight into the perceptions of Computer Science Educators. The primary purpose of this survey is to determine perceived knowledge of specific Computer Science topics, perceived barriers to effective instruction, as well as perceived level of satisfaction. An information letter (Appendix 2) was provided via a downloadable document in the survey. The survey contains two validation point questions, including agreement of participation based on having read and agreed to the Informed Consent Letter. If a respondent selected “I do not agree to participate”, the remaining questions were skipped and the

Qualtrics platform would not present any further questions to the participant. A second validation statement verified the participant was a Computer Science teacher by providing a range of choices from less than a year to 16+ years with a validation response option of “I do not teach Computer Science”. If a participant selected “I do not teach Computer Science”, the validation rule was activated and the survey would exit with no additional questions being presented to the participant.

Individual experience is critical to understanding how teachers rate their preparedness when compared with topics required by Georgia Computer Science standards and professional development options that are currently offered. Individual experience was measured through quantitative measures based on responses to multiple-choice questions.

The survey instrument collected specific demographic data from public high school Computer Science teachers in Georgia. Data collected included (1)total number of years teaching experience, (2) total number of years as a Computer Science teacher, (3) route to Computer Science certification, (4) highest level of education, (5) identification of previous content area if any, (6) primary grade band in which they teach, (7) experiences teaching various Computer Science courses offered in the state of Georgia, (8) gender identity, (9) age range, and (10) ethnicity.

The survey instrument collected data regarding the educational experiences, such as participating as a student in Computer Science related coursework in high school and participation in a teacher induction program. The questions ask (1) if the teachers had ever experienced Computer Science as a student in various education levels, and (2) their participation in a teacher induction program if any.

The survey instrument measured levels of perceived levels of knowledge of Computer Science topics through the use of a 5-point Likert scale. Respondents were instructed to select their perceived level of knowledge based on the scale of (1) Developing Knowledge, (2) Basic Knowledge, (3) Intermediate Knowledge, (4) Advanced Knowledge, and (5) Expert Knowledge. The question included the following definitions of each knowledge level.

- Developing: just beginning to learn topic
- Basic: increased understanding of topic
- Intermediate: working and functional knowledge of topic
- Advanced: in depth application of topic
- Expert: master proficiency of topic

The survey topics listed in the research instrument were derived from core concepts and practices extracted from the K-12 Computer Science Framework (2016). Core topics identified in the research instrument include the ability to (1) develop algorithms, (2) analyze algorithms, (3) cloud based computing, (4) Java, (5) Java Script, (6) C++, (7) C, (8) HTML, (9) Python, (10) computational thinking, (11) debugging programs, (12) networks, (13) Domain Name Systems, (14) servers, (15) encryption, (16) clients, (17) cyber security, (18) parts of a URL, (19) bandwidth, (20) wireless communication, (21) Internet of Things IoT, (22) simulations to solve real world problems, (23) manipulation of data, (24) crowdsourcing, (25) development environments, (26) project management, (27) operating systems, (28) mobile computing, (30) flow charts, (31) storyboards, (32) visual/block programming, (33) website development and design, (34) augmented reality, (35) automation and animation, (36) ethical, social, and legal issues, (37) data analyzation using computational tools, (38) copyright and intellectual property, (39) APIs, and (40) virtual reality.

Respondents were asked to indicate their perceived barriers to teaching Computer Science based on their experience as a Computer Science teacher. The Computer Science teachers were asked to select all of the items they believe to have been barriers to their instruction of Computer

Science from the following items (1) lack of classroom tools, (2) lack of classroom equipment, (3) lack of computer software, (4) lack of sample lab design, (5) lack suggested classroom supplies, (6) lack of sample lesson plans, (7) lack of recommended textbooks, (8) lack of local industry partner contacts, (9) lack of course pacing guides, (10) lack of professional development opportunities, (11) lack of Professional Development Learning Communities, (12) lack of administration support, (13) lack of local technology department support, (14) lack of equipment funding, (15) lack of professional training, (16) lack of student access to internet, (17) lack of advisory committee support, (18) and lack of student devices/ software relevant to Computer Science. Respondents were also instructed to list any additional items they felt were barriers to Computer Science instruction.

Data related to satisfaction as a Computer Science teacher was collected by means of two questions. The first question asked the participating teachers if they would continue teaching Computer Science or would they move to another content area if given the content area based on their current experiences. The answer options for this question were (1) Yes, I would return to my previous content area, (2) No, I would continue to teach Computer Science, (3) Yes, I would move to a new content area, or (4) Unsure. Additionally, the respondents were asked to identify their level of satisfaction teaching Computer Science through the use of a 5-point Likert scale. Participants were instructed to select one of the satisfaction identifiers of (1) very satisfied, (2) satisfied, (3) neutral, (4) not satisfied, and (5) very satisfied. The last question was an open-ended question instructing participants to share any other information they would like to include concerning their current experience teaching Computer Science.

Permission was obtained from the Institutional Review Board (IRB) at Auburn University (Appendix 3) to conduct the study. The IRB granted permission to conduct research on March 4,

2022. Following IRB protocol, the researcher and committee chair completed the required CITI training modules (Appendix 4).

Validity and Reliability

The underlying foundation for survey items was designed from the objectives of the research and the literature review. Topics in the review of literature included K-12 Computer Science Framework which has been adopted by the state of Georgia and several other states. This framework serves as the foundational guidance for multiple Computer Science programs in the United States. Additional topics in the review of literature include innovative and disruptive leadership, trends and barriers in Computer Science, the need for professional development coupled with curriculum, skills sought by employers, and job demand for potential Computer Science graduates.

The data gathered from the responses were pooled and compared statistically. Recorded responses that indicate the respondent is not a Computer Science teacher will not be included in the data analyzation. After agreeing to the Informed Consent, each participant was presented with the researcher design survey in web-based format.

Salkind (2013) defined reliability as the consistency of a test or item used as a measurement tool, such as a survey instrument. To assist in content validity and reliability, a committee of expert evaluators were selected to review the survey instrument. The committee consisted of university faculty members who are accomplished researchers and are known for their expertise in descriptive research design, data collection, and survey design. The committee was asked to assist the researcher in designing a survey that accurately represented the purpose and scope of the study through thorough questioning, content that was organized, and would discover the desired findings.

Data Collection

The survey was distributed via web-based link via email and social media postings. Qualtrics was the survey platform chosen for distribution of this survey due to accessibility for both the researcher and the potential respondents. Online surveys are a popular method of data collection in academic research and typically return higher response rates than paper surveys (Saleh & Bista, 2017, p. 2). Web-based surveys have steadily gained popularity over the past several years due to their multiple advantages over other data collection methods and increased dramatically due to the Covid-19 pandemic (Menon & Muraleedharan, 2020).

In preparation for survey distribution the researcher began gathering email addresses of potential respondents in various way including emails sent to researcher from other Computer Science educators, through professional development activities as a member of the Georgia Computer Science educators' community. Additionally, the researcher asked moderators in various Georgia Computer Science web groups for permission to post to group discussion boards. Verbal permission was received from the Georgia Department of Education EdWeb Community and the Georgia Computer Science Teacher Association moderators during a virtual conference.

Potential respondents were emailed a brief description of the survey and purpose of the survey. To maintain confidentially of each potential participant emails were sent as a blind carbon copy. A link to the survey was included in the email. An online post to the Georgia EdWeb community and the Georgia Computer Science Teacher Association online social networking sites was made and approved for posting by the moderators of each group. The post gave a brief description of the purpose of the survey and included a link to the survey. Participants were provided with electronic consent form with a validation rule question during the survey which asked the participated to provide agreement for consent. Participants who indicate they did not consent were not presented with any additional questions and were thanked for their time. Data were collected for approximately three weeks. To reduce the amount of burden from emails one follow email was sent thanking those who had already participated and reminding those who had not responded about the purpose of the research and provided a link to submit a response. The researcher took in to consideration the possibility of messaging fatigue from possible respondents due to the Covid-10 pandemic. Similar to the effects of information overload on ability, message fatigue can reduce message processing motivation (Jia et al., 2022).

Data Analysis

The survey utilized included mixed methods consisting of both quantitative and qualitative response options. Statistical Package for Social Sciences (SPSS) software was employed to run statistical tests. Descriptive statistics were used to organize, summarize, and describe the collected data to support evidence of relationships between variables.

To analyze research question 1, (What is the perceived level of knowledge of specific Computer Science topics by Georgia K-12 Computer Science Educators) descriptive results were used. To assist in the statistical procedures, variable responses for perceived knowledge levels and satisfaction were recoded. Data for perceived knowledge for forty distinct Computer Science Topics using the following 5-point Likert Scale: Emerging Knowledge, Basic Knowledge, Intermediate Knowledge, Advanced Knowledge, and Expert Knowledge were recoded to assist in statistical analysis. The data for satisfaction was recorded in the inverse to allow for correct statistical measure. The recoded procedure identified as the higher score as the higher satisfaction, were 1-5, 2-4, 3-3, 4-2, 5-1: as the higher satisfaction, the higher score. The categorical variable for gender was downsized to create two categories to allow for binary measures to be applied. A binary variable is a categorical variable that can only take one of two values, such as True or False or a numerical variable such as 0 or 1, indicating that the attribute is absent or present (Karabiber, 2022). The gender variables were coded as female – 0 and male – 1, the response from the previous variable choice of “prefer not to say” were considered to be left blank or unanswered. Two respondents selected prefer not to say for their gender profile.

To analyze research question 2, (Is there a significant difference in the perceived level of knowledge of specific Computer Science topics of Georgia K-12 Computer Science Educators among demographic identifiers), non-parametric equivalent of the parametric One-Way ANOVA were used. Initially, the chosen method of analysis to address the research question was a MANOVA. Given that there exists multiple, continuous dependent variables and levels of the categorical independent variables, this would be the appropriate analysis. However, after collection of the data, it was determined through a series of analyses that the assumptions of normality of data within groups between groups to justify a MANOVA are not satisfied. A series of Shapiro-Wilk tests of normality of data were performed, as well as series of Levene Tests of Homogeneity of Variances of data were performed the results of these results can be seen in Appendix 5. Given the violation of the normality assumption, it is was decided that the method of analysis to test the research question utilizes the non-parametric equivalent of the parametric One-Way ANOVA. Specifically, a series of non-parametric Kruskal-Wallis tests were conducted on each D.V. (Computer Science Topics) to determine statistically significant differences in mean ranks among the age range groupings.

To analyze research question 3, (What are the perceived barriers to effective Computer Science instruction), Descriptive statistics, including frequencies and percentages to summarize, analyze, and describe the data and to provide an indication of the relationships between variables were utilized.to analyze research question 4, recommended that the method of analysis to test the research question utilize the non-parametric equivalent of the parametric One-Way ANOVA. Specifically, the non-parametric Kruskal-Wallis tests were conducted to determine statistically significant differences in mean ranks among the age range groupings. Where statistically significant differences were found, a post-hoc analysis utilizing the Mann-Whitney U test was conducted by comparing each age category with another age category to determine the source of overall statistical significance.

Test of Instrument Reliability

To test reliability, a series of Cronbach's Alpha analyses were performed on each of the 5 core topic areas, as well as the total of all survey items. Each analysis indicates the degree of internal consistency among respondents. A Cronbach's Alpha of .7 or higher indicates satisfactory internal consistency. Below is Table 2 showing Cronbach's Alpha coefficients. These results indicate satisfactory internal consistency for each core topic area and all items collectively. The graduate committee reviewed the survey instrument for content validity and reliability. The graduate committee found the survey instrument to be acceptable and approved the instrument to be used in the research process.

Table 2

Cronbach's Alpha Coefficients Items Within Each Core Topic Area

Core Topic Area	*n*	Cronbach's Alpha
Computing Systems	6	.934
Networks & Internet	10	.959
Data Analysis	5	.948
Impacts of Computing	7	.928
Algorithms & Programming	12	.952

Note. *N* = 40.

Summary

With the growth of Computer Science and initiatives to increase educational opportunities to learners, a resulting lack of certified educators has emerged. The state currently has 181 school districts with multiple schools within districts that will fall under GA SB 108. Computer Science's successful integration into the public school system significantly depends on the perceptions, beliefs, and attitudes of the teachers who are charged with implementing it (Fessakis & Prantsoudi, 2019). The K-12 Computer Science Framework identifies the following five core concepts: Computing Systems, Networks and Internet, Data and Analysis, Algorithms and Programming, and Impacts of Computing as major content areas in the field of Computer Science (K-12 Computer Science Framework, 2016). A researcher designed survey with a total of 18 questions were captured. The survey instrument utilized was a mixed methods survey consisting of both quantitative and qualitative response options. The target population included all K-12 in the state of Georgia who teach a course utilizing the Georgia Computer Science Standards. A list of Georgia courses with individual Computer Science standards can be found in Appendix 6. The primary purpose of this survey is to determine perceived knowledge of specific Computer Science topics, as well as, perceived barriers to effective instruction. The survey utilized included mixed methods consisting of both quantitative and qualitative response options. Statistical Package for Social Sciences (SPSS) software was employed to run statistical tests. Respondents' comments to open ended questions are located in Appendix 7.

The subsequent chapter will provide a culmination of the statistical analysis and results of the study. The results were summarized to provide an understating of the data collected. This chapter presents the analysis of the data collected from Georgia Computer Science Teachers utilizing the researcher-designed survey Computer Science Perceptions. Descriptive statistics, including frequencies and percentages, to summarize, analyze, and describe the data will be presented.

Chapter 4 Statistical Analysis and Results

Introduction and Restatement of the Problem

The vast expansion of Computer Science fields combined with recent Computer Science mandates in public schools is at the heart of a new shift to transition teachers from other content areas such as Math, Science, and Business Education, into Computer Science areas. Successful implementation of Computer Science in K-12 public schools requires educators to have sufficient knowledge of Computer Science in addition to having the necessary resources. With the transition of educators from various other fields into Computer Science, it is important to ensure that these educators have the knowledge and resources needed to successfully teach Computer Science. Therefore, the inherent problem is the lack of research related to the knowledge of Computer Science educators and the resources available to support the implementation of the curriculum. The quantitative study, Computer Science Perceptions, was design to provide insight into the perceptions of Computer Science Educators in Georgia. The research questions are:

1) What is the perceived level of knowledge of specific Computer Science topics by Georgia K-12 Computer Science Educators?

2) Is there a significant difference in the perceived level of knowledge of specific Computer Science topics of Georgia K-12 Computer Science Educators among demographic identifiers?

3) What are the perceived barriers to effective Computer Science instruction?

4) Is there a significant difference in the perceived level of satisfaction of Georgia K-12 Computer Science Educators among demographic identifiers?

In this study, an online survey (Appendix 1) was distributed to Computer Science educators employed in public school systems in the state of Georgia. The data collected were used to determine if specific knowledge gaps exist between specific demographics. The identification of knowledge gaps will lead to recommendations for targeted professional development. This chapter presents the analysis of the data collected from Georgia Computer Science Teachers utilizing the researcher designed survey Computer Science Perceptions.

Descriptive Data Analysis and Results

Descriptive statistics, including frequencies and percentages, were run in SPSS to summarize, analyze, and describe the data and to provide an indication of the relationships between variables. The demographic data was collected using the researcher designed survey instrument, Computer Science Perceptions.

Table 3 presents the data related to sociodemographic characteristics of sex, age, ethnicity, and education. The majority of respondents were females (63%). Additionally, the majority of the respondents were of white (69.8%) ethnicity. The majority of the female respondents were of white ethnicity (63.5%) with African American (33.3%) being the next most selected ethnicity. The most often selected ethnicity among males was white (83.8%) with African American (13.5%) being the next most selected ethnicity. The bulk of research participants who responded were between the ages of 40 and 59 (67.9%). The largest percent of respondents reported earning a Master's Degree (38.7%). Note there is a variance in *N* due the not all respondents answering all questions.

Table 3

Sociodemographic Characteristics

Categories	*n*	%
Sex (*N* = 100)		
Male	37	37.0
Female	63	63.0
Age (*N* = 103)		
20-29 years	1	1.0
30-39 years	21	20.4
40-49 years	33	32.0
50-59 years	37	35.9
60 plus year	11	10.7
Ethnicity (*N* = 106)		
White	74	69.8
African American	26	24.5
Pacific Islander	1	1.0
Other	5	4.7
Highest Degree (*N* = 106)		
Associate	1	0.9
Bachelor	20	18.9
Master	41	38.7
Specialist	27	25.5
Doctorate	14	13.2
Other/Unlisted	3	2.8

The descriptive statistics were also used to identify the various grade band in which respondents taught. Table 4 reflects the collected data. Most of the respondents reported teaching at the High School level (77.4%).

Table 4

Grade Band of Respondents

Grade Band	*n*	%
Elementary/Primary	3	2.8
Middle School	21	19.8
High School	82	77.4

Note. *N* = 106

Table 5 details the years of teaching experience reported by survey participants. The greatest percentage of participants (49.1%) have been teaching for sixteen (16) or more years. Most respondents (40.6%) reported have 1 – 4 years of experience teaching Computer Science. The findings related to years of experience teaching Computer Science are listed in Table 6.

Table 5

Years of Teaching Experience

Number of Years	*n*	%
Less than 1 year	3	2.8
1 -4 years	7	6.6
5 -10 years	24	22.6
11 – 15 years	20	18.9
16 or more years	52	49.1

Note. *N* = 106

As noted previously, Table 6 details the years of experience teaching Computer Science. Most respondents (40.6%) reported have 1 – 4 years of experience teaching Computer Science. The findings related to years of experience teaching Computer Science are listed in Table 6.

Table 6

Years Experience Teaching Computer Science

Number of Years	*n*	%
Less than 1 year	5	4.7
1 -4 years	43	40.6
5 -10 years	38	35.8
11 – 15 years	13	12.3
16 or more years	7	6.6

Note. *N* = 106

Table 7 details the amount of experience respondents reported having participated as a student in a Computer Science classroom. The greatest percentage of the respondents selected some college (36.2%) experience as a student learning Computer Science.

Table 7

Experience as Computer Science Student

Number of Years	*n*	%
No Experience	25	23.8
High School Courses	4	3.8
Some college	38	36.2
2-year degree	6	5.7
4-year degree	17	16.2
Professional Degree	15	14.3

Note. $N = 105$

Survey respondents identified Business Education (51.9%) as the most often previous content area before teaching Computer Science. Four (3.8%) of survey participates reported they had taught in no other primary content area prior to teaching Computer Science. Table 8 reflects the collected data.

Table 8

Primary Content Area Prior to Computer Science

Content Area	*n*	%
Business Education	55	51.9
Technology/Engineering	9	8.5
Math	11	10.4
Science	5	4.7
Industry	13	12.3
Other	9	8.5
None	4	3.8

Note. *N* = 106

Discussion of Research Questions

Research Question 1: What is the perceived level of knowledge of specific Computer Science topics by Georgia K-12 Computer Science Educators?

The K-12 Computer Science Framework identifies the following five core concepts Computing Systems, Networks and Internet, Data and Analysis, Algorithms and Programming, and Impacts of Computing as major content areas in the field of Computer Science (K-12 Computer Science Framework, 2016). Survey respondents were asked to select their level of perceived knowledge for forty distinct Computer Science Topics aligned with the five core concepts using the following 5-point Likert Scale: Developing Knowledge, Basic Knowledge, Intermediate Knowledge, Advanced Knowledge, and Expert Knowledge.

The largest percentages for the Expert perceived knowledge level for Computer Science topic choices were Parts of a URL (16.7%), Computational thinking (14.4%), Ethical, social, and legal issues (13.6%), and Visual (block) programming (13.5%). The top 4 answers for the perceived knowledge level of Advanced were HTML (34.9%), Flow Charts (32.0%), Computational thinking (27.9%), and Parts of a URL (27.5%). Participants assessed themselves as Intermediate knowledge for the topics of Java Script (34.3%), Operating systems (35.0%), Analyze algorithms (34.0%) and Copyright and intellectual property (33.3%). Respondents identified as Basic Knowledge for the topics of Mobile computing (33.7%), Servers (33.3%), Cloud based computing (31.7%), and Crowdsourcing (30.3%). The perceived knowledge level of Developing was selected by respondents for the Computer Science Topics of C (59.8%), C++ (57.3%), Virtual reality (43.7%), and Augmented reality (43.7%). The least selected by participants were Expert Knowledge (7.8%) or Advanced Knowledge (17.0 %) on average than Intermittent Knowledge (26.1%), Basic Knowledge (24.9%), or Developing Knowledge (24.2%). Due to the amount of the data, a table of all topics assessed, and percentages can be found in Appendix 8. The data in the table is based on surveys that were considered complete and did not have missing data.

The top five highest perceived knowledge are Computational Thinking first, followed by Parts of URL, with Ethical, Social, and Legal Issues being selected third most often, next was Website Development and Design followed by HTML. The lowest five topics of perceived knowledge selected were C being selected least often then, C++, Virtual Reality, Augmented Reality, and Crowdsourcing. Table 9 presents the 40 topic areas in order of the highest mean to lowest mean score of perceived knowledge. As shown by the means, on average subjects reported an “intermediate knowledge” ($M = 3$) of those highest-ranked topics. For those lowest-ranked topics, subjects reported on average “developing knowledge” ($M = 1$) to “basic knowledge” ($M = 2$). The average mean (2.6%) for all forty topics was between “basic knowledge” ($M = 2$) and “intermediate knowledge” ($M = 3$). Appendix 9 contains tables of each of the 40 topic areas and the number of times selected on the scaled knowledge level.

