A Conceptual Model for Measuring Technology Capacity in American Higher Education: An Exploratory Analysis

By Jerri L. Bland

B.A. in Political Science, May 1993, The University of New Orleans
M.P.A. in Public Administration, May 1995, The University of North Carolina at Chapel Hill

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Dissertation directed by

Lindsey Malcom-Piqueux
Assistant Professor of Higher Education Administration

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Jerri L. Bland

Dissertation Research Committee

Lindsey Malcom-Piqueux, Assistant Professor of Higher Education Administration, Dissertation Director

Diana Burley, Professor of Human and Organizational Learning, Committee Member

William Dardick, Assistant Professor of Educational Research, Committee Member

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Abstract of the Dissertation

A Conceptual Model for Measuring Technology Capacity in American Higher Education: An Exploratory Analysis

The ubiquity of technology in our daily lives sometimes obscures the fact that there are segments of American society who continue to experience a digital divide. The focus of this quantitative study was to explore a measurement instrument that can assess technology capacities among higher education institutions; thus, helping detect whether digital divides are present in this unit of analysis. A conceptual model of technology capacity based upon Barzilai-Nahon's (2006) digital divide index served as the theoretical foundation for this research.

Employing confirmatory and exploratory factor analyses, this study found that the ability to access technology along with the student experience with technology were the two factors that best defined technology capacity for an institution. Additionally, this study recognized that institutional characteristics such as institution location, size, Carnegie classification, and sector influence differences in institutional technology capacities. The research found the technology capacities of rural institutions trailed the technology capacities of institutions located in cities, suburbs, or towns. It was also found that institutions with more than 20,000 students and doctoral institutions far exceeded the capacities of smaller institutions and those of other Carnegie classifications.

One challenge of this study was the available data sets originally gathered in 2008 and 2009 by EDUCAUSE. The results garnered from these data sets revealed there was a digital divide within higher education. However, with the speed of change in the technology landscape, further research is needed to determine whether these divides

persist today. The validated instrument developed by this study will make future and repeated measures of technology capacity attainable for researchers.

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CHAPTER 1:

INTRODUCTION

If a higher education chief information officer were to write an idyllic recruitment brochure for her institution, what would she say? Perhaps she would paint the vivid picture of students sitting on blankets surrounded by beautiful campus landscapes happily typing away on their laptops. Maybe she would brag about an infrastructure that allows students to wirelessly update their Facebook status on their Androids while walking to class; play Words With Friends on an iPad as they wait for their laundry; or enjoy the relaxation of playing Call of Duty 3 in their dorm rooms after class. She might also boast to faculty and graduate students of high-speed computers that can process thousands of rows of genetic data in mere minutes; classrooms that engage student-faculty collaboration and exploration; or the capacity to use real-time, high-quality videoconferencing to collaborate with colleagues across the globe. Or she could highlight the extensive online research databases available through the library in support of researchers and students alike. Finally, she may trumpet the role her institution is taking to make massive open online courses a standard in providing greater access to education.

It sounds like a wonderful institution to attend or work for, right? Most people assume these types of digital amenities are available at institutions of higher education, and they are—but in differing quantities and varying capacities of delivery and use. Large variances in technology capacities are often referred to as the digital divide and are challenging to characterize and expensive to overcome. Ultimately, higher education needs the ability to understand how the digital divide manifests itself within the sector. Therein lies the problem: How do we effectively measure the differences in technology capacities among higher education institutions? Are there ways to predict, and fix, areas of difference?

The digital divide is often discussed in terms of lack of access to technology (Horrigan & Rainie, 2002). However, the digital divide also exhibits itself through infrastructure (Hoffman, Novak, & Schlosser, 2000), levels and types of technology use (Warschauer, 2002), users' ability to receive training or help with technology (Crump & McIlroy, 2003), and impacts of social demography (Bell, Reddy, & Rainie, 2004). Higher education in the United States is not immune to these elements of the digital divide.

Experiencing elements of the digital divide can make a difference in the level or quality of education offered and received at a higher education institution. The skills and knowledge instilled in students during the pursuit of higher education are critical to the greater success of the individual and society as a whole. The economic, political, and educational ramifications of the digital divide can negatively impact the ability of students to be effective, successful players in the global marketplace. Warschauer (2003a) argued that the link between access and use of technology can be the difference between marginalization or inclusion in this modern era. Institutions of higher education that are not able to assess and address known elements of the digital divide place their students at risk of this marginalization.

This chapter begins with a statement of the problem of measuring the technology capacities in higher education followed by a description of the current study's purpose, research questions, and significance. These sections are followed by a presentation of the conceptual framework used to guide this study as well as an overview of the methodology. This chapter closes with a discussion of the study's delimitations, limitations, and definitions.

Statement of the Problem

The digital divide has been studied at multiple levels of analyses. Global commentary has focused on the growing gap between countries on the uses and extent of information and communications technologies that are presumed to drive social change (Menou, 2001). Perhaps the protests in Turkey and Egypt in which protestors used information and communications technologies to champion their causes to populations across the world are real-life examples of this particular dialogue. The global digital divide discussion has also dissected the relationship between the number of Internet users per country and national economic development, with more developed countries reflecting greater Internet usage (James, 2011). Alternatively, researchers have examined the global digital divide at the individual level in absolute numbers by calculating the number of mobile phone subscribers by geographic region (James, 2009). Digital divide discussions at the local or municipality level often focus on improving quality of life or access to information for constituencies (Chang, Yen, Chang, & Chou, 2012). Governmental institutions play a key role in the impact of the digital divide within the educational arena at all levels (Chang et al., 2012; Hernandez, 2010).

A significantly smaller proportion of the literature on the digital divide has focused on variability of technology capacities across the U.S. postsecondary education sector. A small number of studies have assessed the digital divide at the institution level within community colleges (Katsinas & Moeck, 2002) and minority-serving institutions (NAFEO, 2000; Clinedinst, 2004). However, these studies have been primarily descriptive in nature and have not focused on the complex relationships between the multiple elements of technology capacity and the digital divide. With President Obama's initiative to build American skills, it is expected that community colleges will produce an additional 5 million graduates by 2020 (White House, 2014). It is anticipated that community colleges will develop online course to "…help students learn more, and learn better, in less time" (White House, 2014). However, it is assumed these institutions have the necessary infrastructure to support these desires. For example, while the percentage of students who own their own laptops is a metric relevant to assessing technology capacity, this single measure has not been placed in the context of the institution's ability to support an infrastructure for these laptops. Similarly, whether an institution has the capability to create online courses with the pedagogical and technological effectiveness required to meet the needs to President Obama's initiative is another unknown element of technology capacity.

Additionally, studies have not offered a single survey instrument that purports to measure the digital divide within higher education in a comprehensive, complex manner. When the Institute for Higher Education Policy published its assessment of 320 responses to a digital divide survey from members of the Alliance for Equity in Higher Education, the descriptive findings offered in-depth discussion of the responding universities as a whole and between groupings of institutions based upon institutional characteristics (Clinedinst, 2004). But, it was not evident whether the survey instrument itself was based upon any particular theory or framework that ostensibly measured either technology capacity or the digital divide. The same was true for the National Association for Equal Opportunity in Higher Education (2000) survey of historically black colleges and universities (HBCUs). While both studies are considered seminal publications in measuring the digital divide in higher education, neither offered any formalized assessment of the technology capacities of responding institutions, individually or collectively. Neither study was able to offer an individual institutional measurement of technology capacities, nor did these studies offer the opportunity to compare technology capacities among institutions.

The current study sought to create a single valid, reliable instrument based upon a digital divide conceptual model to measure technology capacities within higher education institutions in the United States. The comparison of technology capacities between and among institutions will enable fuller, more in-depth assessment of the digital divide. The analysis of technology capacities across institutional characteristics such as size, geographic location, special mission, and Carnegie classification may also help identify whether certain characteristics play a significant role in the level of technology capacities exhibited by groups of institutions, which may help inform collective solutions to equalize these capacities across institutions. To fully capture the elements of the digital divide debate within this higher education study, the digital divide was defined as the inequities or inequalities created by the inability to access or use technology to advance learning and scholarship—academically, professionally, or personally.

Purpose and Research Questions

The purpose of the present study was to explore the digital divide within higher education in the United States with emphasis on measuring the technology capacities of higher education institutions based upon a conceptual model of technology capacity factors. Confirmatory factor analysis and exploratory factor analysis were used to test the conceptual model. The presence of significant differences in technology capacities between institutions was acknowledged as indicative of the digital divide. As defined by the conceptual model for this study, the dimensions of technology capacity—technology access, infrastructure, use, user support, and institutional characteristics—were used to address three research questions:

1. Do extant measures of technology dimensions support the underlying construct of institutional technology capacity?
2. Which technology dimensions are most relevant for predicting a higher education institution's technology capacity?
3. Do significant differences in technology capacity exist as a function of institutional characteristics?

For the third research question, nine hypotheses were tested:

$H_0 1$: There is no association between the sector designation of an institution and its technology capacities.

$H_0 2$: There is no association between the control designation of an institution and its technology capacities.

$H_0 3$: There is no association between the HBCU designation of an institution and its technology capacities.

$H_0 4$: There is no association between the tribal colleges and universities designation of an institution and its technology capacities.

$H_0 5$: There is no association between the locality of an institution and its technology capacities.

$H_0 6$: There is no association between the size of an institution and its technology capacities.

$H_0 7$: There is no association between the Hispanic-serving institution designation of an institution and its technology capacities.

$H_0 8$: There is no association between the minority-serving institution designation of an institution and its technology capacities.

$H_0 9$: There is no association between the Carnegie classification of an institution and its technology capacities.

Statement of Potential Significance

While the phenomenon of the digital divide may appear to be focused on technology, at least on the surface, there are more fundamental or basic rights at stake. The Organisation for Economic Co-operation and Development (OECD) (2001) indicated that the digital divide is an issue of social inequality. The National Telecommunications and Information Administration (NTIA) of the U.S. Department of Commerce suggested that for the United States, the digital divide is a leading economic and civil rights issue (NTIA, 1999), referencing the "haves" and "have nots" and the information disadvantaged (NTIA, 1995). Duff (2010) argued that information technology brings social justice to the forefront by discussing technology as a component in the fair distribution of worldly goods.

However, the digital divide is not so easily compartmentalized. In defining the digital divide as "the gap between individuals, households, businesses, and geographic areas at different social-economic levels with regard both to their opportunities to access information and communication technologies and to their use of the Internet for a wide variety of activities," the OECD suggested two facets of the digital divide: access to technology and how technology is used (2001, p. 5). These two facets move the digital divide discussion beyond a simple assessment of "haves" and "have nots" (Selwyn, 2004). Different stratifications of the digital divide suggest that "have nots" in one context may be "haves" in another context, further blurring the definition of the digital divide (Warschauer, 2003b). Refocusing the digital divide discussion might require looking at the social contexts of how technology is used in addition to providing computers and Internet access (Warschauer, 2003b). Resolving the inequalities evidenced as a result of the digital divide may demand focus on the unequal ways computers are used rather than the unequal access (Warschauer, 2003b), and understanding how computers can be used to solve problems rather than simply installing computer hardware (Young, 2001).

Students attending postsecondary institutions must be trained to use technology if they hope to compete for high-paying jobs (Carnevale, 2003). Those students who do not have access to gain these skills are at a distinct disadvantage (Carnevale, 2003). The ultimate fear is that the competitiveness of the United States will be undermined by the digital divide (Carnevale, 2003). Such was the concern about the digital divide that the U.S. House of Representatives passed House Resolution 2183 (2003) to fund a $250 million program to help bridge the digital divide in order to educate and prepare a 21st century workforce. However, this program was never funded by Congress.

By creating a single instrument designed to measure institutional technology capacity, this study has the potential to provide researchers, sector leaders, and government officials the opportunity to assess the extent of the digital divide within higher education at depths not previously available. This study offers the unique opportunity not only to reinvigorate the discussion of the digital divide within higher education, but also to provide a reliable instrument and framework for identifying long-lasting solutions.

Conceptual Framework

Most frameworks for measuring the digital divide have focused on the global unit of analysis. These frameworks focus on measuring the depth of the digital divide between countries. The PingER (Cottrell & Matthews, 2003) framework measured the digital divide by analyzing Internet performance throughput along with the United Nations gross domestic product per capita and the Human Development Index for each country. It was immediately clear that this particular framework would not be effective in measuring the digital divide in higher education, as two of its three factors cannot be calculated at the institutional level.

Although developed for a global unit of analysis, the Balanced Scorecard Framework (Yu & Wang, 2005) moves closer to providing a framework that can be molded to a digital divide measurement instrument for higher education. The pillars of its measurement construct are four dimensions (technology diffusion, equal opportunities, information society/e-readiness, and competitiveness) with four digital divide perspectives (financial, beneficiaries, governmental functions and processes, and nationwide learning and growth). This framework also attempts to identify leading and lagging indicators of the digital divide. Performance measures must be generated for each of the eight dimensions. In the higher education context, this model would potentially require wholesale reevaluation of the eight measurement dimensions for relevancy. This issue made use of this framework a larger task than desired for the timeframe of this study.

Avoiding the inherent pitfalls of using a global framework and an overly complicated evaluation matrix, the integrative measurement framework proposed by Barzilai-Nahon (2006) was used to develop the conceptual model for measuring the digital divide in higher education. This digital divide index framework allows researchers the freedom and flexibility to create a measurement instrument that is both unit of analysis and item independent, but still offers a complex modeling of relationships between digital divide factors. This particular framework avoids some of the pitfalls identified by other frameworks.

After critically analyzing existing indices and frameworks as well as reviewing the digital divide literature, Barzilai-Nahon (2006) proposed that six factors have a direct impact on the ability to describe the status of the digital divide as well as an indirect influence on each other. The six factors in this comprehensive model for measuring the digital divide are as follows:

- *Support*: Training and institutional support, which help reduce the digital divide.
- *Affordability:* The increased affordability of products, services, and software as the digital divide is reduced.
- *Sociodemographic factors:* The correlation of different elements of social demographics, such as race, income, and gender, to the digital divide.
- *Use:* How technology is used, which is a factor in explaining the digital divide.
- *Infrastructure:* The foundational aspects of the digital divide, including networking and broadband access.

- *Access:* A rarely studied factor of access to technology by individuals with physical disabilities.

For this study, the researcher made some modifications to the comprehensive measurement and weightings of the key factors of the digital divide index model to effectively describe and measure the status of the digital divide within higher education. To operationalize the framework for this study, the factors of the digital divide index framework were used to calculate a technology capacity index (TCI) score for individual institutions. Comparisons of TCI scores between groupings of institutions by institutional characteristics were used to define whether a digital divide was evident in higher education.

Table 1.1 shows the adapted factors along with sample measures gathered from the literature and relationships that comprise the TCI for higher education.

Table 1.1
Technology Capacity Index Factors, Measures, and Relationships

TCI factors: Original and as renamed	Example of measures in higher education	Factor relationships
Affordability (Technology access)	• Computers owned per student • Types of online services offered	Use Infrastructure
Infrastructure (Infrastructure)	• Physical layer (infrastructure) • Logical layer (applications and software) • High-performance computing capacities	Use
Use (Use)	• Faculty use of technology in the classroom	N/A
Support (User support)	• Training support for students, faculty, and administrators • FTEs supporting the technical infrastructure • Operating and capital budgets • Help desk support	Technology access
Sociodemographic factors (Institutional characteristics)	• Carnegie classification • Geographic location • Special missions • Institutional control • Size	Technology access Use
Accessibility (not used in the adapted model)	• Not applicable to this study as U.S. federal law mandates accessibility requirements for all organizations.	N/A

Figure 1.1 provides a visual depiction of the TCI model conceptual framework for higher education as adapted from Barzilai-Nahon (2006).

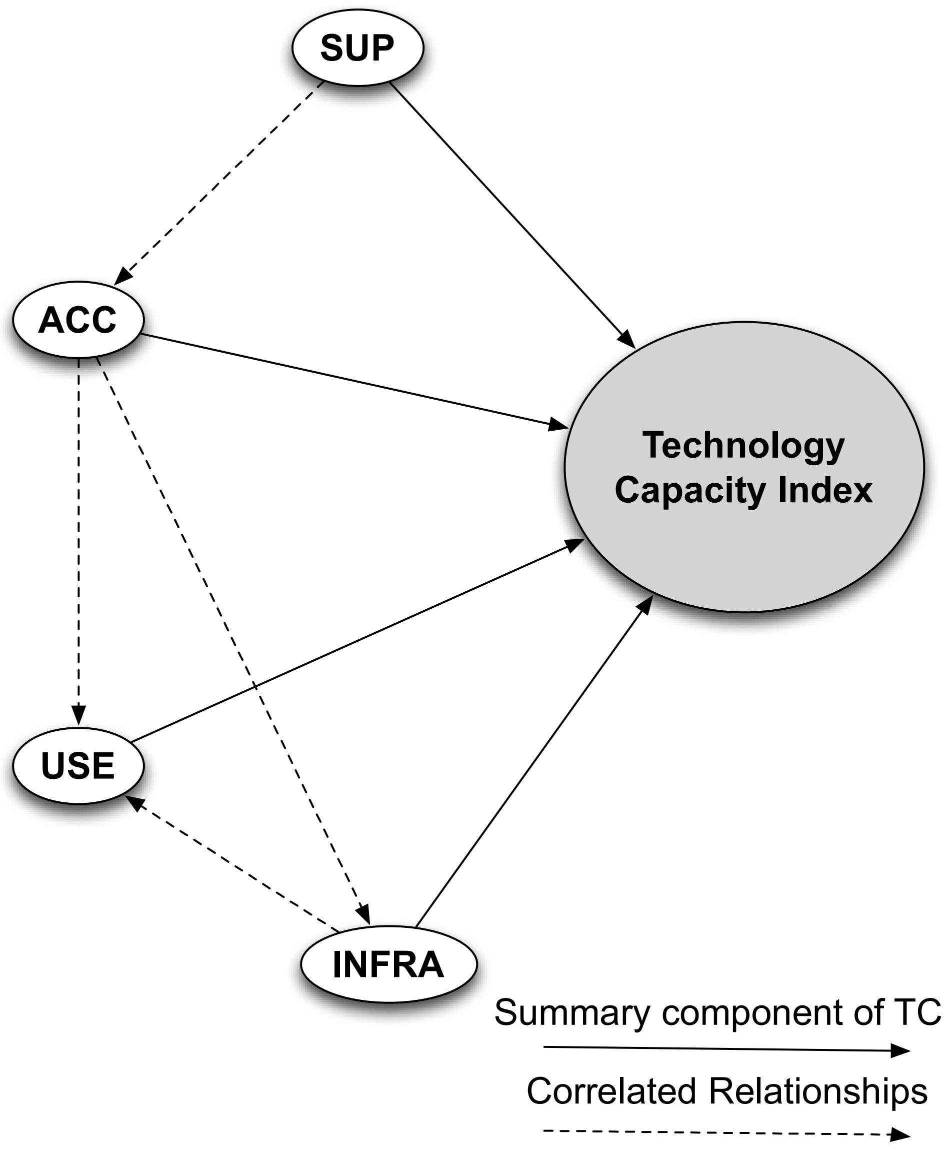


Figure 1.1. Technology capacity index conceptual model. SUP indicates user support; ACC, technology access; USE, use; INFRA, infrastructure. Adapted from “Gaps and Bits: Conceptualizing Measurements for Digital Divides,” by K. Barzilai-Nahon, 2006, *The Information Society*, *22*(5), pp. 269-278.

Summary of the Methodology

A conceptual framework based upon Barzilai-Nahon's digital divide index was developed to measure the digital divide within higher education. The TCI conceptual model identified technology access, infrastructure, use, user support, and institutional characteristics as correlated factors in measuring the digital divide in higher education.

The model was tested with a population of higher education institutions in the United States who were members of EDUCAUSE during the study period and responded to its Core Data Service (CDS) survey. The 2008 CDS data set was used to confirm the structure of the model, and the 2009 CDS data set was used to cross-validate the model as an appropriate instrument to measure technology capabilities within higher education.

Using a web-based survey instrument, EDUCAUSE normally collects CDS survey data beginning in June or July each year. EDUCAUSE accepts survey responses from any higher education institution from across the globe that chooses to participate, but solicitation is normally limited to member organizations. At the close of the survey period, EDUCAUSE joins the CDS survey data with Integrated Postsecondary Education Data System (IPEDS) data published by the National Center for Education Statistics (NCES) to provide a comprehensive data set for each responding institution. The data set includes responses to each of the CDS survey modules completed by the institution as well as demographic information such as institutional full-time equivalents; institutional headcount; Carnegie classification; institutional degree of urbanization (locale); and total revenue and expenses.

The TCI model and digital divide assessments completed as an outcome of this study were conducted using multiple quantitative methods, including confirmatory factor analysis, exploratory factor analysis, scatter plotting, and random permutation testing.

Delimitations and Limitations

Multiple delimitations and limitations were associated with the pursuit of this study:

1. The data collected by EDUCAUSE's CDS survey were self-reported by the institution using a quantitative data collection process. Therefore, no direct or qualitative observation of institutional digital performance was involved. The data collected were representative of the views of the highest-ranking technology officer and/or his or her designated representative for each institution.
2. The CDS survey instrument used to collect data for this study was predefined by EDUCAUSE. The questions asked and the response space could not be changed.
3. The CDS survey instrument was not tested using any psychometric tools or techniques. However, at the end of each survey module, respondents were asked to provide feedback to be considered in adjusting the survey instrument for future years.
4. The data collected in the CDS were based on those institutions that responded to the solicitation for the survey; the solicitation was sent to all EDUCAUSE members. It is assumed that the targeted data sets provided adequate, complete data sets to meet requirements for CFA statistical power.
5. The survey years selected for this study were 2008 and 2009, the last two years in which the CDS survey used the same data collection instrument. The age of the

data introduces some concerns about the relevancy of the data given the speed of change technology baselines. However, outcomes from this study are relevant as of 2009 and should be used as a baseline for future research.

Definition of Key Terms

Carnegie Classification. Framework for recognizing and describing institutional diversity in U.S. higher education (Carnegie, 2015).

Control (of institution). "A classification of whether an institution is operated by publicly elected or appointed officials (public control) or by privately elected or appointed officials and derives its major source of funds from private sources (private control)" (NCES, 2015a).

Digital divide. The inequities or inequalities created by the inability to access or use technology to advance learning and scholarship—academically, professionally, or personally.

HBCU. Historically Black College or University. The Higher Education Act defines HBCU as "…any historically black college or university that was established prior to 1964, whose principal mission was, and is, the education of black Americans…".

HSI. Hispanic-serving institution. As defined by the Higher Education Act, an HSI as an undergraduate institution that has an enrollment of at least 25 percent Hispanic students.

Institution Size. "…derived based on the institution's total students enrolled for credit" (NCES, 2015b).

Internet. A globally networked medium that is quickly diffusing throughout the world as an economic foundation for successful groups and nations in a new global economy.

Level (of institution). “A classification of whether an institution’s programs are 4-year or higher (4 year), 2-but-less-than 4-year (2 year), or less than 2-year” (NCES, 2015c).

Locale. Degree of urbanization. “A code representing the urbanicity (city/suburb/rural) by population size of [an] institution’s location” (NCES, 2015d).

MSI. Minority-serving institution. As defined by this study, an MSI is any institution that is designated as an HBCU, MSI, or TCU.

Sector. Institutional category resulting from the combination of institution control and level (NCES, 2015e).

TCU. Tribal Colleges and Universities. As defined by the Higher Education Act, a TCU is any institution eligible for funding under the Tribally Controlled Colleges and Universities Assistance Act of 1978; the Navajo Community College Act; or is cited in section 532 of the Equity in Educational Land-Grant Status Act of 1994.

Technology Capacity. The ability for an institution to produce services and facilitate innovation using modern information technologies (Daft, 2012).

CHAPTER 2:

LITERATURE REVIEW

This study examined the status of technology capacities within higher education in the United States. Assessing the technology capacity of postsecondary institutions allows for comparisons between institutions and the identification and characterization of the digital divide in the higher education sector. In turn, policy makers and stakeholders can make data-based decisions about where to invest more technology resources to address digital divide concerns. The technology capacities of institutions were examined in the context of the technology capacity index, which identifies the key measurement elements of technology access, infrastructure, use, user support, and institutional characteristics. This chapter reviews the literature associated with the role of technology, measuring technology capacities, and the digital divide within higher education.

The Role of Technology in Higher Education

The role of technology in higher education is becoming inseparable from the educational services provided by the modern postsecondary institution. The effectiveness and efficiencies offered by technology-enabled services that provide "integrated, comprehensive, personalizable, online self-service" are expected by nearly all Internet-savvy students (Graves, 2002, p. 40). The availability of high-performance networks, Internet access, and mobile devices has driven an evolution in the application of technology in the learning environment (Abel, 2007). The magnitude of the demands placed on institutions has grown significantly (Katz, 1999).

The ubiquitous nature of technology within higher education is complex and multifaceted. Ehrmann (1998) used the highly visual conceptual model of "the technology tower" in describing higher education technology practices. The tower, detailed in Table 2.1, has a basement and three stories, each dependent upon the solid foundation of the floor beneath it for support.

Table 2.1
The Technology Tower

Floor	Purpose
Basement	A foundation of infrastructure and well-established technologies to support the institution. This floor might include libraries, textbooks, labs, and audiovisual materials.
First	Technology support for learning instruction, including the hardware and software used to support "learning by doing," real-time conversation, and time-delayed exchanges such as may occur in a learning management system. All of these elements are made possible by the basement floor.
Second	Increased support for first-floor activities including higher-level curriculum content development to include student use of computers, access to institutional resources beyond traditional business hours, and implementation of Chickering and Gamson's *Seven Principles of Good Practice in Undergraduate Education..*
Third	Larger-scale educational support, including campus-based (not necessarily campus-bound) and distributed learning environments.

Adapted from "Using Technology to Transform the College," by S. C. Ehrmann, 1998, *New Directions for Community Colleges*, *101*(Spring), p. 27.

Katz (1999) suggested that campus research computing activities have generated a new form of research with computer simulation of complex phenomena. Katz added that technology could have a bolder impact on higher education in the future through the following developments:

- High-speed, economically accessible networks that could be available globally
- An environment where affordable, capable computers are commonplace with an assumption that students will own their own equipment

- Technical sophistication and educational pricing models that could “leapfrog” new players into the postsecondary education market
- Sharing of course content and intellectual property to create global university outreach
- Technology-enriching course offerings at the right price, quality, and access, with a recognition of the increasing importance of meeting students’ geographical and scheduling requirements
- An increased prevalence of nontraditional sources of courseware development (such as private entities)
- Complex intellectual property rights laws related to digital distribution of copyrighted materials

Technology enables institutions to offer educational services anytime, anywhere, removing the constraint to be on campus or follow a special academic schedule (Katz, 1999). Technology may even create a new manifestation of the mission of the university in the role of “*creating*, *preserving*, *integrating*, *transmitting*, and *applying* knowledge” in contrast to the common trinity of teaching, research, and service (Katz, 1999, p. 6).

Community and junior colleges have also come to recognize that technology can be used to respond to individual learning styles, thus enhancing academic success by increasing the effectiveness of instruction (Weintraub & Cater, 2000). Miami-Dade Community College was able to capitalize on instructional technology to not only reduce attendance costs for full-time students, but also innovate ‘open learning’ with the development of curriculum materials that engaged students through television programming (Kelly, 1977).

From a student perspective, technology offers four major areas of benefit (Dahlstrom et al., 2011):

1. Easy access to resources and help with administrative tasks and keeping track of academic progress
2. Greater productivity
3. A sense of being connected
4. Learning that is more immersive, engaging, and relevant

Students assume their institutions offer basic technology services such as online course registration, financial aid information, online library resources, and online access to grades (Dahlstrom et al., 2011). In general, "effective, frequent, and seamless use of technology by instructors characterizes institutions that make effective use of technology" (Dahlstrom et al., 2011, p. 5)—although students agree that very few institutions meet this level of expectation (Dahlstrom et al., 2011).

Measuring Technology Capacities in Higher Education

Technology capacities can be measured through any number of factors. In relation to the technology capacities index, technology capacity is measured as a component of five factors:

- *Technology access.* When discussing access to technology in higher education, most identify students as the main population to be served. Questions abound about wireless access in residence halls, landline phones, and computer labs with institutionally provided devices (Grajek & Arroway, 2012). However, faculty also need these same conveniences in their offices and classrooms (McKinney, 1996).

- *Infrastructure.* Infrastructure is arguably the largest and most complex element of technology capacity. In terms of this study, infrastructure is defined as the hardware or software capacities needed to support campus computing requirements.
- *Use.* As one community college instructor remarked, technology revolutionized his teaching, allowing the computer to present content while allowing him to tailor his style of instruction to the individual student (McKinney, 1996). Use is reflected in how technology is implemented to meet the learning and administrative missions of the institution. As an example, 99% of public institutions will shortly have mobile apps to engage student's demands for these applications (Green, 2014). This number is compared to private institutions with a proposed 95% support of mobile applications (Green, 2014).
- *User support.* User support often means access to a help desk for receiving individual help with information technology problems. But, help can be provided in a myriad of ways. For faculty, support can include providing core teaching and learning technologies such as learning management systems, instructional design for use of technology in course delivery, support for innovative use of instructional technology, and instructional technology centers (Grajek & Arroway, 2012). Students are sometimes charged a fee in order to fund these services (Grajek & Arroway, 2012; Green, 2010).
- *Institutional characteristics.* Institutional characteristics are defined by a set of demographics that define institutions, including full-time equivalent number, student headcount, organizational control (private or public), Carnegie

classification, locality, and whether the institution fulfills a special mission such as being a historically black college or university (HBCU), a tribal college or university, or a minority-serving institution (MSI).

The Digital Divide in Higher Education

Although there is much discussion of the impact of the digital divide in society, there have been relatively few empirical studies on this phenomenon within American higher education. Two seminal national studies and a cluster of smaller case studies serve as the foundation for understanding the digital divide in higher education. The two seminal studies, published in response to perceived technology capacity deficiencies within HBCUs and other MSIs, offer a broad view of the digital divide through primarily quantitative methods, while the case studies provide mostly qualitative assessments of how technology is being used within higher education institutions.