Table 9

CS Topic Areas by Perceived Knowledge Mean	*n*	*M*	*SD*
Computational thinking	105	3.18	1.19
Parts of a URL	103	3.17	1.25
Ethical, social, and legal issues	104	3.16	1.17
Website development and design	104	3.14	1.10
HTML	104	3.11	1.17
Copyright and intellectual property	106	3.08	1.16
Flow charts	104	3.07	1.20
Visual (block) programming	105	3.06	1.25
Story boards	103	2.97	1.17
Debugging programs	106	2.92	1.22
Develop algorithms	106	2.89	1.20
Operating systems	104	2.85	1.13
Analyze algorithms	104	2.82	1.21
Wireless communication	102	2.77	1.13
Modeling to solve real-world problems	105	2.72	1.21
Manipulation of Data	103	2.71	1.29
Networks	105	2.69	1.15
Simulations to solve real-world problems	104	2.68	1.24
Bandwidth	103	2.66	1.28
Project management	101	2.62	1.22
Mobile computing	102	2.60	1.13
Domain Name Systems	102	2.59	1.15
Data analyzation using computational tools	104	2.51	1.25
Clients	104	2.45	1.22

Table 9

CS Topic Areas by Perceived Knowledge Mean	*n*	*M*	*SD*
Java Script	106	2.42	1.15
Java	105	2.41	1.25
Servers	103	2.41	1.20
IoT	104	2.40	1.22
Cloud based computing	105	2.38	1.17
Cyber security	102	2.33	1.21
Python	103	2.33	1.21
APIs	104	2.30	1.21
Encryption	103	2.28	1.18
Development environments	103	2.24	1.21
Automation and Animation	104	2.14	1.07
Crowdsourcing	103	2.07	1.03
Augmented reality	104	1.94	1.03
Virtual reality	104	1.92	0.99
C++	104	1.80	1.15
C	103	1.74	1.12

Note. Likert Scale (1) Emerging Knowledge, (2) Basic Knowledge, (3) Intermediate Knowledge, (4) Advanced Knowledge, and (5) Expert Knowledge

Table 10 lists the percent total responses from respondents for each Perceived Knowledge level for the identified Computer Science topics associated with Computing Systems. The average times selected were used to determine that Basic Knowledge (27.1%) was selected more often, on average, as the perceived knowledge level for the identified topics, then Intermediate Knowledge (26.6%) as the perceived knowledge with Developing Knowledge selected third most (23.4%) followed by Advance Knowledge (15.0%) and Expert Knowledge (8.0%) selected least often. Basic

Knowledge was selected 166 times followed by Intermediate Knowledge 163 times. Expert knowledge was selected 49 times for the topics associated with Computing Systems.

Table 10

Percent total responses for Perceived Knowledge Core Topic: Computing Systems

Computer Science Topics	Developing Knowledge		Basic Knowledge		Intermediate Knowledge		Advance Knowledge		Expert Knowledge	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%
Clients (N = 101)	31	30.7	29	28.7	22	21.8	13	12.9	6	5.9
Debugging programs (N = 105)	16	15.2	22	21.0	33	31.4	21	21.0	12	11.4
Development environments (N = 102)	35	34.3	30	29.4	21	20.6	9	8.8	7	6.9
Operating systems (N = 103)	13	12.6	26	25.3	36	35.0	19	18.4	9	8.7
Project management (N = 100)	22	22.0	25	25.0	29	29.0	16	16.0	8	8.0
Servers (N = 102)	26	25.5	34	33.3	22	21.6	13	12.7	7	6.9
	143	23.4	166	27.1	163	26.6	91	15.0	49	8.0

Table 11 lists the percent total responses from respondents for each Perceived Knowledge level for the identified Computer Science topics associated with Networks and the Internet. The average times selected were used to determine the perceived level of Basic Knowledge (27.9 %) was selected more often, followed by Intermediate Knowledge (27.0 %) as the perceived knowledge level for the identified topics with Developing Knowledge selected third most (19.2 %) then by Advance Knowledge (17.8 %) and Expert Knowledge (8.2 %) selected least often. For Computer Science topics associated with Networks and the Internet the perceived knowledge level of Basic

Knowledge was selected 285 times with Intermediate knowledge being selected 276 times. Expert knowledge was selected least with 84 respondents identifying to have a perceived knowledge of expert.

Table 11

Percent total responses for Perceived Knowledge Core Topic: Networks and the Internet

Computer Science Topics	Developing Knowledge		Basic Knowledge		Intermediate Knowledge		Advance Knowledge		Expert Knowledge	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%
Bandwidth (*N* = 102)	22	21.6	28	27.5	23	22.5	19	18.6	10	9.8
Cloud based computing (*N* = 104)	27	26.0	33	31.7	27	26.0	10	9.6	7	6.7
Cyber security (*N* = 103)	28	27.2	27	26.2	27	26.2	14	13.6	7	6.8
Domain Name Systems (*N* = 101)	20	19.8	30	29.7	29	28.7	16	15.9	6	5.9
Encryption (*N* = 102)	33	32.4	28	27.5	23	22.5	14	13.7	4	3.9
Mobile computing (*N* = 101)	17	16.8	34	33.7	29	28.7	14	13.9	7	6.9
Networks (*N* = 104)	18	17.3	29	27.9	32	30.8	18	17.3	7	6.7
Parts of a URL (*N* = 102)	10	9.8	24	23.5	23	22.5	28	27.5	17	16.7
Website development and design (*N* = 103)	7	6.8	23	22.3	33	32.0	28	27.2	12	11.7
Wireless communication (*N* = 101)	14	13.9	29	28.7	30	29.7	21	20.8	7	6.9
	196	19.2	285	27.9	276	27.0	182	17.8	84	8.2

Table 12 lists the percent total responses from respondents for each Perceived Knowledge level for the identified Computer Science topics associated with Data and Analysis. Most respondents selected Intermediate Knowledge (26.0%) as the perceived knowledge level for the identified topics. Fewer respondents selected Expert Knowledge (9.9%) as the perceived knowledge level for the identified topics. Respondents selected Intermediate Knowledge 134 times, Basic Knowledge 125 times, Advanced Knowledge 104 times, Developing Knowledge 102 times, and Expert Knowledge 51 times for the identified core topics associated with Data and Analysis.

Table 12

Percent total responses for Perceived Knowledge Core Topic: Data and Analysis

Computer Science Topics	Developing Knowledge		Basic Knowledge		Intermediate Knowledge		Advance Knowledge		Expert Knowledge	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%
Computational Thinking (N = 104)	10	9.6	21	20.2	29	27.9	29	27.9	15	14.4
Data analyzation using computational tools (N = 103)	29	28.2	23	22.3	27	26.2	17	16.5	7	6.8
Manipulation of Data (N = 102)	22	21.6	26	25.5	24	23.5	19	18.6	11	10.8
Modeling to solve real-world problems (N = 104)	19	18.3	29	27.9	27	26.0	20	19.2	9	8.6
Simulations to solve real-world problems (N = 103)	22	21.4	26	25.2	27	26.2	19	18.5	9	8.7
	102	19.8	125	24.2	134	26.0	104	20.1	51	9.9

Table 13 lists the percent total responses from respondents for each Perceived Knowledge level for the identified Computer Science topics associated with Impacts of Computing. The average times selected were used to determine Developing Knowledge (29.8 %) as the perceived knowledge level selected most for the identified topics. Respondents selected Expert Knowledge (5.4%) least as the perceived knowledge level for the identified topics. The perceived knowledge of Developing Knowledge was selected 215 times. Expert Knowledge was selected 39 times.

Table 13

Percent total responses for Perceived Knowledge Core Topic: Impacts of Computing

Computer Science Topics	Developing Knowledge		Basic Knowledge		Intermediate Knowledge		Advance Knowledge		Expert Knowledge	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%
Augmented reality (N = 103)	45	43.7	28	27.2	22	21.4	6	5.8	2	1.9
Automation and Animation (N = 103)	36	35.0	29	28.2	28	27.1	7	6.8	3	2.9
Copyright and intellectual property (N = 105)	12	11.4	18	17.2	35	33.3	28	26.7	12	11.4
Crowdsourcing (N = 102)	37	36.3	31	30.3	25	24.5	7	6.9	2	2.0
IoT (N = 103)	30	29.1	31	30.1	18	17.5	19	18.4	5	4.9
Ethical, social, and legal issues (N = 103)	10	9.7	18	17.5	33	32.0	28	27.2	14	13.6
Virtual reality (N = 103)	45	43.7	28	27.2	23	22.3	6	5.8	1	1.0
	215	29.8	183	25.4	184	25.4	101	13.9	39	5.4

Table 14 lists the percent total responses from respondents for each Perceived Knowledge level for the identified Computer Science topics associated with Algorithms and Programming. The average times selected were used to determine the perceived level of Developing Knowledge (27.3%) as the perceived knowledge level selected most for the identified topics. Respondents selected Expert Knowledge (8.0%) as the perceived knowledge level for the topics associated with

Algorithms and Programming the least. The perceived knowledge level of Developing Knowledge was selected 338 times for the identified topics. The perceived knowledge level of Expert Knowledge was selected 99 times for the identified topics.

Table 14

Percent total responses for Perceived Knowledge Core Topic: Algorithms and Programming

Computer Science Topics	Developing Knowledge		Basic Knowledge		Intermediate Knowledge		Advance Knowledge		Expert Knowledge	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%
Analyze algorithms (*N* = 103)	18	17.5	22	21.3	35	34.0	17	16.5	11	10.7
APIs (*N* = 103)	32	31.1	31	30.1	23	22.3	10	9.7	7	6.8
C (*N* = 102)	61	59.8	20	19.6	12	11.8	4	3.9	5	4.9
C++ (*N* = 103)	59	57.3	21	20.4	12	11.6	6	5.8	5	4.9
Develop algorithms (*N* = 105)	15	14.3	26	24.8	31	29.5	22	20.9	11	10.5
Flow Charts (*N* = 103)	12	11.7	24	23.3	24	22.3	33	32.0	11	10.7
HTML (*N* = 103)	14	13.6	15	14.6	29	28.2	36	34.9	9	8.7
Java (*N* = 104)	32	30.8	24	23.1	28	26.9	12	11.5	8	7.7
Java Script (*N* = 105)	30	28.5	23	21.9	36	34.3	11	10.5	5	4.8
Python (*N* = 102)	36	35.3	18	17.6	28	27.5	17	16.7	3	2.9
Story boards (*N* = 102)	12	11.8	25	24.5	29	28.4	26	25.5	10	9.8
Visual (block) programming (*N* = 104)	17	16.3	14	13.5	33	31.7	26	25.0	14	13.5
	338	27.3	263	21.2	320	25.7	220	17.7	99	8.0

Research Question 2: Is there a significant difference in the perceived level of knowledge of specific Computer Science topics of Georgia K-12 Computer Science Educators among demographic identifiers?

The categorical independent variables of age, gender, and ethnicity were utilized to explore potential correlations among reported perceived knowledge of Computer Science Topics and demographic characteristics. Table 15 lists the ten Computer Science Topics with the highest standard deviation indicating the most variation among responses.

Table 15

Perceived Level of Knowledge Top 10

Topic	*M*	*SD*
Computational thinking	2.95	1.41
Ethical, social, and legal issues	2.92	1.41
Part of a URL	2.89	1.50
HTML	2.86	1.41
Visual (block) programing	2.84	1.45
Flowcharts	2.82	1.43
Story boards	2.71	1.41
Manipulation of Data	2.47	1.46
Bandwidth	2.44	1.44
Project management	2.35	1.41

Note. N = 106. Likert Scale (1) Emerging Knowledge, (2) Basic Knowledge, (3) Intermediate Knowledge, (4) Advanced Knowledge, and (5) Expert Knowledge

The data was initially screened for missing data. Upon inspection, the majority of missing data across multiple variables (>5) was primarily confined to 25 respondents. Missing data among other respondents was minimal and random. Since the "perceived level of knowledge" data collected for each topic were not aggregated to create an overall scaled score, but instead each survey question pertaining to a topic was treated as a single dependent variable, it was decided to conduct the analysis by removing respondents with missing data on the variables being analyzed using a pairwise approach. Specifically, a respondent with missing data was excluded from the analysis. The data was analyzed and tables were produced using IBM SPSS v.28 software.

Initially, the chosen method of analysis to address the research question was a MANOVA. Given that there exists multiple, continuous dependent variables and levels of the categorical independent variables, this would be the appropriate analysis. However, after collection of the data, it was determined through a series of analyses that the assumptions of normality of data within groups and homogeneity of variance between groups to justify a MANOVA are not satisfied. The results of these tests of assumptions specific to each independent variable on the dependent variables are described below.

Age

A series of Shapiro-Wilk tests of normality of data were performed. The dependent variable data within each category of age was found to be statistically significant at the $p < .05$ level. Therefore, the null hypothesis that the data in the population forms a normal distribution was rejected. Specifically, for all but the age category of 60-69, the data failed the assumption of normality. A series of Levene Tests of Homogeneity of Variances of data were performed and with the exception of the topic of Java Script, all other topic groupings based on age categories satisfied the assumption of Homogeneity of Variance based on Mean comparisons.

Given the violation of the normality assumption, the researcher decided that the method of analysis to test the research question utilizes the non-parametric equivalent of the parametric One-Way ANOVA. Specifically, a series of non-parametric Kruskal-Wallis tests were conducted on each dependent variable of Computer Science Topics to determine statistically significant differences in mean ranks among the age range groupings. Where statistically significant differences were found, a post-hoc analysis utilizing the pairwise comparisons test was conducted by comparing each age category with another age category to determine the source of overall statistical significance. The results of the non-parametric Kruskal-Wallis analyses found no statistically significant differences between age categories among any of the Computer Science topic areas at the level of $p < .05$ as show in Table 16. Specifically, in every comparison, the null hypothesis that there is no difference in mean rank ratings of knowledge level on each topic between the age categories cannot be rejected.

Table 16

Kruskal-Wallis (H) of Perceived Level of Knowledge of Computer Science by Age

Computer Science Topic (DV)	*n*	df	H	*p*
Develop Algorithms	103	5	3.39	.641
Analyze Algorithms	102	5	2.24	.815
Cloud Based	102	5	5.06	.409
Java	102	5	5.76	.330
Java Script	103	5	1.93	.859
C++	101	5	3.46	.616
C	100	5	2.19	.822
HTML	101	5	1.18	.947
Python	100	5	3.81	.577
Computational Thinking	102	5	4.20	.522
Debugging Programs	103	5	3.33	.649
Networks	102	5	3.15	.677
Domain Name Systems	99	5	2.52	.773
Servers	100	5	3.66	.598
Encryption	100	5	3.22	.666
Clients	99	5	3.49	.625
Cyber Security	101	5	2.21	.820
URL	100	5	1.28	.937
Bandwidth	100	5	4.14	.529
Wireless Communication	99	5	2.50	.776
IoT	101	5	3.69	.594
Simulations To Solve Real-World Problems	101	5	2.93	.711
Modeling To Solve Real-World Problems	102	5	2.94	.709
Manipulation of Data	100	5	3.51	.621
Crowdsourcing	100	5	6.28	.280
Development Environments	100	5	7.23	.204
Project Management	98	5	3.95	.556
Operating Systems	101	5	2.26	.812
Mobile Computing	99	5	3.41	.636
Flow Charts	101	5	4.05	.543
Story Boards	100	5	3.15	.676
Visual (block) Programming	102	5	2.75	.739
Website Development and Design	101	5	2.61	.760
Augmented Reality	101	5	2.45	.783
Automation and Animation	101	5	1.72	.886
Ethical, Social, and Legal Issues	101	5	4.54	.475
Data Analyzation Using Computational Tools	101	5	1.81	.875
Copyright and Intellectual Property	103	5	2.81	.730
APIs	101	5	2.63	.756
Virtual Reality	102	5	3.98	.552

Degree Earned

The results of the non-parametric Kruskal-Wallis analyses found statistically significant differences between categories among a number of the Computer Science topic areas at the Bonferroni adjusted level of $p < .05$ by degree level. Specifically, the null hypothesis that there is no difference in mean rank ratings of knowledge level on each topic between the Highest Degree Earned categories can be rejected for the topics of: Cloud Based Computing; HTML; Python; Networks; Servers; Encryption; Clients; Cyber Security; Parts of URL; Bandwidth; Wireless Communication; IoT; Simulations to Solve Real-World Problems; Modeling to Solve Real-World Problems; Manipulation of Data; Development of Environments; Project Management; Operating Systems; Mobile Computing; Flowcharts; Story Boards; Website Development and Design; Automation and Animation; Data Analyzation Using Computational Tools; Ethical, Social, and Legal Issues; APIs, and Copyright and Intellectual Property. A series of post-hoc analyses were conducted to determine which Highest Degree Earned category statistically significantly differs from others within each topic area. The majority of differences exist between those holding a doctoral degree compared with Master's and Specialist's holders. Table 17 provides the data for the 40 assessed Computer Science Topic dependent variables of Perceived Level of Knowledge by Highest Degree Earned.

Table 17
Kruskal-Wallis of Perceived Level of Knowledge of Computer Science Highest Degree Earned

Computer Science Topic (DV)	*N*	df	H	*p*
Develop Algorithms	106	5	6.98	.222
Analyze Algorithms	104	5	7.79	.168
Cloud Based Computing	105	5	18.72	.002*
Java	105	5	9.06	.107
Java Script	106	5	6.27	.281
C++	104	5	6.96	.223
C	103	5	7.57	.182
HTML	104	5	11.72	.039*
Python	103	5	14.35	.014*
Computational Thinking	105	5	10.30	.067
Debugging Programs	106	5	7.34	.197
Networks	105	5	11.48	.043*
Domain Name Systems	102	5	10.13	.072
Servers	103	5	13.65	.018*
Encryption	103	5	15.47	.009*
Clients	102	5	13.70	.018*
Cyber Security	104	5	15.84	.007*
URL	103	5	16.10	.007*
Bandwidth	103	5	15.65	.008*
Wireless Communication	102	5	14.40	.013*
IoT	104	5	11.89	.036*
Simulations To Solve Real-World Problems	104	5	15.28	.009*
Modeling To Solve Real-World Problems	105	5	16.23	.006*
Manipulation of Data	103	5	19.07	.002*
Crowdsourcing	103	5	10.92	.053
Development Environments	103	5	10.98	.052
Project Management	101	5	14.29	.014*
Operating Systems	104	5	11.34	.045*
Mobile Computing	102	5	15.90	.007*
Flow Charts	104	5	13.70	.018*
Story Boards	103	5	15.61	.008*
Visual (block) Programming	105	5	6.63	.250
Website Development and Design	104	5	14.84	.011*
Augmented Reality	104	5	7.93	.160
Automation and Animation	104	5	19.04	.002*
Ethical, Social, and Legal Issues	104	5	19.70	.001*
Data Analyzation Using Computational Tools	104	5	17.38	.004*
Copyright and Intellectual Property	106	5	20.81	<.001*
APIs	104	5	11.93	.036*
Virtual Reality	104	5	8.08	.152

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Cloud Based Computing by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a master's degree and those with a doctoral degree is statistically significant after a Bonferroni correction for multiple comparisons (p = .006) as indicated in Table 18.

Table 18

Pairwise Comparisons of Perceived Level of Knowledge of Cloud Based Computing by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. *p*.[a]
Associate's Degree-Other:	-20.33	33.95	-.60	1.000
Associate's Degree-Master's Degree	-29.34	29.76	-.97	1.000
Associate's Degree-Bachelor's Degree	-33.53	30.13	-1.11	1.000
Associate's Degree-Specialist's Degree	-47.90	29.96	-1.60	1.000
Associate's Degree-Doctoral Degree	-61.61	30.43	-2.02	.644
Other:-Master's Degree	9.01	17.58	.51	1.000
Other:-Bachelor's Degree	13.19	18.20	.73	1.000
Other:-Specialist's Degree	27.57	17.93	1.54	1.000
Other:-Doctoral Degree	41.27	18.70	2.21	.410
Master's Degree-Bachelor's Degree	4.18	8.02	.52	1.000
Master's Degree-Specialist's Degree	-18.56	7.37	-2.52	.177
Master's Degree-Doctoral Degree	-32.27	9.10	-3.55	.006*
Bachelor's Degree-Specialist's Degree	-14.38	8.74	-1.64	1.000
Bachelor's Degree-Doctoral Degree	-28.08	10.25	-2.74	.092
Specialist's Degree-Doctoral Degree	-13.70	9.75	-1.41	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.

Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses initially indicated statistically significant differences of Perceived Knowledge Level for the Computer Science HTML by Highest Degree Earned. However, once the Kruskal-Wallis findings were adjusted for the Bonferroni correction for multiple comparisons there were no statistically significant findings as indicated by the pairwise comparisons in Table 19.

Table 19

Pairwise Comparisons of Perceived Level of Knowledge of HTML by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Other:	-40.50	33.57	-1.21	1.000
Associate's Degree-Master's Degree	-41.84	29.43	-1.42	1.000
Associate's Degree-Specialist's Degree	-42.22	29.60	-1.43	1.000
Associate's Degree-Bachelor's Degree	-42.80	29.79	-1.44	1.000
Associate's Degree-Doctoral Degree	-68.39	30.17	-2.27	.351
Other:-Master's Degree	1.34	17.40	.08	1.000
Other:-Specialist's Degree	1.72	17.690	.10	1.000
Other:-Bachelor's Degree	2.30	17.99	.13	1.000
Other:-Doctoral Degree	27.89	18.62	1.50	1.000
Master's Degree-Specialist's Degree	-.39	7.24	-.05	1.000
Master's Degree-Bachelor's Degree	.96	7.96	.12	1.000
Master's Degree-Doctoral Degree	-26.55	9.28	-2.87	.063
Specialist's Degree-Bachelor's Degree	.58	8.58	.07	1.000
Specialist's Degree-Doctoral Degree	-26.16	9.81	-2.67	.115
Bachelor's Degree-Doctoral Degree	-25.59	10.36	-2.47	.202

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Python by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a master's degree and those with a doctoral degree is statistically significant after a Bonferroni correction for multiple comparisons (p = .025) as indicated in Table 20.

Table 20

Pairwise Comparisons of Perceived Level of Knowledge of Python by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Other:	-16.83	33.16	-.51	1.000
Associate's Degree-Master's Degree	-25.06	29.07	-.86	1.000
Associate's Degree-Specialist's Degree	-30.93	29.24	-1.06	1.000
Associate's Degree-Bachelor's Degree	-42.67	29.50	-1.45	1.000
Associate's Degree-Doctoral Degree	-53.07	29.72	-1.79	1.000
Other:-Master's Degree	8.23	17.19	.48	1.000
Other:-Specialist's Degree	14.09	17.48	.81	1.000
Other:-Bachelor's Degree	25.83	17.91	1.44	1.000
Other:-Doctoral Degree	36.24	18.27	1.98	.710
Master's Degree-Specialist's Degree	-5.86	7.15	-.82	1.000
Master's Degree-Bachelor's Degree	17.60	8.15	2.16	.462
Master's Degree-Doctoral Degree	-28.01	8.92	-3.14	.025*
Specialist's Degree-Bachelor's Degree	11.741	8.74	1.34	1.000
Specialist's Degree-Doctoral Degree	-22.15	9.46	-2.34	.288
Bachelor's Degree-Doctoral Degree	-10.41	10.23	-1.02	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant difference of Perceived Knowledge Level for the Computer Science topic Networks by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a specialist's degree and those with a doctoral degree is statistically significant after a Bonferroni correction for multiple comparisons (p = .026) as indicated in Table 21.

Table 21

Pairwise Comparisons of Perceived Level of Knowledge of Networks by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Other:	-11.00	34.05	-.32	1.000
Associate's Degree-Specialist's Degree	-11.67	30.03	-.37	1.000
Associate's Degree-Master's Degree	-17.28	29.85	-.58	1.000
Associate's Degree-Bachelor's Degree	-24.33	30.22	-.81	1.000
Associate's Degree-Doctoral Degree	-42.85	30.60	-1.40	1.000
Other:-Specialist's Degree	.67	17.95	.04	1.000
Other:-Master's Degree	6.28	17.64	.356	1.000
Other:-Bachelor's Degree	13.33	18.26	.730	1.000
Other:-Doctoral Degree	31.85	18.89	1.686	1.000
Specialist's Degree-Master's Degree	5.61	7.31	.768	1.000
Specialist's Degree-Bachelor's Degree	12.66	8.70	1.455	1.000
Specialist's Degree-Doctoral Degree	-31.18	9.96	-3.132	.026*
Master's Degree-Bachelor's Degree	7.05	8.04	.876	1.000
Master's Degree-Doctoral Degree	-25.57	9.39	-2.724	.097
Bachelor's Degree-Doctoral Degree	-18.52	10.51	-1.763	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Servers by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a specialist’s degree and those with a doctoral degree is statistically significant after a Bonferroni correction for multiple comparisons (p = .011) as indicated in Table 22.

Table 22

Pairwise Comparisons of Perceived Level of Knowledge of Servers by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Specialist's Degree	-29.44	29.41	-1.00	1.000
Associate's Degree-Master's Degree	-35.95	29.24	-1.23	1.000
Associate's Degree-Bachelor's Degree	-39.30	29.5	-1.33	1.000
Associate's Degree-Other:	-39.83	33.342	-1.20	1.000
Associate's Degree-Doctoral Degree	-62.42	29.97	-2.09	.559
Specialist's Degree-Master's Degree	6.50	7.23	.90	1.000
Specialist's Degree-Bachelor's Degree	9.86	8.52	1.16	1.000
Specialist's Degree-Other:	-10.39	17.57	-.59	1.000
Specialist's Degree-Doctoral Degree	-32.98	9.75	-3.38	.011*
Master's Degree-Bachelor's Degree	3.35	7.94	.42	1.000
Master's Degree-Other:	-3.89	17.30	-.23	1.000
Master's Degree-Doctoral Degree	-26.47	9.25	-2.87	.063
Bachelor's Degree-Other:	-.53	17.88	-.03	1.000
Bachelor's Degree-Doctoral Degree	-23.12	10.29	-2.25	.369
Other:-Doctoral Degree	22.59	18.50	1.22	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Encryption by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a specialist's degree and those with a doctoral degree is statistically significant after a Bonferroni correction for multiple comparisons (p = .004) as indicated in Table 23.

Table 23

Pairwise Comparisons of Perceived Level of Knowledge of Encryption by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Specialist's Degree	-24.94	29.35	-.85	1.000
Associate's Degree-Other:	-29.17	33.28	-.88	1.000
Associate's Degree-Bachelor's Degree	-32.18	29.57	-1.09	1.000
Associate's Degree-Master's Degree	-34.44	29.19	-1.18	1.000
Associate's Degree-Doctoral Degree	-59.86	29.83	-2.01	.672
Specialist's Degree-Other:	-4.22	17.54	-.241	1.000
Specialist's Degree-Bachelor's Degree	7.24	8.63	.84	1.000
Specialist's Degree-Master's Degree	9.49	7.22	1.32	1.000
Specialist's Degree-Doctoral Degree	-34.91	9.50	-3.68	.004*
Other:-Bachelor's Degree	3.02	17.90	.17	1.000
Other:-Master's Degree	5.27	17.27	.31	1.000
Other:-Doctoral Degree	30.69	18.33	1.68	1.000
Bachelor's Degree-Master's Degree	-2.25	8.06	-.28	1.000
Bachelor's Degree-Doctoral Degree	-27.67	10.15	-2.73	.096
Master's Degree-Doctoral Degree	-25.42	8.98	-2.83	.070

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Clients by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a specialist's degree and those with a doctoral degree is statistically significant after a Bonferroni correction for multiple comparisons (p = .008) as indicated in Table 24.

Table 24

Pairwise Comparisons of Perceived Level of Knowledge of Clients by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Specialist's Degree	-25.50	29.14	-.88	1.000
Associate's Degree-Other:	-28.83	33.02	-.87	1.000
Associate's Degree-Master's Degree	-34.64	28.96	-1.20	1.000
Associate's Degree-Bachelor's Degree	-35.10	29.30	-1.20	1.000
Associate's Degree-Doctoral Degree	-59.04	29.67	-1.99	.700
Specialist's Degree-Other:	-3.33	17.44	-.191	1.000
Specialist's Degree-Master's Degree	9.141	7.24	1.26	1.000
Specialist's Degree-Bachelor's Degree	9.60	8.51	1.13	1.000
Specialist's Degree-Doctoral Degree	-33.54	9.71	-3.45	.008*
Other:-Master's Degree	5.81	17.13	.34	1.000
Other:-Bachelor's Degree	6.27	17.70	.35	1.000
Other:-Doctoral Degree	30.21	18.32	1.65	1.000
Master's Degree-Bachelor's Degree	.46	7.86	.06	1.000
Master's Degree-Doctoral Degree	-24.40	9.16	-2.66	.116
Bachelor's Degree-Doctoral Degree	-23.94	10.19	-2.35	.282

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant difference of Perceived Knowledge Level for the Computer Science topic Cyber Security by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a specialist's degree and those with a doctoral degree (p = .023) and between those subjects with a master's degree and those with a doctoral degree (p = .13) is statistically significant after a Bonferroni correction for multiple comparisons as indicated in Table 25.

Table 25

Pairwise Comparisons of Perceived Level of Knowledge of Cyber Security by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Other:	-28.00	33.78	-.83	1.000
Associate's Degree-Specialist's Degree	-31.09	29.80	-1.04	1.000
Associate's Degree-Master's Degree	-31.39	29.62	-1.06	1.000
Associate's Degree-Bachelor's Degree	-45.16	30.02	-1.50	1.000
Associate's Degree-Doctoral Degree	-61.64	30.28	-2.04	.627
Other:-Specialist's Degree	3.09	17.81	.17	1.000
Other:-Master's Degree	3.39	17.51	.19	1.000
Other:-Bachelor's Degree	17.16	18.18	.94	1.000
Other:-Doctoral Degree	33.64	18.61	1.81	1.000
Specialist's Degree-Master's Degree	.30	7.29	.04	1.000
Specialist's Degree-Bachelor's Degree	14.07	8.76	1.61	1.000
Specialist's Degree-Doctoral Degree	-30.55	9.64	-3.17	.023*
Master's Degree-Bachelor's Degree	13.77	8.15	1.69	1.000
Master's Degree-Doctoral Degree	-30.26	9.09	-3.33	.013*
Bachelor's Degree-Doctoral Degree	-16.49	10.31	-1.60	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant difference of Perceived Knowledge Level for the Computer Science topic Part of a URL by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a master's degree and those with a doctoral degree is statistically significant after a Bonferroni correction for multiple comparisons (p = .046) as indicated in Table 26.

Table 26

Pairwise Comparisons of Perceived Level of Knowledge of Parts of a URL by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Other:	-34.00	33.61	-1.012	1.000
Associate's Degree-Specialist's Degree	-39.24	29.64	-1.324	1.000
Associate's Degree-Bachelor's Degree	-43.92	29.86	-1.471	1.000
Associate's Degree-Master's Degree	-45.96	29.47	-1.560	1.000
Associate's Degree-Doctoral Degree	-73.46	30.21	-2.432	.225
Other:-Specialist's Degree	5.24	17.72	.296	1.000
Other:-Bachelor's Degree	9.92	18.08	.549	1.000
Other:-Master's Degree	11.96	17.42	.687	1.000
Other:-Doctoral Degree	39.46	18.64	2.117	.514
Specialist's Degree-Bachelor's Degree	4.68	8.72	.537	1.000
Specialist's Degree-Master's Degree	6.72	7.25	.927	1.000
Specialist's Degree-Doctoral Degree	-34.22	9.83	-3.483	.007*
Bachelor's Degree-Master's Degree	-2.04	8.11	-.252	1.000
Bachelor's Degree-Doctoral Degree	-29.54	10.48	-2.820	.072
Master's Degree-Doctoral Degree	-27.50	9.29	-2.959	.046*

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Bandwidth by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a specialist's degree and those with a doctoral degree is statistically significant after a Bonferroni correction for multiple comparisons (p = .012) as indicated in Table 27.

Table 27

Pairwise Comparisons of Perceived Level of Knowledge of Bandwidth by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Other:	-17.00	33.64	-.51	1.000
Associate's Degree-Specialist's Degree	-29.48	29.66	-.99	1.000
Associate's Degree-Master's Degree	-39.73	29.50	-1.35	1.000
Associate's Degree-Bachelor's Degree	-45.26	29.89	-1.52	1.000
Associate's Degree-Doctoral Degree	-61.68	30.15	-2.05	.612
Other:-Specialist's Degree	12.48	17.72	.70	1.000
Other:-Master's Degree	22.73	17.45	1.30	1.000
Other:-Bachelor's Degree	28.26	18.10	1.56	1.000
Other:-Doctoral Degree	44.68	18.53	2.41	.239
Specialist's Degree-Master's Degree	10.25	7.29	1.41	1.000
Specialist's Degree-Bachelor's Degree	15.78	8.72	1.81	1.000
Specialist's Degree-Doctoral Degree	-32.20	9.59	-3.36	.012*
Master's Degree-Bachelor's Degree	5.53	8.15	.68	1.000
Master's Degree-Doctoral Degree	-21.95	9.08	-2.42	.234
Bachelor's Degree-Doctoral Degree	-16.42	10.26	-1.60	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Wireless Communication by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a specialist's degree and those with a doctoral degree is statistically significant after a Bonferroni correction for multiple comparisons (p = .038) as indicated in Table 28.

Table 28

Pairwise Comparisons of Perceived Level of Knowledge of Wireless Communication by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Other:	-22.00	33.08	-.67	1.000
Associate's Degree-Specialist's Degree	-37.23	29.20	-1.28	1.000
Associate's Degree-Master's Degree	-41.73	29.01	-1.44	1.000
Associate's Degree-Bachelor's Degree	-48.34	29.40	-1.65	1.000
Associate's Degree-Doctoral Degree	-66.65	29.73	-2.24	.375
Other:-Specialist's Degree	15.23	17.47	.87	1.000
Other:-Master's Degree	19.73	17.15	1.15	1.000
Other:-Bachelor's Degree	26.34	17.80	1.48	1.000
Other:-Doctoral Degree	44.65	18.35	2.43	.224
Specialist's Degree-Master's Degree	4.49	7.22	.62	1.000
Specialist's Degree-Bachelor's Degree	11.11	8.65	1.29	1.000
Specialist's Degree-Doctoral Degree	-29.42	9.73	-3.02	.038*
Master's Degree-Bachelor's Degree	6.62	7.98	.83	1.000
Master's Degree-Doctoral Degree	-24.93	9.15	-2.73	.096
Bachelor's Degree-Doctoral Degree	-18.31	10.31	-1.78	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.

Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses initially indicated statistically significant differences of Perceived Knowledge Level for the Computer Science topic IoT by Highest Degree Earned. However, once the Kruskal-Wallis findings were adjusted for the Bonferroni correction for multiple comparisons there were no statistically significant findings as indicated by the pairwise comparisons in Table 29.

Table 29

Pairwise Comparisons of Perceived Level of Knowledge of IoT by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Other:	-10.17	33.72	-.30	1.000
Associate's Degree-Specialist's Degree	-32.41	29.74	-1.0	1.000
Associate's Degree-Master's Degree	-32.93	29.57	-1.11	1.000
Associate's Degree-Bachelor's Degree	-46.18	29.96	-1.54	1.000
Associate's Degree-Doctoral Degree	-53.43	30.23	-1.77	1.000
Other:-Specialist's Degree	22.24	17.77	1.25	1.000
Other:-Master's Degree	22.76	17.48	1.30	1.000
Other:-Bachelor's Degree	36.02	18.14	1.99	.707
Other:-Doctoral Degree	43.26	18.58	2.33	.298
Specialist's Degree-Master's Degree	.52	7.27	.07	1.000
Specialist's Degree-Bachelor's Degree	13.78	8.74	1.58	1.000
Specialist's Degree-Doctoral Degree	-21.02	9.62	-2.19	.433
Master's Degree-Bachelor's Degree	13.26	8.14	1.63	1.000
Master's Degree-Doctoral Degree	-20.50	9.07	-2.26	.357
Bachelor's Degree-Doctoral Degree	-7.24	10.29	-.70	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant difference of Perceived Knowledge Level for the Computer Science topic Simulations to Solve

Real-World Problems by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a specialist's degree and those with a doctoral degree is statistically significant after a Bonferroni correction for multiple comparisons (p = .008) as indicated in Table 30.

Table 30

Pairwise Comparisons of Perceived Level of Knowledge of Simulations to Solve Real-World Problems by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Specialist's Degree	-33.65	29.92	-1.13	1.000
Associate's Degree-Other:	-34.00	33.93	-1.00	1.000
Associate's Degree-Master's Degree	-37.927	29.74	-1.28	1.000
Associate's Degree-Bachelor's Degree	-42.90	30.15	-1.42	1.000
Associate's Degree-Doctoral Degree	-67.96	30.50	-2.23	.387
Specialist's Degree-Other:	-.35	17.88	-.02	1.000
Specialist's Degree-Master's Degree	4.28	7.28	.59	1.000
Specialist's Degree-Bachelor's Degree	9.25	8.80	1.05	1.000
Specialist's Degree-Doctoral Degree	-34.31	9.92	-3.46	.008*
Other:-Master's Degree	3.93	17.57	.22	1.000
Other:-Bachelor's Degree	8.90	18.25	.49	1.000
Other:-Doctoral Degree	33.96	18.82	1.81	1.000
Master's Degree-Bachelor's Degree	4.97	8.16	.61	1.000
Master's Degree-Doctoral Degree	-30.04	9.35	-3.21	.020*
Bachelor's Degree-Doctoral Degree	-25.07	10.58	-2.37	.267

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Modeling to Solve Real-

World Problems by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a specialist's degree and those with a doctoral degree (p = .007) and between those subjects with a master's degree and those with a doctoral degree (p = .014) is statistically significant after a Bonferroni correction for multiple comparisons as indicated in Table 31.

Table 31

Pairwise Comparisons of Perceived Level of Knowledge of Modeling to Solve Real-World Problems by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Other:	-35.00	34.21	-1.02	1.000
Associate's Degree-Specialist's Degree	-35.26	30.17	-1.17	1.000
Associate's Degree-Master's Degree	-39.09	29.99	-1.30	1.000
Associate's Degree-Bachelor's Degree	-46.55	30.40	-1.53	1.000
Associate's Degree-Doctoral Degree	-69.36	30.67	-2.26	.356
Other:-Specialist's Degree	.26	18.03	.01	1.000
Other:-Master's Degree	4.09	17.72	.23	1.000
Other:-Bachelor's Degree	11.55	18.41	.63	1.000
Other:-Doctoral Degree	34.36	18.85	1.82	1.000
Specialist's Degree-Master's Degree	3.83	7.34	.52	1.000
Specialist's Degree-Bachelor's Degree	11.29	8.87	1.27	1.000
Specialist's Degree-Doctoral Degree	-34.10	9.76	-3.49	.007*
Master's Degree-Bachelor's Degree	7.47	8.22	.91	1.000
Master's Degree-Doctoral Degree	-30.27	9.17	-3.30	.014*
Bachelor's Degree-Doctoral Degree	-22.81	10.44	-2.19	.433

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Manipulation of Data by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a specialist's degree and those with a doctoral degree (p = .008) and between those subjects with a master's degree and those with a doctoral degree (p = .001) is statistically significant after a Bonferroni correction for multiple comparisons as indicated in Table 32.

Table 32

Pairwise Comparisons of Perceived Level of Knowledge of Manipulation of Data by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Other:	-24.83	33.67	-.74	1.000
Associate's Degree-Master's Degree	-34.38	29.52	-1.17	1.000
Associate's Degree-Specialist's Degree	-36.63	29.69	-1.23	1.000
Associate's Degree-Bachelor's Degree	-42.87	29.91	-1.43	1.000
Associate's Degree-Doctoral Degree	-70.65	30.26	-2.34	.293
Other:-Master's Degree	9.54	17.45	.55	1.000
Other:-Specialist's Degree	11.80	17.74	.67	1.000
Other:-Bachelor's Degree	18.04	18.11	1.00	1.000
Other:-Doctoral Degree	45.82	18.67	2.45	.212
Master's Degree-Specialist's Degree	-2.26	7.26	-.31	1.000
Master's Degree-Bachelor's Degree	8.49	8.12	1.05	1.000
Master's Degree-Doctoral Degree	-36.28	9.31	-3.90	.001*
Specialist's Degree-Bachelor's Degree	6.24	8.73	.72	1.000
Specialist's Degree-Doctoral Degree	-34.02	9.84	-3.46	.008*
Bachelor's Degree-Doctoral Degree	-27.79	10.49	-2.65	.122

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Knowledge of Project Management by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a specialist's degree and those with a doctoral degree is statistically significant after a Bonferroni correction for multiple comparisons (p = .017) as indicated in Table 33.

Table 33

Pairwise Comparisons of Perceived Level of Knowledge of Project Management by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Other:	-25.17	32.88	-.77	1.000
Associate's Degree-Specialist's Degree	-33.39	28.99	-1.15	1.000
Associate's Degree-Bachelor's Degree	-36.90	29.22	-1.26	1.000
Associate's Degree-Master's Degree	-38.70	28.85	-1.34	1.000
Associate's Degree-Doctoral Degree	-64.69	29.55	-2.19	.429
Other:-Specialist's Degree	8.22	17.33	.47	1.000
Other:-Bachelor's Degree	11.73	17.70	.66	1.000
Other:-Master's Degree	13.53	17.08	.79	1.000
Other:-Doctoral Degree	39.53	18.24	2.17	.453
Specialist's Degree-Bachelor's Degree	3.51	8.53	.41	1.000
Specialist's Degree-Master's Degree	5.31	7.17	.74	1.000
Specialist's Degree-Doctoral Degree	-31.30	9.62	-3.26	.017*
Bachelor's Degree-Master's Degree	-1.80	8.00	-.23	1.000
Bachelor's Degree-Doctoral Degree	-27.80	10.25	-2.71	.100
Master's Degree-Doctoral Degree	-25.99	9.15	-2.84	.067

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses initially indicated statistically significant differences of Perceived Knowledge Level for the Computer Science topic Knowledge of Operation Systems by Highest Degree Earned. However, once the Kruskal-Wallis findings were adjusted for the Bonferroni correction for multiple comparisons there were no statistically significant findings as indicated by the pairwise comparisons in Table 34.