Both seminal studies are now more than 10 years old. The National Telecommunications and Information Administration (NTIA) within the U.S. Department of Commerce has been a leader in producing reports that discuss the status of the digital divide within the United States. The seminal 2000 report, *Historically Black Colleges and Universities: An Assessment of Networking and Connectivity,* written for the NTIA by the National Association for Equal Opportunity in Higher Education (NAFEO), provides information from 80 of the then 118 HBCUs (NAFEO, 2000). The second seminal study, published by the Institute for Higher Education Policy for the Alliance for Equity in Higher Education, is entitled *Serving the Nation: Opportunities and Challenges in the Use of Information Technology at Minority-Serving Colleges and Universities* (Clinedinst, 2004). This mixed-method study used a quantitative survey as well as qualitative case studies to convey information about the digital divide within MSIs. The quantitative portion of the study solicited feedback from the more than 320 member institutions of the Alliance for Equity in Higher Education, which garnered responses from 36% of HBCUs as well as 54% of Hispanic-serving institutions (HSI) and 10% of tribal colleges and universities (Clinedinst, 2004). The qualitative portion of the study included campus visits to six institutions to gather more information and to highlight successful technology endeavors. Although the two studies were published 4 years apart, they corroborated each other in almost every major category of findings.

A general critique of these studies is that they are highly descriptive in nature and do not offer any inferential statistical discussion of their findings. Neither study was based on an overriding theory or conceptual framework. While both have been influential in the discussion of the digital divide, more in-depth statistical or theoretical propositions likely would have further encouraged empirical debate.

The case studies that have been published delve further into the experiences of students and faculty as they have navigated the technical landscapes of their individual institutions. The case studies represent institutions of varied Carnegie classifications and geographic locations. While these case studies cover a time period of more than 10 years, they mostly continue to corroborate the findings of the NAFEO and Institute for Higher Education Policy. This suggests that even though digital divide concerns have been widely documented and discussed, many institutions are still unable to effectively marshal the appropriate resources to bridge—or keep up with—the ever-changing technology environment in American higher education.

A general critique of the case studies is they cannot be generalized to a larger population of institutions. Although they are highly descriptive and tell a compelling story, the case studies generally focus on a single topic at a single institution. However, the case studies do offer various levels of observation from particular programs to institution-wide initiatives.

Using the seminal studies, the case studies, and all the available literature, this section offers insight into the digital divide as grouped by the factors of the technology capacity index: technology access, infrastructure, use, user support, and institutional characteristics.

Technology Access

Technology access often refers to the ability to afford the products and services to bridge the digital divide. Considering the number of students who do not have their own computers, some institutions have tried to fill the gaps by purchasing computers for student use. As late as 2000, approximately 80% of the computers on HBCU campuses were owned by the institution (NAFEO, 2000). The critical component of this statistic is that approximately 75% of students attending HBCUs are dependent upon the financial, human, and hardware resources of the institution to gain access to technology (NAFEO, 2000). Depending upon the availability of the university-owned equipment (perhaps located in labs or classrooms), access to technology is most likely not on-demand or is in very short supply, further limiting access to the Internet for these students (NAFEO, 2000). An HBCU faculty member at a public rural institution highlighted some of the concerns with this particular digital divide factor (NAFEO, 2000):

Since male and female dorms are on opposite ends of the campus, our computer

> labs must be located with gender equity considerations for males and females. Even though our labs are open seven days a week, 24-hours a day, there is always a waiting list. Maintaining security for students walking from dormitories to computer labs during the middle of the night is quite a security problem. (p. 31)

The inability for HBCU students to access technology in their dorm rooms is a continuing concern. In 2000, NAFEO found that while 88% of central administration offices had access to the institution's network, only 45% of the common areas of the dorms had access. The Institute for Higher Education Policy (Clinedinst, 2004) found 4 years later that a little more than half of MSI dorm rooms were wired for access, but more than a quarter of residences were not wired at all. These two studies from a decade ago suggested that more than half of students attending HBCUs or MSIs were not able to access technology in their dorm rooms where they arguably spent the bulk of their time. Among all institutions of higher education, the Campus Computing Project (Green, 2001) reflected an astounding 100% "port to pillow" ratio, suggesting that students attending the responding institutions had 24/7 access to the Internet in their dorm rooms. The dichotomy between the findings of Green and Clinedinst and the NTIA is rather astounding.

Students participating in focus groups about technology use when accessing personal health information at one public rural HBCU institution echoed accessibility concerns. Students expressed concerns about the lack of access due to insufficient times of operation, hardware quality (when it was available), and the need to purchase Internet service for access in their dorm rooms (Ragon, 2004). The students noted their institution did not have online class registration, offered minimal opportunity to gain web design skills, and offered no online courses, making the students question institutional capacities in reference to other schools (Ragon, 2004). These students also expressed concern that while Internet research and daily computer access were required for a variety of classes, access to computer labs was challenging, as labs closed immediately after normal school hours (Ragon, 2004). However, virtually all of the students felt comfortable with using the Internet, having used it in high school (Ragon, 2004).

Alternatively, consider the case of one mid-sized, public HBCU. After allotting $10 million towards the effort, students enjoyed high-speed Internet access in their dorms (Redd, 2003). These students also enjoyed walk-up computer stations scattered across campus. They sat in classrooms with smartboards that provided video and sound for enhancing the learning environment. These students also had state-of-the-art digital libraries. The institution accepted the responsibility, and the additional debt, to support the expansion of technology across its campus. It leapt ahead of practically every other HBCU and perhaps became one of the most advanced technology campuses in the country.

Students are not the only constituency on campus challenged with access to technology. Part-time faculty at community colleges have also been shown to have less access to technology than full-time faculty (Jackowski & Akroyd, 2010). Given that 2-year institutions employ a majority of part-time faculty (Jackowski & Akroyd, 2010), this finding could be quite troubling.

Infrastructure

Technical infrastructure has generally received the most attention in discussions of the digital divide. High bandwidth capacity is a foundational entry requirement for many research-intensive fields within higher education, as well as more basic digital capacities such as hosting distance courses or browsing digital libraries. In the technical environments of the early 2000s, 85% of HBCUs reported they had access to, and most used, T-1 connections (NAFEO, 2000). Almost half of HBCUs also reported having access T3 connectivity, but less than 10% were actually using the high-speed connectivity available to them (NAFEO, 2000). The inability to capitalize on the available technologies may be a matter of lack of funding or technical skills to implement and maintain modern networks (NAFEO, 2000). A grant from the National Science Foundation was used to bring a T-1 line to Howard University in the 1980s, but few departments opted to devote time or money to access the T-1 line (Redd, 2003).

Differences in infrastructure were also found between urban and rural community colleges. Because urban institutions were more likely to be wired, they were more able to provide their students better access to technology resources (Sink & Jackson, 2000). Although the NTIA acknowledged the challenge of rural access to the Internet in 1995, Horrigan and Murray (2006) found continuing disparities in home broadband access into the mid-2000s, with rural communities trailing suburban communities in access by more than 16 percentage points.

HBCUs reported that more than half of the buildings at their institutions had updated wiring, with libraries, labs, and administration buildings having the most updated technology and classrooms and dorms having the least (NAFEO, 2000). Many institutions have also reflected that technology is rapidly changing and nothing remains up-to-date for any length of time (McKinney, 1996). It is also not economically feasible for many institutions to keep up with these changes during periods of budgetary constraints (McKinney, 1996). In particular, public rural community colleges in states where legislators are cutting funds to institutional operating budgets may be especially hard hit (Katsinas & Moeck, 2002). Financial challenges within the higher education industry have had an impact on infrastructure investments (Green, 2014). Almost half of community colleges responding to the 2010 Campus Computing Survey noted that budget cuts have reduced funding for central IT services (Green, 2014). However, public, four-year institutions reported a decline in budget cuts for the same time period (Green, 2014). But, the pressures to respond to increasing demands for technology services with limit funding resources remain (Green, 2014).

One particular case study suggested that HBCU faculty face challenges in providing or using technology in the classroom. Some faculty continue to use computers that barely meet the minimum requirements for intensive applications, with some using operating systems more than 6 years old (Snipes, Ellis, & Thomas, 2006). New faculty members sometimes went almost 3 months before receiving a computer for their offices (Snipes et al., 2006). Additionally, the infrastructure was not always available to run the applications required by faculty (Snipes et al., 2006). For example, recently hired computer support personnel installed the newly purchased campus-wide licenses of Blackboard on a central server, but only a few faculty were able to access the software (Snipes et al., 2006). This particular case proved to be an issue of not only infrastructure, but also access.

Use

A major factor in the discussion of the use of technology revolves around the ability of students to supply their own computing equipment while on campus. Many institutions have policies that require, recommend, or help students purchase computers. The Campus Computing Project documented that 37.6% of all institutions had such policies, while 70% of students actually owned their own computing equipment (Green, 2001). However, less than 25% of MSIs had similar laptop policies, and less than half of students attending MSIs owned their own computers (Clinedinst, 2004). One challenge in comparing these statistics is that the population groups referenced are not necessarily discrete, so the ability to confidently identify a digital divide in this regard is hampered.

Distance education is the next phase of educational delivery. In a survey of community colleges, Cejda (2007) found that more than 76% of responding institutions offered career and technical education courses online. However, suburban community colleges offered these courses at more than twice the rate of rural institutions (Cejda, 2007). Urban community colleges offered almost double the number (Cejda, 2007), evidencing differences in capacity. There are also a growing number of institutions that are outsourcing their online educational support with private, four-year institutions making up the bulk of schools in this category (Green, 2014).

In another example of use, institutions have focused on creating a baseline level of computer competency for students. The Campus Computing Project (Green, 2000) found that 40% of all institutions had a computer competency requirement for all undergraduates. Of interest on this particular topic, 55% of HBCUs required some level of computer competency (NAFEO, 2000)—a higher percentage than the overall rate for the Campus Computing Project survey. This particular comparison could reflect HBCUs' acknowledgment that their students would be more reliant upon university-provided services and thus their desire to ensure that students received instruction. A competency requirement is one way to ensure students receive pertinent information about technology on campus.

One quantitative case study at a public urban HBCU discussed the use of an online registration system at the institution. A significant percentage of students did not know the online registration system existed; those who were aware of the system were not willing to use it (Miah & Omar, 2011). Perhaps a bit more challenging to understand was that students expected their advisors to register them for class instead of registering themselves (Miah & Omar, 2011), even when the students had access to hardware to register themselves. Whether this phenomenon is related to the digital divide or other sociological factors was not addressed by the researchers (Miah & Omar, 2011).

Faculty face a similar fate in some instances. Even though an institution may be considered very technically capable, academic units within the university still experience elements of the digital divide, including lack of teaching technology, inadequate technical support, and low computer literacy (Redd, 2003). While faculty appear to be familiar with technology such as email, word processing, and Internet searches, which are considered basic survival skills on campus, familiarity with interactive courseware such as Blackboard may be more limited (Snipes et al., 2006). It is acknowledged that some academic units are more effective at using the Internet for instruction, but many would suggest that faculty are only somewhat effective in using technology in the classroom (NAFEO, 2000). It has been suggested that lack of access to interactive courseware may be one reason faculty have not been able to embrace such technologies (Snipes et al., 2006). Although many agree that such technology opens up new possibilities for academic achievement, there is limited capacity to innovate in these areas (NAFEO, 2000).

It was further suggested that lack of strategic planning or lack of faculty motivation or training to use these technologies may also contribute to lack of use. Expanded access to funding and training were identified as potential solutions to maximize available resources and make significant leaps forward in the digital arena (NAFEO, 2000).

User Support

Community colleges have expressed concerns that the technology competence of faculty and students is a barrier to providing support for course delivery and general end-user support (Cejda, 2007). These same schools have also acknowledged that attracting qualified resources to support campus technology needs is problematic (Cejda, 2007). Students have indicated that while faculty use technology in the learning process, many instructors need help to get the technology to work successfully (Abel, 2007). These same students have also suggested that devices need to be used to inspire participation and interactivity beyond current levels (Abel, 2007).

Financial support for technology is a key resource that is lacking at many HBCUs. More than 80% of HBCUs reported that funding was a primary reason for not meeting technology goals (Clinedinst, 2004). Bethune-Cookman College shared its story of wanting to overlay its wired network with a wireless network (Hofmann, 2002). However, the decision about how much wireless coverage to install was driven by cost. Although the preference was total coverage, the college could not afford to blanket the entire campus all at once because it did not have the funds. It only installed as much as it could afford.

Even before the landmark NAFEO study, the National Science Foundation tried to proactively address the digital divide by awarding a $6 million grant to help improve networking and information technology support for MSIs (Foertsch, 2004). The AN-MSI Project recognized very early that $6 million over 4 years would barely scratch the surface of the digital divide concerns faced by MSIs. Interestingly, the AN-MSI Project seemed to have provided infrastructure benefits for tribal colleges, but not as much for HBCUs. The overwhelming benefit from the AN-MSI appeared to revolve around increased networking and planning among peer institutions.

On the individual student level, 64% of HBCU students paying their way through college have annual incomes less than $20,000, while 30% make less than $10,000 (NAFEO, 2000). This suggests that these students are unable to expend the funds to purchase laptops. Only 3% of HBCUs were able to offer financial aid to assist with the purchase of computers—with the form of financial aid being a discount on the cost of the computer (NAFEO, 2000).

Technology fees are charged at many institutions to provide some support for technology initiatives on campus. Students are charged between $10 and $237 annually in technology user fees. The average HBCU charges about $79. The Campus Computing Project (Green, 2009) reported that the average technology fee for all institutions was $125, with public institutions averaging $137 and private institutions averaging $186. The great disparity and range in student technology fee assessments provides some insight into the financial constraints imposed on some campuses in preparing technology support for students.

However, it is not clear how the fees were derived, nor is it clear what particular strategies were targeted by the generated funds. Only 13% of institutions rate their support of student IT training as excellent with only a marginally better 28% rating their support of IT training as excellent (Green, 2014). Green (2014) notes these data highlight the continuing challenge of providing user support to the campus community.

Lack of financial support has also been referenced as one of the reasons faculty are not able to reach their goals to increase the use of classroom technologies. Training is needed to help improve faculty familiarity and use of available technologies (Clinedinst, 2004; Snipes et al., 2006). One campus learned that while it was able to self-support faculty development workshops to learn Microsoft products, it needed to hire full-time support to conduct workshops on classroom technologies like Blackboard (Snipes et al., 2006). Although faculty requested additional support, the college administration responded that other campus financial demands superseded their request (Snipes et al., 2006). Of interest in Snipe et al.'s study is that it offered a retrospective view of how the institution responded to findings of the digital divide. It offered some insight that while particular pockets of the institution were able to bridge aspects of the divide at their own bidding, the institution was faced with differing priorities that impeded the implementation of some institution-wide digital divide solutions.

Institutional Characteristics

The institutional characteristics of higher education institutions have played a significant role in determining whether students and staff experience the effects of the digital divide.

Urban institutions have more options for access to technology than rural ones (NAFEO, 2000). For HBCUs, public and urban schools appeared to have similar technology findings, while private and rural schools had similar findings (NAFEO, 2000). The size and location of the institution also make a difference in the ability to access computing resources (NAFEO, 2000).

In contradiction to the NAFEO study, Ragon (2004) found that HBCUs located in the rural and southern parts of the country had documented technology disadvantages for their students. These students had less access to technology than their counterparts at private universities. While students at private universities used email and the Internet at a significantly higher rate than students at public universities, it was unclear whether the lack of access was a function of user support or infrastructure.

Even though the numbers are comparatively low, there were some potentially significant differences in the HBCU rate of computer ownership based upon the geographic locale of the institution. Nine percent of urban HBCUs reported that 25% to 45% of their students personally owned their own computers, while only 5% of rural schools reported the same levels of ownership (NAFEO, 2000). This suggests that students attending urban HBCUs are more likely to have access to technology they personally own, although there is not a clear indicator as to what is driving this particular statistic.

Summary

This review of the literature has offered insight into the role of technology within higher education and the experiences and potential ramifications of the digital divide within American higher education. The literature identified the importance of being capable and ready to seize new technology opportunities to better serve campus communities. The creation of a single survey instrument mapped to a digital divide conceptual framework would enable a more complex analysis of technology capacities and the digital divide. Chapter 3 offers more details on the methodology used to complete this study.

CHAPTER 3:

METHODOLOGY

This study was unique in its approach to measuring the digital divide. It was not designed as an assessment of institutional quality, nor was its focus subjective or limited in its application. This quantitative study was designed to validate a technology capacity index (TCI) model for measuring technology capacity in higher education in the United States, in response to the three research questions identified in Chapter 1. This *a priori* TCI conceptual model was tested for statistical strength using confirmatory factor analysis (CFA). When the *a priori* model failed to produce a good fit, a scree test was run to determine an approximate number of factors to include in an exploratory factor analysis (EFA) process to identify an appropriately structured model. When a model was ultimately identified through EFA, the model was cross-validated using a final series of CFA tests. Next, Pearson's correlation tests were conducted to determine whether there are relationships between the factors of technology capacity. The final steps of the study applied randomized permutations, independent sample *t* tests, and power analyses to real world data to generate an understanding of the scope of the digital divide in higher education.

Research Method

Data Source

The survey instrument and associated data sets from the EDUCAUSE Core Data Service (CDS) survey served as the primary data input for this study. Formed in 1998, EDUCAUSE has a mission to "advance higher education through the use of information technology” (EDUCAUSE, 2013b). Membership in EDUCAUSE is open to any institutions of higher education as well as corporations, associations, and organizations that serve the higher education information technology (IT) market (EDUCAUSE, 2013c). Currently, more than 1,800 colleges and universities and 300 corporations are members of EDUCAUSE (EDUCAUSE, 2013a). The programs and resources offered by EDUCAUSE include professional development activities; print and electronic applications; advocacy; data, research, and analytics; teaching and learning initiatives; and extensive online information services. EDUCAUSE is a tax-exempt not-for-profit organization (EDUCAUSE, 2013c).

The EDUCAUSE CDS conducts an annual IT benchmarking survey of its membership. In the study years of 2008 and 2009, 2,800 CDS survey solicitations were sent to higher education institutions (EDUCAUSE, 2008, 2009). The resulting responses to the CDS survey were combined with Integrated Postsecondary Education Data System (IPEDS) data from the National Center for Education Statistics (NCES) and then published by EDUCAUSE for the internal use of its member organizations. By linking IPEDS data to the CDS survey data, EDUCAUSE not only captured demographic and classification data for each institution, but also enabled the ability to combine additional IPEDS data variables with the EDUCAUSE data sets. Approval was requested by the researcher and granted by EDUCAUSE to use these data sets as a part of this study. The identified data sets were selected since they are the final 2 years in which the EDUCAUSE survey instrument did not undergo significant change year over year.

The 2008 and 2009 CDS survey questions (which are identical) were used to devise a sub-instrument whose questions served as the observable variables for the data model for this study. The survey responses associated with the sub-instrument items served as the basis for measuring the latent constructs of technology capacity—technology access, infrastructure, use, user support, and institutional characteristics—within the TCI framework.

Data Preparation

After downloading the 2008 and 2009 CDS survey Excel data files from EDUCAUSE, the data were delimited to nonprofit institutions within the United States, purposefully eliminating for-profit institutions.

Since the original EDUCAUSE CDS data sets did not include the locale information for each institution, this data element was downloaded directly from the NCES IPEDS databases. The locale field, along with two additional fields (HSI and MSI), was combined with the EDUCAUSE CDS data file. The HSI field was a manually created binary field to represent whether an institution's undergraduate enrollment comprised 25% or more Hispanic full-time equivalent students. The data for this field for both survey years were captured from lists published by the Hispanic Association of Colleges and Universities (2009, 2010). The MSI field was also a manually created binary field that served as a summary indicator for all institutions designated as HBCU, tribal, or HSI within the survey data. This field was created to provide more robust test numbers to represent MSIs than provided by each of the other categorizations alone. Data elements that were not expressly being used as items for the TCI model were deleted from the test file. Appendix A provides an overview of the 2008 and 2009 CDS file observable variable file names and their relationship to the observed variables in the TCI model.

Due to the format of several of the questions in the original EDUCAUSE CDS survey instrument, significant recoding of data was required. Reasons for recoding included the need to combine multiple response fields, such as check boxes, into a single field of data; to ensure that data fields used similar scale directions (low to high, negative to positive responses); and to adjust for large data value variances in fields such as those reporting dollars. The data coding completed for this study is detailed in Table 3.1.

The most challenging fields in the recoding effort were those representing the funding for centralized IT and the gross funding received from student technology fees. With variances in IT funding ranging between $62,800 and $146,000,000 in 2008, the variance extremes hampered CFA processing. Both fields were recoded using the natural log for each value to reduce the size of the variances while maintaining the relative proportionality of the variances (Kenny, 1987). After completing all of the data coding activities, none of the test cases for either of the study survey years had missing data.

Table 3.1
Data Coding Descriptions

Item	Item description	Measurement scale/codes	Value description	Coding action
control	Institutional control	1. Public 2. Private not-for-profit	Governing control of the institution	None
hbcu	HBCU	1. Yes 2. No	Schools designated as a historically black college or university	None
tribal	Tribal college	1. Yes 2. No	Schools designated as a tribal college or university	None
hsi	Hispanic-serving institutions	1. Yes 2. No	Schools with a student body made up of more than 25% Hispanic students	New variable coded for this study.
instsize	Campus size	1. Under 1,000; 2. 1,000–4,999; 3. 5,000–9,999; 4. 10,000–19,999; 5. 20,000 and above	Population of FTE students	None
locale	Locale	1. City; 2. Suburb; 3. Town; 4. Rural; -3-{Not available}	Geographic description of the institution	Combined categories at the highest logical level
sector	Sector	1. Public 4-year or above; 2. Private not-for-profit, 4-year or above; 3 Public 2-year; 4 Private not-for-profit, 2-year	Governing control plus whether institution offered 2-year or 4-year programs	None
cc	Carnegie classification	1. Doctoral/research universities; 2. Master's colleges and universities; 3. Baccalaureate colleges; 4. Associate colleges; 5. Professional/specialty schools; 6. Tribal colleges	Carnegie 2000 classification	Combined categories at the highest logical level
msi	Minority-serving institutions	1. Yes 2. No	Field created to combine nominal numbers of minority-serving institutions to create larger population numbers	Created new for this study. 'Yes' reflects a designation of HBCU, tribal, or Hispanic-serving institutions.

Item	Item description	Measurement scale/codes	Value description	Coding action
intcnt	Internet bandwidth		Greater bandwidth implies more/faster Internet access	Added .5 to all values and then calculated the natural log to reduce variance.
resspeed	Residence hall network speed	1. 10 mbps; 2. 10-11 mbps; 3. 10/100 mbps; 4. 100 mbps; 5. >100 mbps	Greater speed implies more capacity for access to the Internet	Missing values replaced with 0, as all missing data corresponded with schools that either did not offer connections or did not have residence halls
wireless	Wireless access	1. Not applicable; 2. 0%; 3. 1-25%; 4. 26-50%; 5. 51-75%; 6. 76-100%	Higher percentages of wireless capacity implies improved access	Calculated the mean of all of the responses to the question. Responses of 1 change to 2.
idm	Identity management technologies	1. Not planned; 2. Considering; 3. Experimenting with; 4. Piloting; 5. Deployed	More complete implementation implies greater security sophistication	Reversed order of codes to match direction of other responses; calculated the mean of all of the responses to the question
leascnt	Computers owned or leased by the institution		More computer availability implies greater access to technology	Calculated the natural log to reduce variance.
auth	Authentication for network access	Regarding end-user authentication for all network access: 1. No plans to require; 2. Considering it; 3. Planning to require; 4. In the process of implementing requirement; 5. Currently require; 6. Other	More complete implementation implies greater security sophistication	Reversed order of codes 1-5 to match direction of other responses. 6 coded as 1 (written responses not valid).
firewall	Firewall security	Multiple check boxes	More firewalls implies greater security sophistication	Summed the number of boxes checked.
patch	Campus security-related patches	Multiple check boxes	More security-related practices implies greater security sophistication	Summed the number of boxes checked.
roomtech	Permanent			None.

Item	Item description	Measurement scale/codes	Value description	Coding action
	classroom technology			
hrscnt	Help desk hours		More hours available implies greater ability to provide support.	None.
devcnt	Professional development funding		More spending implies improved knowledge/skills to support technical services	Calculated the square root to reduce variance.
emplcnt	FTE staff (central IT)		More people implies improved ability to support technical services	Calculated natural log to reduce variance.
stucnt	Student employees (central IT)		More people implies improved ability to support technical services	Added .5 to all values and then calculated the natural log to reduce variance.
facsup	Faculty support for teaching and learning	Multiple check boxes	More services provided implies greater support capacities	Summed the number of boxes checked.
dolcnt	Funding for centralized IT		More funding implies improved ability to offer technical services	2008: Calculated natural log to reduce variance. 2009: Calculated percentile ranks to reduce variance.
feecnt	Gross funding from student technology fee		More funding implies improved ability to offer technical services	Added .5 to all values and then calculated the natural log to reduce variance.
netfee	Presence of fee for residence hall access	1. Yes 2. No	Access to more funding implies improved ability to offer technical services	Reversed order. Schools that do not have residence halls or connections were coded as ‘No’ (data analyzed based upon response to another survey

Item	Item description	Measurement scale/codes	Value description	Coding action
				question)
stuown	Undergraduate-owned computer use		More student computer ownership implies more use of technology	Calculated standardized score to reduce variation.
comprec	Student computer policy	1. There are no requirements or recommendations regarding personal computer purchase or lease; 2. Personal computer purchase/lease is recommended but not required for students in some departments or majors; 3. Personal computer purchase/lease is recommended but not required for all students; 4. Students in some departments or majors are required to purchase/lease their own computers; 5. Students in general are required to purchase/lease their own personal computers; 6. All students are provided a personal computer; 7. Other	More comprehensive policies for student computers imply greater technology use	Reversed order of codes 1-6; 7 coded as 1 (written responses not valid).
allstrat	Campus strategic plan for IT	1. Yes 2. No	Strategic planning for IT at the campus level suggests insight for how to incorporate technology more fully as part of the institution	Reversed order.
lonstrat	IT department strategic plan	1. Yes 2. No	Strategic planning for IT at the department level suggests insight for how to incorporate technology; not as comprehensive as a campus-wide strategy	Reversed order.
newcrmn	Course management	1. We have not deployed a course management system and do not plan to; 2. We are planning to	Implementation of a course management system	Realigned responses for least to most orientation: not planned

Item	Item description	Measurement scale/codes	Value description	Coding action
	system availability	deploy one or more course management systems; 3. We are currently reviewing options, considering deploying a course management system or changing our current course management system approach; 4. We support one or more course management systems (of any type)	implies use as a learning technology	(1), under consideration (2), in an experimental mode (3), or is in deployment (4). 2008: Added 1 to all values and then calculated the natural log to reduce variance. 2009: Calculated percentile ranks to reduce variance.
lmstech	Learning technologies or practices	1. Not planned; 2. Considering; 3. Experimenting with; 4. One deployed; 5. More than one deployed	Deployment of various technologies such as blogs or discussion boards implies use as a learning technology	Realigned/recoded responses for least to most orientation: not planned (1), under consideration (2), in an experimental mode (3), or one LMS deployed (4), more than one LMS deployed.

Note. FTE indicates full-time equivalent; IT, information technology.

Characteristics of Participating Institutions

Table 3.2 provides descriptive statistics for the institutions that responded to the CDS survey for the study years. The survey populations were relatively evenly split between public and private institutions. While half of the survey population was located in a city, two-fifths of respondents were in a suburban or town locale. Additionally, 2-year institutions made up 16% to 17% of the responding survey population, while MSIs made up a little more than 7%. Almost half of the institutions surveyed had student populations of 1,000 to 4,999, with very small (under 1,000 students) and very large (20,000 students and above) institutions making up the smallest percentages.

There were 829 responses (34% response rate) for the 2008 survey year and 810 responses (33% response rate) for the 2009 survey year. A key of the statistical power of CFA lies in the size of the sample used to test the underlying construct. According to Kline (2011), the median ("typical") sample size for many studies employing structural equation modeling is 200. Jackson (2003) argued that there is a relationship between sample size and complexity of the model being tested and proposed an ideal ratio of the sampling size to parameters being tested of 20:1. For this study, this ratio would result in a sample size of 20 × 5, or $N = 100$. Since each of the CDS survey data sets had more than 800 cases, this study presumably avoided concerns related to sample size.

Table 3.2
Institutional Characteristics Descriptive Information

		2008		2009	
Item	Measurement scale/codes	*n*	%	*n*	%
Control	1. Public	451	54.4	436	53.8
	2. Private nonprofit	378	45.6	374	46.2
HBCU	1. Yes	20	2.4	13	1.6
	2. No	809	97.6	797	98.4
Tribal	1. Yes	2	.2	2	.2
	2. No	827	99.8	808	99.8
HSI	1. Yes	41	4.9	46	5.7
	2. No	788	95.1	764	94.3
Size	1. Under 1,000	52	6.3	46	5.7
	2. 1,000-4,999	366	44.1	355	43.8
	3. 5,000-9,999	163	19.7	158	19.5
	4. 10,000-19,999	135	16.3	138	17
	5. 20,000 and above	113	13.6	113	14
Locale	-3-Not available	1	.1	1	.1
	1. City	396	47.8	377	46.5
	2. Suburb	170	20.5	177	21.9
	3. Town	166	20	161	19.9
	4. Rural	96	11.6	94	11.6
Sector	1. Public 4-year	322	38.8	302	37.3
	2. Private 4-year	377	45.5	373	46.0
	3. Public 2-year	129	15.6	134	16.5
	4. Private 2-year	1	.1	1	.1
Carnegie classification	-3-Item not available	11	1.3	10	1.2
	1. Doctoral/research universities	178	21.5	176	21.7
	2. Master's colleges and universities	254	30.6	239	29.5
	3. Baccalaureate colleges	198	23.9	195	24.1
	4. Associate colleges	138	16.6	142	17.5
	5. Professional/specialty schools	48	5.8	46	5.7
	6. Tribal colleges	2	.2	2	.2
MSI	1. Yes	63	7.6	61	7.5
	2. No	766	92.4	749	92.5

Note. HBCU indicates historically black colleges and universities; HSI, Hispanic-serving institution; MSI, minority-serving institution.