Table 34

Pairwise Comparisons of Perceived Level of Knowledge of Operating Systems by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Other:	-30.50	33.64	-.91	1.000
Associate's Degree-Specialist's Degree	-37.89	29.66	-1.28	1.000
Associate's Degree-Master's Degree	-43.18	29.50	-1.46	1.000
Associate's Degree-Bachelor's Degree	-53.05	29.85	-1.78	1.000
Associate's Degree-Doctoral Degree	-62.32	30.15	-2.07	.581
Other:-Specialist's Degree	7.39	17.73	.42	1.000
Other:-Master's Degree	12.68	17.45	.73	1.000
Other:-Bachelor's Degree	22.55	18.04	1.25	1.000
Other: -Doctoral Degree	31.82	18.53	1.72	1.000
Specialist's Degree-Master's Degree	5.29	7.29	.73	1.000
Specialist's Degree-Bachelor's Degree	15.16	8.59	1.76	1.000
Specialist's Degree-Doctoral Degree	-24.43	9.59	-2.55	.163
Master's Degree-Bachelor's Degree	9.87	8.01	1.23	1.000
Master's Degree-Doctoral Degree	-19.14	9.08	-2.11	.524
Bachelor's Degree-Doctoral Degree	-9.27	10.15	-.91	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant difference of Perceived Knowledge Level for the Computer Science topic Mobile Computing by

Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a specialist's degree and those with a doctoral degree (p = .011) and between those subjects with a master's degree and those with a doctoral degree (p = .036) is statistically significant after a Bonferroni correction for multiple comparisons as indicated in Table 35.

Table 35

Pairwise Comparisons of Perceived Level of Knowledge of Mobile Computing by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Other:	-28.00	32.93	-.85	1.000
Associate's Degree-Specialist's Degree	-34.33	29.07	-1.18	1.000
Associate's Degree-Master's Degree	-39.45	28.88	-1.37	1.000
Associate's Degree-Bachelor's Degree	-47.82	29.26	-1.64	1.000
Associate's Degree-Doctoral Degree	-67.08	29.60	-2.27	.352
Other:-Specialist's Degree	6.33	17.39	.36	1.000
Other:-Master's Degree	11.45	17.07	.67	1.000
Other:-Bachelor's Degree	19.82	17.72	1.19	1.000
Other:-Doctoral Degree	39.08	18.27	2.14	.486
Specialist's Degree-Master's Degree	5.12	7.19	.71	1.000
Specialist's Degree-Bachelor's Degree	13.49	8.61	1.57	1.000
Specialist's Degree-Doctoral Degree	-32.75	9.69	-3.38	.011*
Master's Degree-Bachelor's Degree	8.37	7.95	1.05	1.000
Master's Degree-Doctoral Degree	-27.63	9.11	-3.04	.036*
Bachelor's Degree-Doctoral Degree	-19.26	10.27	-1.88	.909

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant difference of Perceived Knowledge Level for the Computer Science topic Mobile Computing by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a specialist's degree and those with a doctoral degree is statistically significant after a Bonferroni correction for multiple comparisons (p = .016) as indicated in Table 36.

Table 36

Pairwise Comparisons of Perceived Level of Knowledge of Flow Charts by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Specialist's Degree	-33.39	29.80	-1.12	1.000
Associate's Degree-Master's Degree	-47.50	29.62	-1.60	1.000
Associate's Degree-Bachelor's Degree	-48.16	30.02	-1.60	1.000
Associate's Degree-Other:	-53.00	33.79	-1.57	1.000
Associate's Degree-Doctoral Degree	-64.90	30.29	-2.14	.482
Specialist's Degree-Master's Degree	14.11	7.29	1.94	.793
Specialist's Degree-Bachelor's Degree	14.77	8.76	1.67	1.000
Specialist's Degree-Other:	-19.61	17.81	-1.10	1.000
Specialist's Degree-Doctoral Degree	-31.50	9.64	-3.27	.016*
Master's Degree-Bachelor's Degree	.66	8.15	.08	1.000
Master's Degree-Other:	-5.50	17.56	-.31	1.000
Master's Degree-Doctoral Degree	-17.40	9.07	-1.91	.834
Bachelor's Degree-Other:	-4.84	18.18	-.27	1.000
Bachelor's Degree-Doctoral Degree	-16.73	10.31	-1.63	1.000
Other:-Doctoral Degree	11.89	18.62	.64	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Story Boards by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a specialist's degree and those with a doctoral degree is statistically significant after a Bonferroni correction for multiple comparisons (p = .005) as indicated in Table 37.

Table 37

Pairwise Comparisons of Perceived Level of Knowledge of Story Boards by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Specialist's Degree	-35.89	29.53	-1.215	1.000
Associate's Degree-Bachelor's Degree	-42.71	29.76	-1.435	1.000
Associate's Degree-Master's Degree	-46.14	29.37	-1.571	1.000
Associate's Degree-Other:	-46.17	33.49	-1.378	1.000
Associate's Degree-Doctoral Degree	-70.92	30.10	-2.356	.277
Specialist's Degree-Bachelor's Degree	6.82	8.67	.785	1.000
Specialist's Degree-Master's Degree	10.25	7.23	1.419	1.000
Specialist's Degree-Other:	-10.28	17.65	-.582	1.000
Specialist's Degree-Doctoral Degree	-35.04	9.79	-3.578	.005*
Bachelor's Degree-Master's Degree	-3.43	8.08	-.424	1.000
Bachelor's Degree-Other:	-3.46	18.02	-.192	1.000
Bachelor's Degree-Doctoral Degree	-28.22	10.44	-2.702	.103
Master's Degree-Other:	-.02	17.36	-.002	1.000
Master's Degree-Doctoral Degree	-24.79	9.26	-2.677	.112
Other:-Doctoral Degree	24.76	18.58	1.333	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Website Design and Development by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a specialist’s degree and those with a doctoral degree (p = .038) and between those subjects with a master’s degree and those with a doctoral degree (p = 0.013) is statistically significant after a Bonferroni correction for multiple comparisons as indicated in Table 38.

Table 38

Pairwise Comparisons of Perceived Level of Knowledge of Website Development and Design by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Master's Degree	-43.57	29.49	-1.48	1.000
Associate's Degree-Other:	-44.33	33.65	-1.32	1.000
Associate's Degree-Specialist's Degree	-44.85	29.67	-1.51	1.000
Associate's Degree-Bachelor's Degree	-49.71	29.90	-1.66	1.000
Associate's Degree-Doctoral Degree	-74.54	30.24	-2.47	.205
Master's Degree-Other:	-.76	17.43	-.04	1.000
Master's Degree-Specialist's Degree	-1.28	7.22	-.18	1.000
Master's Degree-Bachelor's Degree	6.14	8.09	.76	1.000
Master's Degree-Doctoral Degree	-30.97	9.27	-3.34	.013*
Other:-Specialist's Degree	.52	17.73	.03	1.000
Other:-Bachelor's Degree	5.38	18.10	.30	1.000
Other:-Doctoral Degree	30.21	18.66	1.61	1.000
Specialist's Degree-Bachelor's Degree	4.86	8.73	.56	1.000
Specialist's Degree-Doctoral Degree	-29.69	9.84	-3.02	.038*
Bachelor's Degree-Doctoral Degree	-24.83	10.49	-2.37	.269

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses initially indicated statistically significant differences of Perceived Knowledge Level for the Computer Science topic Automation and Animation by Highest Degree Earned. However, once the Kruskal-Wallis findings were adjusted for the Bonferroni correction for multiple comparisons there were no statistically significant findings as indicated by the pairwise comparisons in Table 39.

Table 39

Pairwise Comparisons of Perceived Level of Knowledge of Automation and Animation by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Other:	-11.00	33.32	-.33	1.000
Associate's Degree-Specialist's Degree	-26.35	29.38	-.90	1.000
Associate's Degree-Master's Degree	-27.87	29.20	-.95	1.000
Associate's Degree-Bachelor's Degree	-49.76	29.60	-1.68	1.000
Associate's Degree-Doctoral Degree	-54.12	29.94	-1.81	1.000
Other:-Specialist's Degree	15.35	17.56	.88	1.000
Other:-Master's Degree	16.87	17.27	.978	1.000
Other:-Bachelor's Degree	38.76	17.93	2.16	.459
Other:-Doctoral Degree	43.12	18.48	2.33	.295
Specialist's Degree-Master's Degree	1.51	7.15	.21	1.000
Specialist's Degree-Bachelor's Degree	23.41	8.64	2.71	.101
Specialist's Degree-Doctoral Degree	-27.77	9.74	-2.85	.065
Master's Degree-Bachelor's Degree	21.90	8.01	2.74	.094
Master's Degree-Doctoral Degree	-26.25	9.18	-2.86	.064
Bachelor's Degree-Doctoral Degree	-4.35	10.3	-.42	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .050.
a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Ethical, Social and Legal Issues by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a specialist’s degree and those with a doctoral degree is statistically significant after a Bonferroni correction for multiple comparisons (p = .001) as indicated in Table 40.

Table 40

Pairwise Comparisons of Perceived Level of Knowledge of Ethical, Social and Legal Issues by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. *p*[a]
Associate's Degree-Specialist's Degree	-33.72	29.77	-1.13	1.000
Associate's Degree-Other:	-37.17	33.76	-1.10	1.000
Associate's Degree-Bachelor's Degree	-42.68	29.99	-1.42	1.000
Associate's Degree-Master's Degree	-51.31	29.60	-1.74	1.000
Associate's Degree-Doctoral Degree	-71.61	30.26	-2.37	.269
Specialist's Degree-Other:	-3.44	17.79	-.20	1.000
Specialist's Degree-Bachelor's Degree	8.96	8.75	1.02	1.000
Specialist's Degree-Master's Degree	17.59	7.28	2.42	.236
Specialist's Degree-Doctoral Degree	-37.89	9.63	-3.94	.001*
Other:-Bachelor's Degree	5.52	18.16	.30	1.000
Other:-Master's Degree	14.15	17.50	.81	1.000
Other:-Doctoral Degree	34.44	18.60	1.85	.961
Bachelor's Degree-Master's Degree	-8.63	8.15	-1.06	1.000
Bachelor's Degree-Doctoral Degree	-28.92	10.30	-2.81	.075
Master's Degree-Doctoral Degree	-20.30	9.08	-2.24	.381

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .050.
a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Data Analyzation Using Computational Tools by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a master’s degree and those with a doctoral degree (p = .005), between those subjects with a specialist’s degree and those with a doctoral degree (p = .006), and between those subjects with a bachelor's degree and those with a doctoral degree (p = .039) is statistically significant after a Bonferroni correction for multiple comparisons as indicated in Table 41.

Table 41

Pairwise Comparisons of Perceived Level of Knowledge of Data Analyzation Using Computational Tools by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Other:	-24.67	33.84	-.73	1.000
Associate's Degree-Specialist's Degree	-32.39	29.85	-1.09	1.000
Associate's Degree-Master's Degree	-33.78	29.67	-1.14	1.000
Associate's Degree-Bachelor's Degree	-36.13	30.03	-1.20	1.000
Associate's Degree-Doctoral Degree	-67.54	30.42	-2.22	.396
Other:-Specialist's Degree	7.72	17.84	.43	1.000
Other:-Master's Degree	9.11	17.54	.52	1.000
Other:-Bachelor's Degree	11.46	18.15	.63	1.000
Other:-Doctoral Degree	42.87	18.77	2.28	.336
Specialist's Degree-Master's Degree	1.39	7.30	.19	1.000
Specialist's Degree-Bachelor's Degree	3.74	8.65	.43	1.000
Specialist's Degree-Doctoral Degree	-35.15	9.90	-3.55	.006*
*Master's Degree-Bachelor's Degree	2.35	8.03	.29	1.000
Master's Degree-Doctoral Degree	-33.76	9.35	-3.61	.005*
Bachelor's Degree-Doctoral Degree	-31.41	10.44	-3.01	.039*

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic APIs by Highest Degree Earned. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with a specialist's degree and those with a doctoral degree is statistically significant after a Bonferroni correction for multiple comparisons (p = .037) as indicated in Table 42.

Table 42

Pairwise Comparisons of Perceived Level of Knowledge of APIs by Highest Degree Earned

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Associate's Degree-Other:	-19.67	33.59	-.59	1.000
Associate's Degree-Specialist's Degree	-28.07	29.62	-.95	1.000
Associate's Degree-Master's Degree	-34.43	29.44	-1.17	1.000
Associate's Degree-Bachelor's Degree	-37.47	29.85	-1.26	1.000
Associate's Degree-Doctoral Degree	-57.81	30.18	-1.92	.832
Other:-Specialist's Degree	8.41	17.70	.48	1.000
Other:-Master's Degree	14.76	17.40	.85	1.000
Other:-Bachelor's Degree	17.81	18.07	.99	1.000
Other:-Doctoral Degree	38.14	18.63	2.05	.609
Specialist's Degree-Master's Degree	6.35	7.21	.88	1.000
Specialist's Degree-Bachelor's Degree	9.40	8.71	1.08	1.000
Specialist's Degree-Doctoral Degree	-29.73	9.82	-3.03	.037*
Master's Degree-Bachelor's Degree	3.05	8.07	.34	1.000
Master's Degree-Doctoral Degree	-23.38	9.26	-2.53	.173
Bachelor's Degree-Doctoral Degree	-20.33	10.47	-1.94	.782

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .050.
a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

Ethnicity

The results of the non-parametric Kruskal-Wallis analyses find no statistically significant differences between ethnicity categories among any of the Computer Science topic areas at the level of $p < .05$ or less. Specifically, in every comparison, the null hypothesis that there is no difference in mean rank ratings of knowledge level on each topic between the ethnicity categories cannot be rejected. Table 43 provides the data for the 40 assessed Computer Science Topic dependent variables of Perceived Level of Knowledge by Ethnicity.

Table 43

Kruskal-Wallis (H) of Perceived Level of Knowledge of Computer Science Knowledge by Ethnicity

Computer Science Topic (DV)	*N*	df	H	*p*
Develop Algorithms	102	3	1.43	.699
Analyze Algorithms	101	3	1.81	.612
Cloud Based	101	3	4.69	.196
Java	101	3	2.60	.458
Java Script	102	3	4.07	.254
C++	100	3	4.22	.238
C	99	3	3.94	.268
HTML	100	3	4.72	.194
Python	99	3	3.01	.391
Computational Thinking	101	3	2.15	.542
Debugging Programs	102	3	1.60	.660
Networks	101	3	1.64	.651
Domain Name Systems	98	3	.58	.902
Servers	99	3	3.48	.324
Encryption	99	3	2.60	.457
Clients	98	3	1.08	.781
Cyber Security	100	3	2.11	.550
URL	99	3	1.09	.779
Bandwidth	100	3	.59	.900
Wireless Communication	98	3	1.98	.577
IoT	100	3	.89	.828
Simulations To Solve Real-World Problems	100	3	1.85	.605
Modeling To Solve Real-World Problems	101	3	1.15	.764
Manipulation of Data	99	3	6.49	.090
Crowdsourcing	99	3	5.82	.121
Development Environments	99	3	5.17	.160
Project Management	97	3	2.52	.471
Operating Systems	101	3	2.22	.528
Mobile Computing	98	3	3.88	.275
Flow Charts	100	3	4.38	.224
Story Boards	99	3	.77	.856
Visual (block) Programming	101	3	1.26	.738
Website Development and Design	100	3	3.41	.333
Augmented Reality	100	3	1.38	.710
Automation and Animation	100	3	4.89	.180
Ethical, Social, and Legal Issues	100	3	.99	.803

Table 43 Continued				
Computer Science Topic (DV)	*N*	df	H	*p*
Data Analyzation Using Computational Tools	100	3	7.076	.070
Copyright and Intellectual Property	102	3	1.011	.798
APIs	100	3	3.818	.282
Virtual Reality	101	3	2.905	.407

Gender

The results of the non-parametric Kruskal-Wallis analyses find statistically significant differences between categories among a number of the Computer Science topic areas at the Bonferroni adjusted level of $p < .05$. Specifically, the null hypothesis that there is no difference in mean rank ratings of knowledge level on each topic between the Gender categories can be rejected for the topics of: Develop Algorithms; Analyze Algorithms; Java; C++; C; Python; Debugging Programs; Networks; Bandwidth; IoT; manipulation of data; Flowcharts; Automation and Animation; APIs. Table 44 provides the data for the 40 assessed Computer Science Topic dependent variables of Perceived Level of Knowledge by Gender.

Table 44

Kruskal-Wallis (H) of Perceived Level of Knowledge of Computer Science Knowledge by Gender

Computer Science Topic (DV)	*N*	df	H	*p*
Develop Algorithms	102	2	8.59	.014*
Analyze Algorithms	101	2	8.55	.014*
Cloud Based	102	2	2.24	.326
Java	101	2	8.64	.013*
Java Script	102	2	3.18	.204
C++	101	2	11.09	.004*
C	100	2	10.99	.004*
HTML	100	2	2.80	.247
Python	99	2	12.52	.002*
Computational Thinking	101	2	5.55	.062
Debugging Programs	102	2	7.33	.026*
Networks	101	2	6.04	.049*
Domain Name Systems	99	2	3.66	.161

Computer Science Topic (DV)	*N*	df	H	*p*
Servers	99	2	1.77	.412
Encryption	99	2	2.67	.264
Clients	99	2	2.62	.271
Cyber Security	100	2	3.39	.184
URL	99	2	1.22	.545
Bandwidth	99	2	6.90	.032*
Wireless Communication	99	2	2.59	.274
IoT	100	2	6.55	.038
Simulations To Solve Real-World Problems	100	2	4.88	.087
Modeling To Solve Real-World Problems	101	2	4.13	.127
Manipulation of Data	99	2	6.16	.046*
Crowdsourcing	99	2	4.45	.108
Development Environments	99	2	3.25	.197
Project Management	97	2	1.90	.388
Operating Systems	100	2	2.39	.303
Mobile Computing	98	2	2.56	.278
Flow Charts	100	2	6.14	.046*
Story Boards	99	2	1.35	.510
Visual (block) Programming	101	2	3.99	.136
Website Development and Design	100	2	1.40	.496
Augmented Reality	100	2	3.32	.190
Automation and Animation	100	2	12.32	.002*
Ethical, Social, and Legal Issues	100	2	1.28	.526
Data Analyzation Using Computational Tools	100	2	5.80	.055
Copyright and Intellectual Property	102	2	1.08	.582
APIs	100	2	6.04	.049*
Virtual Reality	101	2	5.19	.075

A series of post-hoc analyses were conducted to determine which Gender category statistically significantly differs from others within each topic area. A statistically significant difference exists between those identifying as Male compared with Female. The result of the analysis is presented in the following tables.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Develop Algorithms by

Gender. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with the selected gender of female and those with the selected gender of male is statistically significant after a Bonferroni correction for multiple comparisons (p = .01) as indicated in Table 45.

Table 45

Pairwise Comparisons of Perceived Level of Knowledge of Develop Algorithms by Gender

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Female-Prefer not to Answer	-10.53	20.68	-.51	1.000
Female-Male	17.44	5.96	2.92	.010*
Prefer not to Answer-Male	6.91	20.90	.33	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Analyze Algorithms by Gender. Subjects with the selected gender of male on average reported a higher level of perceived knowledge than subjects with the selected gender of female. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with the selected gender of female and those with the selected gender of male is statistically significant after a Bonferroni correction for multiple comparisons (p = .011) as indicated in Table 46.

Table 46

Pairwise Comparisons of Perceived Level of Knowledge of Analyze Algorithms by Gender

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Female-Prefer not to Answer	-12.03	20.42	-.59	1.000
Female-Male	17.18	5.90	2.91	.011*
Prefer not to Answer-Male	5.15	20.63	.25	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Java by Gender. Subjects with the selected gender of male reported on average a higher level of perceived knowledge than subjects with the selected gender of female. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with the selected gender of female and those with the selected gender of male is statistically significant after a Bonferroni correction for multiple comparisons (p = .010) as indicated in Table 47.

Table 47

Pairwise Comparisons of Perceived Level of Knowledge of Java by Gender

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Female-Prefer not to Answer	-7.24	20.39	-.36	1.000
Female-Male	17.33	5.90	2.94	.010*
Prefer not to Answer-Male	10.09	20.61	.49	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic C++ by Gender. Subjects with the selected gender of male reported on average a higher level of perceived knowledge than subjects with the selected gender of female. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with the selected gender of female and those with the selected gender of male is statistically significant after a Bonferroni correction for multiple comparisons (p = .003) as indicated in Table 48.

Table 48

Pairwise Comparisons of Perceived Level of Knowledge of C++ by Gender

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Female-Prefer not to Answer	-4.26	18.94	-.23	1.000
Female-Male	18.22	5.48	3.33	.003*
Prefer not to Answer-Male	13.96	19.14	.73	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic C by Gender. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with the selected gender of female and those with the selected gender of male is statistically significant after a Bonferroni correction for multiple comparisons (p = .004) as indicated in Table 49.

Table 49

Pairwise Comparisons of Perceived Level of Knowledge of C by Gender

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Female-Male	17.25	5.34	3.23	.004*
Female-Prefer not to Answer	-25.64	25.91	-.99	.967
Male-Prefer not to Answer	-8.39	26.05	-.32	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Python by Gender. Subjects with the selected gender of male reported on average a higher level of perceived knowledge than subjects with the selected gender of female. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with the selected gender of female and those with the selected gender of male is statistically significant after a Bonferroni correction for multiple comparisons (p = .001) as indicated in Table 50.

Table 50

Pairwise Comparisons of Perceived Level of Knowledge of Python by Gender

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Prefer not to Answer-Female	.26	19.80	.013	1.000
Prefer not to Answer-Male	20.76	20.04	1.04	.901
Female-Male	20.50	5.83	3.52	.001*

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Debugging Programs by Gender. Subjects with the selected gender of male reported on average a higher level of perceived knowledge than subjects with the selected gender of female. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with the selected gender of female and those with the selected gender of male is statistically significant after a Bonferroni correction for multiple comparisons (p = .024) as indicated in Table 51.