Data Model Development

The survey instrument that served as the foundation for the items in the TCI -1 model was a subset of all of the items from the 2008 and 2009 EDUCAUSE CDS surveys. Based upon the IT expertise of the primary researcher for this study, the initial TCI-1 instrument was developed by reviewing the full CDS survey, selecting key items, and mapping these items to factors in the TCI-1 model. To assess the construct validity of the TCI-1 instrument, the initial model was submitted to six additional IT experts to examine the item-to-factor mappings. The selected experts had executive appointments within technology departments in the higher education sector, and two had prior experience responding to portions of the EDUCAUSE CDS survey.

The two experts experienced with the CDS survey were sent an Excel spreadsheet that listed the definition for each factor and the item-to-factor mapping. They were asked to note in the spreadsheet where they had differing opinions on the proposed mapping. The remaining four experts were engaged in person and asked to provide feedback in a meeting setting using the same spreadsheet as the other two experts. While there were dissenting opinions on individual item mappings, there were no majority dissenting opinions on any given item, so the model specification remained unchanged.

The CDS survey items selected for TCI-1 and associated latent variables are listed in Appendix A. A visual depiction of the TCI-1 model construct used for the CFA for this study is shown in Figure 3.1. The items that reflect the support factor focus on tangible resources available to the institutional community for technology support: the number of hours the help desk is available, the number of employees and student workers supporting central IT, and the type of support available to faculty. The accessibility factor items focus on the dollars available to make technology available including the amount dollars budgeted for central IT, gross student technology fees, and whether there is a fee for accessing the residence hall network. The items related to the use factor involve how technology is used on campus. The presence of technology strategies at both the campus and IT department levels, student access to personal computing devices, technologies available in the classroom, and use of technology by faculty in the classroom all reflect technology use. The final factor in the TCI-1 model is infrastructure with items reflecting the hardware that defines the technical architecture of an institution. The coverage of the wireless network, the speed of residence hall networks, technology in the classroom, and the number of computers leased by the institution are representative of the infrastructure factor. The factors of the TCI-1 model were fully correlated as reflected in the conceptual model for this study.

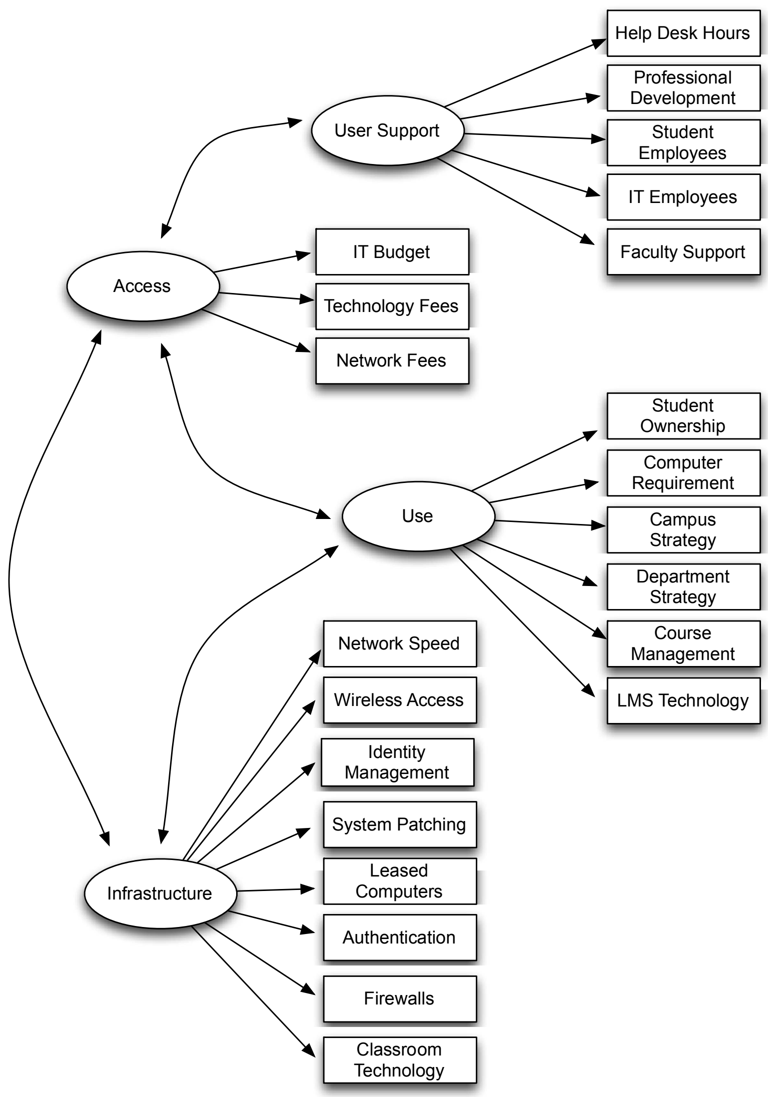


Figure 3.1. Higher education technology capacity index model (TCI-1). Item abbreviations are defined in Table 3.1.

Analytical Procedures

CFA was the analytical procedure used to measure the latent constructs of technology capacity. CFA is a structural equation modeling statistical technique that allows measurement models of relations of indicators (observed CDS survey data) to factors (latent technology capacity constructs) as well as relationships among the factors

(Pedhazur & Schmelkin, 1991). CFA informs whether a proposed model, in this case TCI-1, accurately measures the observed and latent variables in the ways anticipated (Pedhazur & Schmelkin, 1991). CFA also identifies structural or causal relations between unobserved latent factors and their indicators (Mueller & Hancock, 2008). In the event the hypothesized model does not prove to be a good fit between the variables, CFA allows the researcher to "discover" a model that makes theoretical sense, is reasonably parsimonious, and corresponds to the data being measured (Kline, 2011).

Research Question 1. In preparation for CFA testing, SPSS was used to conduct tests on the 2008 CDS data to ensure that the data exhibited multivariable normality and homogeneity of variances (Burdenski, 2000). Both the Mahalanobis distance and Shapiro-Wilk tests showed that the CDS survey data were not normally distributed. Due to the lack of multivariate normality, the data set's unequal sample sizes, and the sensitivity of the test, a Box's M test for multivariate homogeneity was not conducted and lack of homogeneity of variances was an assumed parameter for this study. To determine whether the violation of normality could be overcome by the robustness of the CFA procedure, tests for TCI item skewness and kurtosis were conducted to determine if data skewness was in the acceptable range of ±2 and kurtosis in the range of ±7 (Curran, West, & Finch, 1996). All the TCI items met these criteria. All records were exported from SPSS into a file for CFA testing using the Mplus statistical modeling program (Muthén & Muthén, 2012) in preparation for response to Research Question 1.

Using the 2008 CDS survey data as input, the Mplus CFA input file (see Appendix B) was coded using the four proposed latent variables (Use, Accessibility, Support, and Infrastructure), the observed items, and the latent variable correlations as proposed by the TCI-1 model (see Figure 3.1). The categorical variables were defined as network fee, campus strategy, and department strategy. The analysis iterations were set to 5,000. The output was standardized. The initial processing of the 2008 CDS data file resulted in a status of no convergence and a message to increase the number of iterations. The number of iterations was increased to 50,000. Re-running the processes resulted in a model (TCI-1) that did not fit as explained in detail in the CFA section of Chapter 4. To confirm these findings, the 2009 CDS data set was processed using the same Mplus input parameters as the 2008 CDS data file. The 2009 CDS data file reaffirmed the lack of model fit for TCI-1.

Due to these results, it appeared that a viable model to measure technology capacity would best be identified through re-specification of the model. Although CFA is still best for testing hypotheses of latent constructs, exploratory factor analysis (EFA) was used to determine if a proposed model for measuring technology capacity (TCI-2) could be identified (Schmitt, 2011). Prior to beginning the EFA analysis, a scree test conducted in SPSS using all of the observed times from the 2008 CDS survey data as listed in Table 3.1 (with the exception of the institutional characteristics) identified the TCI-2 model should consider models with between one and five factors.

A new Mplus input file (see Appendix C) using the 2008 CDS survey data was coded using all of the observed items (with the exception of the institutional characteristics). Models with between one and five factors were analyzed using a promax oblique rotation (Costello & Osborne, 2005). Oblique rotation allowed the magnitude of interrelation of factors to be more realistically represented (Carnevale, 2003). The analysis iterations were set to 10,000. The default Mplus estimator (WLMSV) for categorical factor models was used. Categorical variables were network fee, campus strategy, and department strategy. The EFA process identified a viable two-factor model for measuring technology capability (TCI-2). The EFA section of Chapter 4 outlines the results of the scree test and the processing of EFA models with between one and five factors.

To cross-validate the TCI-2 framework, a final CFA process was conducted using a new Mplus input file (see Appendix D) and the 2009 CDS survey data to verify the model fit. The residence hall network fee was identified as the single categorical item for the process. The analysis iterations were set to 5,000. Starting values of Internet bandwidth for both the campus support and student experience was set to one. The output was standardized.

The first CFA for the TCI-2 framework process resulted in an error of no convergence and a message that the number of iterations was exceeded. The number of iterations was increased to 50000 for the second CFA process. The results of the second CFA process identified a model with a good fit. However, a review of the item estimates showed that computer requirement had a very low association with the model. This item was dropped from the model and another CFA process was run in Mplus that resulted in an error of no convergence and a message that the number of iterations was exceeded. The number of iterations was increased to 150000 and the process was run again.

The results of this CFA run showed the TCI-2 model continued to meet the criteria for a good fit. However, Internet bandwidth exhibited a very low association and was also dropped from the model. The final CFA process identified a model without any low item associations. The factored data from this final Mplus process was saved to a file in preparation for responding to Research Questions 2 and 3. The detailed results from the TCI-2 model validation process are located in the validation section of Chapter 4.

Research Question 2. Using SPSS and the factor data calculated in Mplus, the individual factor scores for the access and student experience items were summed together to compute a technology capacity index score for each institution in the 2009 CDS data file. These scores allowed either individual or groups of institutions to be compared to each other, with each of the factors having equal weight (Pedhazur & Schmelkin, 1991). SPSS scatterplots and correlation matrices provided a representation of the strength and direction of the bivariate correlations of the TCI-2 factors. The results for Research Question 2 are provided in Chapter 4.

Research Question 3. Due to concerns with data normality and homogeneity of variance identified in the data assumption tests, identifying the appropriate statistical significance test to compare differences in means in order to respond to the hypotheses tests identified in Research Question 3 was in question. The independent *t* test to compare differences in means can be robust in situations of nonnormality as long as the sample sizes are equal, there is homogeneity of variance, and the distributions are symmetrical (Boneau, 1960). The CDS survey data violated all of these conditions in various degrees; therefore, there was a concern the *t* test may generate distorted *t* values.

Conducting both a nonparametric and a parametric test on the same data was one response to addressing the question of which statistic to use in order to respond to Research Question 3. Permutation distributions resulting from randomization permutation tests approximate sampling distributions. If a permutation distribution is roughly a normal shape, we can assume that a sampling distribution will be close to normal and therefore an independent samples *t* test can be safely applied (Moore, McCabe, Duckworth, & Sclove, 2003). If the permutation distribution was not normal, the *p* values from the permutation test would be accurate given the permutation test works directly with the difference of means rather than the standardized difference of means of the *t* test (Moore et al., 2003).

Randomization permutation tests in R statistical software (Gentleman & Ihaka, 2014) using the Mosaic package (Prium, Kaplan, & Horton, 2014) were used to determine both the shape of the randomization permutation distributions as well as the significance of the differences between the group means of TCI scores by institutional characteristics. The randomization tests used the eight institutional characteristic data elements from 2009 CDS data file, the calculated TCI, and 999 resamples as input parameters. Appendix E shows the R code used to process the randomization permutation tests, which included data resampling, histogram creation, and *p* value calculation. The randomization permutation test focused on whether patterns in data were likely to arise by chance and was interpreted in the same way as conventional tests of significance (Manly, 1997). The randomization permutation group comparisons that resulted in normal distribution were further analyzed using an independent samples *t* test in SPSS.

As a secondary measure of significance, the effect size for each difference in means was also determined using an online effect size calculator (Becker, 1999). Effect size attempts to identify the magnitude of practical significance (Cohen, 1992). Small, medium, and large effect sizes for independent means differences are respectively referenced as Cohen's *d* values of .20, .50, and .80 (Cohen, 1992). For the purposes of this study, the larger the Cohen's *d* value, the larger the practical significance of the difference in means between groups.

As a final step in response to Research Question 3, a power analysis was conducted to minimize the occurrence of Type II errors while assessing the results of the hypothesis testing (Cohen, 1992). Cohen's (1992) statistical power analysis method engages statistical significance (.05 for this study), power (.80 as a general convention), sample size (conditional on the proposed effect size), and effect size as criterion for decreasing the instance of Type II error. Type II errors occur when the null hypothesis fails to be rejected when it should be rejected. Using mean differences as the effect size test, a large effect size requires a sample size of 26 cases for each group being compared (Cohen, 1992). The large effect size was chosen for this analysis given the large data sample. The power analysis methodology, as applied in this study, follows that if each group has at least 26 cases and the *t* test is not significant (suggesting a failure to reject the null hypothesis), then Cohen's *d* must be smaller than .80 to avoid incorrectly failing to reject the null hypothesis. Chapter 4 provides a detailed explanation of the power analysis results for this study.

Reliability and Validity

CDS Survey Instrument. Using the EDUCAUSE CDS survey as the starting point for data collection significantly reduced the burden of creating a custom survey instrument to complete this study. Although the EDUCAUSE CDS survey instrument has not undergone any psychometric or cognitive protocols, each section of the survey requests respondent feedback on survey questions, which was used to update subsequent survey instruments for clarity. As a measure of reliability, SPSS was used to calculate the

Cronbach’s alpha for the proposed TCI-1 data (.754). A Cronbach’s alpha between .70 and .80 suggests a satisfactory measure of an instrument’s reliability (Bland & Altman, 1997).

CDS survey respondents were representative of a wide range of institutions of varying institutional characteristics, including size, location, control, and Carnegie classification. The broad spectrum of higher education institutional types providing measurable responses to the CDS survey offers external validity. However, because institutions self-select their participation in the CDS survey, the potential for biased data existed. In particular, some respondents may not have the requisite technology resources and/or knowledge to accurately complete the CDS survey and therefore chose not to respond. Overall, the CDS survey could become a stronger source of data by targeting solicitations from institutions who do not traditionally participate in large numbers (i.e., TCUs, HSIs, and MSIs) or creating condensed versions of the survey that do not require extensive expertise to complete.

TCI-2 Framework. After identifying the TCI-2 model in an exploratory fashion with the 2008 CDS data, testing the TCI-2 model using the 2009 CDS data, provided cross-validation of the model on a second sample of data (Byrne, Shavelson, & Muthén, 1989). This allowed the TCI-2 model to be confirmed in a manner that is not influenced by the data providing a true test of the model (Cliff, 1983).

Ethical Considerations

The current study was based upon evaluation of secondary data as collected by the EDUCAUSE CDS survey. While data specific to individual institutions were recognizable, no data were specific to individuals associated with the institutions;

therefore, this study did not present any concerns related to human subject research. In lieu of completing institutional review board (IRB) procedures, the appropriate paperwork requesting exclusion from IRB requirements was submitted and approved by the department chair.

Summary

The quantitative methods used in this study were based upon survey responses from the 2008 and 2009 EDCUASE CDS surveys. The CDS survey offered a self-selected data set of responses from a wide range of higher education institutions that was used to conduct CFA, EFA, and sample tests to validate a model proposed to measure the technology capacity of higher education institutions. The validated model was used to calculate technology capacity index scores that were used to compare the extent of capacity differences between groups of institutions. Results of these tests are reported in the next chapter.

CHAPTER 4:

RESULTS

This study was conducted to identify a construct to measure the technology capacity of higher education institutions as well as identify which dimensions are best able to predict technology capacities. It was anticipated that the results of this study would inform higher education officials where funding and policy changes should be directed to address potential digital divide situations. This chapter presents the results by research question.

Research Question 1

Data Assumption Testing

The normality of the 2008 CDS data was tested using the Mahalanobis distance test for multivariate normality, the Shapiro-Wilk test for univariate normality, and tests for skewness and kurtosis. The results of the Mahalanobis distance test for multivariate normality of the technology capacity index (TCI-1) factors identified in Figure 3.1 suggested the CDS survey data did not display multivariate normality as assumed for CFA (Table 4.1). Q-Q plots of the Mahalanobis distance results (Figure 4.1) for each proposed factor further supported the lack of normality of the proposed test data. Table 4.2 presents results from a Shapiro-Wilk test for univariate normality, which shows that each of the individual items of the TCI-1 model also failed to exhibit normality.

Table 4.1

Mahalanobis Distance Statistics for Technology capacity Index Factors

	Minimum	Maximum	*M*	*df*	Outliers ($p < .001$)
Support	.019	28.05	4.99	5	8
Access	.222	20.81	2.99	3	7
Use	.859	25.95	5.99	6	1
Infrastructure	1.30	42.95	7.99	8	3

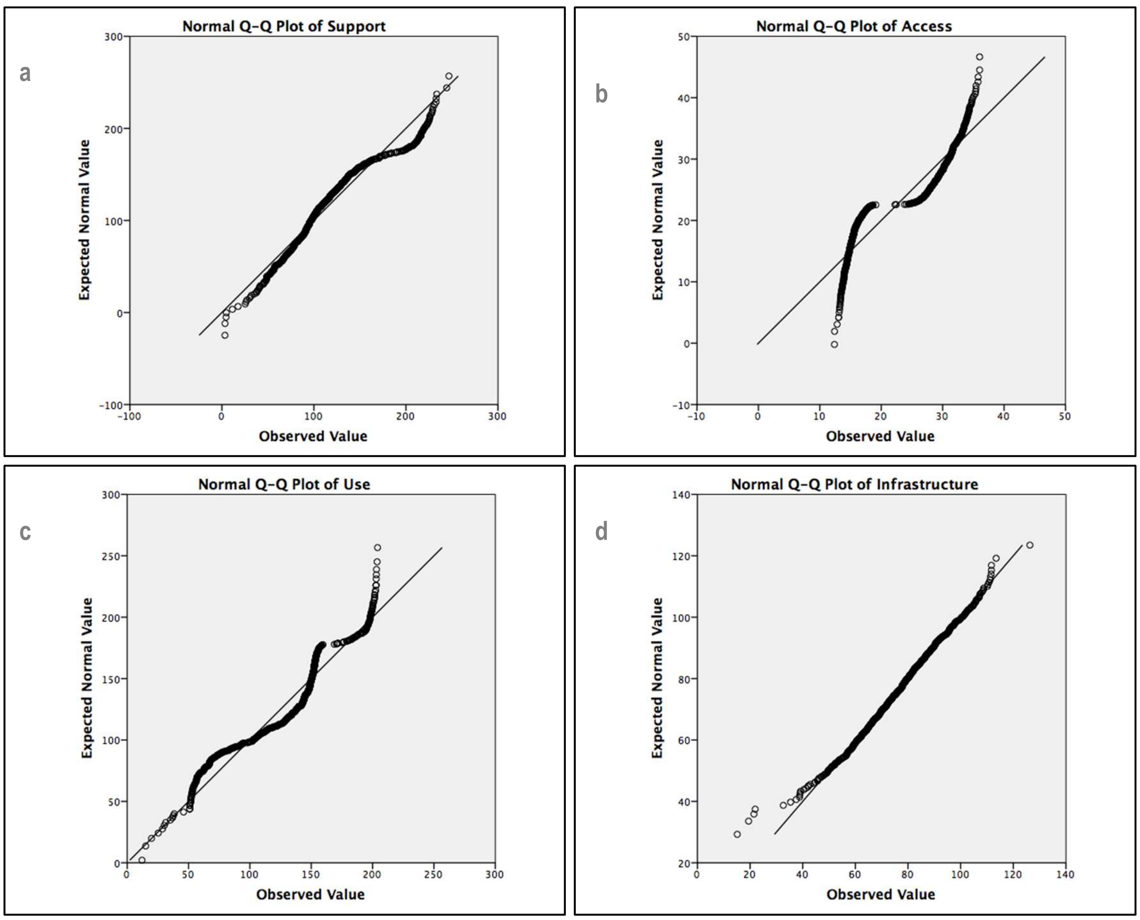


Figure 4.1. Q-Q plot of Mahalanobis distance results for the (a) Support factor; (b) Accessibility factor; (c) Use factor; and (d) Infrastructure factor.

Table 4.2
Technology capacity Index (TCI-1) Item Normality Tests

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	*df*	Sig.	Statistic	*df*	Sig.
Residence hall network speed	.294	826	.000	.826	826	.000
Wireless access	.100	826	.000	.947	826	.000
Identity management technologies	.111	826	.000	.948	826	.000
Computers owned or leased by the institution	.068	826	.000	.982	826	.000
Network Authentication	.345	826	.000	.708	826	.000
Firewall security	.209	826	.000	.881	826	.000
Campus security-related patches	.169	826	.000	.895	826	.000
Classroom technology	.039	826	.006	.996	826	.016
Help desk hours	.138	826	.000	.878	826	.000
Professional development funding	.117	826	.000	.950	826	.000
FTE staff (central IT)	.038	826	.008	.989	826	.000
Student employees (central IT)	.088	826	.000	.963	826	.000
Teaching and learning support	.138	826	.000	.952	826	.000
Funding for centralized IT	.040	826	.004	.994	826	.001
Funding from student technology fee	.319	826	.000	.718	826	.000
Fee for residence hall access	.361	826	.000	.713	826	.000
Undergraduate-owned computer use	.226	826	.000	.786	826	.000
Student computer policy	.210	826	.000	.896	826	.000
Campus strategic plan includes IT	.488	826	.000	.497	826	.000
IT department strategic plan	.446	826	.000	.572	826	.000
Course management system availability	.437	826	.000	.613	826	.000
Learning technologies	.153	826	.000	.918	826	.000

Note. FTE indicates full-time equivalent; IT, information technology.

Tests for TCI-1 item skewness and kurtosis were conducted, resulting in all items meeting acceptable levels of asymmetry. Table 4.3 provides the results of these tests.

Table 4.3
Descriptive Statistics for Technology Capacity Index (TCI-1) Item Distribution Shape

		Skewness		Kurtosis	
Item	*M*	Statistic	*SE*	Statistic	*SE*
Residence hall network speed	2.75	-.702	.085	-.799	.170
Wireless access	4.85	-.674	.085	-.192	.170
Identity management technologies	3.44	-.734	.085	.051	.170
Computers owned or leased by the institution	7.65	.456	.085	-.018	.170
Network Authentication	4.01	-1.354	.085	.707	.170
Firewall security	2.28	.165	.085	-.851	.170
Campus security-related patches	4.31	-.541	.085	-.516	.170
Classroom technology	47.10	-.007	.085	.423	.170
Help desk hours	72.80	1.025	.085	.839	.170
Professional development funding	31.77	-.584	.085	.113	.170
FTE staff (central IT)	3.48	.230	.085	-.480	.170
Student employees (central IT)	1.87	-.244	.085	-.645	.170
Teaching and learning support	6.15	-.401	.085	-.713	.170
Funding for centralized IT	15.30	.178	.085	-.323	.170
Funding from student technology fee	6.96	-.095	.085	-1.929	.170
Fee for residence hall access	.96	.435	.085	1.827	.170
Undergraduate-owned computer use	71.24	-1.044	.085	-.420	.170
Student computer policy	2.58	.273	.085	-.565	.170
Campus strategic plan includes IT	1.79	-1.449	.085	.099	.170
IT department strategic plan	1.71	-.905	.085	-1.184	.170
Course management system availability	50.00	.598	.085	1.491	.170
Learning technologies	2.09	.869	.085	.143	.170

Note. FTE indicates full-time equivalent; IT, information technology.

Confirmatory Factor Analysis

The initial CFA processing to assess the fit of the TCI-1 model yielded five model fit indices: chi-square test of model fit, root mean square error of approximation (RMSEA), comparative fit index (CFI)/Tucker-Lewis index (TLI), chi-square test of model fit for the baseline model, and weighted root mean square residual. Given the large sample size tested, RMSEA and TLI were selected as the primary indices to determine model fit, as they are both sensitive to model complexity and/or sample size in their calculations (Hu & Bentler, 1998). A good model fit has an RMSEA estimate of 0.06 or less and a TLI estimate of 0.95 or more (Hu & Bentler, 1998). The RMSEA estimate for this study's 2008 data set was 0.083, which suggests a poor model fit for TCI-1. The TLI calculated for the model was .604, again suggesting a poor model fit.

After processing the 2009 CDS data to re-affirm the lack of fit for the TCI-1 model, the RMSEA estimate obtained was 0.082 and the TLI estimate was 0.648. With model measurements for both survey years resulting in a poor fit, the resulting analysis of Research Question 1 suggested that this study's *a priori* TCI-1 model was not an appropriate measurement instrument for technology capacity within higher education. An overview of the estimates received for all TCI-1 model indices for both survey data years is provided in Table 4.4.

Table 4.4
Technology Capacity Index Model (TCI-1) Confirmatory Factor Analysis Fit Estimates

	Estimate	
	2008	2009
Chi-square test of model fit	1373.877	1298.520
Root mean square error of approximation	.083	.082
Comparative fit index	.652	.693
Tucker-Lewis index	.604	.651
Chi-square test of model fit (baseline model)	3528.579	3800.485
Weighted root mean square residual	2.133	2.110

Exploratory Factor Analysis

With the inability to confirm the TCI-1 model for this study, an exploratory factor analysis (EFA) was conducted to determine whether another potential technology capacity model (TCI-2) could be estimated using the 2008 CDS data set. Prior to beginning the EFA, a scree test was conducted in SPSS to create a visual graph of eigenvalues for each of the TCI-2 items (Figure 4.2). The scree test helped determine the break point at which a factor is a major component of the variance in a model (Hayton, 2004). The analysis to determine the ‘break’ in the scree curve suggests the EFA process should focus on models with between one and five factors.

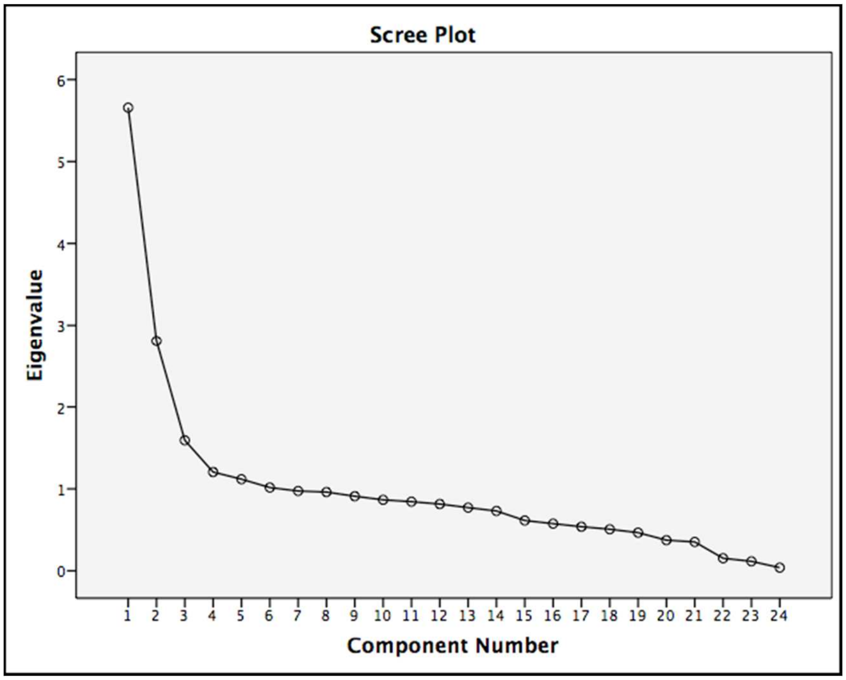


Figure 4.2. Scree test graph.

After running the EFA processes in Mplus and using an RMSEA cutoff of 0.06, models with between one and five factors were accessed for fit for the TCI-2 framework. Factor loadings for each of items on the proposed models were also assessed. Given the CDS sample size of more than 800 cases, an absolute factor loading threshold of 0.300 or less (Hair, 1998) suggested a weak communality between item and factor while a threshold of at least 0.500 suggested a much stronger association. Models were also accessed for factors that had fewer than three associated items which implied these models may have had too many factors extracted for the number of items (Guilford, 1952) and therefore excluded the model from being a viable option. Finally, cross-loading items were reviewed. Strong item to factor loadings were kept as integral communality in the model, while cross-loaded items were reviewed for both strength of communality and theoretical relevance before determining viability within the model. The results of each of the models follows.

One-factor model. The one-factor model proposed that all 24 factors of the TCI-2 model were associated with a single technology capacity factor. However, this model obtained an RMSEA of 0.089 suggesting it was not a good fit for measuring technology capacity. Table 4.5 provides an overview of the factor loadings for this model.

Table 4.5
Promax Rotated Loadings for One-Factor Technology Capacity Index Model (TCI-2)

	Factor
Item	1
Internet Bandwidth	**0.701**
Residence Hall Network Speed	**0.353**
Residence Hall Network Type	**0.396**
Wireless Access	**0.355**
Identity Management	-0.249
Leased Computers	**0.751**
Network Authentication	-0.160
Firewalls	**0.516**
System Patching	0.297
Classroom Technology	0.054
Help Desk Hours	**0.390**
Professional Development Budget	0.113
Employee Count	**0.814**
Student Employees	**0.684**
Faculty Support	**0.522**
Central IT Budget	**0.818**
Student Tech Fee	0.034
Residence Hall Network Fee	**0.457**
Student Ownership	**0.450**
Computer Requirement	**0.405**
Campus IT Strategy	-0.074
IT Department Strategy	0.183
Course Management Software	0.176
LMS Technology	-0.172

Note. Definitions for each item are provided in Table 3.1.

Two-factor model. The two-factor model achieved an RMSEA of 0.051 which met the anticipated 0.06 measure for a good model fit. The first factor of the model had nine factors that met the 0.300 threshold with central IT budget having the highest communality (0.902) (see Table 4.6). The second factor had eight factors that met the 0.300 threshold with residence hall network having the highest communality (0.913).

Table 4.6
Promax Rotated Loadings for Two-Factor Technology Capacity Index Model (TCI-2)

Item	Factor 1	Factor 2
Internet Bandwidth	**0.692**	**0.331**
Residence Hall Network Speed	0.185	**0.829**
Residence Hall Network Type	0.203	**0.913**
Wireless Access	0.286	**0.325**
Identity Management	-0.276	-0.027
Leased Computers	**0.852**	0.180
Network Authentication	-0.172	-0.031
Firewalls	**0.504**	0.247
System Patching	0.275	0.173
Classroom Technology	0.073	-0.024
Help Desk Hours	**0.413**	0.124
Professional Development Budget	0.082	0.119
Employee Count	**0.900**	0.265
Student Employees	**0.602**	**0.485**
Faculty Support	**0.573**	0.117
Central IT Budget	**0.902**	0.272
Student Tech Fee	0.084	-0.170
Residence Hall Network Fee	0.251	**0.681**
Student Ownership	0.289	**0.752**
Computer Requirement	**0.318**	**0.416**
Campus IT Strategy	-0.006	-0.230
IT Department Strategy	0.266	-0.149
Course Management Software	0.170	0.080
LMS Technology	-0.192	0.002

Note. Definitions for each item are provided in Table 3.1.

In assessing the two factors of this model in relation to the conceptual model for this study, the items meeting the 0.300 threshold on factor one were associated with access to technology on campus (Internet bandwidth, leased computers, firewalls, help desk hours, number of central IT employees, student employees, faculty support, central IT budget, and the computer requirement). Factor two items (Internet bandwidth, student employees, computer requirement, network fee, student computer ownership, residence hall network fee, and type of residence hall network) were all associated with the student experience with technology on campus. Three of the items (Internet, student employees, and computing requirements) cross-loaded on both factors. The association between Internet bandwidth and access was very strong (0.692), so the relationship was retained. As a component of student experience, the Internet bandwidth experienced by students can have a significant impact on how well students embrace technology on campus, therefore this relationship was retained as well. Student employees also cross-loaded on the model. In addition to augmenting central IT employee support, student employees are in the unique position to provide feedback and insights to improve the overall student experience with technology at an institution. Both student employee loadings were retained. The computer requirement reflects the impetus for both actively engaging technologies on campus as well as a procurement of a built-in infrastructure for student support. The cross loading for this item was also maintained. Items that did not have any threshold level factor loadings were discarded from the model. A revised view of the two-factor model can be viewed in Table 4.7.

Table 4.7
Revised Two-Factor Technology Capacity Index Model (TCI-2)

	Factor	
Item	Campus Support	Student Experience
Internet Bandwidth	**0.692**	**0.331**
Leased Computers	**0.852**	
Firewalls	**0.504**	
Help Desk Hours	**0.413**	
Employee Count	**0.900**	
Student Employees	**0.602**	**0.485**
Faculty Support	**0.573**	
Central IT Budget	**0.902**	
Computer Requirement	**0.318**	**0.416**
Residence Hall Network Fee		**0.681**
Student Ownership		**0.752**
Residence Hall Network Speed		**0.829**
Residence Hall Network Type		**0.913**
Wireless Access		**0.325**

Note. Definitions for each item are provided in Table 3.1.

Three-factor model. An RMSEA of 0.033 was achieved by the proposed three-factor model; this meets the anticipated 0.06 measure for a good model fit. Central IT employee count had the highest communality with the first factor with a factor loading of 0.937 followed by nine other items (Internet bandwidth, leased computers, firewalls, help desk hours, student employees, faculty support, central IT budget, and computer requirement) (see Table 4.8). Factor two had six items loaded with at least a moderate association (residence hall network speed, residence hall network type, student employees, network fee, student ownership, and computer requirement); residence hall network had the highest association with the second factor (0.922). The third factor did not have an item that exhibited as strong an item/factor association as the first two factors, but 12 items were associated with the factor (Internet bandwidth, wireless access, identity management, leased computers, firewalls, patching, classroom technology, help desk hours, central IT employees, student employees, faculty support, and central IT budget) with faculty support having the highest association (0.562). In accessing the three factors of this model in relation to the conceptual model for this study, the items on factor one were associated with campus support. Factor two was associated with student experience and factor three items associated with infrastructure.

Table 4.8
Promax Rotated Loadings for Three-Factor Technology Capacity Index Model (TCI-2)

	Factor		
Item	1	2	3
Internet Bandwidth	**0.693**	0.297	**0.374**
Residence Hall Network Speed	0.172	**0.820**	0.233
Residence Hall Network Type	0.213	**0.922**	0.122
Wireless Access	0.228	0.288	**0.547**
Identity Management	-0.249	0.010	**-0.303**
Leased Computers	**0.890**	0.140	**0.388**
Network Authentication	-0.209	-0.051	0.112
Firewalls	**0.481**	0.208	**0.399**
System Patching	0.232	0.124	**0.445**
Classroom Technology	0.021	-0.069	**0.361**
Help Desk Hours	**0.396**	0.091	**0.310**
Professional Development Budget	0.065	0.104	0.147
Employee Count	**0.937**	0.223	**0.427**
Student Employees	**0.592**	**0.452**	**0.395**
Faculty Support	**0.530**	0.051	**0.562**
Central IT Budget	**0.924**	0.226	**0.458**
Student Tech Fee	0.080	-0.180	0.050
Residence Hall Network Fee	0.255	**0.686**	0.139
Student Ownership	0.272	**0.738**	0.287
Computer Requirement	**0.307**	**0.397**	0.251
Campus IT Strategy	-0.025	-0.253	0.097
IT Department Strategy	0.243	-0.188	0.261
Course Management Software	0.155	0.058	0.192
LMS Technology	-0.178	0.026	-0.190

Note. Definitions for each item are provided in Table 3.1.

Of the 24 items factored with this model, ten items cross-loaded. Six of the items were retained fully in the model: Internet bandwidth, leased computers, firewalls, faculty support, central IT budget, and competency requirement. These items were retained not only on the strength of their associations, but also based upon the decision that these items theoretically serve multiple purposes in the model. All were contributors to the physical technical infrastructure of an institution while also serving as a tool for campus support. As noted in the two-factor model, student employees serve an important role on both the campus support and student experience factor. However, student employees also loaded on the infrastructure factor with this model. As people are not theoretically considered infrastructure, this association was dropped from the model. Similarly, central IT employees and help desk were also dropped from cross loading on the infrastructure factor, but retained on the campus support factor. Items that did not have threshold factor loadings above 0.300 were discarded from the model. Table 4.9 provides an overview of the revised three-factor model.

Table 4.9
Revised Three-Factor Technology Capacity Index Model (TCI-2)

	Factor		
Item	Campus Support	Student Experience	Infrastructure
Internet Bandwidth	**0.693**		**0.374**
Leased Computers	**0.890**		**0.388**
Firewalls	**0.481**		**0.399**
Help Desk Hours	**0.396**		
Employee Count	**0.937**		
Faculty Support	**0.530**		**0.562**
Central IT Budget	**0.924**		**0.458**
Student Employees	**0.592**	**0.452**	
Computer Requirement	**0.307**	**0.397**	
Residence Hall Network Fee		**0.686**	
Student Ownership		**0.738**	
Residence Hall Network Speed		**0.820**	
Residence Hall Network Type		**0.922**	
Wireless Access			**0.547**
Identity Management			**-0.303**
System Patching			**0.445**
Classroom Technology			**0.361**

Note. Definitions for each item are provided in Table 3.1.

Four-factor model. The four-factor model had an RMSEA of 0.025 that met the appropriate threshold for fit. However, the fourth factor of the model only had two associated items (see Table 4.10). Per the assessment criteria for each model, this excluded the four-factor model from being a viable candidate for TCI-2.

Table 4.10
Promax Rotated Loadings for Four-Factor Technology Capacity Index Model (TCI-2)

Item*	Factor 1	Factor 2	Factor 3	Factor 4
Internet Bandwidth	**0.665**	0.095	-0.033	0.063
Residence Hall Network Speed	-0.132	**0.850**	0.060	0.039
Residence Hall Network Type	-0.025	**0.941**	-0.077	-0.039
Wireless Access	-0.042	0.100	-0.016	**0.791**
Identity Management	-0.132	0.068	-0.224	-0.076
Leased Computers	**0.945**	-0.115	-0.011	-0.038
Network Authentication	**-0.393**	0.049	**0.300**	0.039
Firewalls	**0.311**	0.121	0.260	0.001
System Patching	-0.101	0.151	**0.555**	0.012
Classroom Technology	-0.112	-0.187	0.037	**0.547**
Help Desk Hours	**0.325**	-0.018	0.109	0.071
Professional Development Budget	-0.047	0.110	0.135	0.030
Employee Count	**0.945**	-0.024	0.036	-0.065
Student Employees	**0.456**	**0.309**	0.046	0.062
Faculty Support	**0.337**	-0.079	**0.342**	0.138
Central IT Budget	**0.919**	-0.026	0.041	-0.020
Student Tech Fee	0.144	-0.241	-0.015	0.062
Residence Hall Network Fee	0.098	**0.662**	-0.089	-0.001
Student Ownership	-0.010	**0.734**	0.085	0.039
Computer Requirement	0.131	**0.373**	0.140	-0.030
Campus IT Strategy	-0.123	-0.179	**0.393**	-0.159
IT Department Strategy	0.143	-0.207	**0.376**	-0.089
Course Management Software	0.065	0.031	0.137	0.037
LMS Technology	-0.098	0.047	-0.202	0.026

*Definitions for each item are provided in Table 3.1.

Five-factor model. The final model proposed for TCI-2 was the five-factor model with an RMSEA of 0.021 that met the fit threshold. However, both the fourth and fifth factors for this model each had only two associated items (see Table 4.11) suggesting over-factoring of the model. This model was excluded from consideration for TCI-2.

Table 4.11
Promax Rotated Loadings for Five-Factor Technology Capacity Index Model (TCI-2)

	Factor				
Item	1	2	3	4	5
Internet Bandwidth	**0.671**	0.077	-0.045	0.063	0.014
Residence Hall Network Speed	-0.163	**0.839**	0.068	0.039	0.053
Residence Hall Network Type	-0.065	**0.952**	-0.057	-0.045	0.022
Wireless Access	-0.039	0.081	-0.045	**0.794**	0.007
Identity Management	-0.148	0.102	-0.203	-0.082	-0.056
Leased Computers	**0.921**	-0.022	0.018	-0.043	-0.173
Network Authentication	**-0.393**	0.039	0.294	0.046	0.042
Firewalls	**0.306**	0.122	0.257	0.004	0.011
System Patching	-0.095	0.121	**0.530**	0.026	0.082
Classroom Technology	-0.125	-0.150	0.029	**0.571**	-0.091
Help Desk Hours	**0.339**	-0.050	0.091	0.074	0.045
Professional Development Budget	0.011	-0.051	0.072	0.039	0.266
Employee Count	**0.972**	-0.067	0.012	-0.066	0.047
Student Employees	**0.416**	**0.371**	0.078	0.055	-0.090
Faculty Support	**0.324**	-0.051	**0.350**	0.140	-0.035
Central IT Budget	**0.963**	-0.099	0.000	-0.018	0.091
Student Tech Fee	0.054	0.041	0.083	0.074	**-0.525**
Residence Hall Network Fee	0.047	**0.725**	-0.053	-0.009	-0.072
Student Ownership	0.040	**0.545**	0.009	0.048	**0.348**
Computer Requirement	0.169	0.247	0.093	-0.028	0.228
Campus IT Strategy	-0.169	-0.073	**0.454**	-0.173	-0.128
IT Department Strategy	0.122	-0.142	**0.401**	-0.090	-0.084
Course Management Software	0.060	0.038	0.137	0.039	-0.005
LMS Technology	-0.092	0.035	-0.210	0.029	0.006

Note. Definitions for each item are provided in Table 3.1.

Model Validation

With the assessment of the five EFA models completed, the two-factor and three-factor models both remained viable options for TCI-2. The items associated with the access factor in TCI-2 mostly relate to providing appropriate resources to support the use and function of technology at an institution. The items that most explain the variation in the factor score for the access factor were the amount of the central IT budget, the number of central IT employees, and the number of computers leased by the institution. All three theoretically correspond to access and affordability of technology. Student employees also fit in this category, but to a lesser extent presumably because of both their part-time status and smaller numbers of availability. The amount of Internet bandwidth in residence halls, computer requirement, and the capacity of firewalls for network security were another extension of access as these infrastructure items can either help or hinder technology capacities through the level of services provided by the institution. Finally, help desk availability and faculty support allow campus constituents to reach out for help with everyday technology concerns or to receive training to increase technology skills and knowledge; again, enabling access and use of technology at the institution. The infrastructure, use, access, and support dimensions of the digital divide are all encompassed in the access factor of TCI-2.

The student experience factor item associations were all related to enabling and creating the best environment for students to experience and use technology on campus. Items focused on whether not students are proactive in the providing their own technology (computer requirement and student ownership), have adequate network options to use technology (Internet bandwidth, residence hall network type, residence hall network speed, residence hall network fee, and amount of wireless access), or put students in a position to help define the technical environment along with central IT staff (student employees). From a theory perspective, the student experience factor covered the infrastructure, use, and access dimensions of the digital divide.

Comparing the items in the two-factor model to the items in the three-factor model, a one-to-one alignment of items was identified with the exception of the identity management, patching, and LMS technology items introduced by the three-factor model. Another review of the loadings (see Table 4.9) for these items showed that none of these items were strongly associated with the infrastructure factor and therefore potentially would not have a major role in defining the factor or the model. Given the items in the two-factor model cover each theoretical dimension of the digital divide with some empirical strength, and in the interest of parsimony of the model, the two-factor model was selected as the basis for the TCI-2 framework.

A cross-validation of the TCI-2 framework was conducted using the 2009 CDS survey data. The results of the cross-validation CFA process were a good fit for measuring technology capacity with an RMSEA estimate of 0.050 and a TLI estimate of 0.964. A review of the item estimates showed that computer requirement had a very low association (0.182) with the access factor. This item, which was cross-loaded in the exploratory phase, was dropped from the model and another CFA processed in Mplus that resulted in an error of no convergence and a message that the number of iterations exceeded.

After increasing the number of iterations, the results of the CFA run showed the TCI-2 model with an RMSEA of 0.056 and a TLI of 0.954 that still meets the target criteria for a good fit. Another review of the estimates showed Internet bandwidth as associated with the student experience factor exhibited a very low association (0.137); so this item, which was also cross-loaded in the exploratory phase, was dropped from the model. The final RMSEA for the model was 0.059 and the TLI was 0.949 (see Table 4.12 for a complete estimates list). The standardized estimates for all remaining items were above the 0.300 threshold. The removal of computer requirement and Internet bandwidth items from the respective factors did not impact the theoretical reasoning for the model as both items are still represented within the model. Figure 4.3 provides an overview of the validated TCI-2 model with standard estimates for all items, residual errors, and the correlation estimate between the access and student experience factors (.406).

Table 4.12
Technology Capacity Index Model (TCI-2) Confirmatory Factor Analysis Fit Estimates

	Estimates
Chi-square test of model fit	284.654
Root mean square error of approximation	.059
Comparative fit index	.958
Tucker-Lewis index	.949
Chi-square test of model fit (baseline model)	5075.932
Weighted root mean square residual	1.406

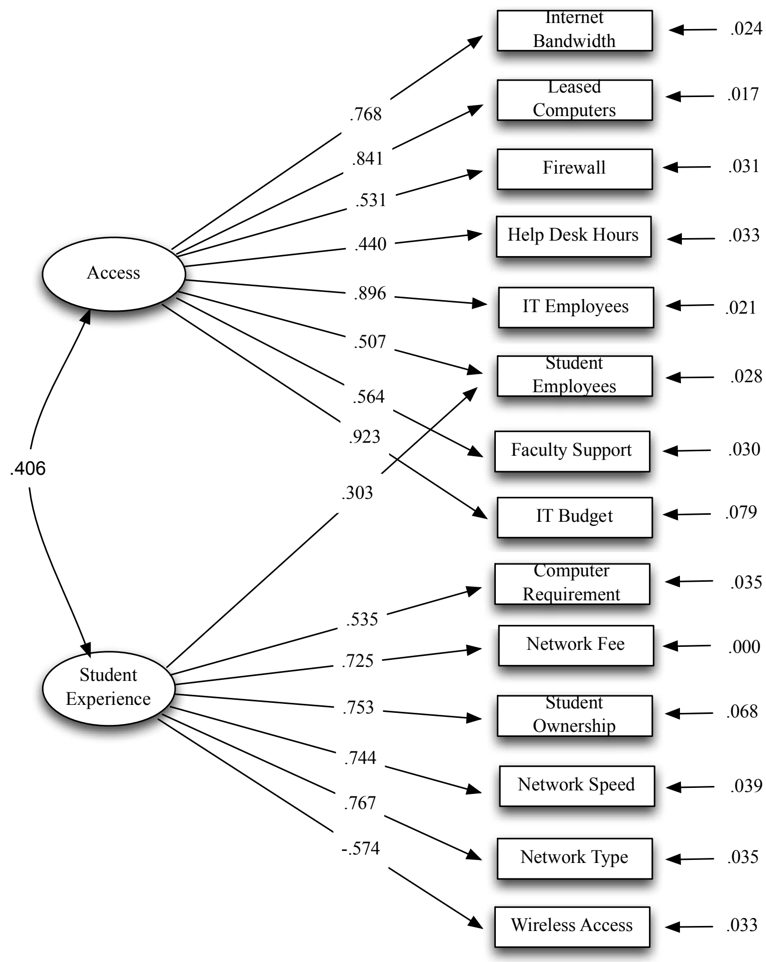


Figure 4.3. Technology capacity index (TCI-2) model. The two factors were campus support and student experience. Model shown with factor correlations, standard estimates between factors and items, and residual variance errors for individual items. Definitions for the individual items are provided in Table 3.1.

Research Question 2

The second research question for this study was focused on identifying which technology dimensions were most interdependent with a higher education institution's technology capacity. The validated TCI-2 model and 2009 factor data was used as the foundation for responding to this research question. To assess the relationships between access, student experience, and technology capacity, a scatterplot matrix (Figure 4.4) summarized their pairwise relationships.

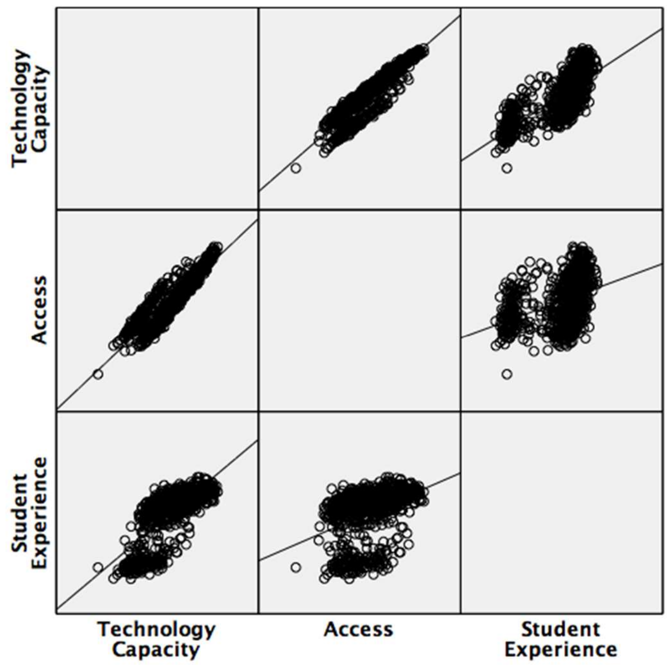


Figure 4.4. Scatterplot matrix of technology capacity index (TCI-2) model pairwise relationships.

Analysis of the pairwise comparisons of the dimensions of TCI-2 in the scatterplot matrix suggested there was a strong, positive relationship between access and technology capacity with data tightly hugging the correlation line. Based on these data, this study inferred that institutions with strong technology access also had high technology capacity. To further corroborate this assessment, Table 4.13 highlights the correlations between the TCI-2 factors and technology capacity. All correlations were significant at the .01 level; however, access had the strongest correlation to overall technology capacity. Thus, access was deemed most relevant dimension associated with an institution's technology capacity.

Table 4.13

Correlation of Technology Capacity Index Factors

		Technology Capacity	Access	Student Experience
Technology Capacity	Pearson Correlation	1	.910	.744
	Sig. (2-tailed)		.000	.000
	N	810	810	810
Access	Pearson Correlation	.910	1	.400
	Sig. (2-tailed)	.000	.000	.000
	N	810	810	810
Student Experience	Pearson Correlation	.744	.400	1
	Sig. (2-tailed)	.000	.000	
	N	810	810	810

Research Question 3

To determine if significant differences in technology capacities existed as a function of institutional characteristics, the means of the calculated TCI scores (using the sum of the 2009 TCI-2 model factor data) were compared for the identified institutional characteristics: sector, control, historically black colleges and universities (HBCU) designation, locale, institutional size, Hispanic-serving institution (HSI) designation, minority-serving institution (MSI) designation, and Carnegie classification. Tribal colleges and universities were included in the data file, but analysis was not conducted with this characteristic due to an exceptionally low number of survey responses.

Four types of procedures were conducted to complete the analysis of the differences in means for each group comparisons. The first test was a randomization permutation procedure to determine distribution normality. The second test was the generation of both nonparametric and parametric *p* values to assess the level of statistical significance of the differences in means. The third test was a calculation of the effect size of the difference using Cohen's *d* to determine practical significance of the differences in means. The final test was a power analysis to assess the validity of the disposition of each null hypothesis.

Randomization Permutation Distribution

The permutation results were presented as histograms of the distribution of the mean differences of the groups being compared. Histograms provide a visual assessment of the normality of the distribution for each permutation test. Based upon a review of the histograms from the permutation tests (See Appendix F), the distributions of each pairing of groups being compared were judged to be normal. This assessment cleared the path to conduct comparisons of the significance of the differences in means with parametric (independent sample *t* test and Cohen's *d*) and nonparametric (permutation calculations) tests. The results of these comparisons are provided in the next section.

Significance Testing

This section of results describes the comparisons of levels of significance between the mean differences in technology capacity scores for each of the nine institutional characteristic groups. Each section is presented in a similar format with boxplots of the means for each group, descriptive data about the groups, and presentation of the group significance data. The statistical significance levels calculated from the nonparametric tests were compared with the significance levels from the parametric independent samples *t* tests. Significant results at the .05 level for both tests suggested technology capacity was influenced by the characteristic. The two significance tests did not generate any contradictory results.

Cohen's *d* was calculated to determine the effect size of the differences in means. A Cohen's *d* of less than .20 implied there is a small practical significance in the difference in means; .50 reflected a medium difference. A Cohen's *d* greater than .80 reflected a large practical significance in the differences in means.

Sector. *H_01: There is no association between the sector designation of an institution and its technology capacities.* The boxplots presented in Figure 4.5 highlighted that public 4-year and private 4-year institutions have overlapping TCI scores in the lower quartile of the public institution range and the upper quartile of the private institution range. The boxplots also showed the median of private 4-year institutions was below the lower quartile for public 4-year institutions. Also, the middle 50% of TCI scores for public 2-year institutions was below the lower quartile of both of the other groups and almost equal to the lowest extreme of public 4-year institutions. Table 4.14 highlights that while public 4-year institutions had the highest mean score (.9106), public 2-year institutions had the lowest mean (-1.9439) by a large margin.

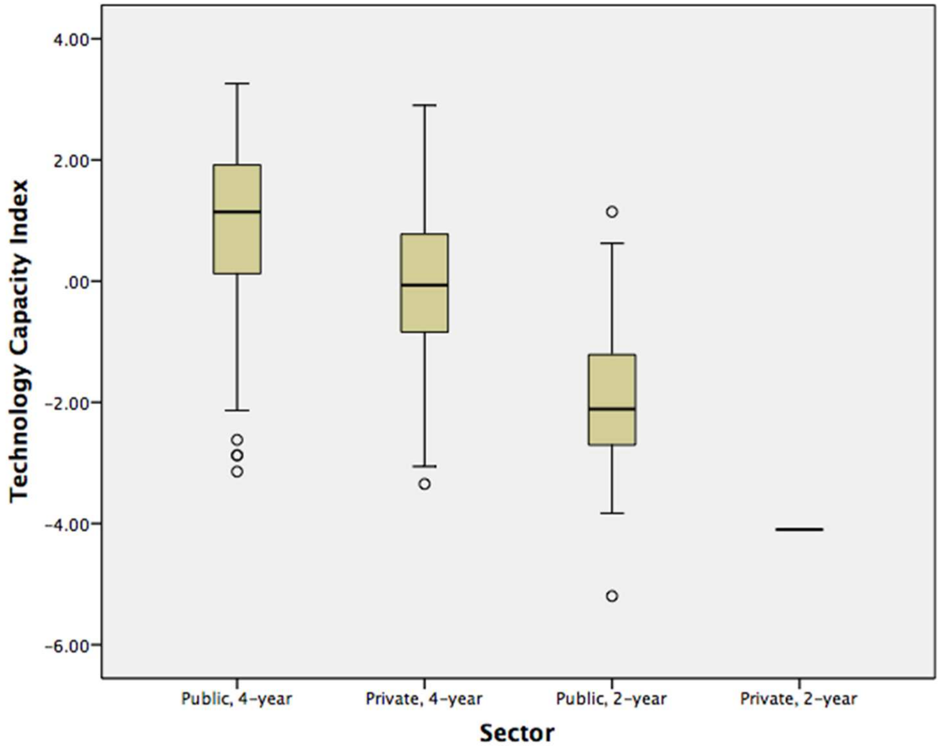


Figure 4.5. Technology capacity index boxplots for each sector of higher education institution.

Table 4.14
Sector Variable Descriptive Statistics

Dependent variable	Sector	*n*	*M*	*SD*	*SE*
TCI	1. Public, 4-year	302	.9106	1.312	.075
	2. Private, 4-year	373	-.0124	1.234	.064
	4. Public, 2-year	134	-1.9439	1.008	.087

* One private, not-for-profit, 2-year institution included in total, but not calculated as a group

Both the randomization permutation and *t* tests had significant test results for each sector group comparison (see Table 4.15), with the largest difference occurring between public, 4-year and public, 2-year institutions (2.854). The smallest difference was between public, 4-year institutions and private, 4-year institutions (.923). Table 4.15 also suggested the Cohen's effect sizes for each grouping comparison (d = .725, d = 1.714, and d = 2.440) were moderate to very high in their practical significance. The power analysis for the sector characteristic suggested the null hypothesis be rejected. A summary of the power analysis is provided later in this chapter.

Table 4.15
Sector Significance Test Results

	Randomization permutation test			Independent samples test				Effect Size
Groups	Obs Diff	*M* > Obs Diff	Sig.	*t*	*df*	Sig. (2-tailed)	*SE*	Cohen's *d*
1. Public, 4-year 2. Private, 4-year	.923	0	.001	9.333	626.635	.000	.099	.725
1. Public, 4-year 4. Public, 2-year	2.854	0	.001	24.769	326.444	.000	.115	1.714
2. Private, 4-year 4. Public, 2-year	1.932	0	.001	17.881	285.190	.000	.108	2.440

Control. *$H_0$2: There is no association between the control designation of an institution and its technology capacities.* The boxplots for TCI scores for the control characteristic (Figure 4.6) showed privately controlled institutions having a slightly lower mean TCI score than publically controlled institutions. The boxplots also reflected the range of TCI scores for private institutions was smaller than the range for public institutions. Public institutions also have a much broader range of institutions in the lower extreme of scores than private institutions. Table 4.16 provides descriptive statistics for each control group that reaffirmed the slightly lower mean for private institutions as well as a smaller standard deviation from the mean. The difference in means between public and private institutions was not significant (p = .589 and p = .600) for both the randomization permutation and independent sample t tests (see Table 4.17). Further, the Cohen's effect size for the comparison was small (d = .037) suggesting a low practical significance in the differences. The power analysis for the control characteristic suggested the null hypothesis could not be rejected. A summary of the power analysis is provided later in this chapter.

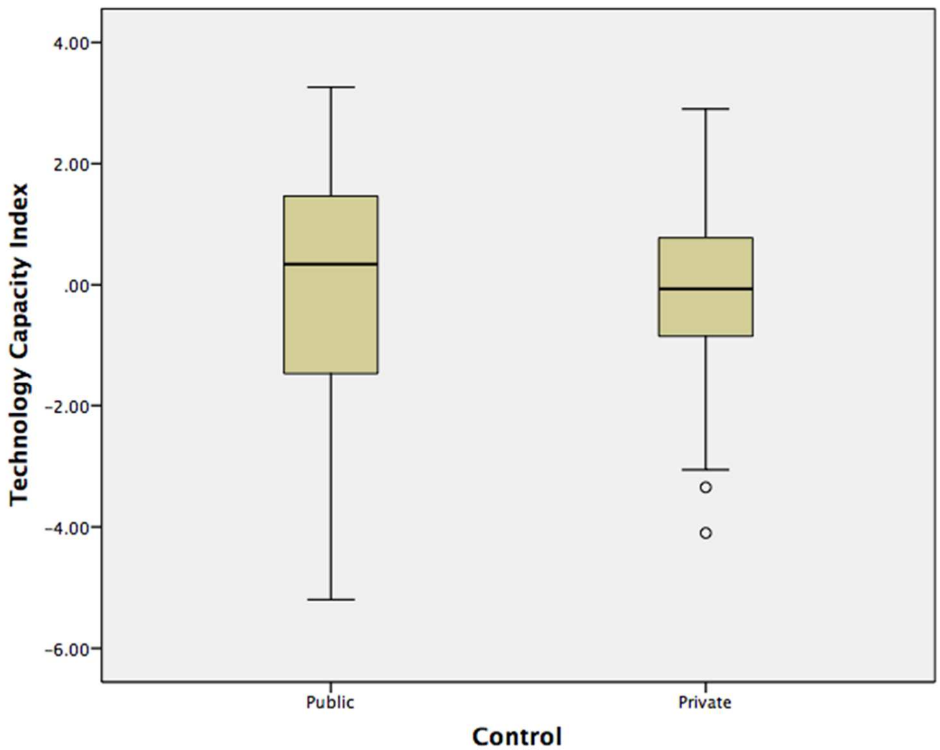


Figure 4.6. Technology capacity index boxplots for each control type of higher education institution.