Table 51

Pairwise Comparisons of Perceived Level of Knowledge of Debugging Programs by Gender

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Prefer not to Answer-Female	5.63	20.67	.27	1.000
Prefer not to Answer-Male	21.43	20.90	1.03	.916
Female-Male	15.80	5.96	2.65	.024*

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.
a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses initially indicated statistically significant differences of Perceived Knowledge Level for the Computer Science topic Knowledge of Networks by Gender. However, once the Kruskal-Wallis findings were adjusted for the Bonferroni correction for multiple comparisons there were no statistically significant findings as indicated by the pairwise comparisons in Table 52.

Table 52

Pairwise Comparisons of Perceived Level of Knowledge of Networks by Gender

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Prefer not to Answer-Female	40.08	20.40	1.97	.148
Prefer not to Answer-Male	47.49	20.61	2.30	.064
Female-Male	7.41	5.90	1.26	.628

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.
a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Bandwidth by Gender. Subjects with the selected gender of male reported on average a higher level of perceived knowledge than subjects with the selected gender of female. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with the selected gender of female and those with the selected gender of male is statistically significant after a Bonferroni correction for multiple comparisons (p = .031) as indicated in Table 53.

Table 53

Pairwise Comparisons of Perceived Level of Knowledge of Bandwidth by Gender

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Prefer not to Answer-Female	10.51	28.24	.37	1.00
Prefer not to Answer-Male	25.47	28.39	.90	1.00
Female-Male	14.96	5.84	2.56	.031*

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic IoT by Gender. Subjects with the selected gender of male reported on average a higher level of perceived knowledge than subjects with the selected gender of female. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with the selected gender of female and those with the selected gender of male is statistically significant after a Bonferroni correction for multiple comparisons (p = .032) as indicated in Table 54.

Table 54

Pairwise Comparisons of Perceived Level of Knowledge of IoT by Gender

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Prefer not to Answer-Female	.50	28.31	.02	1.000
Prefer not to Answer-Male	15.38	28.46	.54	1.000
Female-Male	14.88	5.83	2.55	.032*

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.
a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Manipulation of Data by Gender. Subjects with the selected gender of male reported on average a higher level of perceived knowledge than subjects with the selected gender of female. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with the selected gender of female and those with the selected gender of male is statistically significant after a Bonferroni correction for multiple comparisons (p = .042) as indicated in Table 55.

Table 55

Pairwise Comparisons of Perceived Level of Knowledge of Manipulation of Data by Gender

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Female-Male	14.354	5.841	2.458	.042*
Female-Prefer not to Answer	-15.016	28.259	-.531	1.000
Male-Prefer not to Answer	-.662	28.406	-.023	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant difference of Perceived Knowledge Level for the Computer Science topic Knowledge of Flowcharts by Gender. Subjects with the selected gender of male reported on average a higher level of perceived knowledge than subjects with the selected gender of female. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with the selected gender of female and those with the selected gender of male is statistically significant after a Bonferroni correction for multiple comparisons (p = .046) as indicated in Table 56.

Table 56

Pairwise Comparisons of Perceived Level of Knowledge of Flow Charts by Gender

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Female-Male	14.19	5.86	2.42	.046*
Female-Prefer not to Answer	-15.82	20.20	-.78	1.000
Male-Prefer not to Answer	-1.63	20.41	-.08	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic Automation and Animation by Gender. Subjects with the selected gender of male reported on average a higher level of perceived knowledge than subjects with the selected gender of female. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with the selected gender of female and those with the selected gender of male is statistically significant after a Bonferroni correction for multiple comparisons (p = .002) as indicated in Table 57.

Table 57

Pairwise Comparisons of Perceived Level of Knowledge of Automation and Animation by Gender

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Prefer not to Answer-Female	10.19	19.93	.51	1.000
Prefer not to Answer-Male	29.82	20.14	1.48	.416
Female-Male	19.63	5.78	3.40	.002*

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Knowledge Level for the Computer Science topic APIs by Gender. Subjects with the selected gender of male reported on average a higher level of perceived knowledge than subjects with the selected gender of female. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived knowledge level between those subjects with the selected gender of female and those with the selected gender of male is statistically significant after a Bonferroni correction for multiple comparisons (p = .045) as indicated in Table 58.

Table 58

Pairwise Comparisons of Perceived Level of Knowledge of APIs by Gender

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Prefer not to Answer-Female	1.27	20.12	.06	1.000
Prefer not to Answer-Male	15.47	20.33	.76	1.000
Female-Male	14.20	5.83	2.43	.045*

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.
a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

Research Question 3: What are the perceived barriers to effective Computer Science instruction?

Research participants were asked to identify what they perceived to be a barrier to Computer Science instruction from a list of 18 possible barriers. Selected barriers were then coded as 0 if not selected and 1 if selected to allow for data analysis. One hundred six (106) survey instruments were used to complete this section of data analysis. The surveys selected completed all of the responses related to barriers to Computer Science instruction.

The barrier selected most frequently was Lack of sample lesson plans (47.2%) while the barrier selected the least was Lack of advisory committee support (10.4%), excluding the free text response option of Other (6.6%). Lack of computer software (43.4%) and Lack of local industry partner contacts (40.6%) were the second and third most frequently selected barrier respectively.

Lack of administrative support (15.1%) and Lack of student Access (17.0%) to the Internet were the second and third least frequently selected barrier respectively. The full table of results demonstrating the number of times respondents selected an item as a barrier to Computer Science instruction in their classroom is listed Table 59. The predominant category of most frequently selected barriers centered around suboptimal supplies, equipment, and resources.

Table 59

Selected Barriers to instruction of Computer Science

Barrier	Over All *n*	*%*
Lack of sample lesson plans	50	47.2
Lack of computer software	46	43.4
Lack of local industry partner contacts	43	40.6
Lack of classroom tools	38	35.8
Lack of recommended textbooks	38	35.8
Lack of classroom equipment	37	34.9
Lack of student devices/ software relevant to Computer Science	35	33.0
Lack of professional training	34	32.1
Lack of sample lab design	33	31.1
Lack of course pacing guides	32	30.2
Lack of equipment funding	30	28.3
Lack of professional development opportunities	29	27.4
Lack of Professional Development Learning Communities	26	24.5
Lack of local technology department support	26	24.5
Lack suggested classroom supplies	21	19.8
Lack of student access to internet	18	17.0
Lack of administration support	16	15.1
Lack of advisory committee support	11	10.4
Other? Please specify:	7	6.6

Table 60 reports the number of times each barrier to Computer Science instruction in the classroom was with consideration of gender. Of the one hundred six (106) surveys used for this question sixty-three (63) selected female as their gender, thirty-seven (37) selected the gender male, and six (6) choose to prefer not to say. Male respondents identified Lack of Computer Software

(40.5%) and Lack of Classroom Equipment (40.5%) as the top barriers. Respondents who identified as female listed Lack of Sample Lesson Plans (55.6%) as the primary barrier to Computer Science instruction in the classroom with Lack of Recommend Textbooks (44.4%) as the second most selected barrier. Respondents with non-identified gender selected Lack of Computer Software (66.7%) as the primary barrier to Computer Science instruction with Lack of local industry partner contacts (50%) as the second most selected barrier. Female (63) respondents selected on average 5.7 barriers for a total of 359 selections. Male (37) respondents selected an average of 5.0 barriers for a total of 186 barriers. Gender not identified (6) respondents selected an average of 4.2 barriers for a total of 25 barriers. The least selected barriers to Computer Science instruction in the classroom by female respondents were Lack of administration support (11.1%) and Lack of advisory committee support (12.7%). The least selected barriers to Computer Science instruction in the classroom by male respondents were Lack of advisory committee support (8.1%) and Lack of student access to internet (8.1%). The least selected barriers to Computer Science instruction in the classroom by respondents with non-identified gendered were Lack of recommended textbooks (0.0%), Lack of professional training (0.0%), Lack of professional development learning communities (0.0%), Lack of suggested classroom supplies (0.0%), Lack of administration support (0.0%), and Lack of advisory committee support (0.0%).

Table 60
CS Barriers with gender

Barrier	Female *n*	Female %	Male *n*	Male %	Gender Not Identified *n*	Gender Not Identified %
Lack of sample lesson plans	35	55.6	14	37.8	1	16.7
Lack of computer software	27	42.9	15	40.5	4	66.7
Lack of local industry partner contacts	27	42.9	13	35.1	3	50.0
Lack of classroom tools	22	34.9	14	37.8	2	33.3
Lack of recommended textbooks	28	44.4	10	27.0	0	0.0
Lack of classroom equipment	20	31.7	15	40.5	2	33.3
Lack of student devices/ software relevant to Computer Science	23	36.5	10	27.0	2	33.3
Lack of professional training	24	38.1	10	27.0	0	0.0
Lack of sample lab design	22	34.9	9	24.3	2	33.3
Lack of course pacing guides	20	31.7	10	27.0	2	33.3
Lack of equipment funding	15	23.8	14	37.8	1	16.7
Lack of professional development opportunities	19	30.2	9	24.3	1	16.7
Lack of Professional Development Learning Communities	16	25.4	10	27.0	0	0.0
Lack of local technology department support	14	22.2	10	27.0	2	33.3
Lack suggested classroom supplies	17	27.0	4	10.8	0	0.0
Lack of student access to internet	13	20.6	3	8.1	2	33.3
Lack of administration support	7	11.1	9	24.3	0	0.0
Lack of advisory committee support	8	12.7	3	8.1	0	0.0
Other? Please specify:	2	3.2	4	10.8	1	16.7

Research Question 4: Is there a significant difference in the perceived level of satisfaction of Georgia K-12 Computer Science Educators among demographic identifiers?

The results of the non-parametric Kruskal-Wallis analyses found no statistically significant differences between demographic variables of age, ethnicity, and highest degree earned for perceived satisfaction teaching Computer Science at the Bonferroni adjusted level of $p < .05$ by degree level. Specifically, the null hypothesis that there is no difference in mean rank ratings of perceived satisfaction between the age categories, ethnicity, and highest degree earned cannot be rejected. The results of the non-parametric Kruskal-Wallis analyses found statistically significant differences between the demographic variable of gender and perceived satisfaction teaching Computer Science at the Bonferroni adjusted level of $p < .05$ by degree level. Specifically, the null hypothesis that there is no difference in mean rank ratings of perceived satisfaction for the demographic characteristics of gender can be rejected. Table 61 provides the data for Kruskal-Wallis analysis of Perceived Satisfaction Teaching Computer Science by Age, Gender, Ethnicity, and Highest Degree Earned.

Table 61

Kruskal-Wallis (H) of Perceived Satisfaction Teaching Computer Science by Age, Gender, Ethnicity, and Highest Degree Earned

Demographic Variables (IV)	*N*	df	H	*p*
Age	103	5	3.683	.596
Gender	102	2	8.607	.014*
Ethnicity	102	3	1.251	.741
Highest Degree Earned	103	5	8.522	.130

The results of the non-parametric Kruskal-Wallis analyses indicated a statistically significant differences of Perceived Satisfaction Teaching Computer Science by Gender. The Kruskal-Wallis finding is explained by a pairwise comparison in which the difference of perceived satisfaction teaching Computer Science between those subjects with the selected gender of female and those with the selected gender of male is statistically significant after a Bonferroni correction for multiple comparisons ($p = .014$) as indicated in Table 62.

Table 62

Pairwise Comparisons of Perceived Satisfaction Teaching Computer Science by Gender

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Adj. p^a
Male-Female	-16.39	5.79	-2.83	.014*
Male-Prefer not to Answer	-25.62	20.28	-1.26	.619
Female-Prefer not to Answer	-9.24	20.06	-.46	1.000

Note. Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

Summary

Through the analysis of the data received from the survey, the research questions were answered. The purpose of the research questions was to address the identified problem of Computer Science educators feeling overwhelmed, under-supported, and under-qualified to prepare students in Computer Science related content due to perceptions of competency, available professional development, and perceived barriers to Computer Science education. In addition, the purpose of this research was to evaluate how Computer Science teachers perceive their competency to teach Computer Science related content standards and effectiveness of professional development and to examine the relationship between professional development and perceived level of competency, importance and availability of resources, level of satisfaction teaching Computer Science, and perceived barriers to Computer Science education. The procedures and research methods have been detailed in this chapter. Additionally, guidelines and proper procedures for conducting research were followed and approved through Auburn University following IRB protocols.

The following chapter will provide information related to the research findings, conclusions, and recommendations based on the research findings. The chapter will give meaning to the results of the research and provide ideas for future research.

Chapter 5 Findings, Conclusions, and Recommendations

Introduction

Computer Science is a quickly growing field area and there is a shortage in the workforce to fill current vacancies and expected new positions. As the demand for a knowledgeable Computer Science workforce grows, many states are reaching out to public education as a solution. The Georgia Legislature, for example, passed Senate Bill 108 (GA SB 108) during the 2019 legislative session. GA SB 108 will require all middle schools and high schools in Georgia to offer Computer Science courses by the 2024-2025 school year. Georgia has already approved standards for multiple courses in various grade bands. The extensive growth in the field of Computer Science and the recent mandates for more Computer Science options in education has created need of cultivating Computer Science teachers from other disciplines (Dooley et al, 2018). A research survey instrument (Appendix 1) was developed to assess the perceived knowledge of Computer Science teachers in the state of Georgia. Analyses were conducted to determine the perceived level of knowledge of Georgia Computer Science Teachers in relation to 40 Computer Science related topics and to determine the perceived barriers to Computer Science Education. Analyses were also conducted to determine if specific demographic groups of age, degree level, ethnicity, or gender displayed trends in perceived knowledge of 40 Computer Science Topics and the perceived barriers to Computer Science Education.

In the previous chapter, data collected from Computer Science Educators currently teaching a Computer Science related course in a K-12 public school in Georgia utilizing the researcher designed survey Computer Science Perceptions were presented and analyzed. This chapter contains a summary of the findings, conclusions, and recommendations.

Findings

The majority of the respondents in this study were High School 9-12 teachers (77.4%). Most of the Computer Science Teachers that responded to the survey were female (63.0%). The majority of the respondents were of white (69.8%) ethnicity. The majority of the female respondents were of white ethnicity (63.5%) with African American (33.3%) being the next most selected ethnicity. The most often selected ethnicity among males was white (83.8%) The bulk of research participants who responded were between the ages of 40 and 59 (67.9%). The largest percent of respondents reported earning a Master's Degree (38.7%). The majority of the participants (49.1%) have been teaching for sixteen (16) or more years. Most respondents (40.6%) reported having 1 – 5 years of experience teaching Computer Science. The majority of the respondents selected some college (35.8%) experience as a student learning Computer Science. Survey respondents identified Business Education (51.9%) as the most often chosen previous content area before teaching Computer Science.

The top five highest perceived knowledge are Computational Thinking first, followed by Parts of URL, with Ethical, Social, and Legal Issues being selected third most often, next was Website Development and Design followed by HTML. The lowest five topics of perceived knowledge selected were C being selected least often then, C++, Virtual Reality, Augmented Reality, and Crowdsourcing. On average subjects reported an "intermediate knowledge" (M = 3) of those highest-ranked topics. For those lowest-ranked topics, subjects reported on average "developing knowledge" (M = 1) (to "basic knowledge" (M = 2).

Results from Descriptive Statistics indicated the majority (75.2%) of survey respondents indicated a perceived level of knowledge ranging from Developing (24.2%), Basic (24.8%), and Intermediate (26.2%) for the presented 40 topics related to Computer Science. The results of the non-parametric Kruskal-Wallis analyses find no statistically significant differences between age categories among any of the Computer Science topic areas at the level of $p < .05$. The results of the non-parametric Kruskal-Wallis analyses find statistically significant differences between categories among a number of the Computer Science topic areas at the Bonferroni adjusted level of $p < .05$ by degree level. A series of post-hoc analyses were conducted to determine which Highest Degree Earned category statistically significantly differs from others within each topic area. The vast majority of differences exist between those holding a doctoral degree compared with Master's and Specialist's holders. The results of the non-parametric Kruskal-Wallis analyses find no statistically significant differences between ethnicity categories among any of the Computer Science topic areas at the level of $p < .05$ or less. The results of the non-parametric Kruskal-Wallis analyses find statistically significant differences between categories among a number of the Computer Science topic areas at the Bonferroni adjusted level of $p < .05$.

Respondents were asked to identify perceived barriers to Computer Science Instruction. The top 3 highest perceived barriers are 1st) Lack of Sample Lesson Plans; 2nd) Lack of Computer Software; 3rd) Lack of Local Industry Partner Contacts. The lowest 3 barriers are 18th) Lack of Advisory Committee Support; 17th) Lack of Administration Support; 16th) Lack of Student Access to Internet. Female (63) respondents selected on average 5.7 barriers for a total of 359 selections. Male (37) respondents selected an average of 5.0 barriers for a total of 186 barriers. Gender not identified (6) respondents selected an average of 4.2 barriers for a total of 25 barriers**.** This indicates females were more likely than males to select barriers to Computer Science Instruction. The results of the non-parametric Kruskal-Wallis analyses found no statistically significant differences between age categories at the level of $p < .05$ for perceived satisfaction based on the demographics age, degree level earned, ethnicity, or gender.

Conclusions

The following conclusions were based on the findings of the study.

1. The highest percentage of survey respondents were 50-59 (35.9%) years old. An additional 10% reported an age of 60+. Therefore, a large percentage of the respondents are nearing retirement.
2. The majority (49.1%) of the survey respondents reported 16 or more years of teaching experience, and the majority (51.9%) had a previous teaching background in Business Education. Only 3.8% had no previous background in another teaching content area. The implication is that at this time very few Computer Science Educators are entering the field at the beginning of their career as an initial teaching certification area.
3. The four highest areas reported for 'Expert Knowledge" were: Parts of a URL (16.7%), Computational Thinking (14.4%), Ethical, Social, and Legal issues (13.6%), and Visual (block) Programming (13.5%).
4. The four highest areas reported for "Developing Knowledge" were: C (59%), C++ (57.3%), Virtual Reality (43.7%), and Augmented Reality (43.7%). Therefore, these areas should be considered for professional development design.

5. Based on the data collected and analyzed, other areas that should be considered for professional development include: Mobile Computing, Servers, Cloud-Based Computing, and Crowdsourcing.
6. Age nor ethnicity had an impact on the respondents' perceived knowledge. However, degree-level did have a significance for certain topics.
7. Male respondents responded with a higher level of overall perceived knowledge than female respondents.
8. The highest reported perceived barriers to effective Computer Science instruction were: Lack of Sample Lesson Plans, Lack of Computer Software, and Lack of Industry Partner Contacts. Respondents did not report lack of administrative support, student Internet access, or lack of advisory committee support as barriers to effective Computer Science instruction.
9. A difference was found in the perceived level of satisfaction of Georgia K-12 Computer Science Educators based on gender; with males perceiving a higher level of satisfaction on average than females. There were no differences found in perceived level of satisfaction based on age, degree earned, or ethnicity.

Recommendations

Based on the conclusions, the following recommendations are made:

1. The development of an aggressive Computer Science Teacher recruitment plan is needed to attract more entry-career teachers into the field, as well as ensuring demographic diversity.

2. A repository of lesson plans for various Computer Science courses and topics should be created and available.
3. Professional development should be developed in the areas indicated in the study (see Table 9).
4. Additional analysis and research are needed to determine why males perceive higher knowledge levels than females.
5. Strategies should be put in place to minimize the barriers that were identified. Specifically, the top barriers identified: Lack of Sample Lesson Plans, Lack of Computer Software, and Lack of Industry Partner Contacts.
6. Additional analysis and research are needed to determine why females perceive more barriers to Computer Science instruction than their male counterparts. Female respondents were more likely to select additional barriers than male respondents.
7. A follow up study should be conducted within a reasonable amount of time to more clearly define the barriers and indicate if the barriers are due to sub optimal supplies, equipment, or instructional related.
8. Similar studies should be conducted in other states.
9. Evaluation of the qualitative responses should be completed to identify themes within the responses related to specific topics.
10. Articles derived from this research should be submitted to professional CTE journals for publication.

Limitations

While the research yielded valuable findings if the survey were to be replicated the researcher would clarify the validation question related to time teaching "Computer Science" in a manner that would be more inclusive to teachers who may have confused the discipline of Computer Science with one of the many courses which include Computer Science in the course title. Additionally, the researcher would have reformatted questions which identified barriers to teaching Computer Science to allow for a scaled ranking of the provided limitations.

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Appendices

Appendix 1: Survey Instrument

Computer Science Perceptions

Dear fellow educator,

This survey is being completed as part of dissertation research.

This survey is designed to provide insight into the perceptions of Computer Science Educators. The primary purpose of this survey is to determine perceived knowledge of specific Computer Science topics, as well as, perceived barriers to effective instruction.

Personal and identifying information will not be collected through this survey. Any information provided will be kept confidential and used only for the purpose of research.

This survey consists of 18 questions based on a Likert-type scale. This survey should take less than 20 minutes, and provide invaluable insight for Computer Science Professional Development.

Thank you for your willingness to participate.

Please click the link below to download and read the Informed Consent Letter. You may withdrawal your participation by closing your web browser. Information letter irb approved HAVING READ THE INFORMATION ABOVE, YOU MUST DECIDE IF YOU WANT TO PARTICIPATE IN THIS RESEARCH PROJECT.