Table 4.16
Control Variable Descriptive Statistics

Dependent variable	Control	*n*	*M*	*SD*	*SE*
TCI	1. Public	436	.0333	1.800	.086
	2. Private	374	-.0233	1.250	.065

Table 4.17
Control Significance Test Results

	Randomization permutation test			Independent samples test				Effect Size
Groups	Obs Diff	*M*s > Obs Diff	Sig.	*t*	*df*	Sig. (2-tailed)	*SE*	Cohen's *d*
1. Public 2. Private	.057	590	0.589	.525	775.791	.600	.057	.037

Locale. *$H_0$5: There is no association between the locality of an institution and its technology capacities.* Figure 4.7 provides boxplots of the TCI scores for each locale group in the study population. The boxplots showed overlapping of scores for each of the groups. However, the median score for rural institutions was below the lower quartile for city institutions; it is also just about even with the beginning of the lower quartile for suburban institutions. The larger the population of the locale designation, the larger the mean TCI score, with institutions located in cities having the largest mean score (.4220) and rural institutions having the lowest mean (-1.0039) (see Table 4.18). Rural institutions scores reflect an exceptionally large standard error (*SE* = .158), while mean TCI scores for institutions located in towns have a lower standard of deviation (*SD* = 1.372) than any other group.

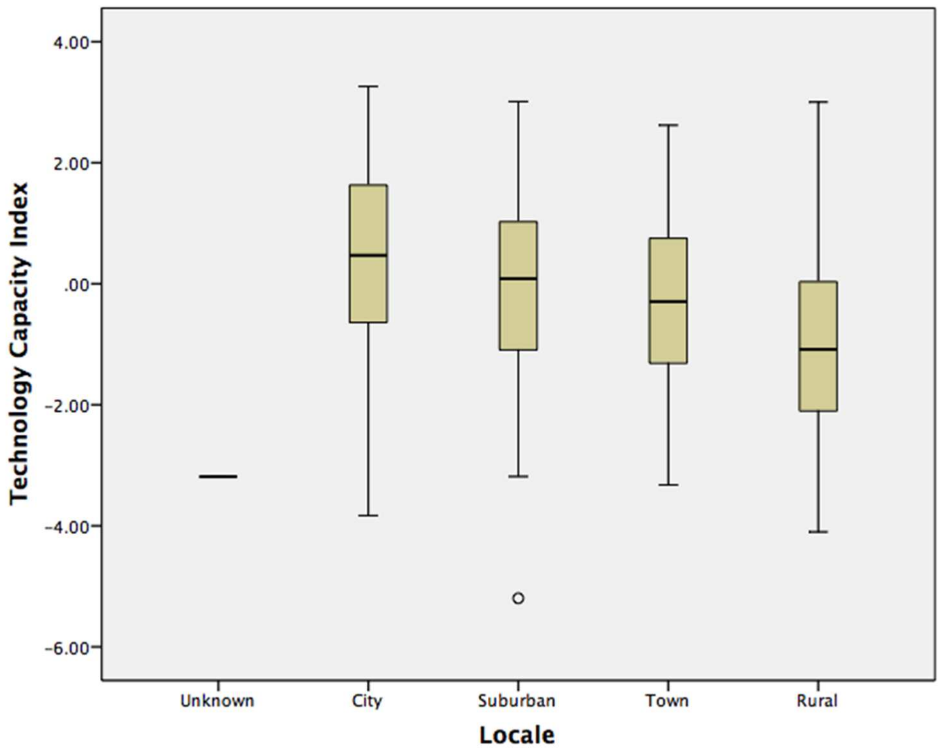


Figure 4.7. Technology capacity index boxplots for each locale type of higher education institution.

Table 4.18
Locale Variable Descriptive Statistics

Dependent variable	Locale	*n*	*M*	*SD*	*SE*
TCI	1. City	377	.4220	1.527	.079
	2. Suburb	177	-.0334	1.526	.115
	3. Town	161	-.3097	1.372	.108
	4. Rural	94	-1.0039	1.527	.158

* One institution with unknown locale included in total, but not calculated as a group

The test for significance showed that mean difference comparisons (see Table 4.19) between suburban and town institutions (p = .082 and p = .081) were not significant. However, all comparisons to a rural institution were significant suggesting that at least in the case of rural institutions, locale does have an impact on technology capacity. The Cohen's effect size for the city and rural local comparison (d = .934) reflected a strong practical significance in the mean differences. The remaining Cohen's effect sizes were small to moderate in practical significance. The power analysis for the locale characteristic suggested the null hypothesis be rejected except in the case of differences between suburban and town locales. A summary of the power analysis is provided later in this chapter.

Table 4.19
Locale Significance Test Results

	Randomization permutation test			Independent samples test				Effect Size
Groups	Obs Diff	*M* > Obs Diff	Sig.	*t*	*df*	Sig. (2-tailed)	*SE*	Cohen's *d*
1. City 2. Suburban	.455	1	.002	3.274	344.740	.001	.139	.298
1. City 3. Town	.732	6	.007	5.472	334.328	.000	.134	.504
1. City 4. Rural	1.426	0	.001	8.097	142.949	.000	.176	.934
2. Suburban 3. Town	.276	81	.082	1.753	335.956	.081	.158	.190
2. Suburban 4. Rural	.971	0	.001	4.980	189.594	.000	.195	.636
3. Town 4. Rural	.694	0	.001	3.633	178.254	.000	.191	.478

Institutional size. *$H_0$6: There is no association between the size of an institution and its technology capacities.* The boxplots for the institutional size characteristic are shown in Figure 4.8. As demonstrated by the boxplots, the median TCI scores for institutions with more than 20,000 students is above or well into the upper extremes of the medians for all other groups. The largest institutions also had the smallest range of scores for this characteristic. As noted with the locale, the larger the population of the institution, the larger the TCI mean score, with institutions with more than 20,000 students having the largest mean scores (1.902) and institutions with under 1,000 students having the lowest (-1.599) as shown in Table 4.20. Institutions with between 5,000 and 9,999 students had the highest standard deviation from the mean (1.379).

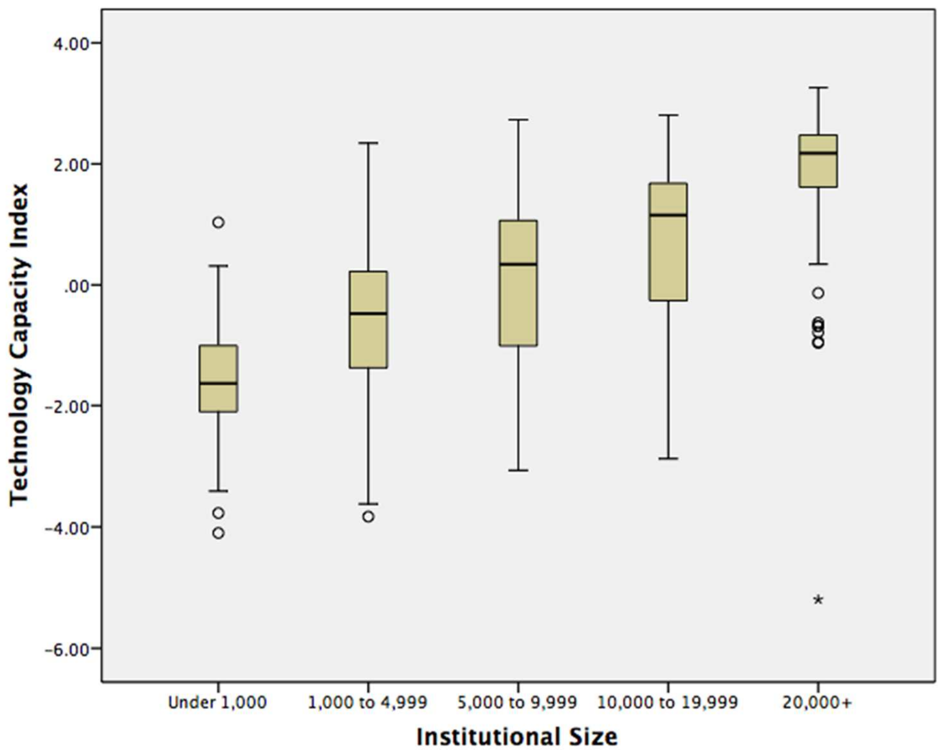


Figure 4.8. Technology capacity index boxplots for each institutional size grouping.

Table 4.20
Institutional Size Variable Descriptive Statistics

Dependent variable	Institutional size	*n*	*M*	*SD*	*SE*
TCI	1. Under 1,000	46	-1.5993	1.027	.151
	2. 1,000 to 4,999	355	-.6724	1.184	.063
	3. 5,000 to 9,999	158	.0134	1.379	.110
	4. 10,000 to 19,999	138	.7320	1.334	.114
	5. 20,000+	113	1.9023	1.134	.107

Randomization permutation and *t* tests showed that all comparisons of institutional size were significant (see table 4.21). The largest observed mean difference of 13.701 was between the largest and smallest institutions. The smallest observed difference of 1.678 was between institutions with 1,000 to 4,999 students and institutions with 5,000 to 9,999 students. The Cohen's effect sizes for all the comparisons except for institutions with 1,000 to 4,999 students and institutions with 5,000 to 9,999 students (d = .534) and institutions with 5,000 to 9,999 students and institutions with 10,000 to 19,999 students (d = .530) suggested a large to very large practical significance in their mean differences. The power analysis for the institutional size characteristic suggested the null hypothesis be rejected. However, due to the small number of cases of institutions with less than 1,000 students, there still may be some concern of Type II error for differences found in comparison with these institutions. A summary of the power analysis is provided later in this chapter.

Table 4.21
Institutional Size Significance Test Results

Groups	Randomization permutation test Obs Diff	*M*s > Obs Diff	Sig.	Independent samples test *t*	*df*	Sig. (2-tailed)	*SE*	Effect Size Cohen's *d*
1. Under 1,000 2. 1,000 to 4,999	-.927	0	.001	-5.653	61.594	.000	.164	.836
1. Under 1,000 3. 5,000 to 9,999	-1.612	0	.001	-8.624	96.935	.000	.187	1.326
1. Under 1,000 4. 10,000 to 19,999	-2.331	0	.001	-12.296	99.971	.000	.190	1.958
1. Under 1,000 5. 20,000+	13.701	0	.001	-18.902	91.677	.000	.185	3.236
2. 1,000 to 4,999 3. 5,000 to 9,999	-.686	0	.001	-5.426	264.346	.000	.126	.534
2. 1,000 to 4,999 4. 10,000 to 19,999	-1.404	0	.001	-10.784	224.746	.000	.130	1.114
2. 1,000 to 4,999 5. 20,000+	-2.575	0	.001	-20.795	195.719	.000	.124	2.221
3. 5,000 to 9,999 4. 10,000 to 19,999	-.719	0	.001	-4.541	290.639	.000	.158	.530
3. 5,000 to 9,999 5. 20,000+	-1.889	0	.001	-12.345	263.706	.000	-1.889	1.496
4. 10,000 to 19,999 5. 20,000+	-1.170	0	.001	-7.493	248.716	.000	.156	.945

Historically black colleges and universities. *$H_0$3: There is no association between the HBCU designation of an institution and its technology capacities.* Figure 4.9 provides boxplots of the TCI scores grouped by whether an institution was classified as an HBCU, with HBCUs having a slightly higher median score than non-HBCUs. However, considering that HBCUs had a mean TCI score of -.5178, it was apparent that some number of the HBCU institutions had low enough TCI scores to negatively skew the TCI distribution for the group. The differences in sample sizes of the HBCU groupings were the most extreme of the study, with 60 times more non-HBCUs (n = 797) than HBCUs (n = 13) in the study population (see Table 4.22). The mean differences between the two groups were not significant (p = .204 and p = .223), with an observed difference of -.534 (see Table 4.23). Further, the Cohen's effect size was small (d = .349) suggesting low practical significance in this comparison. The power analysis for the HBCU characteristic suggested disposition of the null hypothesis could not be determined. The small number of cases of institutions that are HBCUs did not meet the criteria to conduct a valid power analysis implying concerns for a Type II error. A summary of the power analysis is provided later in this chapter.

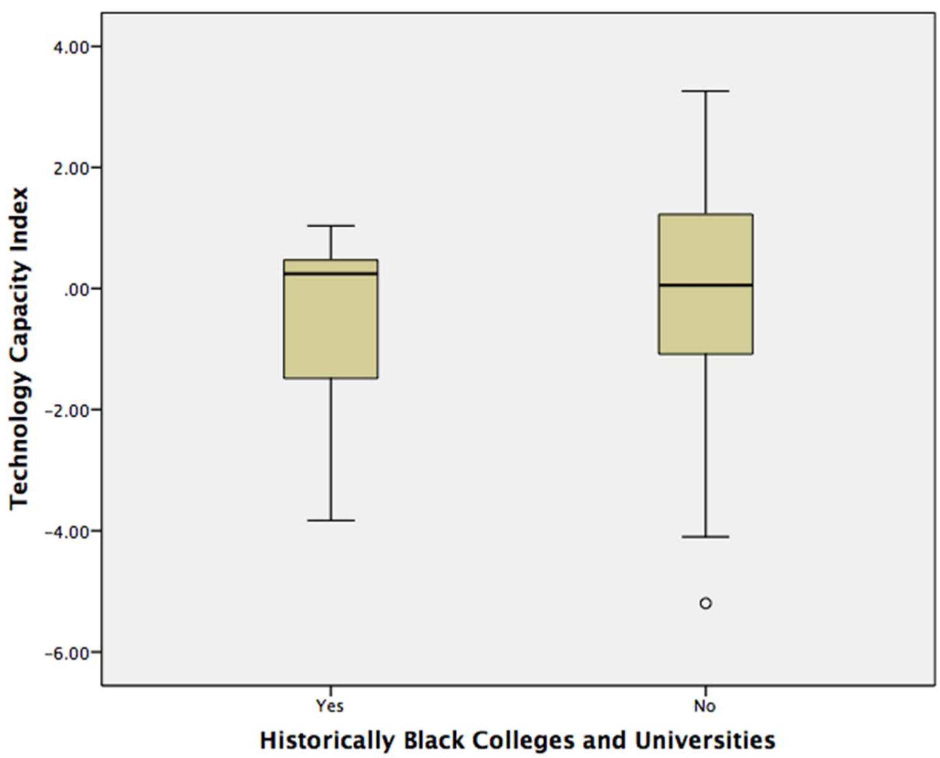


Figure 4.9. Technology capacity index boxplots based on historically black colleges and universities designation.

Table 4.22
Historically Black Colleges and Universities Variable Descriptive Statistics

Dependent variable	HBCU	*n*	*M*	*SD*	*SE*
TCI	1. Yes	13	-.5178	1.488	.413
	2. No	797	.0157	1.570	.056

Table 4.23
Historically Black Colleges and Universities Significance Test Results

	Randomization permutation test			Independent samples test				Effect Size
Groups	Obs Diff	*M* > Obs Diff	Sig.	*t*	*df*	Sig. (2-tailed)	*SE*	Cohen's *d*
1. Yes	.534	203	.204	-1.281	12.440	.223	.416	.349
2. No								

Tribal colleges and universities. *$H_0$4: There is no association between the tribal college or university designation of an institution and its technology capacities.* There was not enough information on tribal institutions to conduct any testing for this characteristic.

Hispanic-serving institutions. *$H_0$7: There is no association between the HSI designation of an institution and its technology capacities.* As presented in Figure 4.10, institutions characterized as an HSI had a slightly higher TCI median score than non-HSI designated institutions, but HSIs also had a smaller range of scores. While the HSI group was much smaller (n = 46) than the non-HSI group (n = 764) (see Table 4.24), the observed difference of .129 was not significant (p = .594 and p = .553) (see Table 4.25). Further, the Cohen's effect size (d = .078) suggested a very low practical significance. The power analysis for the HSI characteristic suggested the null hypothesis fail to be rejected. However, due to the small number of cases of institutions designated as HSI, there still may be some concern of a Type II error. A summary of the power analysis is provided later in this chapter.

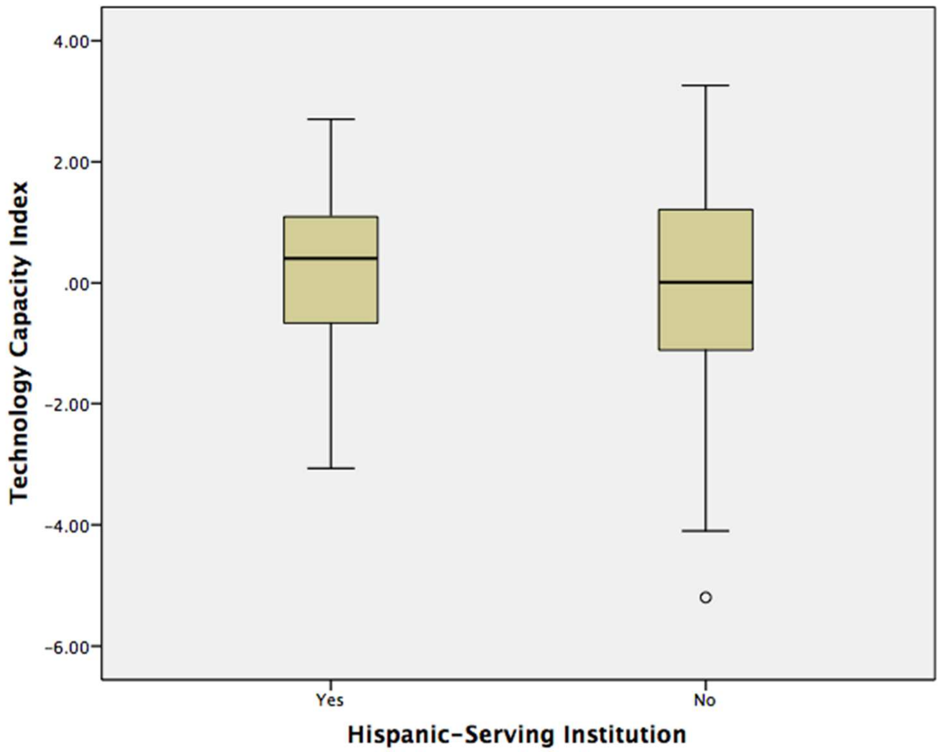


Figure 4.10. Technology capacity index boxplots based on Hispanic-serving institution designation.

Table 4.24
Hispanic-Serving Institution Variable Descriptive Statistics

Dependent variable	HSI	*n*	*M*	*SD*	*SE*
TCI	1. Yes	46	.1290	1.416	.209
	2. No	764	-.0002	1.879	.057

Table 4.25
Hispanic-Serving Institution Significance Test Results

	Randomization permutation test	Independent samples test	Effect Size

Groups	Obs Diff	*M* > Obs Diff	Sig.	*t*	*df*	Sig. (2-tailed)	*SE*	Cohen's *d*
1. Yes	.129	593	.594	.597	51.973	.553	.217	.078
2. No								

Minority-serving institutions. *$H_0$8: There is no association between the MSI designation of an institution and its technology capacities.* Similar to HBCUs and HSIs, MSIs had a higher median TCI score than institutions not designated as an MSI (see Figure 4.11 and Table 4.26). Similar to HBCUs, the median TCI score for MSIs was negatively skewed to the upper portion of the upper quartile of scores. The results from the permutation and *t* test results for the MSI characteristic, show the mean differences between the groups are not significant (p = .589 and p = .466) (see Table 4.27). Further, the Cohen's effect size (d = .097) suggested a very low practical significance. The power analysis for the MSI characteristic suggested the null hypothesis fail to be rejected. However, due to the small number of cases of MSIs, there still may be some concern of a Type II error. A summary of the power analysis is provided later in this chapter.

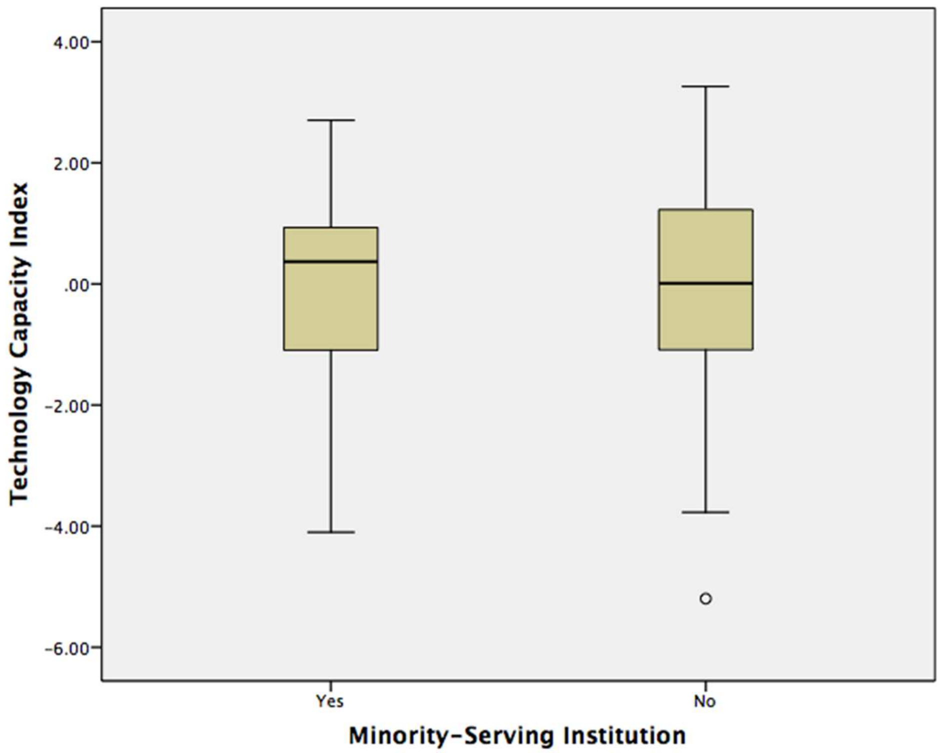


Figure 4.11. Technology capacity index boxplots based on minority-serving institution designation.

Table 4.26
Minority-Serving Institution Variable Descriptive Statistics

Dependent variable	MSI	*n*	*M*	*SD*	*SE*
TCI	1. Yes	61	-.1343	1.569	.201
	2. No	749	.0187	1.570	.057

Table 4.27
Minority-Serving Institution Significance Test Results

	Randomization permutation test			Independent samples test				Effect Size
Groups	Obs Diff	*M* > Obs Diff	Sig.	*t*	*df*	Sig. (2-tailed)	*SE*	Cohen's *d*
1. Yes	-.153	590	.589	-.732	70.156	.466	.209	.097
2. No								

Carnegie classification. *$H_0$9: There is no association between the Carnegie classification of an institution and its technology capacities.* Figure 4.12 is boxplots of TCI scores for each Carnegie classification group. The boxplots showed that the lower quartile of TCI scores for doctoral institutions is well above the upper quartile for any other classification group. The boxplots also showed that the upper quartile for associate institutions was at or below the lower quartile for any other group (except Tribal). Table 4.28 affirms doctoral institutions had the highest mean TCI score (1.9094) by far with associate institutions almost two points (1.8771) behind doctoral institutions.

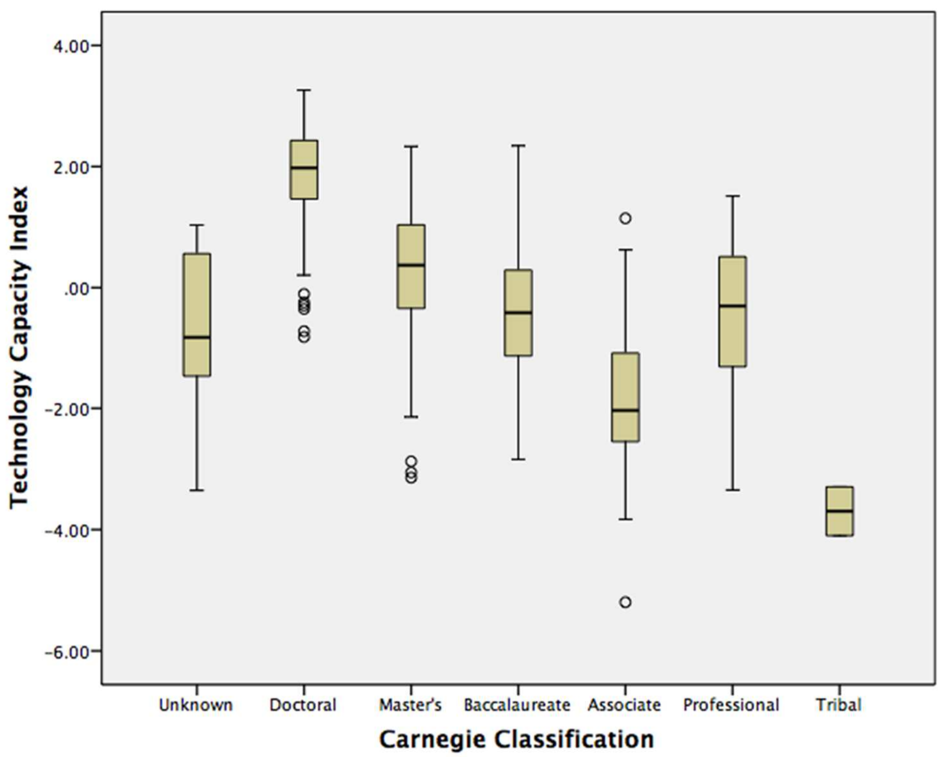


Figure 4.12. Technology capacity index boxplots based on Carnegie classification designation of higher education institutions.

Table 4.28
Carnegie Classification Variable Descriptive Statistics

Dependent variable	Carnegie classification	*n*	*M*	*SD*	*SE*
TCI	-3- Unknown	10	-.7907	1.367	.432
	1. Doctoral/research	176	1.9094	.775	.058
	2. Master's	239	.2486	1.027	.066
	3. Baccalaureate	195	-.4441	.925	.066
	4. Associate	142	-1.8771	.998	.084
	5. Professional/specialty	46	-3.6980	.569	.402

* Two tribal institutions included in total, but not calculated as a group

When comparing the differences between groups, all groups had mean TCI scores differences that were significant (see Table 4.29), except for comparisons between baccalaureate and professional/specialty institutions (p = .927 and p = .931). Further, with the exception of the master's and baccalaureate comparison (d = .709), the Cohen's effect sizes suggested a very large practical significance. The power analysis for the Carnegie classification characteristic suggested the null hypothesis be rejected except in the case of differences between baccalaureate and professional/specialty institutions. However, due to the small number of cases of institutions designated as professional/specialty, there still may be some concern of a Type II error for differences found in comparison with these institutions. A summary of the power analysis is provided later in this chapter.

Table 4.29
Carnegie Classification Significance Test Results

Groups	Randomization permutation test			Independent samples test				Effect Size
	Obs Diff	*M* > Obs Diff	Sig.	*t*	*df*	Sig. (2-tailed)	*SE*	Cohen's *d*
1. Doctoral/research 2. Master's	1.661	0	.001	18.776	412.738	.000	.089	1.826
1. Doctoral/research 3. Baccalaureate	2.353	0	.001	26.653	367.024	.000	.088	2.758
1. Doctoral/research 4. Associate	3.787	0	.001	37.078	261.636	.000	.102	4.238
1. Doctoral/research 5. Professional/ specialty	2.371	0	.001	11.914	53.764	.000	.199	8.248
2. Master's 3. Baccalaureate	.693	0	.001	7.387	427.770	.000	.094	.709
2. Master's 4. Associate	2.126	0	.001	19.886	303.049	.000	.107	2.099
2. Master's 5. Professional/ specialty	.710	0	.001	3.525	56.480	.001	.202	4.754
3. Baccalaureate 4. Associate	1.433	0	.001	13.420	289.993	.000	.107	1.489
3. Baccalaureate 5. Professional/ specialty	.018	926	.927	.087	56.375	.931	.201	4.237
4. Associate 5. Professional/ specialty	-1.416	0	.001	-6.810	63.381	.000	.208	2.242

Power Analysis

The power analysis methodology focuses primarily on the group comparisons whose results did not reflect significant differences in means. To reduce the potential of committing a Type II error in failing to reject the null hypothesis a power analysis was conducted. The power analysis methodology verified that if each group has at least 26 cases and the *t* test is not significant (suggesting a failure to reject the hypothesis), then Cohen's *d* must be smaller than .80 to avoid incorrectly failing to reject the null hypothesis. Table 4.30 outlines each of the parameters of the power analysis, a disposition of the null hypothesis based upon the parameters of the power analysis, and a rationale if the hypothesis fails to be rejected.

Table 4.30
Institutional Characteristics Null Hypotheses Power Analysis

Item	Group (*N*)	*t* test significant (Y/N)	Cohen's *d*	Null Hypothesis Disposition	Disposition Rationale
Sector	1. Public, 4-year (302) 2. Private, 4-year (373)	Y	.725	Rejected	
	1. Public, 4-year (302) 4. Public, 2-year (134)	Y	1.714	Rejected	
	1. Private, 4-year (373) 4. Public, 2-year (134)	Y	2.440	Rejected	
Control	1. Public (436) 2. Private (374)	N	.037	Failed to reject	Meets all power analysis requirements to avoid Type II error.
Locale	1. City (377) 2. Suburban (177)	Y	.298	Rejected	
	1. City (377) 3. Town (161)	Y	.504	Rejected	
	1. City (377) 4. Rural (94)	Y	.934	Rejected	
	2. Suburban (177) 3. Town (161)	N	.190	Failed to reject	Meets all power analysis requirements to avoid Type II error.
	2. Suburban (177) 4. Rural (94)	Y	.636	Rejected	
	3. Town (161)	Y	.478	Rejected	

Item	Group (*N*)	*t* test significant (Y/N)	Cohen's *d*	Null Hypothesis Disposition	Disposition Rationale
	4. Rural (94)				
Size	1. Under 1,000 (46) 2. 1,000 to 4,999 (355)	Y	.836	Rejected*	
	1. Under 1,000 (46) 3. 5,000 to 9,999 (158)	Y	1.326	Rejected*	
	1. Under 1,000 (46) 4. 10,000 to 19,999 (138)	Y	1.958	Rejected*	
	1. Under 1,000 (46) 5. 20,000+ (113)	Y	3.236	Rejected*	
	2. 1,000 to 4,999 (355) 3. 5,000 to 9,999 (158)	Y	.534	Rejected	
	2. 1,000 to 4,999 (355) 4. 10,000 to 19,999 (138)	Y	1.114	Rejected	
	2. 1,000 to 4,999 (355) 5. 20,000+ (113)	Y	2.221	Rejected	
	3. 5,000 to 9,999 (158) 4. 10,000 to 19,999 (138)	Y	.530	Rejected	
	3. 5,000 to 9,999 (158) 5. 20,000+ (113)	Y	1.496	Rejected	
	4. 10,000 to 19,999 (138) 5. 20,000+ (113)	Y	.945	Rejected	
HBCU	1. Yes (13) 2. No (797)	N	.349	Inconclusive*	HBCU *N* does not meet power threshold of 26 cases suggesting possibility of Type II error.
HSI	1. Yes (46) 2. No (764)	N	.078	Failed to reject*	Meets all power analysis requirements to avoid Type II error.
MSI	1. Yes (61) 2. No (749)	N	.097	Failed to reject*	Meets all power analysis requirements to avoid Type II error.

Item	Group (*N*)	*t* test significant (Y/N)	Cohen's *d*	Null Hypothesis Disposition	Disposition Rationale
Carnegie classification	1. Doctoral/research (176) 2. Master's (239)	Y	1.826	Rejected	
	1. Doctoral/research (176) 3. Baccalaureate (195)	Y	2.758	Rejected	
	1. Doctoral/research (176) 4. Associate (142)	Y	4.238	Rejected	
	1. Doctoral/research (176) 5. Professional/ specialty (46)	Y	8.248	Rejected*	
	2. Master's (239) 3. Baccalaureate (195)	Y	.709	Rejected	
	2. Master's (239) 4. Associate (142)	Y	2.099	Rejected	
	2. Master's (239) 5. Professional/ specialty (46)	Y	4.754	Rejected*	
	3. Baccalaureate (195) 4. Associate (142)	Y	1.489	Rejected	
	3. Baccalaureate (195) 5. Professional/ specialty (46)	N	4.237	Inconclusive*	Cohen's *d* larger than .80 suggesting possibility of Type II error.
	4. Associate (142) 5. Professional/ specialty (46)	Y	2.242	Rejected*	

Note. HBCU indicates historically black colleges and universities; HSI, Hispanic-serving institution; MSI, minority-serving institution. *Due to potential selection bias and low relative response rates for specialized groups, data may not be representative of the group population. Caution should be exercised when generalizing findings to institutional populations.

Summary

The first research question of this study, which asked whether extant measures of technology dimensions supported the underlying construct of institutional technology capacity (TCI-1), was not initially successfully tested. A CFA of the *a priori* TCI-1 model resulted in a poor model fit for both CDS survey years that were analyzed. An EFA was conducted to determine whether there was a model that could appropriately measure technology capacity. Ultimately, a two-factor model (TCI-2) composed of access and student experience factors was identified as a model for measuring technology capacity within the higher education context.

Analysis of a scatterplot matrix for the factors of the TCI-2 model suggested that the factor most relevant for measuring an institution's technology capacity was access. Institutions with greater access often had higher TCI scores. While the student experience factor was not irrelevant in measuring technology capacities, it was not as strong as access.

Finally, random permutation tests highlighted that technology capacity existed as a function of institutional characteristics for four of the eight characteristics tested. Sector, locale (portions), institutional size, and Carnegie classification (portions) all showed a significant association. Tests for control, locale (portions), HSI, MSI characteristics suggested there is not significant difference in means. Tests for HBCUs and Carnegie classification (portions) were inconclusive in their findings.

CHAPTER 5:

DISCUSSION

Significance of the Study

The purpose of this study was to validate a conceptual framework and instrument to measure technology capacities within higher education. Prior to this research, no instrument had been identified to measure technology capacity in this context. Based upon the integrative measurement framework proposed by Barzilai-Nahon (2006), this study explored the creation of a technology capacity index (TCI) model to identify and measure the factors of the technical capacity in higher education.

A review of the literature helped structure the initial measurement instrument, the TCI-1 model. The TCI-1 model framework (see Figure 3.1) consisted of four factors and 22 items. The four factors were based upon silos in the digital divide literature: technology access, infrastructure, use, and user support. The 22 items were distilled from the Core Data Service (CDS) survey conducted annually by EDUCAUSE. Ultimately, the TCI-2 model (see Figure 4.3) was developed and validated after a series of factor analyses were conducted to identify a viable model. The TCI-2 model is as available as the first instrument to help conduct comparative measurements of technology capacity within higher education at any unit of analysis, using any desired grouping mechanism. By focusing on a small subset of items with clear and concise definitions, the TCI-2 model can also standardize how practitioners discuss the meaning of technical capacity. The initial measurements completed by this study help highlight how the TCI-2 model can be employed to influence decision-makers as well as provide directional support for steering the conversation regarding the technology capacities in higher education.

Discussion of the Findings

Measuring Technology Capacity in Higher Education

Based upon Barzilai-Nahon's (2006) six-factor digital divide index, this study adopted a four-factor TCI model to assess technology capacity within higher education. A CFA of the original TCI-1 did not result in a validated model. Although the TCI-1 factors and item mappings were based upon assessment of the digital divide literature and positional expertise of the primary researcher, neither the EDUCAUSE 2008 nor 2009 CDS data (as described in Table 3.1) supported the model.

With an exploratory analysis using the 2008 CDS data as the foundation, two new potential TCI-2 models were specified. After reviewing both a two-factor and a three-factor model, the two-factor model was ultimately identified as the basis for TCI-2. At this point of the study, two elements became apparent. The TCI-1 model addressed the access factor as a purely financial endeavor with reliance upon the central IT budget, student technology fees, and the presence of networks fees as the defining items. The TCI-2 model only incorporated the central IT budget as the only financial component of the model. However, it should be noted that the central IT budget item on the access factor has the highest association of any factor in the model suggesting the IT budget plays a major role in explaining variation in technology capacity across institutions. The overall assessment of the factor-to-item mapping of the access factor of TCI-2 used a much broader definition of access than the TCI-1 model.

Similarly, the TCI-1 model adopted a very literal definition of infrastructure – meaning hardware – in assessing its factor-to-item relationship. Each of the TCI-1 items was assumed to represent a physical, tangible component to be purchased and implemented as a reflection of technology capacity. While the TCI-2 factor-to-item mapping for student experience could be accessed in the same manner, there were differences in how the TCI-2 addressed hardware. Not all of the hardware items were loaded on the same factor for the TCI-2 model as on the TCI-1 model. For instance, firewalls and leased computers were loaded on a different factor from residence hall network speed and type. Taking a step back and reviewing how the TCI-2 model was compiled, each of the items associated with the student experience factor has a direct ability to impact student experience with technology on campus. It was considered more important to acknowledge the student experience rather than the technical orientation of the items when referencing the TCI-2 model.

As previously noted, the TCI-2 model encapsulates measurement of elements critical to providing a solid foundation of infrastructure to support institutional needs (Ehrmann, 1998) including Internet bandwidth, the number of leased computers, availability of student owned hardware and wireless access. The National Telecommunications and Information Administration (NAFEO, 2000) found that HBCUs owned more than 80% of the computers on campus and students were heavily dependent upon the provided equipment. In its annual survey, the Campus Computing Project documented that 70% of students owned their computing equipment (Green, 2001), but less than half of students attending MSIs owned their own computers (Clinedinst, 2004).

Similarly, residence hall connectivity in general was one of the key areas of disagreement among several large published studies in the digital divide literature. Green (2001) reported almost 100% coverage, while NAFEO (2000) and Clinedinst (2004) reported numbers below 50% for their populations. Residence hall technology is a key component of the TCI-2 with high communality items such as network speed, network type, and fees for these networks being key elements of measuring technology capacities.

Influencing Technology Capacity

After identifying TCI-2 as a viable model for measuring technology capacity, access to technology at the institution was determined to have the highest correlation to an institution's technology capacity (see Table 4.12). However, the correlation between access and student experience is lower than expected. Generally there was an assumption that greater access presumes a better student experience. Many of the items associated with student experience (speed of residence hall networks, residence hall network types, wireless access, and computer requirements) imply that the more or better the service, the greater reciprocal gain in access. However, the CDS data does not bear out this assumption with a high degree of confidence.

Institutional Differences in Technology Capacity

The final research question for this study presented perhaps the most challenging findings of the study. The findings related to technology capacity for community colleges perhaps stand out the most. Community colleges are highlighted with significant differences in technology capacity in three of the institutional characteristics: sector, control, and Carnegie classification. Based upon the sector characteristic, public, 2-year institutions are significantly behind both public and private, 4-year institutions. The sector findings are underscored by the control characteristic finding that suggested differences were not significant between the two control groups – the opposite result from the sector finding. These finding suggest the low TCI for community colleges (expressed in the sector characteristic) brings down the overall TCI for public institutions, making the differences in TCI between public and private institutions (the control characteristic) insignificant. Finally, the Carnegie classification characteristic provided the largest practical significance of the study. In every instance, associate institutions trail the capacities of every other type institution.

The literature suggests that rural community colleges may be hard hit by state legislatures who are cutting institutional operating budgets, further compounding not only locational inequities, but also providing a double punch for these institutions who lag significantly behind the technical capacity of 4-year institutions (Katsinas, et. al., 2002). While Green (2010) notes that public, 4-year institutions reporting a decline the number of budget cuts, community colleges saw increases; nearly half of community colleges responding to the survey reported budget reductions. Although these differences exist, Cejda (2007) affirmed that these institutions are providing online educational courses despite concerns about faculty members' and students' personal technology competence as a barrier to providing support for course delivery and general end-user support. Finally, 2-year institutions have acknowledged the challenge of attracting qualified resources to support campus technology needs (Cejda, 2007), which could further underscore the community college findings.

As already noted, differences in technology capacities when grouped by Carnegie classification were a significant finding with doctoral institutions (which are often larger in size) exhibiting a higher level of capacity than all other classifications; the mean TCI of doctoral institutions is almost 8 times that of baccalaureate institutions (the next closest classification group). Associate institutions lagged behind the other Carnegie classifications, reaffirming the significant findings from the sector characteristic. However, the differences in TCI between baccalaureate and professional/specialty institutions were found to be inconclusive as a result of concerns with Type II errors. Although the comparison of differences in TCI was found to be statistically insignificant, the practical significance was found to be very large (see Table 30) suggesting there are other mitigating factors that should be researched for further understanding.

With President Obama's initiative to build skills through community colleges, the strong reinforcement of the study's findings with the literature should be considered troubling. Despite the age of the CDS survey data in comparison to what potential technology capacities may exist today, the differences in means between community colleges and other types of institutions are quite large and undoubtedly closing such a gap is expensive. If community colleges are expected to produce millions of new graduates prior to 2020, it is appropriate to use the current study findings as a baseline for future studies using TCI-2 to update measurement of technology capacities within community colleges. Using the knowledge gained from the TCI scores to determine whether any strides in improving technology capacities over the last few years have been successful will be imperative in understanding what additional steps are required to bring these institutions on par technically with other institutions.

The remaining findings of significant differences for institutional characteristics are related to institution locale and size characteristics whose findings were reflective of the literature. That rural higher education institutions significantly lag the technology capacity of institutions in cities, suburbs, and towns is supported by the digital divide literature. As late as 2006, Horrigan and Murray found continuing disparities in home broadband access, with rural communities trailing suburban communities in access by more than 16 percentage points. The NTIA (2000) agreed that the location of an institution makes a difference in the ability to access computing resources. Again, noting the time lag between the NTIA study and the current study, this particular finding continues to persist almost 10 years later. Students at one rural HBCU questioned their institution's capacities in reference to other schools (Ragon, 2004). Even within the challenged ranks of public 2-year institutions, urban community colleges offer almost double the number of online courses of rural community colleges (Cejda, 2007). Ultimately, because urban institutions are more likely to be wired than other institutions, they are better able to provide their students better access to technology resources (Sink & Jackson, 2000). The TCI-2 model should be used to help direct where energies should be placed in order to close the capacity gap for rural institutions.

Similar to locale, institution size makes a difference in the ability to access computing resources (NTIA, 2000). Every comparison group exhibited significant differences in TCI means. Arguably, larger institutions have more financial resources to meet the technology demands of their campuses. While central IT budget played a significant role in defining the access factor of the TCI-2 model, this study did not specifically analyze financial resource commitments and TCI. This is a suggestion for future research.

The insignificant findings related to the technology capacities of HBCUs, HSIs, and MSIs as a group were also concerning given the relatively low response rates from these institutions. For both HBCUs and HSIs, the number of institutions responding to the 2009 CDS survey was a very small subset of the institutional population. With just over 100 HBCUs (Department of Education, 2015), only 13 responded to the survey. HSIs number near 280 (HACU, 2010; Excelencia in Education, 2015), but there were only 46 survey responses. TCU responses to the survey were essentially non-existent. Logically, this means the overall MSI numbers are in turn also small in comparison to the larger population of institutions. While the findings for HSIs and MSIs failed to find a significant difference in TCI means as compared to non-HSIs and non-MSIs, respectively, these results should be interpreted with caution. These findings likely do not reflect a generalized statement about the technical capacity of these institutions, especially considering the concerns related to selection bias. And although the number of cases for each of these subgroups passed the minimum requirements for the completion of a power analysis, the relatively low numbers of responses raised red flags overall. Further, the insignificant findings for HBCUs could not be verified after the power analysis could not exclude the possibility of a Type II error for the HBCU null hypothesis due to the very low number of survey responses. Type II errors along with potential selection bias called for caution when interpreting the findings about technology capacity at HBCUs.

Additionally, these particular findings should be further scrutinized given the differing results obtained by this study as compared to the two seminal studies on the digital divide in higher education, which found potential evidence of the digital divide in HBCUs and MSIs (NAFEO, 2000; Clinedinst, 2004). The literature offered a mixed picture on the status of the digital divide at HBCUs and MSIs. Exemplifying the elements of the divide, students were not able to access campus networks in their dorm rooms and were unable to get financial aid to purchase computers (NAFEO, 2000). Campuses were able to hire campus support personnel, but they were not necessarily able to provide hardware to support faculty access to software used in the classroom, and sometimes faculty went months before getting access to technology (Snipes et al., 2006). Clinedinst (2004) identified that more than half of dorm rooms at MSIs were not wired for Internet access, and a quarter were not wired at all. On the other hand, the AN-MSI Project funded by the National Science Foundation invested $6 million to help bridge the divide (Foertsch, 2004); and at least one campus made such significant improvements that students had broad access to high-speed networks and publicly available kiosks allowing that particular HBCU to become one of the most technologically advanced institutions in the country (Redd, 2003).

While it is possible that concerns over the digital divide have been mitigated over time for these institutions, the voluntary nature of responding to the primary research instrument potentially influenced the type of institutions that respond to the CDS survey. Future researchers focused on measuring TCI scores for HBCUs, HSIs, TCUs, or MSIs should make an effort to increase response rates from these special populations to minimize the concerns associated with the findings of this study.

Even though there was no significant difference in technology capacities as stratified by institutional control type, the digital divide literature highlighted that while public institutions had a lower technology fee than private institutions (Green, 2009), the institutions led the charge to deploy mobile apps with almost 99% offering mobile applications vs. 95% for private institutions (Green, 2010). However, it should be noted that although the portion of institutions under study was essentially equally split between public and private institutions, public institutions have a much broader range of capacities than private institutions especially at the lower tail of the spectrum (see Figure 4.6) – most likely as a result of including community colleges in the public institution equation.

Limitations and Recommendations for Future Research

One of the areas of challenge with this study revolved around the age of both the data under study and the associated digital divide literature. The data from the 2009 CDS survey were six years old at the time of the current study. The data were almost 10 years removed from the NAFEO study published in 2000 and 5 years removed from the Clinedinst study published in 2004. Respectively, these studies are 15 and 11 years old in relation to this study. However, the ability to measure technology capacity will always be challenged by the component of time. The NAFEO and Clinedinst studies precede the introduction of the iPhone and both the studies and the data precede the advent of the iPad. However, these data can still provide insight into the technical capabilities of institutions at a given point in time as well as offer a view of the potential progression (or lack thereof) of technology within higher education between the publication of the NAFEO and Clinedinst studies and the 2009 CDS survey data collection.

It should perhaps also be noted that there is a general perception across all levels of higher education that the sector is slow to embrace change – technology being only one facet of change. The primary researcher's own experience with technology in higher education underscores the difficulty in assessing when and how higher education embraces change in technology at a single large, urban, doctoral institution: a 30 year-old phone system whose replacement is hampered by physical infrastructure (old buildings) and a very large price tag; wireless connectivity that is not ubiquitous across campus; continued reliance upon 20+ year-old mainframe systems which now requires web-enabled bolt-ons to mimic more current technology for student consumption; and delayed migration from the same mainframe to a web-enabled system due to the anticipated very large price tag. But, this same institution is exceptionally advanced in digitizing library archival materials for public access. None of this description takes into account the economic ups and downs experienced by the institution over the last four to five years which potentially slowed the rate of technology adoption.

Because of these variations in technology capacities (as exhibited by this one institution) and the speed at which the technology market moves, one cannot gain a full understanding of the technology capacities of higher education institutions by measuring it at a single point in time. Technology capacity should and must be measured over time to gain an accurate portrayal of status across the sector. The TCI-2 model provides a framework to support a longitudinal study to measure technology capacity change over a period of time beginning with the findings of this study. While there are annual studies conducted by EDUCAUSE and the Campus Computing Project on the general status of technology within the higher education sector, neither study specifically allows group comparisons or provide an accessible tool to conduct the measurement. The Campus Computing Project comes close to providing status year over year, but the data are not available to researchers for analysis. As a first step, the TCI-2 model provides the measurement instrument. Future research should adapt a simple, technology agnostic survey that collaborates with the TCI-2 model.

Whether the digital divide and technology capacity are still a topic of concern for higher education is a topic for debate. Since no major studies have been published since 2004, this is a viable question; perhaps the assumed ubiquity of technology in our daily interactions overshadows the concerns of the digital divide. However, the Pew Research Center and the NTIA continue to publish research about the status of the digital divide and access to broadband technology as experienced by Americans in general. It stands to reason that higher education is a microcosm of the larger population and will exhibit similar problems. Additionally, multiple grant programs such as BroadbandUSA and the Broadband Technology Opportunities Program continue to award funding to improve technical infrastructure. The contribution of the TCI-2 model and the addition of the findings of this study to the literature are an opportunity to re-start the conversation about the digital divide in higher education.

Another limitation that potentially impacted survey responses was that the CDS survey is a very long, complicated survey to complete. The CDS survey was intended to capture a full spectrum of data about technology at individual institutions – a significant portion of which is beyond the scope/not inclusive of data needed for the current study. The sub-instrument identified as a result of the validation of the TCI-2 model could be used as the foundation for a survey instrument that is condensed, more direct, and presumably easier to complete than the more extensive and intensive CDS survey. Creating a condensed survey should negate the dependence on specialized skills or resources make responding to the survey quicker and easier than the existing CDS survey. The lack of responses from some of the special constituency groups may relate to the possibility that only schools with highly skilled personnel responded to the CDS survey, skewing the data for this study and ultimately influencing the findings. A smaller, but more directed survey instrument based upon the TCI-2 framework could increase institutional responses from these desired constituent groups.

Another potential option for future research is to adapt the most current CDS survey as input for the TCI-2 model. The 2008 and 2009 CDS survey responses were chosen for this study to facilitate comparison of two different survey populations to validate the TCI-2 model. The most recent CDS survey instrument should be assessed for use as a sub-instrument survey based upon the TCI-2 model for analysis; although this approach does not address the complexity concerns with the CDS instrument that has already been highlighted.

The intersection of national broadband availability and the location of higher education institutions within the United States is another area of future research interest. This could be an alternative method for understanding aspects of institutional technology capacity, in particular for the access factor. A study of this sort could also stratify its results based upon other institutional characteristics for further insight.

Given that financial resources are a critical component of measuring and understanding the digital divide, future research should focus on the multiple aspects of institutional financial resources such as available funding, multiyear budget analyses, and more in-depth awareness of the itemization of IT funding across institutions. This analysis could provide additional insight into TCI scores and the digital divide in higher education. This research could also be valuable as an attempt to assess the return on investment of technology dollars as it relates to TCI. This research would be an excellent companion with a TCI longitudinal study. Again, stratification by institutional characteristics may identify correlations between financial resources and other indicators that may provide further understanding of the digital divide within higher education.

The current study focused on a single dimension of TCI and institution characteristic. Future research could focus on multiple intersections of characteristics should be measured. For example, are TCI means significantly different between community colleges located in rural locations vs. city locations? Are TCIs significantly different between doctoral institutions with more than 20,000 students and doctoral institutions of other sizes? More understanding of these multiple levels of analysis could provide more discrete information on technology capacity.

Conclusion

The role of technology within higher education is becoming an inseparable component of the educational experience for anyone who engages with an institution of higher learning. The capacity of an institution to meet the technological demands of the populations it supports will be a key component of an institution's success in fulfilling its mission. The TCI-2 model provides administrators and leaders within higher education the opportunity to prepare a focused agenda to address the differences in the access and student experience components of technology capacity in order to conquer the digital divide within higher education.

REFERENCES

Abel, R. (2007). Innovation, adoption, and learning impact: Creating the future of it. *EDUCAUSE Review*, *42*(2), 12-30. Retrieved from http://www.educause.edu/ero/article/innovation-adoption-and-learning-impact-creating-future-it

Barzilai-Nahon, K. (2006). Gaps and bits: Conceptualizing measurements for digital divide/s. *The Information Society*, *22*(5), 269-278. doi:10.1080/01972240600903953

Becker, L. A. (1999). Effect size calculator. Available from http://www.uccs.edu/lbecker/index.html#Calculate d and r using t values (separate groups)

Bell, P., Reddy, P., & Rainie, L. (2004). *Rural areas and the Internet*. Washington, DC: Pew Internet and American Life Project. Retrieved from http://www.pewInternet.org/~/media//Files/Reports/2004/PIP_Rural_Report.pdf.pdf

Bland, J. M., & Altman, D. G. (1997). Statistics notes: Cronbach's alpha. *Bmj, 314*(7080), 572. Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC2126061/pdf/9055718.pdf

Boneau, C. A. (1960). The effects of violations of assumptions underlying the *t* test. *Psychological Bulletin*, *57*(1), 49-64. Retrieved from http://psycnet.apa.org/journals/bul/57/1/49/

Burdenski, T. K., Jr. (2000). *Evaluating univariate, bivariate, and multivariate normality using graphical procedures*. Paper presented at the annual meeting of the American Educational Research Association, New Orleans, LA. Retrieved from http://files.eric.ed.gov/fulltext/ED440989.pdf

Byrne, B. M., Shavelson, R. J., & Muthén, B. (1989). Testing for the equivalence of factor covariance and mean structures: The issue of partial measurement invariance. *Psychological bulletin*, *105*(3), 456.

Carnegie (2015). *The Carnegie Classification of institutions of higher education.* Retrieved from http://carnegieclassifications.iu.edu/

Carnevale, D. (2003, February 14). Senators hear testimony favoring a $250-million technology program for minority colleges. *Chronicle of Higher Education*. Retrieved from http://chronicle.com/article/Senators-Hear-Testimony/110699/

Cejda, B. D. (2007). Distance education in rural community colleges. *Community College Journal of Research and Practice*, *31*(4), 291-303. doi:10.1080/10668920701242688

Chang, S.-I. I., Yen, D. C., Chang, I.-C. C., & Chou, J.-C. C. (2012). Study of the digital divide evaluation model for government agencies—a Taiwanese local government's perspective. *Information Systems Frontiers*, *14*(3), 693-709. doi:10.1007/s10796-011-9297-x

Cliff, N. (1983). Some cautions concerning the application of causal modeling methods. *Multivariate behavioral research*, *18*(1), 115-126.

Clinedinst, M. (2004). *Serving the nation: Opportunities and challenges in the use of information technology at minority-serving colleges and universities*. Alexandria, VA: Alliance for Equity in Higher Education. Retrieved from http://www.ihep.org/assets/files/publications/s-z/ServingTheNation.pdf

Cohen, J. (1992). A power primer. *Psychological bulletin*, *112*(1), 155.

Costello, A. B., & Osborne, J. W. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research & Evaluation, 10*(7), 1-9. Retrieved from http://pareonline.net/pdf/v10n7.pdf

Cottrell, R. L., & Matthews, W. (2003). *Measuring the digital divide with PingER.* Presented at the 2003 Round Table on Developing Countries' Access to Scientific Knowledge, Trieste, Italy. Retrieved from http://www.osti.gov/ bridge/purl.cover.jsp?purl=/826455-AcaA2A/native/

Crump, B., & McIlroy, A. (2003). The digital divide: Why the "don't-want-tos" won't compute: Lessons from a New Zealand ICT project. *First Monday*, *8*(12). Retrieved from http://pear.accc.uic.edu/ojs/index.php/fm/article/view/1106/1026

Curran, P. J., West, S. G., & Finch, J. F. (1996). The robustness of test statistics to nonnormality and specification error in confirmatory factor analysis. *Psychological Methods*, *1*(1), 16. Retrieved from http://www.unc.edu/ ~curran/pdfs/Curran,West&Finch(1996).pdf

Daft, R. (2012). *Organization theory and design.* Cengage learning.

Dahlstrom, E., de Boor, T., Grunwald, P., & Vockley, M. (2011). *The ECAR national study of undergraduate students and information technology, 2011*. Boulder, CO: EDUCAUSE Center for Applied Research. Retrieved from http://net.educause.edu/ir/library/pdf/ERS1103/ERS1103W.pdf

Department of Education. (2015). Accredited HBCU Listing. Retrieved from http://www.ed.gov/edblogs/whhbcu/files/2013/05/Copy-of-List-of-Accredited-HBCUs.xls

Duff, A. S. (2010). The Rawls-Tawney theorem and the digital divide in postindustrial society. *Journal of the American Society for Information Science and Technology*, 62(3), 604-612. doi:10.1002/asi.21470

EDUCAUSE. (2008). *Understanding the Core Data Service (2008).* Retrieved from http://net.educause.edu/ir/library/pdf/PUB8006a.pdf

EDUCAUSE. (2009). *Understanding the Core Data Service (2009).* Retrieved from http://net.educause.edu/ir/library/pdf/PUB8007l.pdf

EDUCAUSE. (2013a). *About EDUCAUSE.* Retrieved from http://www.educause.edu/about

EDUCAUSE. (2013b). *Roots of EDUCAUSE.* Retrieved from http://www.educause.edu/about/mission-and-organization/roots-educause

EDUCAUSE. (2013c). *Mission and organization: Welcome.* Retrieved from http://www.educause.edu/about/mission-and-organization

Ehrmann, S. C. (1998). Using technology to transform the college. *New Directions for Community Colleges*, *101*(Spring), 27-33. doi:10.1002/cc.10103

Excelencia in Education. (2015). HSI by Sector, 1994-95 to 2012-13. Retrieved from http://www.edexcelencia.org/hsi-cp2/research/hsis-sector-1994-95-2012-13

Foertsch, J. (2004). *Summative evaluation report for the AN-MSI project.* Retrieved from http://net.educause.edu/ir/library/pdf/EAF0416.pdf

Gentleman, R. & Ihaka, R. (2014). *R: A language and environment for statistical computing.* Retrieved from http://www.R-project.org

Grajek, S., & Arroway, P. (2012). *The EDUCAUSE 2011 Core Data Service report: Highlights and insights into higher education information technology*. Retrieved from http://www.educause.edu/library/resources/educause-2011-core-data-service-report-highlights-and-insights-higher-education-information-technology

Graves, W. I. H. (2002). New educational wealth as a return on investment in technology. *EDUCAUSE Review* (July/August), 38-48. Retrieved from http://net.educause.edu/ir/library/pdf/erm0242.pdf

Green, K. C. (2000). *2000 campus computing survey*. Retrieved from http://www.campuscomputing.net/sites/www.campuscomputing.net/files/2000-CCP.pdf

Green, K. C. (2001). *2001 campus computing survey*. Retrieved from http://www.campuscomputing.net/sites/www.campuscomputing.net/files/2001-CCP.pdf

Green, K. C. (2009). *2009 campus computing survey*. Retrieved from http://www.campuscomputing.net/sites/www.campuscomputing.net/files/CampusComputing2009_2.pdf

Green, K. C. (2010). *2010 campus computing survey*. Retrieved from http://www.campuscomputing.net/sites/www.campuscomputing.net/files/Green-CampusComputing2010.pdf

Green, K. C. (2014). *2014 campus computing survey*. Retrieved from http://www.campuscomputing.net/item/campus-computing-2014

Guilford, J. P. (1952). When not to factor analyze. *Psychological Bulletin*, *49*(1), 26-37. doi:10.1037/h0054935

H.R. 2183, Minority Serving Institution Digital and Wireless Technology Opportunity Act of 2003: Hearing before the Subcommittee on Research, Committee on

Science, House of Representatives, One Hundred Eighth Congress, first session, July 9, 2003. (2003). Retrieved from http://catalog.hathitrust.org/Record/008525149

Hair, J. F. (1998). *Multivariate data analysis*. Upper Saddle River, NJ: Prentice-Hall.

Hayton, J. C., Allen, D. G., & Scarpello, V. (2004). Factor retention decisions in exploratory factor analysis: A tutorial on parallel analysis. *Organizational Research Methods, 7*(2), 191-205. Retrieved from http://ezproxy.cul.columbia.edu/login?url=http://search.proquest.com/docview/195090780?accountid=10226

Hernandez, A. (2010). Status update: HBCUs' share of stimulus money, with few exceptions, did little to improve the beleaguered condition of the institutions. *Diverse Issues in Higher Education*, *27*(14), 30-32. Retrieved from http://go.galegroup.com/ps/i.do?id=GALE%7CA235721034&v=2.1&u=unc_main&it=r&p=AONE&sw=w

Higher Education Act of 1965, 20 U.S.C. § 1059c.

Higher Education Act of 1965, 20 U.S.C. § 1061.

Higher Education Act of 1965, 20 U.S.C. § 1101a.