- I agree to participate
- I do not agree to participate.

In your role as a classroom teacher, how many total years of teaching experience do you have?

- Less than 1 year
- 1-4 years
- 5-10 years
- 11-15 years

○ 16 + years

In your role as a classroom teacher, how many years have you taught Computer Science courses? (Computer science is a general term and not the specific course.)

○ Less than 1 year

○ 1-4 years

○ 5-10 years

○ 11-15 years

○ 16 + years

○ I do not teach Computer Science

How much experience have you had as a STUDENT learning Computer Science?

○ None

○ High school course

○ Some college

○ 2-year degree

○ 4-year degree

○ Professional degree

Using the scale below, indicate your perceived level of knowledge of the following Computer Science topics.

Developing: just beginning to learn topic

Basic: increased understanding of topic

Intermediate: working and functional knowledge of topic

Advanced: in depth application of topic

Expert: master proficiency of topic

	Developing Knowledge	Basic Knowledge	Intermediate Knowledge	Advanced Knowledge	Expert Knowledge
Develop algorithms	○	○	○	○	○
Analyze algorithms	○	○	○	○	○
Cloud based computing	○	○	○	○	○
Java	○	○	○	○	○
Java Script	○	○	○	○	○
C++	○	○	○	○	○
C	○	○	○	○	○
HTML	○	○	○	○	○
Python	○	○	○	○	○
Computational thinking	○	○	○	○	○

Debugging programs					
Networks					
Domain Name Systems					
Servers					
Encryption					
Clients					
Cyber security					
Parts of a URL					
Bandwidth					
Wireless communication					
IoT					
Simulations to solve real-world problems					
Modeling to solve real-world problems					

Manipulation of Data	○	○	○	○	○
Crowdsourcing	○	○	○	○	○
Development environments	○	○	○	○	○
Project management	○	○	○	○	○
Operating systems	○	○	○	○	○
Mobile computing	○	○	○	○	○
Flow charts	○	○	○	○	○
Story boards	○	○	○	○	○
Visual (block) programming	○	○	○	○	○
Website development and design	○	○	○	○	○
Augmented reality	○	○	○	○	○
Automation and Animation	○	○	○	○	○
Ethical, social, and legal issues	○	○	○	○	○

Data analyzation using computational tools	○	○	○	○	○
Copyright and intellectual property	○	○	○	○	○
APIs	○	○	○	○	○
Virtual reality	○	○	○	○	○

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science.

- ☐ Lack of classroom tools
- ☐ Lack of classroom equipment
- ☐ Lack of computer software
- ☐ Lack of sample lab design
- ☐ Lack suggested classroom supplies
- ☐ Lack of sample lesson plans
- ☐ Lack of recommended textbooks
- ☐ Lack of local industry partner contacts
- ☐ Lack of course pacing guides

- Lack of professional development opportunities
- Lack of Professional Development Learning Communities
- Lack of administration support
- Lack of local technology department support
- Lack of equipment funding
- Lack of professional training
- Lack of student access to internet
- Lack of advisory committee support
- Lack of student devices/ software relevant to Computer Science
- Other? Please specify:

Considering your education training program, which ONE of the following most closely describes the teacher induction program you completed?

- Traditional Teacher Induction Program: Obtained a degree of any level with a focus in education
- Alternative Teacher Induction Program: TAPPS, Teach Georgia, other similar program
- No Teacher Induction Program
- Other Please Specify ____

Please select the option that best identifies your route to Computer Science certification.

- GACE - passed GACE Computer Science exam
- Endorsement Program
- Degree in Computer Science
- Not Computer Science Certified
- Other, please specify. ____

In relation to your educational training, which ONE choice most closely identifies your highest completed education level?

- Associate's Degree
- Bachelor's Degree
- Master's Degree
- Specialist's Degree
- Doctoral Degree
- Other: ____

Prior to teaching Computer Science, what was your primary content area?

- Business Education
- Technology/Engineering
- Math
- Science
- Industry ~ non teacher

○ None

○ Other, please specify. ____

Which grade band do you PRIMARILY teach?

○ Elementary/Primary

○ Middle School

○ High School

Please indicate all of the Computer Science courses you have experience teaching:

☐ AP Computer Science A

☐ AP Computer Science Principles

☐ Advanced Cybersecurity

☐ Artificial Intelligence Applications

☐ Artificial Intelligence Concepts

☐ Cloud Computing

☐ Coding for FinTech

☐ Computer Science Principles

☐ Data Science I

☐ Data Science II

☐ Digital Design

- [ ] Embedded Computing
- [ ] E-Sports
- [ ] Financial Technologies and Services
- [ ] Foundations of Artificial Intelligence
- [ ] Game Design: Animation and Simulation
- [ ] IB Computer Science Year 1
- [ ] IB Computer Science Year 2
- [ ] Introduction to Cybersecurity
- [ ] Introduction to Digital Technology
- [ ] Introduction to Financial Technology
- [ ] Introduction to Python Programming
- [ ] Introduction to Software Technology
- [ ] Introduction to Hardware Technology
- [ ] IT Essential
- [ ] IT Support
- [ ] Networking Fundamentals
- [ ] Networking Systems and Support

- [ ] Programming, Games, Apps, and Society
- [ ] Web Design
- [ ] Web Development
- [ ] Other

My gender identity is:

- ○ Male
- ○ Female
- ○ Prefer not to Answer

Please provide your age range:

- ○ 20-29
- ○ 30-39
- ○ 40-49
- ○ 50-59
- ○ 60-69
- ○ 70 +

Please select your ethnicity.

- ○ White
- ○ Black or African American
- ○ American Indian or Alaska Native

- Asian
- Native Hawaiian or Pacific Islander
- Other

If you were given the option to continue teaching Computer Science or move to another content area, would you leave Computer Science content area?

- Yes, I would return to my previous content area
- No, I would continue to teach Computer Science
- Yes, I would move to a new content area
- Unsure

Based on your current experience; how would you rank your satisfaction teaching Computer Science?

- Very Satisfied
- Satisfied
- Neutral
- Not Satisfied
- Very Dissatisfied

Please share any other information that you would like to include about your experience teaching Computer Science.

Appendix 2: Information letter

AUBURN
UNIVERSITY

COLLEGE OF EDUCATION

CURRICULUM & TEACHING

(NOTE: DO NOT AGREE TO PARTICIPATE UNLESS IRB APPROVAL INFORMATION WITH CURRENT DATES HAS BEEN ADDED TO THIS DOCUMENT.)

INFORMATION LETTER
for a Research Study entitled
"Computer Science Perceptions."

You are invited to participate in a research study to provide insight into perceptions and professional development needs in Computer Science education. The study is being conducted by Melissa Busbin, Ph. D. student, under the direction of Dr. Leane Skinner, Professor in the Auburn University Department of Curriculum and Teaching. You are invited to participate because you are listed as a Computer Science teacher and are age 19 or older.

What will be involved if you participate? Your participation is completely voluntary. If you decide to participate in this research study, you will be asked to answer 18 questions by completing an online survey. Your total time commitment will be approximately 20 minutes.

Are there any risks or discomforts? The risks associated with participating in this study are possible loss of anonymity. To minimize these risks, we will secure software and servers.

Are there any benefits to yourself or others? If you participate in this study, you can expect to help shape the future of Career and Technical Education, Computer Science Education, and strength economies associated with such fields. However, participants will not directly benefit from participation in study.

Will you receive compensation for participating? While your time, input, and commitment are appreciated, compensation for participation will not be provided.

Are there any costs? If you decide to participate, you are not expected to incur any costs resulting in participation.

If you change your mind about participating, you can withdraw at any time by closing your browser window. Once you've submitted anonymous data, it cannot be withdrawn since it will be unidentifiable. Your decision about whether or not to participate or to stop participating will not

5040 HALEY CENTER
AUBURN, AL 36849-5212
TELEPHONE:
334-844-4434
FAX:
334-844-6789
www.auburn.edu

Version Date (date document created): February 15, 2022

The Auburn University Institutional Review Board has approved this Document for use from 03/02/2022 to -------- Protocol # 22-093 EX 2203

AUBURN UNIVERSITY

COLLEGE OF EDUCATION

CURRICULUM & TEACHING

jeopardize your future relations with Auburn University, the Department of Curriculum and Teaching or Career and Technical Education.

Any data obtained in connection with this study will remain anonymous. We will protect your privacy and the data you provide by not collecting personal information through the survey instrument. Information collected through your participation may be used to fulfill an educational requirement.

If you have questions about this study, please contact Melissa Busbin at mjb0065@auburn.edu or Dr. Leane Skinner at skinnal@auburn.edu.

If you have questions about your rights as a research participant, you may contact the Auburn University Office of Research Compliance or the Institutional Review Board by phone (334) 844-5966 or e-mail at IRBadmin@auburn.edu or IRBChair@auburn.edu.

HAVING READ THE INFORMATION ABOVE, YOU MUST DECIDE IF YOU WANT TO PARTICIPATE IN THIS RESEARCH PROJECT. IF YOU DECIDE TO PARTICIPATE, PLEASE CLICK ON THE LINK BELOW. YOU MAY PRINT A COPY OF THIS LETTER TO KEEP.

The Auburn University Institutional Review Board has approved this document for use from __________ to _________. Protocol #________

LINK TO SURVEY

5040 HALEY CENTER

AUBURN, AL 36849-5212

TELEPHONE:

334-844-4434

FAX:

334-844-6789

www.auburn.edu

The Auburn University Institutional Review Board has approved this Document for use from
03/02/2022 to -------------
Protocol # 22-093 EX 2203

Version Date (date document created): February 15, 2022

Appendix 3 IRB Approval

8/14/22, 3:23 PM Mail - Melissa Busbin - Outlook

Busbin Approval, Exempt Protocol #22-093 EX 2203, "Perceptions in Computer Science"

IRB Administration <irbadmin@auburn.edu>
Fri 3/4/2022 2:59 PM
To: Melissa Busbin <mjb0065@auburn.edu>
Cc: Leane Skinner <skinnal@auburn.edu>;Marilyn Strutchen <strutme@auburn.edu>

2 attachments (2 MB)
Investigators Responsibilities rev 1-2011.docx; Busbin 22-093 EX 2203 New Revisions.pdf;

Use IRB Submission Page for protocol-related submissions and IRBadmin@auburn.edu for questions and information.
The IRB only accepts forms posted at https://cws.auburn.edu/vpr/compliance/humansubjects/?Forms and submitted electronically.

Dear Ms. Busbin,

Your protocol entitled "Perceptions in Computer Science" has been approved by the IRB as "Exempt" under federal regulation 45 CFR 46.101(b)(2). Attached is a copy of your approved request.

Official notice:
This e-mail serves as official notice that your protocol has been approved. By accepting this approval, you also accept your responsibilities associated with this approval. Details of your responsibilities are attached. Please print and retain.

Expiration:
Continuing review of this Exempt protocol is not required; however, all modification/revisions to the approved protocol must be reviewed and approved by the IRB.

When you have completed all research activities, have no plans to collect additional data and have destroyed all identifiable information as approved by the IRB, please notify this office via e-mail. A final report is no longer required for Exempt protocols.

PLEASE NOTE: If any unfunded, IRB-approved study should later receive funding, you must submit a MODIFICATION REQUEST for IRB review. In the request, identify the funding source/sponsor and AU OSP number. Also, revise IRB-stamped consent documents to include the Sponsor at the top of page 1 and the "Who will see study data?" section of consent documents." (see online template consent documents).

Best wishes for success with your research!

IRB Admin
Office of Research Compliance
Auburn University
540 Devall Drive
Auburn, AL

https://outlook.office.com/mail/id/AAQkADMyMDI2NmI3LTVlNmYtNGNmNy1hMzk5LTQzZDBkZGVlZWE3MAAQAGwVusI%2BmUqMq2p7Av6fICE%3D 1/1

Appendix 4 CITI Training Certificates

CITI PROGRAM

Completion Date 09-Feb-2023
Expiration Date 09-Feb-2026
Record ID 53144356

This is to certify that:

Melissa Busbin

Not valid for renewal of certification through CME.

Has completed the following CITI Program course:

IRB Additional Modules
(Curriculum Group)
Students in Research
(Course Learner Group)
1 - Basic Course
(Stage)

Under requirements set by:

Auburn University

CITI
Collaborative Institutional Training Initiative

Verify at www.citiprogram.org/verify/?w477b5cb3-aea0-4634-bef1-ca1a1ef92ef4-53144356

Completion Date 11-Feb-2023
Expiration Date 11-Feb-2026
Record ID 53144357

This is to certify that:

Melissa Busbin

Not valid for renewal of certification through CME.

Has completed the following CITI Program course:

IRB # 2 Social and Behavioral Emphasis - Non-AU Personnel
(Curriculum Group)
IRB # 2 Social and Behavioral Emphasis - Non-AU Personnel
(Course Learner Group)
1 - Basic Course
(Stage)

Under requirements set by:

Auburn University

CITI
Collaborative Institutional Training Initiative

Verify at www.citiprogram.org/verify/?w80caae4f-97d0-4977-a029-480502e318f7-53144357

Completion Date 09-Feb-2023
Expiration Date 09-Feb-2026
Record ID 53144355

This is to certify that:

Melissa Busbin

Not valid for renewal of certification through CME.

Has completed the following CITI Program course:

IRB Additional Modules
(Curriculum Group)
Research in Public Elementary and Secondary Schools - SBE
(Course Learner Group)
1 - Basic Course
(Stage)

Under requirements set by:

Auburn University

Collaborative Institutional Training Initiative

Verify at www.citiprogram.org/verify/?w0d281ae4-7c26-4203-ab31-f5f7840f4ff8-53144355

CITI PROGRAM

Completion Date 11-Feb-2023
Expiration Date 11-Feb-2026
Record ID 54323070

This is to certify that:

Melissa Busbin

Not valid for renewal of certification through CME.

Has completed the following CITI Program course:

Responsible Conduct of Research
(Curriculum Group)
AU Basic RCR Training for ALL Faculty, Staff, Postdocs, and Students
(Course Learner Group)
1 - RCR
(Stage)

Under requirements set by:

Auburn University

CITI
Collaborative Institutional Training Initiative

Verify at www.citiprogram.org/verify/?w896c6b3b-8001-4c1b-ac74-f3af806163d9-54323070

CITI PROGRAM

Completion Date 22-Oct-2020
Expiration Date 22-Oct-2023
Record ID 26580321

This is to certify that:

Leane Skinner

Has completed the following CITI Program course:

Not valid for renewal of certification through CME.

IRB Additional Modules
(Curriculum Group)
Social, Behavioral and Education Sciences
(Course Learner Group)
1 - Basic Course
(Stage)

Under requirements set by:

Auburn University

CITI
Collaborative Institutional Training Initiative

Verify at www.citiprogram.org/verify/?w40b50d92-5ef4-406b-a04c-def3e46d02fe-26580321

CITI PROGRAM

Completion Date 21-Oct-2020
Expiration Date 21-Oct-2023
Record ID 24536029

This is to certify that:

Leane Skinner

Has completed the following CITI Program course:

Not valid for renewal of certification through CME.

IRB Additional Modules
(Curriculum Group)
Research in Public Elementary and Secondary Schools
(Course Learner Group)
1 - Basic Course
(Stage)

Under requirements set by:

Auburn University

CITI
Collaborative Institutional Training Initiative

Verify at www.citiprogram.org/verify/?wa756ba70-b696-42e4-be66-01e187615694-24536029

Appendix 5 Analysis Perceived Knowledge by Age

Independent-Samples Kruskal-Wallis Test

Hypothesis Test Summary

Null Hypothesis	p [a,b]
Develop algorithms	0.641
Analyze algorithms.	0.815
Cloud based computing	0.409
Java	0.330
Java Script	0.859
C++	0.616
C	0.822
HTML	0.947
Python	0.577
Computational thinking	0.522
Debugging programs	0.649
Networks	0.677
Domain Name Systems	0.773
Servers	0.598
Encryption	0.666
Clients	0.625
Cyber security	0.820
Parts of a URL	0.937
Bandwidth	0.529
Wireless communication	0.776
IoT	0.594
Simulations to solve real-world problems	0.711
Modeling to solve real-world problems	0.709
Manipulation of Data	0.621

Independent-Samples Kruskal-Wallis Test

Hypothesis Test Summary

Null Hypothesis	p [a,b]
Operating systems	0.812
Mobile computing	0.636
Flow charts	0.543
Story boards	0.676
Visual (block) programming	0.739
Website development and design	0.760
Augmented reality	0.783
Automation and Animation	0.886
Ethical, social, and legal issues	0.475
Data analyzation using computational tools	0.875
Copyright and intellectual property	0.730
APIs	0.756
Virtual reality	0.552

a. The significance level is .050.
b. Asymptotic significance is displayed.

Additional Analysis Computer Science Topics by Age

Tests of Normality

	Please provide your age range:	Kolmogorov-Smirnov[b]			Shapiro-Wilk		
		Statistic	df	*p*	Statistic	df	*p*
Develop algorithms	30-39	.23	21	.004*	.853	21	.005*
	40-49	.20	33	.001*	.905	33	.007*
	50-59	.18	37	.004*	.908	37	.005*
	60-69	.6	10	.062	.853	10	.062
Analyze algorithms	30-39	.27	21	<.001*	.845	21	.003*
	40-49	.16	33	.026*	.908	33	.009
	50-59	.19	36	.002*	.902	36	.004*
	60-69	.26	10	.062	.853	10	.062
Cloud based computing	30-39	.19	21	.034*	.874	21	.012*
	40-49	.22	33	<.001*	.887	33	.002*
	50-59	.20	36	<.001*	.854	36	<.001*
	60-69	.17	10	.200	.908	10	.268
Java	30-39	.22	21	.010*	.882	21	.016*
	40-49	.23	33	<.001*	.843	33	<.001*
	50-59	.24	36	<.001*	.837	36	<.001*
	60-69	.23	10	.158	.866	10	.089
Java Script	30-39	.25	21	.001*	.853	21	.005*
	40-49	.26	33	<.001*	.815	33	<.001*
	50-59	.18	37	.005*	.892	37	.002*
	60-69	.19	10	.200**	.905	10	.249
C++	30-39	.28	21	<.001*	.801	21	<.001*
	40-49	.33	33	<.001*	.724	33	<.001*
	50-59	.39	35	<.001*	.605	35	<.001*
	60-69	.23	10	.148	.859	10	.074
C	30-39	.29	21	<.001*	.803	21	<.001*
	40-49	.37	33	<.001*	.666	33	<.001*
	50-59	.38	35	<.001*	.641	35	<.001*
	60-69	.32	9	.009*	.767	9	.009*
HTML	30-39	.25	21	.001*	.874	21	.012*
	40-49	.22	33	<.001*	.886	33	.002*
	50-59	.20	35	.001*	.901	35	.004*
	60-69	.20	10	.200**	.918	10	.344

	Please provide your age		Kolmogorov-Smirnov[b]			Shapiro-Wilk	
		Statistic	df	*p*	Statistic	df	*p*
Python	30-39	.24	20	.003*	.859	20	.008*
	40-49	.22	33	<.001*	.856	33	<.001*
	50-59	.24	37	<.001*	.844	37	<.001*
	60-69	.30	8	.037*	.781	8	.018*
Computational thinking	30-39	.25	21	.001*	.897	21	.031*
	40-49	.17	33	.018*	.908	33	.008*
	50-59	.19	36	.003*	.915	36	.009*
	60-69	.20	10	.200**	.878	10	.124
Debugging programs	30-39	.25	21	.002*	.804	21	<.001*
	40-49	.16	33	.040*	.915	33	.013*
	50-59	.19	37	.001*	.905	37	.004*
	60-69	.22	10	.200**	.896	10	.198
Networks	30-39	.18	21	.083	.921	21	.092*
	40-49	.19	33	.005*	.917	33	.015*
	50-59	.22	36	<.001*	.897	36	.003*
	60-69	.26	10	.047*	.920	10	.359
Domain Name Systems	30-39	.17	21	.103	.915	21	.071
	40-49	.19	32	.004*	.897	32	.005*
	50-59	.18	34	.007*	.896	34	.004*
	60-69	.22	10	.168	.911	10	.287
Servers	30-39	.25	21	.001*	.888	21	.020*
	40-49	.24	33	<.001*	.885	33	.002*
	50-59	.22	34	<.001*	.845	34	<.001*
	60-69	.32	10	.004*	.839	10	.043*
Encryption	30-39	.19	21	.043*	.906	21	.045*
	40-49	.23	33	<.001*	.881	33	.002*
	50-59	.27	35	<.001*	.815	35	<.001*
	60-69	.26	9	.071	.892	9	.208
Clients	30-39	.18	21	.077	.918	21	.079
	40-49	.23	33	<.001*	.871	33	.001*
	50-59	.24	33	<.001*	.824	33	<.001*
	60-69	.18	10	.200**	.907	10	.258