Hispanic Association of Colleges and Universities. (2009). *HACU list of Hispanic serving institutions 2008-2009.* Retrieved from http://www.hacu.net/images/hacu/OPAI/2008%20Fed%20HSI%20list.pdf

Hispanic Association of Colleges and Universities. (2010). *HACU List of Hispanic serving institutions 2009-2010*. Retrieved from http://www.hacu.net/images/hacu/OPAI/2009%20Fed%20HSI%20list.pdf

Hoffman, D. L., Novak, T. P., & Schlosser, A. (2000). The evolution of the digital divide: How gaps in Internet access may impact electronic commerce. *Journal of Computer-Mediated Communication*, *5*(3). doi:10.1111/j.1083-6101.2000.tb00341.x

Hofmann, J. (2002). *Wireless implementation at Bethune-Cookman College*. Retrieved from http://net.educause.edu/ir/library/pdf/EAF0232.pdf

Horrigan, J., & Murray, K. (2006). *Rural broadband Internet use.* Washington, DC: Pew Internet & American Life Project. Retrieved from http://www.pewInternet.org/~/media/Files/Reports/2006/PIP_Rural_Broadband.pdf.pdf

Horrigan, J. B., & Rainie, L. (2002). *The broadband difference*. Washington, DC: Pew Internet & American Life Project. Retrieved from http://pewInternet.org/~/media//Files/Reports/2002/PIP_Broadband_Report.pdf.pdf

Hu, L., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods*, *3*(4), 424-453. Retrieved from http://people.cehd.tamu.edu/~okwok/epsy651R/Articles/HuBentler1998.pdf

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1-55. Retrieved from http://www.tandfonline.com/doi/abs/10.1080/10705519909540118

Jackowski, M. B., & Akroyd, D. (2010). Technology usage among community college faculty. *Community College Journal of Research and Practice*, *34*(8), 624-644. doi:10.1080/10668920701831530

Jackson, D. (2003). Revisiting sample size and number or parameter estimates: Some support for the N:Q hypothesis. *Structural Equation Modeling: A Multidisciplinary Journal, 10*(1), 128-141.

James, J. (2009). Measuring the global digital divide at the level of individuals. *Current Science*, *96*(2), 194-197. Retrieved from http://www.currentscience.ac.in/Downloads/article_id_096_02_0194_0197_0.pdf

James, J. (2011). Are changes in the digital divide consistent with global equality or inequality? *The Information Society*, *27*(2), 121-128. doi:10.1080/01972243.2011.548705

Katsinas, S. G., & Moeck, P. (2002). The digital divide and rural community colleges: Problems and prospects. *Community College Journal of Research and Practice*, *26*(3), 207-224. doi:10.1080/106689202317245419

Katz, R. N. (1999). *Dancing with the devil: Information technology and the new competition in higher education*. San Francisco, CA: Jossey-Bass.

Kenny, D. A. (1987). *Statistics for the social and behavioral sciences* (p. 215). Boston: Little, Brown.

Kelly, J. T. (1977). Technology and productivity in a community college. *Public Productivity Review*, *2*(5), 27. doi:10.2307/3379841

Kline, R. B. (2011). *Principles and practice of structural equation modeling* (3rd ed.). New York, NY: Guilford.

Manly, B. F. J. (1997). *Randomization, bootstrap and Monte Carlo methods in biology.* Boca Raton, FL: CRC Press.

McKinney, K. (1996). *Technology in community colleges*. Los Angeles, CA: ERIC Clearinghouse for Community Colleges. Retrieved from http://files.eric.ed.gov/fulltext/ED399992.pdf

Menou, M. J. (2001). The global digital divide; beyond hICTeria. *Aslib Proceedings*, *53*(4), 112-114. doi:10.1108/EUM0000000007045

Miah, M., & Omar, A. (2011). A case study on awareness, willingness and utilization of resources by students at HBCU. *International Journal of Education and Development using ICT*, *7*(2). Retrieved from http://www.editlib.org/p/42206/

Moore, D. S., McCabe, G. P., Duckworth, W. M., & Sclove, S. L. (2003). *The practice of business statistics: Using data for decisions*. New York, NY: W. H. Freeman.

Muller, R. O., & Hancock, G. R. (2008). Best practices in structural equation modeling. *Best practices in quantitative methods*, 488-509. Retrieved from http://www.corwin.com/upm-data/18067_Chapter_32.pdf

Muthén, L.K. & Muthén, B.O. (1998-2012). *Mplus user's guide.* Seventh Edition. Los Angeles, CA: Muthén & Muthén. Retrieved from http://www.statmodel.com

National Association for Equal Opportunity in Higher Education. (2000). *Historically black colleges and universities: An assessment of networking and connectivity.* Retrieved from http://www.ntia.doc.gov/report/2000/historically-black-colleges-and-universities-assessment-networking-and-connectivity

National Center for Education Statistics. (2015a). *Integrated postsecondary education data system.* Retrieved from http://nces.ed.gov/ipeds/glossary/index.asp?searchtype=term&keyword=control&Search=Search

National Center for Education Statistics. (2015b). *Integrated postsecondary education data system.* Retrieved from http://nces.ed.gov/ipeds/glossary/index.asp?searchtype=term&keyword=institution+size&Search=Search

National Center for Education Statistics. (2015c). *Integrated postsecondary education data system.* Retrieved from http://nces.ed.gov/ipeds/glossary/index.asp?searchtype=term&keyword=level&Search=Search

National Center for Education Statistics. (2015d). *Integrated postsecondary education data system.* Retrieved from http://nces.ed.gov/ipeds/glossary/index.asp?searchtype=term&keyword=locale&Search=Search

National Center for Education Statistics. (2015e). *Integrated postsecondary education data system.* Retrieved from http://nces.ed.gov/ipeds/glossary/index.asp?searchtype=term&keyword=sector&Search=Search

National Telecommunications and Information Administration. (1995). *Falling through the net: A survey of the "have nots" in rural and urban America.* Washington, DC: Author. Retrieved from http://www.ntia.doc.gov/ntiahome/fallingthru.html

National Telecommunications and Information Administration. (1999). *Falling through the net: Defining the digital divide.* Washington, DC: Author. Retrieved from http://www.ntia.doc.gov/legacy/ntiahome/fttn99/contents.html

Organisation for Economic Co-operation and Development. (2001). *Understanding the digital divide.* Paris, France: Author. Retrieved from http://www.oecd.org/sti/1888451.pdf

Pedhazur, E. J., & Schmelkin, L. P. (1991). *Measurement, design, and analysis: An integrated approach*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Prium, R., Kaplan, D., & Horton, N. (2014). *Mosaic: Project MOSAIC (mosaic-web.org) statistics and mathematics teaching utilities.* Retrieved from http://CRAN.R-project.org/package=mosaic

Ragon, B. M. (2004). The use of technology by students at an HBCU. *International Electronic Journal of Health Education*, *7*, 63-68. Retrieved from http://www.eric.ed.gov/ERICWebPortal/detail?accno=EJ794041

Redd, T. M. (2003). “Tryin to make a dolla outa fifteen cent”: Teaching composition with the Internet at an HBCU. *Computers and Composition*, *20*(4), 359-373. doi:10.1016/j.compcom.2003.08.012

Schmitt, T. A. (2011). Current methodological considerations in exploratory and confirmatory factor analysis. *Journal of Psychoeducational Assessment*, *29*(4), 304-321. Retrieved from http://www.statmodel.com/download/Schmitt%202011-Jour%20of%20Psychoed%20Assmt%20-%20EFA%20and%20CFA.pdf

Selwyn, N. (2004). Reconsidering political and popular understandings of the digital divide. *New Media & Society*, *6*(3), 341-362. doi:10.1177/1461444804042519

Sink, D., & Jackson, K. L. (2000). Bridging the digital divide: A collaborative approach. *Community College Journal*, *71*(2), 38-41. Retrieved from http://www.eric.ed.gov/ERICWebPortal/detail?accno=EJ620250

Snipes, V. T., Ellis, W., & Thomas, J. (2006). Are HBCUs up to speed technically? One case study. *Journal of Black Studies*, *36*(3), 382-395. doi:10.2307/40035016

Warschauer, M. (2002). Reconceptualizing the digital divide. *First Monday*, *7*(7). Retrieved from http://firstmonday.org/ojs/index.php/fm/article/viewArticle/967/888

Warschauer, M. (2003a). *Technology and social inclusion: Rethinking the digital divide*. Cambridge, MA: MIT Press.

Warschauer, M. (2003b). Demystifying the digital divide. *Scientific American*, 289(2), 42-47. doi:0.1038/scientificamerican0803-42

Weintraub, T., & Cater, J. (2000). Technology partnerships on community college campuses. *Community & Junior College Libraries*, *9*(1), 5-19. doi:10.1300/J107v09n01_02

The White House. (2015). Building American skills through community colleges. Retrieved from https://www.whitehouse.gov/issues/education/higher-education/building-american-skills-through-community-colleges

Young, J. R. (2001, November 9). Does ‘digital divide’ rhetoric do more harm than good? *Chronicle of Higher Education*. Retrieved from http://chronicle.com/article/Does-Digital-Divide-/3058

Yu, C.-C. C., & Wang, H.-I. I. (2005). Measuring the performance of digital divide strategies: The balanced scorecard approach. *Electronic Government*, *3591*, 151-162. doi:10.1007/11545156_15

APPENDIX A:

TCI CODEBOOK

2008 CDS variable name	2009 CDS variable name	IPEDS variable name	Data input file variable name	CDS section	CDS question number	Survey question	Data codes
Q421_1	Q490_1		intcnt	Networking and Security	**1**	What is the total bandwidth available to the Internet?	
Q413_2	Q482_2		resspeed	Faculty and Student Computing	**4**	Speed of network connections in residence halls	1. 10 mbps; 2. 10-11 mbps; 3. 10/100 mbps; 4. 100 mbps; 5. >100 mbps
Q413_3	Q482_3		restype	Faculty and Student Computing	**4**	Technology of network connections in residence halls	1. Ethernet; 2. Cable modem; 3. DSL; 4. Wireless; 5. Other
Q424_1, _2, _3, _4, _5, _6, _7, _8, _9	Q493_1, _2, _3, _4, _5, _6, _7, _8, _9		wireless	Networking and Security	**4**	Presence of wireless access	1. Not applicable; 2. 0%; 3. 1-25%; 4. 26-50%; 5. 51-75%; 6. 76-100%
Q428_1, _2, _3, _4, _5, _6, _7	Q497_1, _2, _3, _4, _5, _6, _7		Idm	Networking and Security	**8**	Status of identity management technologies	1. Deployed; 2. Piloting; 3. In progress; 4. Considering; 5. Not planned
Q401	Q470		leascnt	IT Financing and Management	**9**	Computers owned or leased by the campus	
Q429	Q498		Auth	Networking and Security	**9**	Authentication for network (wired and	1. We currently require end-user authentication for all network access; 2. We are in the process of implementing an

2008 CDS variable name	2009 CDS variable name	IPEDS variable name	Data input file variable name	CDS section	CDS question number	Survey question	Data codes
						wireless) access	end-user authentication requirement for all network access; 3. We are planning to require end-user authentication for all network access; 4. We are considering an end-user authentication requirement for all network access; 5. We have no plans for requiring end-user authentication for all network access; 6. Other
D430_1, _2, _3, _4, _5	D499_1, _2, _3, _4, _5		firewall	Networking and Security	**10**	Use of firewalls for security	
D431_1, _2, _3, _4, _5, _6, _7	D500_1, _2, _3, _4, _5, _6, _7		Patch	Networking and Security	**11**	Campus security-related practices	
Q420_1, _2, _3, _4, _5, _6, _7, _8, _10	Q489_1, _2, _3, _4, _5, _6, _7, _8, _10		roomtech	Faculty and Student Computing	**11**	Classrooms permanently equipped with technology	
		sector	sector			Control and level of the campus	0. Administrative unit; 1. Public 4-year or above; 2. Private not-for-profit, 4-year or above; 3. Private for-profit, 4-year or above; 4. Public 2-year; 5. Private not-for-profit, 2-year; 6. Private for-profit, 2-year; 7. Public less than 2 year; 8. Private not-for-profit, less than 2 year; 9. Private for-profit, less than 2 year; 99. Sector unknown (not active)
		control	control			Control of the campus	1. Public; 2. Private not-for-profit; 3. Private for-profit

2008 CDS variable name	2009 CDS variable name	IPEDS variable name	Data input file variable name	CDS section	CDS question number	Survey question	Data codes
		hbcu	hbcu			HBCU special mission	1. Yes; 2. No
		tribal	tribal			Tribal college special mission	1. Yes; 2. No
		locale	locale			Degree of urbanization	11. City: large; 12. City: midsize; 13. City: small; 21. Suburb: large; 22. Suburb: midsize; 23. Suburb: small; 31. Town: fringe; 32. Town: distant; 33. Town: remote; 41. Rural: fringe; 42. Rural: distant; 43. Rural: remote; -3-{Not available}
		instsize	instsize			Campus size category	1. Under 1,000; 2. 1,000-4,999; 3 5,000-9,999; 4. 10,000-19,999; 5. 20,000 and above; -1-Not reported; -2-Not applicable
		hsi	hsi			Hispanic-serving institution	1. Yes; 2. No
		carnegie	cc			Carnegie classification	15. Doctoral/research universities-extensive; 16. Doctoral/research universities-intensive; 21. Master's colleges and universities I; 22. Master's colleges and universities II; 31. Baccalaureate colleges-liberal arts; 32. Baccalaureate colleges-general; 33. Baccalaureate/associate's colleges; 40. Associate's colleges; 51. Theological seminaries and other specialized faith-related institutions; 52. Medical schools and medical centers; 53. Other separate

2008 CDS variable name	2009 CDS variable name	IPEDS variable name	Data input file variable name	CDS section	CDS question number	Survey question	Data codes
							health profession schools; 54. Schools of engineering and technology; 55. Schools of business and management; 56. Schools of art, music, and design; 57. Schools of law; 58. Teachers colleges; 59. Other specialized institutions; 60. Tribal colleges; -3-{Item not available}
Q410	Q479		hdhrs	Faculty and Student Computing	**1**	Weekly operational hours of the help desk	
Q387_1_1, _2_1, _3_1, _4_1, _5_1, _6_1, _7_1, _8_1, _9_1, _10_1, _11_1, _12_1, _13_1, _14_1	Q456_1_1, _2_1, _3_1, _4_1, _5_1, _6_1, _7_1, _8_1, _9_1, _10_1, _11_1, _12_1, _13_1, _14_1		empcnt	IT Organization, Staffing and Planning	**5**	Number of FTE staff employed by the centralized IT organization	
Q387_1_2, _2_2, _3_2, _4_2, _5_2, _6_2, _7_2, _8_2, _9_2, _10_2, _11_2, _12_2, _13_2, _14_2	Q456_1_2, _2_2; _3_2, _4_2, _5_2, _6_2, _7_2, _8_2, _9_2, _10_2, _11_2, _12_2, _13_2, _14_2		stucnt	IT Organization, Staffing and Planning	**5**	Number of students employed by the centralized IT organization	

2008 CDS variable name	2009 CDS variable name	IPEDS variable name	Data input file variable name	CDS section	CDS question number	Survey question	Data codes
D417_1, _2, _3, _4, _5, _6, _7, _8, _9, _10	D486_1, _2, _3, _4, _5, _6, _7, _8, _9, _10		facsup	Faculty and Student Computing	**8**	Campus support for faculty in the use of technology in teaching and learning	
Q393_1, _2, _3, _4, _5, _6, _7, _8, _9, _11	Q462_1, _2, _3, _4, _5, _6, _7, _8, _9, _11		dolcnt	IT Financing and Management	**1**	Funding for centralized IT organization	
Q399_total _dollar	Q468_total _dollar		feecnt	IT Financing and Management	**7**	Gross funding from general student technology fee	
Q400	Q469		netfee	IT Financing and Management	**8**	Fee for residence-hall network connections	1. Yes; 2. No; 3-There are no residence-hall network connections; 4-There are no residence halls
Q411	Q480		stuown	Faculty and Student Computing	**2**	Undergraduate use of their own personal computers on campus	
Q412	Q481		comprec	Faculty and Student Computing	**3**	Student computer policy	1. All students are provided a personal computer; 2. Students in general are required to purchase/lease their own personal computers; 3. Students in some departments or majors are required to purchase/lease their own PCs; 4. Personal

2008 CDS variable name	2009 CDS variable name	IPEDS variable name	Data input file variable name	CDS section	CDS question number	Survey question	Data codes
							computer purchase/lease is recommended but not required for all students; 5. Personal computer purchase/lease is recommended but not required for students in some departments or majors; 6. There are no requirements or recommendations regarding personal computer purchase or lease; 7. Other
Q391_1	Q460_1		allstrat	IT Organization, Staffing and Planning	**9**	Strategic planning for IT as part of the campus strategic plan	1. Yes; 2. No
Q391_2	Q460_2		lonstrat	IT Organization, Staffing and Planning	**9**	Stand-alone strategic planning for IT	1. Yes; 2. No
Q418_1	Q487_1		newcrmn	Faculty and Student Computing	**9**	Course management system availability	1. We have not deployed a course management system and do not plan to; 2. We are planning to deploy one or more course management systems; 3. We are currently reviewing options, considering deploying a course management system or changing our current course management system approach; 4. We support a single commercial product course management system; 5. We support more than one commercial

2008 CDS variable name	2009 CDS variable name	IPEDS variable name	Data input file variable name	CDS section	CDS question number	Survey question	Data codes
							product course management system; 6. We support a single homegrown course management system; 7. We support more than one homegrown course management system; 8. We support a single open source course management system or a commercial product based on open source; 9. We support more than one open source course management system or commercial product based on open source; 10. We employ a hybrid approach (support a combination of homegrown, open source, and/or commercial course management systems); 11. Other
Q419_1, _2, _3, _4, _5, _6, _7, _8	Q488_1, _2, _3, _4, _5, _6, _7, _8		lmstech	Faculty and Student Computing	**10**	Learning technologies or practices	1. Deployed; 2. Experimenting with; 3. Considering; 4. Not planned

APPENDIX B:

MPLUS CFA CODE

```
Title:
        Four Factor Technology capacity Index CFA Model
Data:
        File is …;
        Format is free;
Variable:
        Names are
                intcnt resspeed restype
                wireless idm leascnt auth firewall patch
                roomtech hrscnt devcnt empcnt
                stucnt facsup
                dolcnt feecnt netfee
                stuown comprec allstrat
                lonstrat newcrmn lmstech;
        usevariables are
                stuown comprec allstrat lonstrat newcrmn lmstech
                dolcnt feecnt netfee
                hrscnt devcnt stucnt empcnt facsup
                resspeed wireless
                idm leascnt auth firewall patch roomtech;
        Categorical are
                netfee allstrat lonstrat;
 Analysis:
        iterations is 50000;
 Model:
        Use BY stuown comprec allstrat lonstrat newcrmn lmstech;
        Acc BY dolcnt feecnt netfee;
        Sup BY hrscnt devcnt stucnt empcnt facsup;
        Infra BY resspeed wireless
        idm leascnt auth firewall patch roomtech;
        Acc With Sup;
        Use With Acc;
        Infra With Acc;
        Use With Infra;
Output:         standardized; tech1;
```

APPENDIX C:

MPLUS EFA CODE

```
Title:
        Technology capacity Index EFA Model
Data:
        File is …;
        Format is free;
Variable:
        Names are
                intcnt resspeed restype
                wireless idm leascnt auth firewall patch
                roomtech hrscnt devcnt empcnt
                stucnt facsup
                dolcnt feecnt netfee
                stuown comprec allstrat
                lonstrat newcrmn lmstech;
        usevariables are
                intcnt resspeed restype
                wireless idm leascnt auth firewall patch
                roomtech hrscnt devcnt empcnt
                stucnt facsup
                dolcnt feecnt netfee
                stuown comprec allstrat
                lonstrat newcrmn lmstech;
        Categorical are
                netfee allstrat lonstrat;
Analysis:
        Type = EFA 1 5;
        Iterations is 5000;
        Rotation = promax;
```

APPENDIX D:

MPLUS CFA VALIDATION CODE

```
Title:
        Two Factor Technology capacity Index CFA Verification
 Data:
        File is…;
        Format is free;
 Variable:
        Names are
                intcnt resspeed restype
                wireless idm leascnt auth firewall patch
                roomtech hrscnt devcnt empcnt
                stucnt facsup
                dolcnt feecnt netfee
                stuown comprec allstrat
                lonstrat newcrmn lmstech;
        usevariables are
                intcnt leascnt empcnt dolcnt stucnt
                resspeed restype netfee stuown comprec
                firewall facsup hrscnt wireless;
        Categorical are
                netfee ;
   Analysis:
        iterations is 150000;

   Model:
        CS BY intcnt leascnt firewall hrscnt
                empcnt stucnt facsup dolcnt ;

        SE BY comprec netfee stucnt stuown resspeed
                restype wireless;
        CS WITH SE;

  Output: standardized;
  Savedata:
        File is "/users/me/dropbox/dissertation documents/spss/tci2output.dat";
        Save = fscores;
```

APPENDIX E:

R PERMUTATION TEST CODE

```
#define input file
ds = read.csv("~/Documents/R/rdissy.csv")
library(mosaic)
****************
#control permutation code
#calculate mean by group
mean(tci ~ control, data=ds)
#observed mean difference calculation
obsdiff = compareMean(tci ~ control, data=ds)
#sampling of data
nulldist = do(999) * compareMean(tci ~ shuffle(control), data=ds)
#histogram input
histogram(~ result, xlab="Permutation Mean Differences", density=TRUE, n=50,
data=nulldist)
obsdiff
tally(~ abs(nulldist) > abs(obsdiff), data=nulldist)
#significance calculation
pvalue=((sum(~abs(nulldist) >= abs(obsdiff)))+1 )/(999+1); pvalue
****************
#MSI permutation code
mean(tci ~ msi, data=ds)
obsdiff = compareMean(tci ~ msi, data=ds)
nulldist = do(999) * compareMean(tci ~ shuffle(msi), data=ds)
#histogram input
histogram(~ result, xlab="Permutation Mean Differences", density=TRUE, n=50,
data=nulldist)
obsdiff
tally(~ abs(nulldist) > abs(obsdiff), data=nulldist)
#significance calculation
pvalue =((sum(abs(nulldist) >= abs(obsdiff)))+1 )/(999+1); pvalue
****************
#HSI permutation code
mean(tci ~ hsi, data=ds)
obsdiff = compareMean(tci ~ hsi, data=ds)
nulldist = do(999) * compareMean(tci ~ shuffle(hsi), data=ds)
#histogram input
histogram(~ result, xlab="Permutation Mean Differences", density=TRUE, n=50,
data=nulldist)
obsdiff
tally(~ abs(nulldist) > abs(obsdiff), data=nulldist)

#significance calculation
```

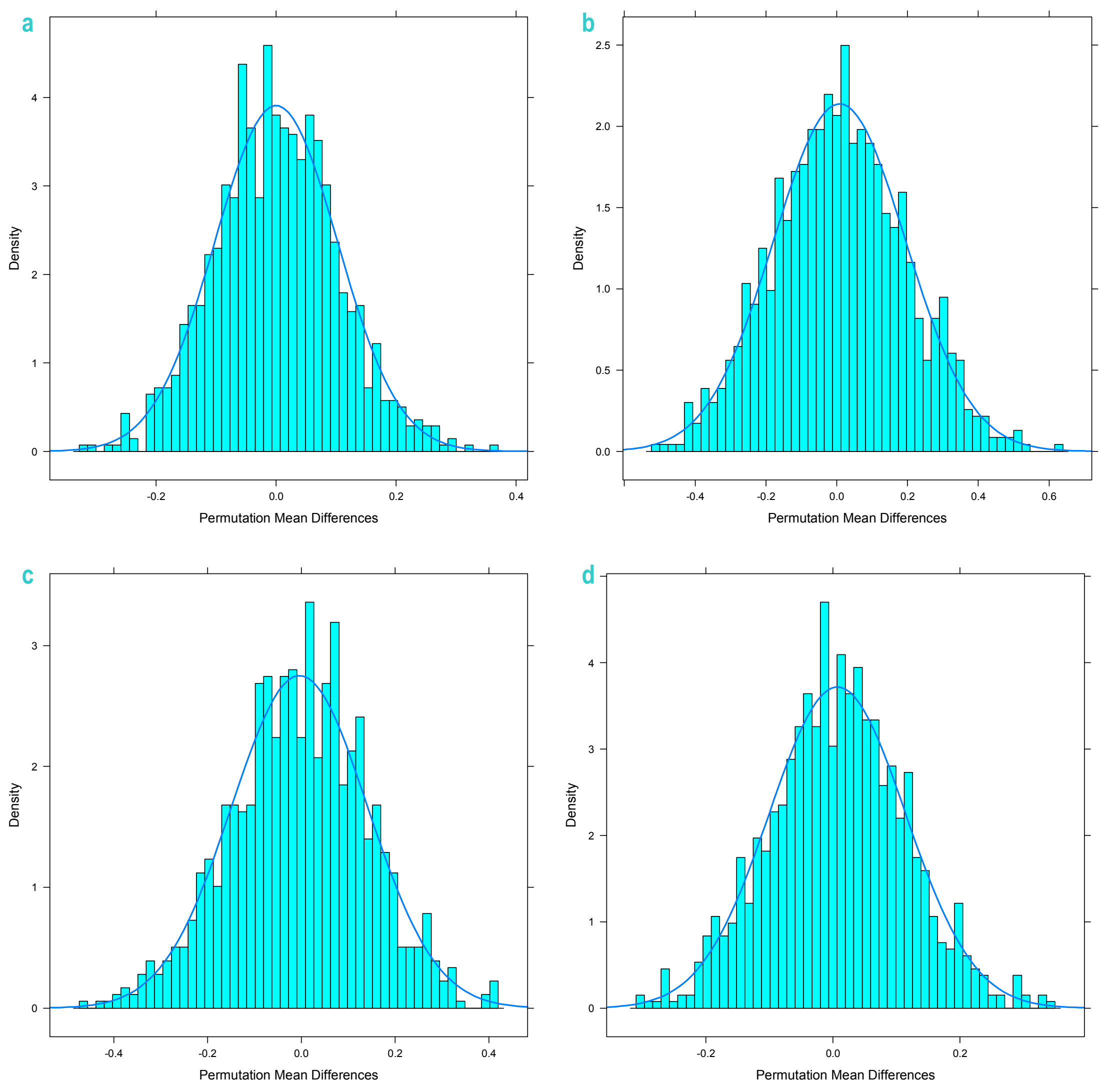
```
pvalue =((sum(abs(nulldist) >= abs(obsdiff)))+1 )/(999+1); pvalue
****************
#HBCU permutation code
mean(tci ~ hbcu, data=ds)
obsdiff = compareMean(tci ~ hbcu, data=ds)
nulldist = do(999) * compareMean(tci ~ shuffle(hbcu), data=ds)
#histogram input
histogram(~ result, xlab="Permutation Mean Differences", density=TRUE, n=50,
data=nulldist)
obsdiff
tally(~ abs(nulldist) > abs(obsdiff), data=nulldist)
#significance calculation
pvalue =((sum(abs(nulldist) >= abs(obsdiff)))+1 )/(999+1); pvalue
****************
#Sector permutation code
#create subset data input based upon distinct groups, X substituted with valid group
dsnew = subset(ds, sector==X | sector==X,select=c(tci,sector))
#calculate mean by group
mean(tci ~ sector, data=dsnew)
#observed mean difference calculation
obsdiff = compareMean(tci ~ sector, data=dsnew)
nulldist = do(999) * compareMean(tci ~ shuffle(sector), data=dsnew)
#histogram input
histogram(~ result, xlab="Permutation Mean Differences", density=TRUE, n=50,
data=nulldist)
obsdiff
tally(~ abs(nulldist) > abs(obsdiff), data=nulldist)
#significance calculation
pvalue =((sum(abs(nulldist) >= abs(obsdiff)))+1 )/(999+1); pvalue
****************
#Locale permutation code
dsnew = subset(ds, locale==X | locale==X,select=c(tci,locale))
mean(tci ~ locale, data=dsnew)
obsdiff = compareMean(tci ~ locale, data=dsnew)
nulldist = do(999) * compareMean(tci ~ shuffle(locale), data=dsnew)
#histogram input
histogram(~ result, xlab="Permutation Mean Differences", density=TRUE, n=50,
data=nulldist)
obsdiff
tally(~ abs(nulldist) > abs(obsdiff), data=nulldist)
#significance calculation
pvalue =((sum(abs(nulldist) >= abs(obsdiff)))+1 )/(999+1); pvalue
****************
#Instsize permutation code

dsnew = subset(ds, instsize==X | instsize ==X,select=c(tci, instsize))
```

```
mean(tci ~ instsize, data=dsnew)
obsdiff = compareMean(tci ~ instsize, data=dsnew)
nulldist = do(999) * compareMean(tci ~ shuffle(instsize), data=dsnew)
#histogram input
histogram(~ result, xlab="Permutation Mean Differences", density=TRUE, n=50,
data=nulldist)
obsdiff
tally(~ abs(nulldist) > abs(obsdiff), data=nulldist)
#significance calculation
pvalue =((sum(abs(nulldist) >= abs(obsdiff)))+1 )/(999+1); pvalue
****************
#Carnegie Classification permutation code
dsnew = subset(ds, cc==X | cc==X,select=c(tci, cc))
mean(tci ~ cc, data=dsnew)
obsdiff = compareMean(tci ~ cc, data=dsnew); obsdiff
nulldist = do(999) * compareMean(tci ~ shuffle(cc), data=dsnew)
#histogram input
histogram(~ result, xlab="Permutation Mean Differences", density=TRUE, n=50,
data=nulldist)
obsdiff
tally(~ abs(nulldist) > abs(obsdiff), data=nulldist)
#significance calculation
pvalue =((sum(abs(nulldist) >= abs(obsdiff)))+1 )/(999+1); pvalue
```

APPENDIX F:

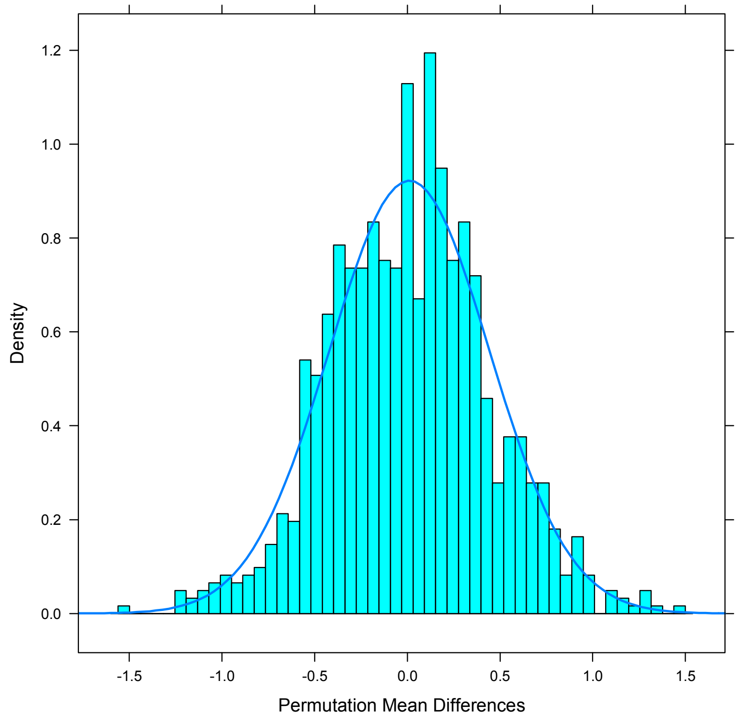
PERMUTATION HISTOGRAMS

Sector and control. Histogram results by sector (parts a, b, and c) and control (part d).