	Please provide your age	Kolmogorov-Smirnov[b] Shapiro-Wilk			Shapiro-Wilk		
		Statistic	df	*p*	Statistic	df	*p*
Cyber security	40-49	.19	33	.003*	.872	33	.001*
	50-59	.20	35	.001*	.867	35	<.001*
	60-69	.25	10	.090	.892	10	.177
Parts of a URL	30-39	.27	21	<.001*	.889	21	.022*
	40-49	.18	33	.006*	.888	33	.003*
	50-59	.24	34	<.001*	.867	34	<.001*
	60-69	.23	10	.168	.911	10	.287
Bandwidth	30-39	.16	21	.146	.916	21	.072
	40-49	.20	33	.002*	.909	33	.009*
	50-59	.26	34	<.001*	.837	34	<.001*
	60-69	.30	10	.011*	.841	10	.045*
Wireless communication	30-39	.21	21	.022*	.906	21	.046*
	40-49	.22	33	<.001*	.907	33	.008*
	50-59	.26	33	<.001*	.868	33	<.001**
	60-69	.35	10	.001*	.820	10	.026*
IoT	30-39	.26	21	<.001*	.869	21	.009*
	40-49	.21	33	.001*	.872	33	.001*
	50-59	.27	35	<.001*	.801	35	<.001*
	60-69	.18	10	.200**	.907	10	.258
Simulations to solve real-world problems	30-39	.18	21	.070	.918	21	.081
	40-49	.18	33	.012*	.914	33	.013*
	50-59	.24	35	<.001*	.863	35	<.001*
	60-69	.25	10	.090	.892	10	.177
Modeling to solve real-world problems	30-39	.20	21	.032*	.926	21	.116
	40-49	.18	33	.009*	.915	33	.013*
	50-59	.29	36	<.001*	.852	36	<.001*
	60-69	.22	10	.168	.838	10	.042
*Manipulation of Data	30-39	.22	21	.010*	.916	21	.072
	40-49	.18	33	.010*	.913	33	.012*
	50-59	.22	34	<.001*	.849	34	<.001*
	60-69	.15	10	.200**	.918	10	.341
Crowdsourcing	30-39	.20	21	.028*	.883	21	.016*
	40-49	.20	33	.002*	.880	33	.002*
	50-59	.29	34	<.001*	.779	34	<.001*
	60-69	.23	10	.148	.859	10	.074*

	Please provide your age	Kolmogorov-Smirnov[b] Statistic	df	p	Shapiro-Wilk Statistic	df	p
Development environments	30-39	.24	21	.002*	.864	21	.008*
	40-49	.26	33	<.001*	.862	33	<.001*
	50-59	.28	34	<.001*	.711	34	<.001*
	60-69	.20	10	.200**	.878	10	.124
Project management	30-39	.22	21	.008*	.838	21	.003*
	40-49	.19	33	.004*	.894	33	.004*
	50-59	.22	32	<.001*	.875	32	.002*
	60-69	.29	10	.018*	.855	10	.067
Operating systems	30-39	.23	21	.004*	.915	21	.070
	40-49	.19	33	.005*	.920	33	.018*
	50-59	.20	35	.001*	.909	35	.007*
	60-69	.26	10	.047*	.920	10	.359
Mobile computing	30-39	.22	20	.009*	.907	20	.057*
	40-49	.20	33	.002*	.912	33	.011*
	50-59	.26	34	<.001*	.871	34	<.001*
	60-69	.31	10	.009*	.781	10	.008*
Flow charts	30-39	.35	21	<.001*	.806	21	<.001*
	40-49	.21	33	<.001*	.900	33	.005*
	50-59	.17	35	.013*	.916	35	.011*
	60-69	.27	10	.037*	.848	10	.055
Story boards	30-39	.30	21	<.001*	.830	21	.002*
	40-49	.23	33	<.001*	.902	33	.006*
	50-59	.19	34	.004*	.912	34	.009*
	60-69	.26	10	.047*	.920	10	.359
Visual (block) programming	30-39	.20	21	.037*	.887	21	.019*
	40-49	.21	33	<.001*	.899	33	.005*
	50-59	.18	36	.007*	.914	36	.009*
	60-69	.27	10	.036*	.866	10	.089
Website development and design	30-39	.21	21	.017*	.910	21	.055*
	40-49	.17	33	.018*	.917	33	.015*
	50-59	.18	35	.005*	.913	35	.009*
	60-69	.26	10	.047*	.920	10	.359
Augmented reality*	30-39	.23	21	.005*	.844	21	.003*
	40-49	.21	33	<.001*	.842	33	<.001*
	50-59	.32	35	<.001*	.755	35	<.001*
	60-69	.26	10	.063	.769	10	.006*

	Please provide your age	Kolmogorov-Smirnov[b] Shapiro-Wilk			Shapiro-Wilk		
		Statistic	df	*p*	Statistic	df	*p*
Automation and Animation	30-39	.18	21	.098	.879	21	.014*
	40-49	.21	33	<.001*	.859	33	<.001*
	50-59	.26	35	<.001*	.814	35	<.001*
	60-69	.26	10	.063	.769	10	.006*
Ethical, social, and legal issues	30-39	.23	21	.007*	.884	21	.017*
	40-49	.17	33	.018*	.921	33	.019*
	50-59	.17	35	.015*	.918	35	.012*
	60-69	.30	10	.010*	.781	10	.008*
Data analyzation using computational tools	30-39	.21	21	.021*	.888	21	.021*
	40-49	.16	33	.024*	.895	33	.004*
	50-59	.23	35	<.001* *	.851	35	<.001*
	60-69	.16	10	.200**	.942	10	.575
Copyright and intellectual property	30-39	.23	21	.005*	.872	21	.010*
	40-49	.18	33	.007*	.911	33	.011*
	50-59	.16	37	.013*	.910	37	.006*
	60-69	.28	10	.023*	.890	10	.172
APIs	30-39	.22	21	.012*	.902	21	.038*
	40-49	.24	33	<.001*	.883	33	.002*
	50-59	.25	35	<.001*	.806	35	<.001*
	60-69	.17	10	.200**	.908	10	.268
Virtual reality	30-39	.22	20	.011*	.865	20	.010*
	40-49	.22	33	<.001*	.845	33	<.001*
	50-59	.35	37	<.001*	.717	37	<.001*
	60-69	.32	10	.005*	.713	10	.001*

Note: **. This is a lower bound of the true significance.

Additional Analysis Computer Science Topics by Age

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	*p*
Develop algorithms	Based on Mean	1.739	3	97	.164
	Based on Median	1.209	3	97	.311
	Based on Median and with adjusted df	1.209	3	91.945	.311
	Based on trimmed mean	1.940	3	97	.128
Analyze algorithms	Based on Mean	1.372	3	96	.256
	Based on Median	1.029	3	96	.383
	Based on Median and with adjusted df	1.029	3	93.856	.384
	Based on trimmed mean	1.539	3	96	.209
Cloud based computing	Based on Mean	.851	3	96	.470
	Based on Median	.837	3	96	.477
	Based on Median and with adjusted df	.837	3	93.874	.477
	Based on trimmed mean	.826	3	96	.483
Java	Based on Mean	1.307	3	96	.277
	Based on Median	1.022	3	96	.386
	Based on Median and with adjusted df	1.022	3	90.845	.387
	Based on trimmed mean	1.214	3	96	.309
Java Script	Based on Mean	3.633	3	97	.016*
	Based on Median	1.523	3	97	.213
	Based on Median and with adjusted df	1.523	3	90.361	.214
	Based on trimmed mean	3.647	3	97	.015*

		Levene Statistic	df1	df2	*p*
C++	Based on Mean	.217	3	95	.884
	Based on Median	.167	3	95	.919
	Based on Median and with adjusted df	.167	3	78.024	.919
	Based on trimmed mean	.127	3	95	.944
C	Based on Mean	.572	3	94	.635
	Based on Median	.032	3	94	.992
	Based on Median and with adjusted df	.032	3	79.425	.992
	Based on trimmed mean	.342	3	94	.795
HTML	Based on Mean	.307	3	95	.820
	Based on Median	.267	3	95	.849
	Based on Median and with adjusted df	.267	3	93.445	.849
	Based on trimmed mean	.310	3	95	.818
Python	Based on Mean	.444	3	94	.722
	Based on Median	.169	3	94	.917
	Based on Median and with adjusted df	.169	3	86.770	.917
	Based on trimmed mean	.407	3	94	.749
Computational thinking	Based on Mean	.679	3	96	.567
	Based on Median	.702	3	96	.553
	Based on Median and with adjusted df	.702	3	91.434	.553
	Based on trimmed mean	.680	3	96	.566

		Levene Statistic	df1	df2	*p*
Debugging programs	Based on Mean	.121	3	97	.948
	Based on Median	.062	3	97	.980
	Based on Median and with adjusted df	.062	3	95.065	.980
	Based on trimmed mean	.131	3	97	.941
Networks	Based on Mean	.411	3	96	.745
	Based on Median	.249	3	96	.862
	Based on Median and with adjusted df	.249	3	93.992	.862
	Based on trimmed mean	.374	3	96	.772
Domain Name Systems	Based on Mean	.480	3	93	.697
	Based on Median	.467	3	93	.706
	Based on Median and with adjusted df	.467	3	90.008	.706
	Based on trimmed mean	.475	3	93	.700
Servers	Based on Mean	.825	3	94	.483
	Based on Median	.497	3	94	.685
	Based on Median and with adjusted df	.497	3	92.210	.685
	Based on trimmed mean	.672	3	94	.571
Encryption	Based on Mean	.236	3	94	.871
	Based on Median	.248	3	94	.862
	Based on Median and with adjusted df	.248	3	90.999	.862
	Based on trimmed mean	.185	3	94	.906

		Levene Statistic	df1	df2	*p*
Clients	Based on Mean	.162	3	93	.922
	Based on Median	.054	3	93	.983
	Based on Median and with adjusted df	.054	3	87.563	.983
	Based on trimmed mean	.088	3	93	.966
Cyber security	Based on Mean	.750	3	95	.525
	Based on Median	.441	3	95	.724
	Based on Median and with adjusted df	.441	3	91.488	.724
	Based on trimmed mean	.718	3	95	.544
Parts of a URL	Based on Mean	1.644	3	94	.184
	Based on Median	1.360	3	94	.260
	Based on Median and with adjusted df	1.360	3	83.060	.261
	Based on trimmed mean	1.693	3	94	.174
Bandwidth	Based on Mean	1.766	3	94	.159
	Based on Median	.834	3	94	.478
	Based on Median and with adjusted df	.834	3	86.624	.479
	Based on trimmed mean	1.485	3	94	.224
Wireless communication	Based on Mean	2.318	3	93	.081*
	Based on Median	1.174	3	93	.324
	Based on Median and with adjusted df	1.174	3	84.621	.325
	Based on trimmed mean	2.357	3	93	.077

		Levene Statistic	df1	df2	*p*
IoT	Based on Mean	.248	3	95	.862
	Based on Median	.083	3	95	.969
	Based on Median with adjusted df	.083	3	85.023	.969
	Based on trimmed mean	.182	3	95	.909
Simulations to solve real-world problems	Based on Mean	.602	3	95	.615
	Based on Median	.280	3	95	.840
	Based on Median with adjusted df	.280	3	89.442	.840
	Based on trimmed mean	.522	3	95	.668
Modeling to solve real-world problems	Based on Mean	1.082	3	96	.361
	Based on Median	.229	3	96	.876
	Based on Median and with adjusted df	.229	3	86.145	.876
	Based on trimmed mean	.978	3	96	.406
Manipulation of Data	Based on Mean	1.459	3	94	.231
	Based on Median	.843	3	94	.474
	Based on Median and with adjusted df	.843	3	87.484	.474
	Based on trimmed mean	1.337	3	94	.267
Crowdsourcing	Based on Mean	.027	3	94	.994
	Based on Median	.016	3	94	.997
	Based on Median and with adjusted df	.016	3	93.766	.997
	Based on trimmed mean	.017	3	94	.997

		Levene Statistic	df1	df2	*p*
Development environments	Based on Mean	.048	3	94	.986
	Based on Median	.085	3	94	.968
	Based on Median and with adjusted df	.085	3	87.774	.968
	Based on trimmed mean	.031	3	94	.993
Project management	Based on Mean	.413	3	92	.744
	Based on Median	.182	3	92	.908
	Based on Median and with adjusted df	.182	3	86.387	.908
	Based on trimmed mean	.436	3	92	.728
Operating systems	Based on Mean	.845	3	95	.473
	Based on Median	.838	3	95	.477
	Based on Median and with adjusted df	.838	3	94.358	.477
	Based on trimmed mean	.842	3	95	.474
Mobile computing	Based on Mean	1.180	3	93	.322
	Based on Median	.620	3	93	.604
	Based on Median and with adjusted df	.620	3	79.887	.604
	Based on trimmed mean	1.084	3	93	.360
Flow charts	Based on Mean	.407	3	95	.748
	Based on Median	.919	3	95	.435
	Based on Median and with adjusted df	.919	3	87.996	.435
	Based on trimmed mean	.465	3	95	.708

		Levene Statistic	df1	df2	*p*
Story boards	Based on Mean	.657	3	94	.581
	Based on Median	.422	3	94	.738
	Based on Median and with adjusted df	.422	3	87.531	.738
	Based on trimmed mean	.656	3	94	.581
Visual (block) programming	Based on Mean	.416	3	96	.742
	Based on Median	.424	3	96	.736
	Based on Median and with adjusted df	.424	3	93.221	.736
	Based on trimmed mean	.415	3	96	.743
Website development and design	Based on Mean	.223	3	95	.880
	Based on Median	.210	3	95	.889
	Based on Median and with adjusted df	.210	3	92.439	.889
	Based on trimmed mean	.223	3	95	.880
Augmented reality	Based on Mean	.846	3	95	.472
	Based on Median	.214	3	95	.886
	Based on Median and with adjusted df	.214	3	64.454	.886
	Based on trimmed mean	.706	3	95	.551
Automation and Animation	Based on Mean	.516	3	95	.672
	Based on Median	.498	3	95	.684
	Based on Median and with adjusted df	.498	3	90.214	.684
	Based on trimmed mean	.519	3	95	.670

		Levene Statistic	df1	df2	*p*
Ethical, social, and legal issues	Based on Mean	.396	3	95	.756
	Based on Median	.333	3	95	.802
	Based on Median and with adjusted df	.333	3	90.680	.802
	Based on trimmed mean	.402	3	95	.752
Data analyzation using computational tools	Based on Mean	.055	3	95	.983
	Based on Median	.028	3	95	.994
	Based on Median and with adjusted df	.028	3	93.995	.994
	Based on trimmed mean	.021	3	95	.996
Copyright and intellectual property	Based on Mean	.741	3	97	.530
	Based on Median	.784	3	97	.506
	Based on Median and with adjusted df	.784	3	95.551	.506
	Based on trimmed mean	.772	3	97	.513
APIs	Based on Mean	1.084	3	95	.360
	Based on Median	.932	3	95	.428
	Based on Median and with adjusted df	.932	3	91.640	.428
	Based on trimmed mean	.984	3	95	.404
Virtual reality	Based on Mean	.854	3	96	.468
	Based on Median	.215	3	96	.886
	Based on Median and with adjusted df	.215	3	65.867	.886
	Based on trimmed mean	.776	3	96	.510

Appendix 6 Information Technology Courses Georgia DOE

Information Technology

Cybersecurity

- Introduction to Digital Technology
- Introduction to Cybersecurity
- Advanced Cybersecurity

Game Design

- Introduction to Digital Technology
- Computer Science Principles or AP Computer Science Principles
- Game Design: Animation and Simulation

Internet of Things

- Introduction to Digital Technology
- Computer Science Principles or AP Computer Science Principles
- Embedded Computing

Programming

- Introduction to Digital Technology
- Computer Science Principles or AP Computer Science Principles
- Programming, Games, Apps,and Society

Web Development

- Introduction to Digital Technology
- Computer Science Principles or AP Computer Science Principles
- Web Development

Computer Science

- Introduction to Digital Technology
- Computer Science Principles or AP Computer Science Principles
- AP Computer Science (Contact College Board for standards)

Information Support and Services

- Introduction to Digital Technology
- IT Essentials
- IT Support

Networking

- Introduction to Digital Technology
- Networking Fundamentals
- Networking Systems and Support

Web and Digital Design

- Introduction to Digital Technology
- Digital Design
- Web Design

New Middle School Georgia Standards of Excellence Computer Science Courses

- 11.01100 Foundations of Secure Information Systems
- 11.01200 Foundations of Computer Programming
- 11.01300 Foundations of Interactive Design

Appendix 7 Respondents Comments

Comments

“I too am a Computer Science teacher and would love to collaborate with you. Do you recommend a particular textbook for my classes? I teach Computer Science Principles and Programming Games Apps and Society. We spend a lot of time on programming and I need more programming exercises for my students to practice.”

“I use Georgia Virtual Learning as a teaching resource but it would be great if there was a high school level textbook. Mostly everything I've been teaching I've learned on my own or taken professional development. “

“I'm going back to school to get my degree in the field because I absolutely love it!”

I just completed the survey, but I'd like to give you a little insight on my experience teaching IT for the last 2 years. I was hired by [redacted] to teach the Information Systems and Support Pathway. I am the only teacher in the District teaching it, as well as likely being the only one in the entire state teaching it. I have nearly 20 years industry experience as an Infrastructure Engineer and Architect. I rewrote the State Standards for the Intro to Hardware course (used by the ISS, Networking, and Cyber Security pathways,) the IT Essentials and IT Support courses last summer. I have spent the last 2 years banging my head against a brick wall trying to get a simple text book from Cengage that includes online labs to teach this pathway.

Rather than appreciating the unicorn nature of this course in the District and treating it as a positive, I have been repeatedly refused materials to effectively teach the courses. Being a SME and an Educator to the point of being able to write the Standards has had zero sway in being provided simple materials. CS gets all the attention with multiple app/dev softwares, but any Pathway outside of CS does not get any consideration. Being denied materials and having given up on getting the appropriate support from my school "leadership" and the District CTAE "leadership" has led me to decide to completely leave teaching after 5 years and go back to industry making real money, not having to deal with never having PD appropriate to my Pathway, and having the ability to get the necessary items to actually do my job.

Am I upset? I used to be, but at this point I am completely numb to the fact that my Pathway does not matter. It is all well and good to teach kids how to code, but who is going to be there to fix the computers when they break? Who is going to set up the networks to run the computers, who is going to secure the environment so that app/devs can do their jobs. This is a sad reality that people in education who have never worked in the real world simply do not understand. I thought I could make a difference with my skills, education, and knowledge, but instead I am leaving the profession completely dismayed at how CTAE is treated, at least inxxxxxxxxxx Sadly I am not alone as I know several of the CTAE teachers at my school are either getting out or looking to.

I believe that the foundation of CTAE needs to be addressed before any talk of effective PDs can be realized. We need foundational support so that we can effectively teach our Pathways, so that the students can fully immerse themselves in the learning, well before we can start to present PD to teachers who are simply trying to keep their heads above water. I do hope that your research can affect some movement towards the field, and I applaud you for continued pursuit of education in CS.