Sector and control: Histogram of sampling distribution of mean differences (a) between public 4-year institutions and private 4-year institutions; (b) between public 4-year institutions and public 2-year institutions; (c) between private 4-year institutions and public 2-year institutions; and (d) between publicly and privately held institutions.

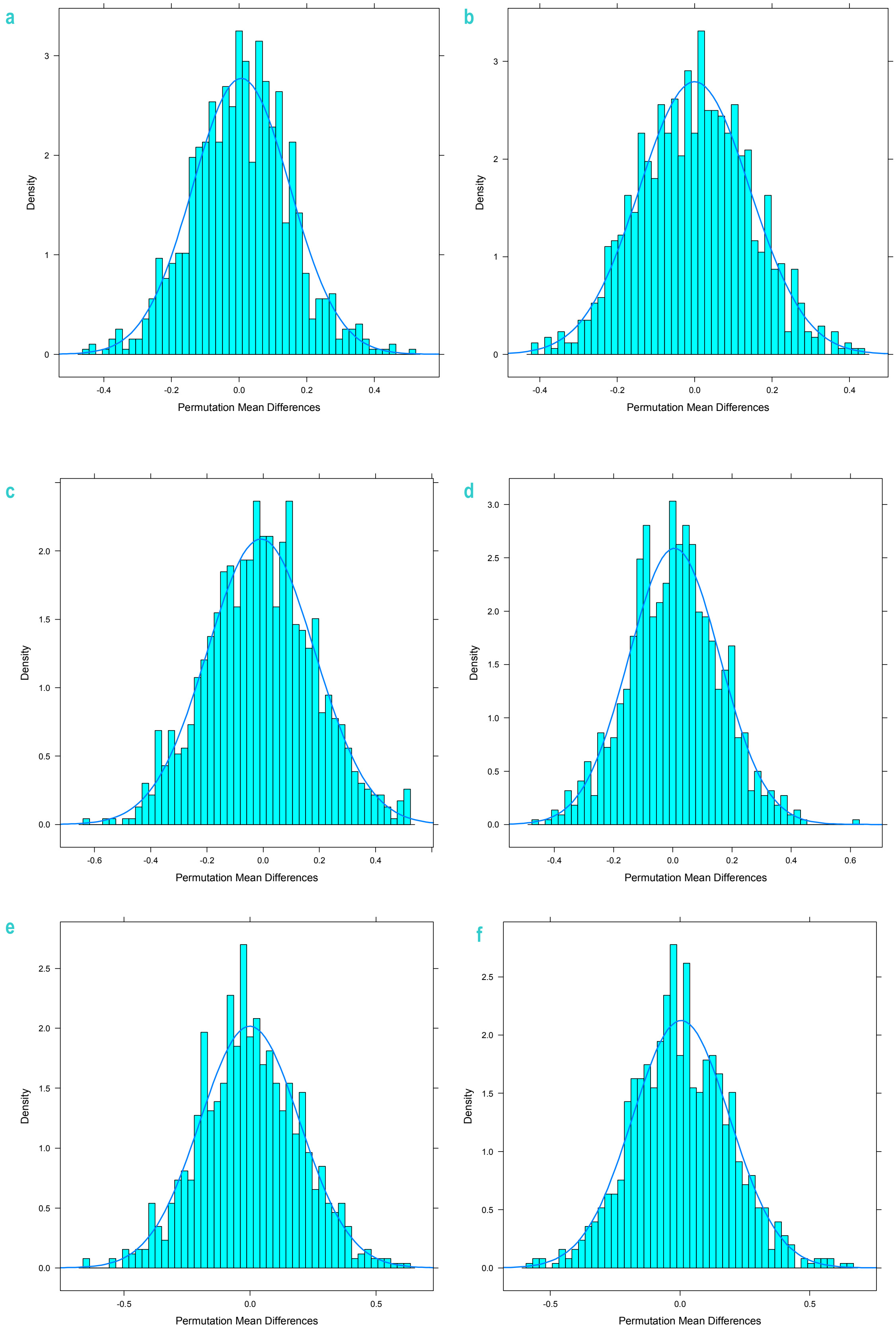
Historically black colleges and universities. Histogram results by HBCU Indicator.



Historically black colleges and universities: Histogram of sampling distribution of mean differences between institutions based upon HBCU designation.

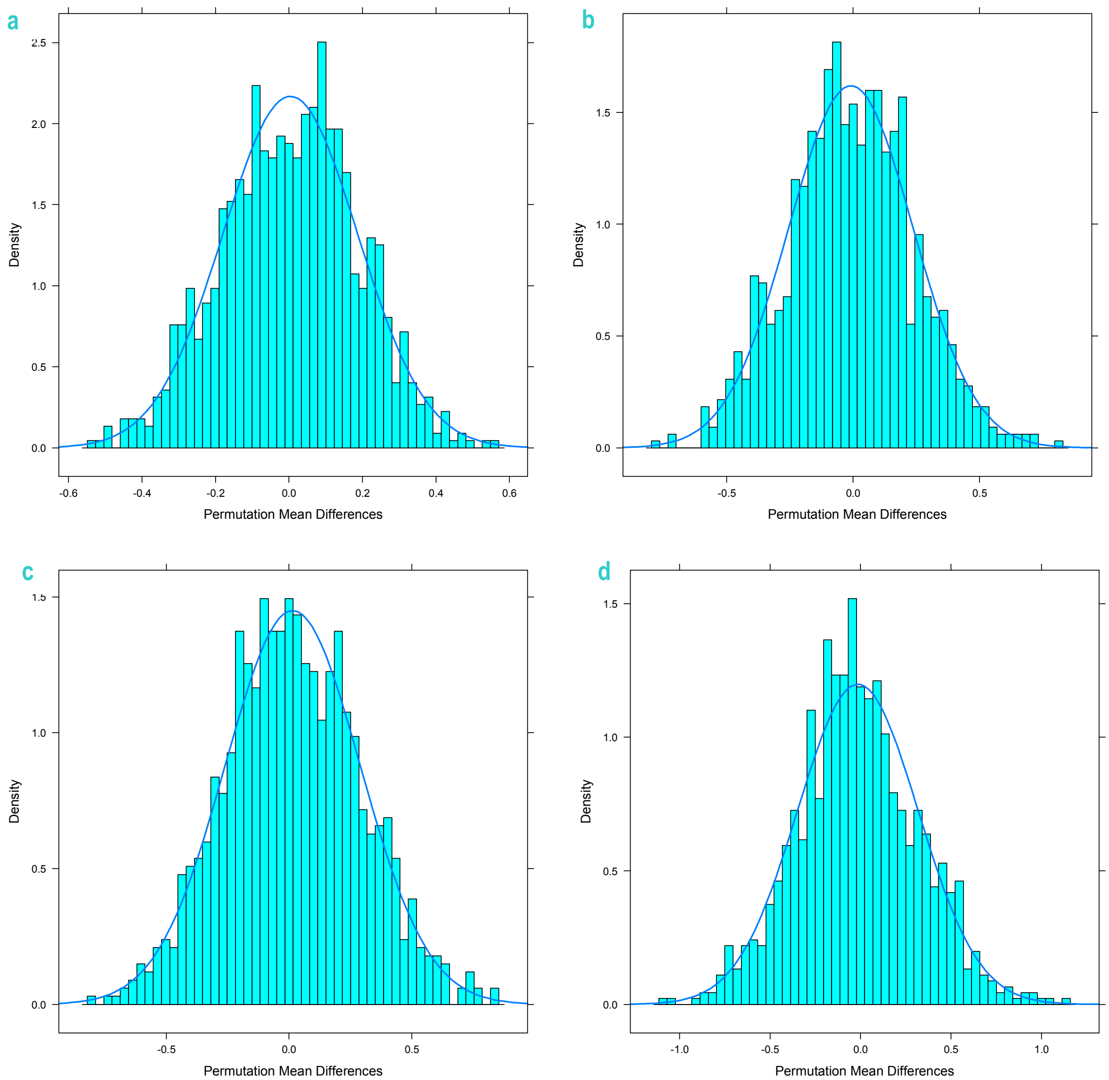
Tribal colleges and universities. There was not enough information on tribal institutions to conduct any testing for this characteristic.

Locale. Histogram results by locale.

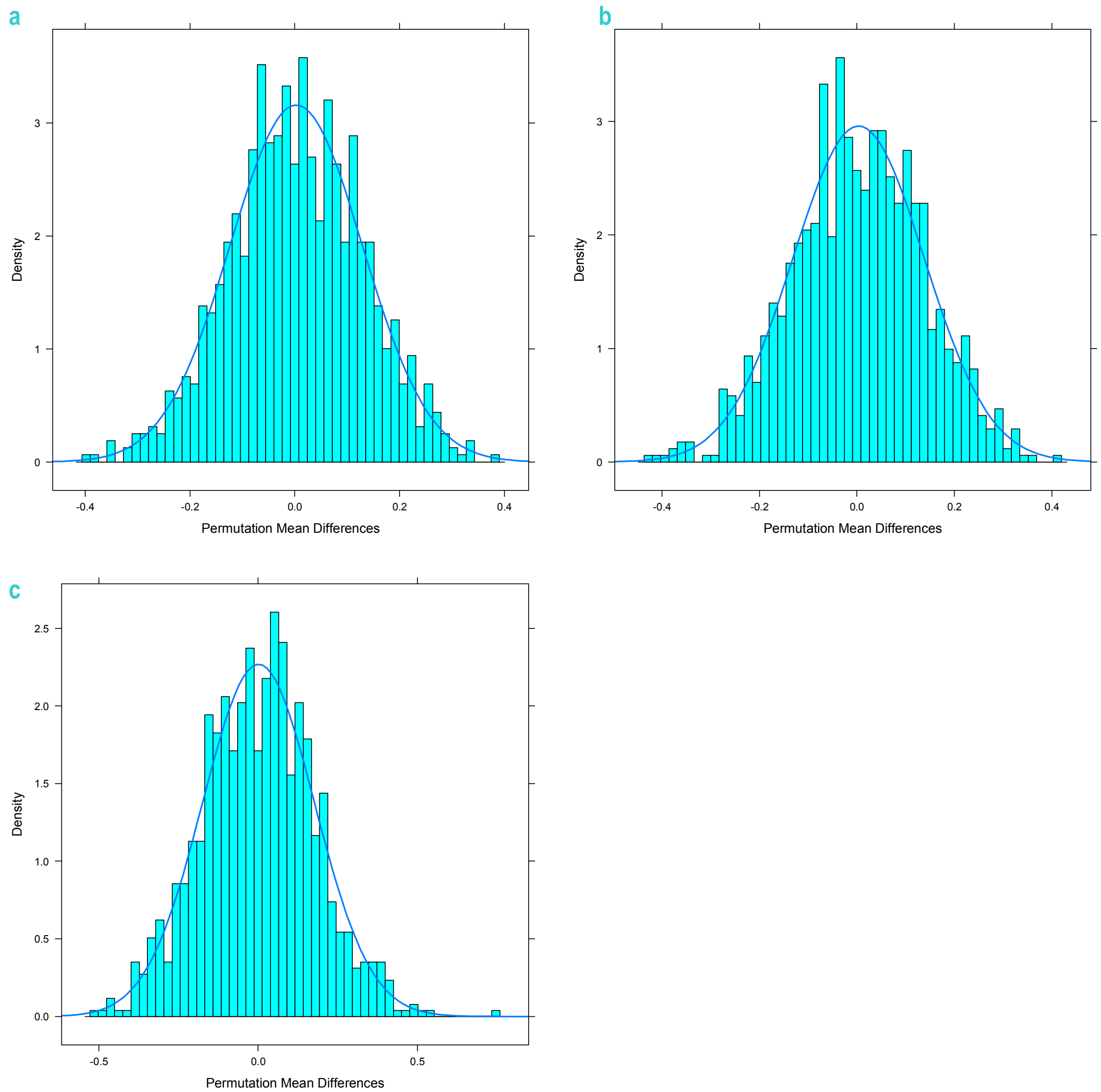

a
b
c
d
e
f
Density
Permutation Mean Differences

Locale. Histogram of sampling distribution of mean differences
(a) between city institutions and suburban institutions;
(b) between city institutions and town institutions;
(c) between city institutions and rural institutions;
(d) between suburban institutions and town institutions;
(e) between suburban institutions and rural institutions;
(f) between town institutions and rural institutions.

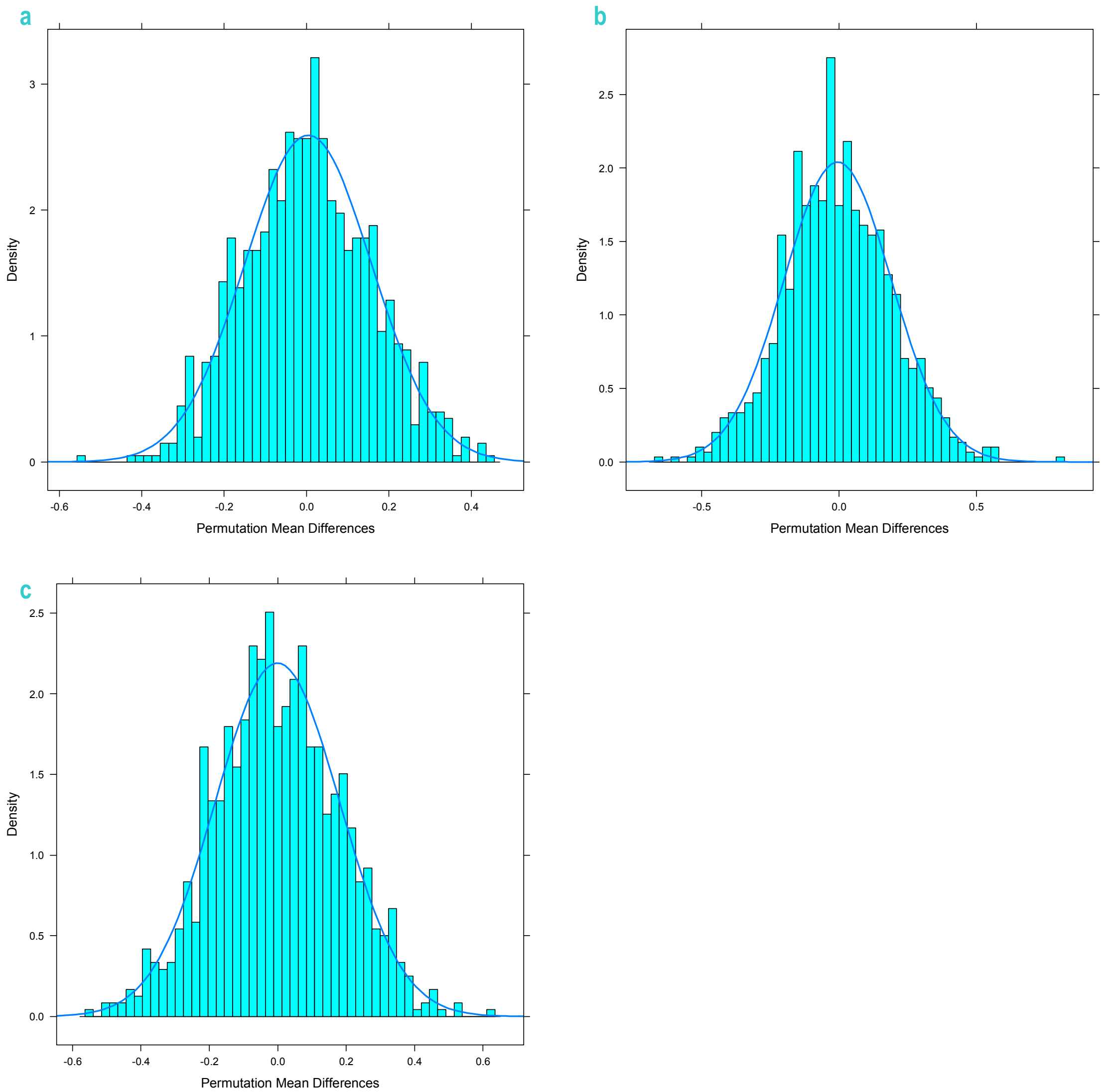
Institutional size. Histogram results by institutional size.



Institutional size part 1: Histogram of sampling distribution of mean differences (a) between institutions with less than 1,000 students and institutions with 1,000 to 4,999 students; (b) between institutions with less than 1,000 students and institutions with 5,000 to 9,999 students; (c) between institutions with less than 1,000 students and institutions with 10,000 to 19,999 students; (d) between institutions with less than 1,000 students and institutions with more than 20,000 students.

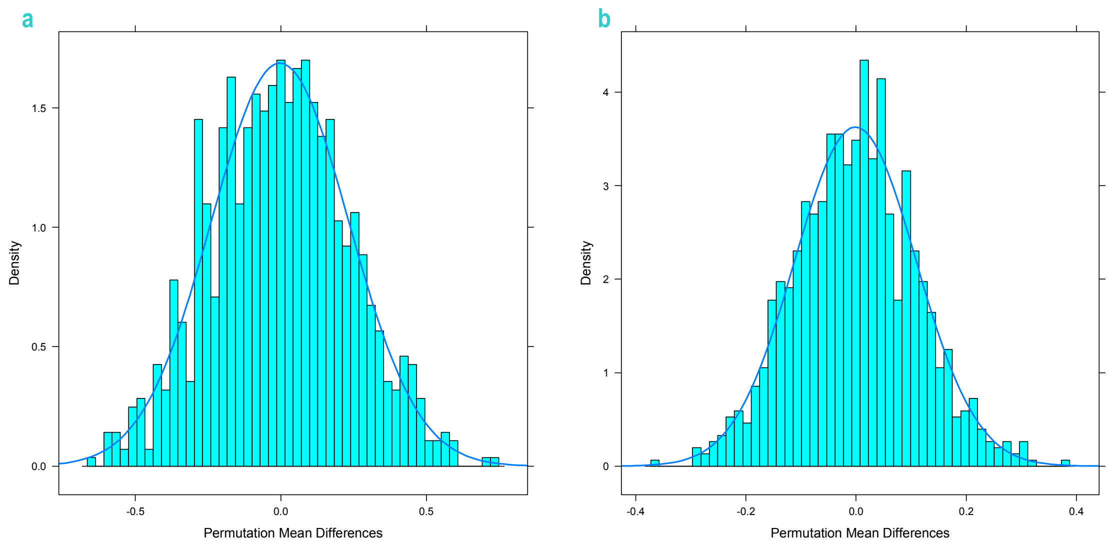


Institutional size part 2: Histogram of sampling distribution of mean differences (a) between institutions with 1,000 to 4,999 students and institutions with 5,000 to 9,999 students; (b) between institutions with 1,000 to 4,999 students and institutions with 10,000 to 19,999 students; (c) between institutions with 1,000 to 4,999 students and institutions with more than 20,000 students.



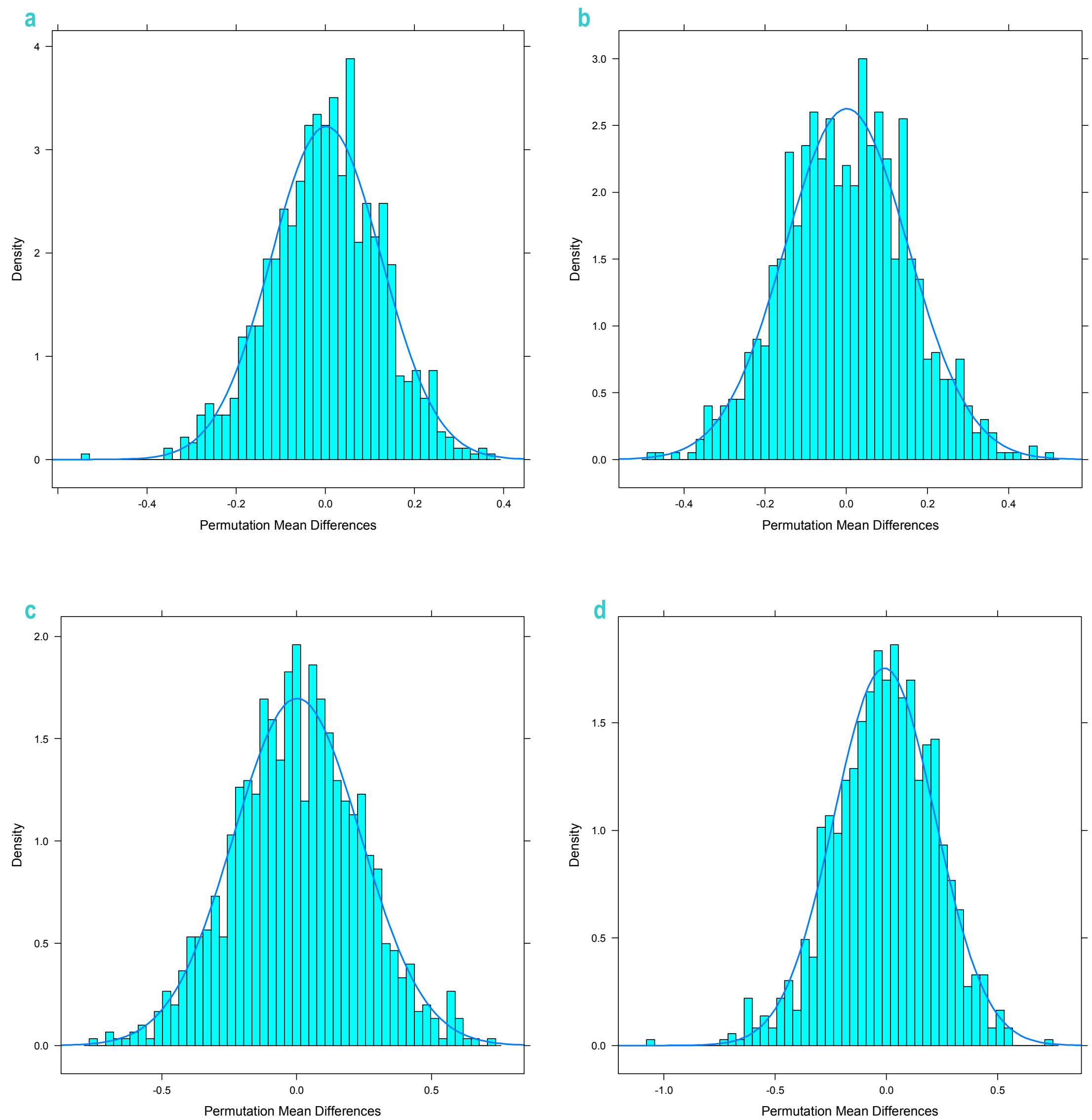
Institutional size part 3: Histogram of sampling distribution of mean differences (a) between institutions with 5,000 to 9,999 students and institutions with 10,000 to 19,999 students; (b) between institutions with 5,000 to 9,999 students and institutions with more than 20,000 students; (c) between institutions with 10,000 to 19,999 students and institutions with more than 20,000 students.

Hispanic-serving institutions and minority-serving institutions. Histogram results by HSI and MSI Indicator.

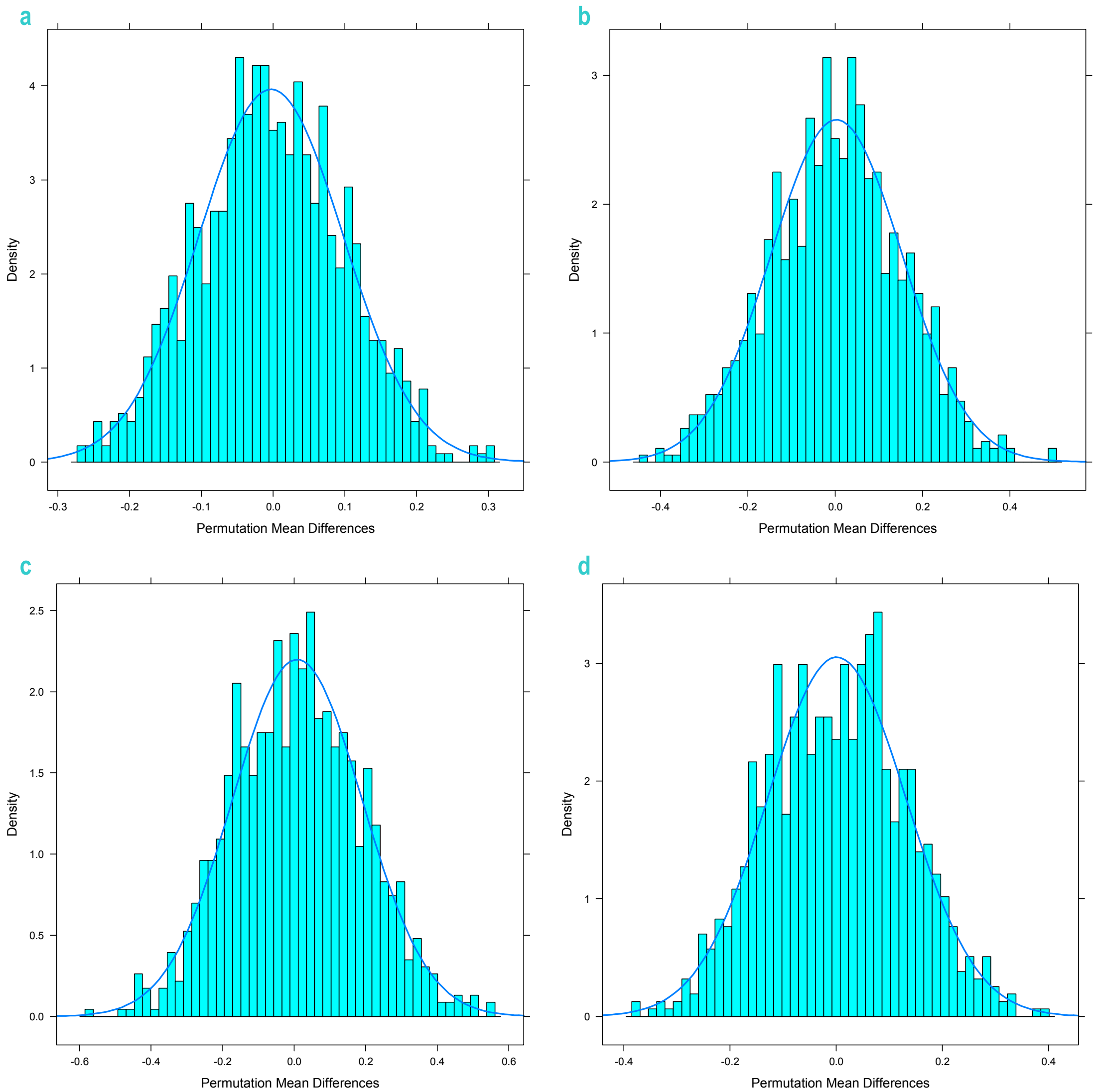


Hispanic-serving and minority-serving institutions: Histogram of sampling distribution of mean differences between institutions based upon (a) HSI designation and (b) MSI designation.

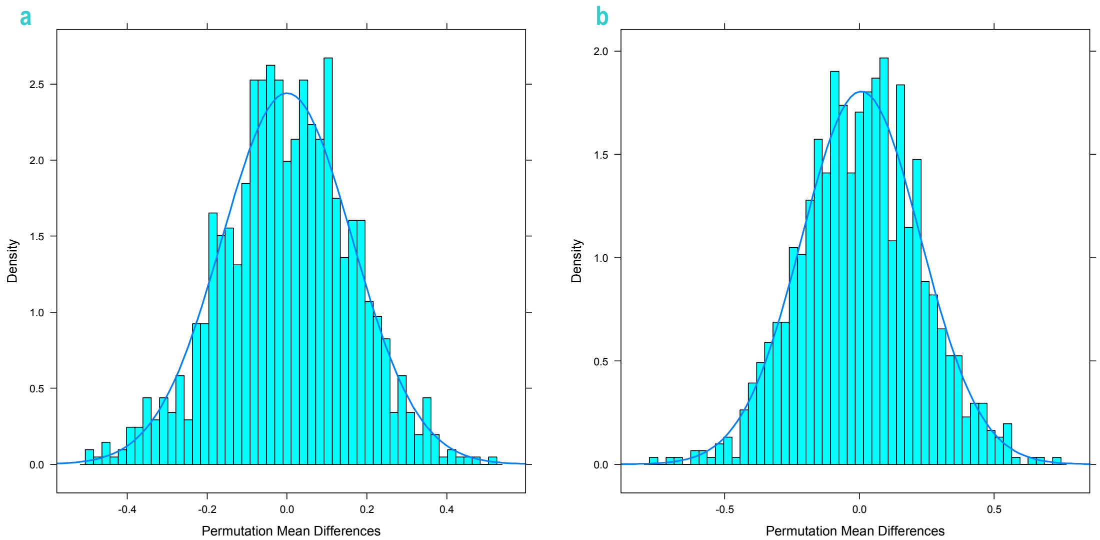
Carnegie classification. Histogram results by Carnegie classification.



Carnegie classification part 1: Histogram of sampling distribution of mean differences (a) between doctoral institutions and master's institutions; (b) between doctoral institutions and baccalaureate institutions; (c) between doctoral institutions and associate institutions; (d) between doctoral institutions and professional institutions.



Carnegie classification part 2: Histogram of sampling distribution of mean differences (a) between master's institutions and baccalaureate institutions; (b) between master's institutions and associate institutions; (c) between master's institutions and professional institutions; and (d) between baccalaureate institutions and associate institutions.



Carnegie classification part 3: Histogram of sampling distribution of mean differences (a) between baccalaureate institutions and professional/specialty institutions; (b) between associate institutions and professional/specialty institutions.