Respectfully,

Appendix 8

Percent total responses for Perceived Knowledge

Computer Science Topics	Developing Knowledge		Basic Knowledge		Intermediate Knowledge		Advance Knowledge		Expert Knowledge	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%
Clients (N = 101)	31	30.7	29	28.7	22	21.8	13	12.9	6	5.9
Debugging programs (N = 105)	16	15.2	22	21.0	33	31.4	21	21.0	12	11.4
Development environments (N = 102)	35	34.3	30	29.4	21	20.6	9	8.8	7	6.9
Operating systems (N = 103)	13	12.6	26	25.3	36	35.0	19	18.4	9	8.7
Project management (N = 100)	22	22.0	25	25.0	29	29.0	16	16.0	8	8.0
Servers (N = 102)	26	25.5	34	33.3	22	21.6	13	12.7	7	6.9
Bandwidth (N = 102)	22	21.6	28	27.5	23	22.5	19	18.6	10	9.8
Cloud based computing (N = 104)	27	26.0	33	31.7	27	26.0	10	9.6	7	6.7
Cyber security (N = 103)	28	27.2	27	26.2	27	26.2	14	13.6	7	6.8
Domain Name Systems (N = 101)	20	19.8	30	29.7	29	28.7	16	15.9	6	5.9
Encryption (N = 102)	33	32.4	28	27.5	23	22.5	14	13.7	4	3.9
Mobile computing (N = 101)	17	16.8	34	33.7	29	28.7	14	13.9	7	6.9
Networks (N = 104)	18	17.3	29	27.9	32	30.8	18	17.3	7	6.7
Parts of a URL (N = 102)	10	9.8	24	23.5	23	22.5	28	27.5	17	16.7
Website development and design (N = 103)	7	6.8	23	22.3	33	32.0	28	27.2	12	11.7

Computer Science Topics	Developing Knowledge		Basic Knowledge		Intermediate Knowledge		Advance Knowledge		Expert Knowledge	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%
Wireless communication (*N* = 101)	14	13.9	29	28.7	30	29.7	21	20.8	7	6.9
Computational Thinking (*N* = 104)	10	9.6	21	20.2	29	27.9	29	27.9	15	14.4
Data analyzation using computational tools (*N* = 103)	29	28.2	23	22.3	27	26.2	17	16.5	7	6.8
Manipulation of Data (*N* = 102)	22	21.6	26	25.5	24	23.5	19	18.6	11	10.8
Modeling to solve real-world problems (*N* = 104)	19	18.3	29	27.9	27	26.0	20	19.2	9	8.6
Simulations to solve real-world problems (*N* = 103)	22	21.4	26	25.2	27	26.2	19	18.5	9	8.7
Augmented reality (*N* = 103)	45	43.7	28	27.2	22	21.4	6	5.8	2	1.9
Automation and Animation (*N* = 103)	36	35.0	29	28.2	28	27.1	7	6.8	3	2.9
Copyright and intellectual property (*N* = 105)	12	11.4	18	17.2	35	33.3	28	26.7	12	11.4
Crowdsourcing (*N* = 102)	37	36.3	31	30.3	25	24.5	7	6.9	2	2.0
Ethical, social, and legal issues (*N* = 103)	10	9.7	18	17.5	33	32.0	28	27.2	14	13.6
Virtual reality (*N* = 103)	45	43.7	28	27.2	23	22.3	6	5.8	1	1.0
Analyze algorithms (*N* = 103)	18	17.5	22	21.3	35	34.0	17	16.5	11	10.7

Computer Science Topics	Developing Knowledge		Basic Knowledge		Intermediate Knowledge		Advance Knowledge		Expert Knowledge	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%
APIs (N = 103)	32	31.1	31	30.1	23	22.3	10	9.7	7	6.8
C (N = 102)	61	59.8	20	19.6	12	11.8	4	3.9	5	4.9
C++ (N = 103)	59	57.3	21	20.4	12	11.6	6	5.8	5	4.9
Develop algorithms (N = 105)	15	14.3	26	24.8	31	29.5	22	20.9	11	10.5
Flow Charts (N = 103)	12	11.7	24	23.3	24	22.3	33	32.0	11	10.7
HTML (N = 103)	14	13.6	15	14.6	29	28.2	36	34.9	9	8.7
Java (N = 104)	32	30.8	24	23.1	28	26.9	12	11.5	8	7.7
Java Script (N = 105)	30	28.5	23	21.9	36	34.3	11	10.5	5	4.8
Python (N = 102)	36	35.3	18	17.6	28	27.5	17	16.7	3	2.9
Story boards (N = 102)	12	11.8	25	24.5	29	28.4	26	25.5	10	9.8
IoT (N = 103)	30	29.1	31	30.1	18	17.5	19	18.4	5	4.9
Visual (block) programming (N = 104)	17	16.3	14	13.5	33	31.7	26	25.0	14	13.5
Totals	994	34.2	1022	24.9	1077	26.1	698	17.0	322	7.8

Appendix 9 Perceived Knowledge by Topic Area

By Topic Area

Topic Computational thinking	*n*	%
Developing Knowledge (1)	10	7.8
Basic Knowledge (2)	21	16.3
Intermediate Knowledge (3)	29	22.5
Advanced Knowledge (4)	30	23.3
Expert Knowledge (5)	15	11.6
Missing System (0)	24	18.6

Note. *N* = 129 Mean – 3.18 SD – 1.191

Topic Parts of a URL	*n*	%
Developing Knowledge (1)	10	7.8
Basic Knowledge (2)	25	19.4
Intermediate Knowledge (3)	23	17.8
Advanced Knowledge (4)	28	21.7
Expert Knowledge (5)	17	13.2
Missing System (0)	26	20.2

Note. *N* = 129 Mean – 3.17 SD – 1.245

Ethical, social, and legal issues	*n*	%
Developing Knowledge (1)	10	7.8
Basic Knowledge (2)	19	14.7
Intermediate Knowledge (3)	33	25.6
Advanced Knowledge (4)	28	21.7
Expert Knowledge (5)	14	10.9
Missing System (0)	25	19.4

Note. *N* = 129 Mean – 3.16 SD – 1.167

Website development and design	*n*	%
Developing Knowledge (1)	7	5.4
Basic Knowledge (2)	23	17.8
Intermediate Knowledge (3)	34	26.4
Advanced Knowledge (4)	28	21.7
Expert Knowledge (5)	12	9.3
Missing System (0)	25	19.4

Note. *N* = 129 Mean – 3.14 SD – 1.101

HTML	*n*	%
Developing Knowledge (1)	14	10.9
Basic Knowledge (2)	15	11.6
Intermediate Knowledge (3)	30	23.3
Advanced Knowledge (4)	36	27.9
Expert Knowledge (5)	9	7.0
Missing System (0)	25	19.4

Note. *N* = 129 Mean – 3.11 SD – 1.173

Copyright and intellectual property	*n*	%
Developing Knowledge (1)	12	9.3
Basic Knowledge (2)	19	14.7
Intermediate Knowledge (3)	35	27.1
Advanced Knowledge (4)	28	21.7
Expert Knowledge (5)	12	9.3
Missing System (0)	23	17.8

Note. *N* = 129 Mean – 3.08 SD – 1.164

Flow charts	*n*	%
Developing Knowledge (1)	12	9.3
Basic Knowledge (2)	24	18.6
Intermediate Knowledge (3)	24	18.6
Advanced Knowledge (4)	33	25.6
Expert Knowledge (5)	11	8.5
Missing System (0)	25	19.4

Note. *N* = 129 Mean – 3.07 SD – 1.201

Visual (block) programming	*n*	%
Developing Knowledge (1)	17	13.2
Basic Knowledge (2)	14	10.9
Intermediate Knowledge (3)	34	26.4
Advanced Knowledge (4)	26	20.2
Expert Knowledge (5)	14	10.9
Missing System (0)	24	18.6

Note. *N* = 129 Mean – 3.06 SD – 1.254

Story boards	*n*	%
Developing Knowledge (1)	12	9.3
Basic Knowledge (2)	25	19.4
Intermediate Knowledge (3)	30	23.3
Advanced Knowledge (4)	26	20.2
Expert Knowledge (5)	10	7.8
Missing System (0)	26	20.2

Note. *N* = 129 Mean – 2.97 SD – 1.167

Debugging programs	*n*	%
Developing Knowledge (1)	16	12.4
Basic Knowledge (2)	22	17.1
Intermediate Knowledge (3)	34	26.4
Advanced Knowledge (4)	22	17.1
Expert Knowledge (5)	12	9.3
Missing System (0)	23	17.8

Note. *N* = 129 Mean – 2.92 SD – 1.217

Develop algorithms	*n*	%
Developing Knowledge (1)	15	11.6
Basic Knowledge (2)	26	20.2
Intermediate Knowledge (3)	32	24.8
Advanced Knowledge (4)	22	17.1
Expert Knowledge (5)	11	8.5
Missing System (0)	23	17.8

Note. *N* = 129 Mean – 2.89 SD – 1.198

Operating systems	*n*	%
Developing Knowledge (1)	13	10.1
Basic Knowledge (2)	27	20.9
Intermediate Knowledge (3)	36	27.9
Advanced Knowledge (4)	19	14.7
Expert Knowledge (5)	9	7.0
Missing System (0)	25	19.4

Note. *N* = 129 Mean – 2.85 SD – 1.13

Analyze algorithms	*n*	%
Developing Knowledge (1)	18	14.0
Basic Knowledge (2)	22	17.1
Intermediate Knowledge (3)	36	27.9
Advanced Knowledge (4)	17	13.2
Expert Knowledge (5)	11	8.5
Missing System (0)	25	19.4

Note. *N* = 129 Mean – 2.82 SD – 1.213

Wireless communication	*n*	%
Developing Knowledge (1)	14	10.9
Basic Knowledge (2)	30	23.3
Intermediate Knowledge (3)	30	23.3
Advanced Knowledge (4)	21	16.3
Expert Knowledge (5)	7	5.4
Missing System (0)	27	20.9

Note. *N* = 129 Mean – 2.77 SD – 1.134

Modeling to solve real-world problems	*n*	%
Developing Knowledge (1)	19	14.7
Basic Knowledge (2)	29	22.5
Intermediate Knowledge (3)	28	21.7
Advanced Knowledge (4)	20	15.5
Expert Knowledge (5)	9	7.0
Missing System (0)	24	18.6

Note. *N* = 129 Mean – 2.72 SD – 1.213

Manipulation of Data	*n*	%
Developing Knowledge (1)	22	17.1
Basic Knowledge (2)	27	20.9
Intermediate Knowledge (3)	24	18.6
Advanced Knowledge (4)	19	14.7
Expert Knowledge (5)	11	8.5
Missing System (0)	26	20.2

Note. *N* = 129 Mean –2.71 SD – 1.288

Networks	*n*	%
Developing Knowledge (1)	18	14.0
Basic Knowledge (2)	29	22.5
Intermediate Knowledge (3)	33	25.6
Advanced Knowledge (4)	18	14.0
Expert Knowledge (5)	7	5.4
Missing System (0)	24	18.6

Note. *N* = 129 Mean –2.69 SD – 1.146

Simulations to solve real-world problems	*n*	%
Developing Knowledge (1)	22	17.1
Basic Knowledge (2)	26	20.2
Intermediate Knowledge (3)	28	21.7
Advanced Knowledge (4)	19	14.7
Expert Knowledge (5)	9	7.0
Missing System (0)	25	19.4

Note. N = 129 Mean –2.68 SD – 1.241

Bandwidth	*n*	%
Developing Knowledge (1)	23	17.8
Basic Knowledge (2)	28	21.7
Intermediate Knowledge (3)	23	17.8
Advanced Knowledge (4)	19	14.7
Expert Knowledge (5)	10	7.8
Missing System (0)	26	20.2

Note. N = 129 Mean –2.66 SD – 1.28

Project management	*n*	%
Developing Knowledge (1)	22	17.1
Basic Knowledge (2)	26	20.2
Intermediate Knowledge (3)	29	22.5
Advanced Knowledge (4)	16	12.4
Expert Knowledge (5)	8	6.2
Missing System (0)	28	21.7

Note. N = 129 Mean –2.62 SD – 1.215

Mobile computing	*n*	%
Developing Knowledge (1)	17	13.2
Basic Knowledge (2)	35	27.1
Intermediate Knowledge (3)	29	22.5
Advanced Knowledge (4)	14	10.9
Expert Knowledge (5)	7	5.4
Missing System (0)	27	20.9

Note. *N* = 129 Mean –2.6 SD – 1.128

Domain Name Systems	*n*	%
Developing Knowledge (1)	20	15.5
Basic Knowledge (2)	30	23.3
Intermediate Knowledge (3)	30	23.3
Advanced Knowledge (4)	16	12.4
Expert Knowledge (5)	6	4.7
Missing System (0)	27	20.9

Note. *N* = 129 Mean –2.59 SD – 1.146

Data analyzation using computational tools	*n*	%
Developing Knowledge (1)	29	22.5
Basic Knowledge (2)	24	18.6
Intermediate Knowledge (3)	27	20.9
Advanced Knowledge (4)	17	13.2
Expert Knowledge (5)	7	5.4
Missing System (0)	25	19.4

Note. *N* = 129 Mean –2.51 SD – 1.246

Cyber security	*n*	%
Developing Knowledge (1)	29	22.5
Basic Knowledge (2)	27	20.9
Intermediate Knowledge (3)	27	20.9
Advanced Knowledge (4)	14	10.9
Expert Knowledge (5)	7	5.4
Missing System (0)	25	19.4

Note. N = 129 Mean –2.45 SD – 1.222

Java Script	*n*	%
Developing Knowledge (1)	30	23.3
Basic Knowledge (2)	23	17.8
Intermediate Knowledge (3)	37	28.7
Advanced Knowledge (4)	11	8.5
Expert Knowledge (5)	5	3.9
Missing System (0)	23	17.8

Note. N = 129 Mean –2.42 SD – 1.145

Java	*n*	%
Developing Knowledge (1)	33	25.6
Basic Knowledge (2)	24	18.6
Intermediate Knowledge (3)	28	21.7
Advanced Knowledge (4)	12	9.3
Expert Knowledge (5)	8	6.2
Missing System (0)	24	18.6

Note. N = 129 Mean –2.41 SD – 1.253

Servers	*n*	%
Developing Knowledge (1)	27	20.9
Basic Knowledge (2)	34	26.4
Intermediate Knowledge (3)	22	17.1
Advanced Knowledge (4)	13	10.1
Expert Knowledge (5)	7	5.4
Missing System (0)	26	20.2

Note. *N* = 129 Mean –2.41 SD – 1.2

IoT	*n*	%
Developing Knowledge (1)	30	23.3
Basic Knowledge (2)	31	24.0
Intermediate Knowledge (3)	19	14.7
Advanced Knowledge (4)	19	14.7
Expert Knowledge (5)	5	3.9
Missing System (0)	25	19.4

Note. *N* = 129 Mean –2.4 SD – 1.219

Cloud based computing	*n*	%
Developing Knowledge (1)	28	21.7
Basic Knowledge (2)	33	25.6
Intermediate Knowledge (3)	27	20.9
Advanced Knowledge (4)	10	7.8
Expert Knowledge (5)	7	5.4
Missing System (0)	24	18.6

Note. *N* = 129 Mean –2.38 SD – 1.172

Python	*n*	%
Developing Knowledge (1)	37	28.7
Basic Knowledge (2)	18	14.0
Intermediate Knowledge (3)	28	21.7
Advanced Knowledge (4)	17	13.2
Expert Knowledge (5)	3	2.3
Missing System (0)	26	20.2

Note. *N* = 129 Mean –2.33 SD – 1.208

Clients	*n*	%
Developing Knowledge (1)	32	24.8
Basic Knowledge (2)	29	22.5
Intermediate Knowledge (3)	22	17.1
Advanced Knowledge (4)	13	10.1
Expert Knowledge (5)	6	4.7
Missing System (0)	27	20.9

Note. *N* = 129 Mean –2.33 SD – 1.213

APIs	*n*	%
Developing Knowledge (1)	33	25.6
Basic Knowledge (2)	31	24.0
Intermediate Knowledge (3)	23	17.8
Advanced Knowledge (4)	10	7.8
Expert Knowledge (5)	7	5.4
Missing System (0)	25	19.4

Note. *N* = 129 Mean –2.3 SD – 1.206

Encryption	*n*	%
Developing Knowledge (1)	34	26.4
Basic Knowledge (2)	28	21.7
Intermediate Knowledge (3)	23	17.8
Advanced Knowledge (4)	14	10.9
Expert Knowledge (5)	4	3.1
Missing System (0)	26	20.2

Note. *N* = 129 Mean –2.28 SD – 1.175

Development environments	*n*	%
Developing Knowledge (1)	35	27.1
Basic Knowledge (2)	31	24.0
Intermediate Knowledge (3)	21	16.3
Advanced Knowledge (4)	9	7.0
Expert Knowledge (5)	7	5.4
Missing System (0)	26	20.2

Note. *N* = 129 Mean –2.24 SD – 1.208

Automation and Animation	*n*	%
Developing Knowledge (1)	36	27.9
Basic Knowledge (2)	30	23.3
Intermediate Knowledge (3)	28	21.7
Advanced Knowledge (4)	7	5.4
Expert Knowledge (5)	3	2.3
Missing System	25	19.4

Note. *N* = 129 Mean –2.14 SD – 1.065

Crowdsourcing	*n*	%
Developing Knowledge (1)	38	29.5
Basic Knowledge (2)	31	24.0
Intermediate Knowledge (3)	25	19.4
Advanced Knowledge (4)	7	5.4
Expert Knowledge (5)	2	1.6
Missing System (0)	26	20.2

Note. N = 129 Mean –2.07 SD – 1.031

Augmented reality	*n*	%
Developing Knowledge (1)	46	35.7
Basic Knowledge (2)	28	21.7
Intermediate Knowledge (3)	22	17.1
Advanced Knowledge (4)	6	4.7
Expert Knowledge (5)	2	1.6
Missing System (0)	25	19.4

Note. N = 129 Mean – 1.94 SD – 1.032

Virtual reality	*n*	%
Developing Knowledge (1)	46	35.7
Basic Knowledge (2)	28	21.7
Intermediate Knowledge (3)	23	17.8
Advanced Knowledge (4)	6	4.7
Expert Knowledge (5)	1	0.8
Missing System (0)	25	19.4

Note. N = 129 Mean – 1.92 SD – .992

C++	*n*	%
Developing Knowledge	60	46.5
Basic Knowledge	21	16.3
Intermediate Knowledge	12	9.3
Advanced Knowledge	6	4.7
Expert Knowledge	5	3.9
Missing System	25	19.4

Note. N = 129 Mean – 1.8 SD – 1.152

C	*n*	%
Developing Knowledge (1)	62	48.1
Basic Knowledge (2)	20	15.5
Intermediate Knowledge (3)	12	9.3
Advanced Knowledge (4)	4	3.1
Expert Knowledge (5)	5	3.9
Missing System (0)	26	20.2

Note. N = 129 Mean – 1.74 SD – 1.12

Appendix 10 Barriers by Frequency

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science. Lack of sample lesson plans

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of sample lesson plans	50	38.8	100.0	100.0
Missing	System	79	61.2		
Total		129	100.0		

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science. Lack of computer software

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of computer software	46	35.7	100.0	100.0
Missing	System	83	64.3		
Total		129	100.0		

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science. Lack of local industry partner contacts

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of local industry partner contacts	43	33.3	100.0	100.0
Missing	System	86	66.7		
Total		129	100.0		

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science. Lack of recommended textbooks

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of recommended textbooks	38	29.5	100.0	100.0
Missing	System	91	70.5		
Total		129	100.0		

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science. Lack of classroom tools

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of classroom tools	38	29.5	100.0	100.0
Missing	System	91	70.5		
Total		129	100.0		

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science. Lack of classroom equipment

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of classroom equipment	37	28.7	100.0	100.0
Missing	System	92	71.3		
Total		129	100.0		

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science. Lack of student devices/ software relevant to Computer Science

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of student devices/ software relevant to Computer Science	35	27.1	100.0	100.0
Missing	System	94	72.9		
Total		129	100.0		

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science. Lack of professional training

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of professional training	34	26.4	100.0	100.0
Missing	System	95	73.6		
Total		129	100.0		

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science. Lack of sample lab design

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of sample lab design	33	25.6	100.0	100.0
Missing	System	96	74.4		
Total		129	100.0		

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science. Lack of course pacing guides

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of course pacing guides	32	24.8	100.0	100.0
Missing	System	97	75.2		
Total		129	100.0		

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science. Lack of equipment funding

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of equipment funding	30	23.3	100.0	100.0
Missing	System	99	76.7		
Total		129	100.0		

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science. Lack of professional development opportunities

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of professional development opportunities	29	22.5	100.0	100.0
Missing	System	100	77.5		
Total		129	100.0		

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science. Lack of Professional Development Learning Communities

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of Professional Development Learning Communities	26	20.2	100.0	100.0
Missing	System	103	79.8		
Total		129	100.0		

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science. Lack of local technology department support

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of local technology department support	26	20.2	100.0	100.0
Missing	System	103	79.8		
Total		129	100.0		

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science. Lack suggested classroom supplies

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack suggested classroom supplies	21	16.3	100.0	100.0
Missing	System	108	83.7		
Total		129	100.0		

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science. Lack of student access to internet

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of student access to internet	18	14.0	100.0	100.0
Missing	System	111	86.0		
Total		129	100.0		

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science. Lack of administration support

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of administration support	16	12.4	100.0	100.0
Missing	System	113	87.6		
Total		129	100.0		

Based on your experience teaching Computer Science, please select all of the items below that have been barriers to your instruction of Computer Science. Lack of advisory committee support

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of advisory committee support	11	8.5	100.0	100.0
Missing	System	118	91.5		
Total		129	100.0		

Appendix 11 Permissions

[EXTERNAL]Re: Request Permission to Use Disruptive Innovation Model in Dissertation

Rikke Friis Dam <rikke.friis.dam@interaction-design.org>
Wed 10/28/2020 1:38 PM
To: Melissa Busbin <mjb0065@auburn.edu>

NOTICE: This email originated from Gmail. Please report any phishing activity to phishing@auburn.edu.

Hi Melissa,

Sure, no problem. You have our permission to use it as long as you credit the source and keep the links to our content.

If we can do anything else for you, please let me know.

Best wishes,

Rikke Friis Dam
Co-founder and Editor-in-Chief

Interaction Design Foundation
Website | Facebook | Twitter | LinkedIn

Mobile: +45 5153 8333
Email: rikke.friis.dam@interaction-design.org
Skype: rikkefriisdam
About: www.interaction-design.org/about

On Mon, Oct 26, 2020 at 1:08 AM Paul Mateescu <paul@team.interaction-design.org> wrote:

> ---------- Forwarded message ---------
> From: **Melissa Busbin** <mjb0065@auburn.edu>
> Date: Sun, Oct 25, 2020 at 7:14 PM
> Subject: Request Permission to Use Disruptive Innovation Model in Dissertation
> To: paul@team.interaction-design.org <paul@team.interaction-design.org>
>
> Good Afternoon,
>
> My name is Melissa Busbin and I am a Ph.D. Student at Auburn University. I am writing you today to request permission to include the following image in my dissertation as it relates to my subject matter of Computer Science Professional Development and shifting experienced educators into the new field.
>
> Figure Retrieved from: https://www.interaction-design.org/literature/book/the-encyclopedia-of-human-computer-interaction-2nd-ed/disruptive-innovation

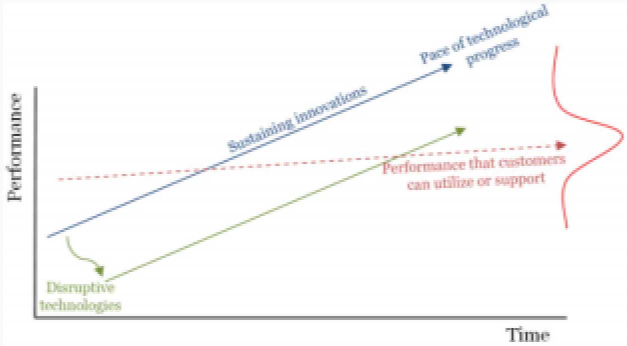

Figure 17.1: The Disruptive Innovation Model

Thank you Melissa Busbin
Lead Professor: Leane Skinner [skinnal@auburn.edu]