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Perceived Attributes of Diffusion of Innovation Theory as Predictors of Postsecondary Faculty Adoption of Text Expander Technology

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This is to certify that the doctoral dissertation by

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Abstract

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MA, Valdosta State University, 2008

BA, Valdosta State University, 2005

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

Postsecondary faculty do not provide detailed, individualized, and timely feedback to students, although faculty and students consider feedback an integral aspect of higher education. Text expander technology, or software programs that automatically convert snippets of predetermined text into longer phrases, can aid postsecondary faculty in providing digital written feedback, but little quantitative research exists regarding postsecondary faculty adoption of text expander technology. The purpose of this quantitative study was to examine the perceived attributes of Rogers' diffusion of innovation theory that predict postsecondary faculty adoption of text expander technology. The research questions were related to the frequency at which postsecondary faculty adopt text expander technology to provide digital written feedback and to what perceived attributes of innovation predict postsecondary faculty adoption of text expander technology. The study included the use of an online survey and a random sample of 321 participants regarding the relationship between postsecondary faculty adoption of text expander technology and the perceived attributes of innovation, followed by data analysis using binary logistic regression. The results showed that 208 (64.8%) postsecondary faculty considered themselves adopters of text expander technology, while 113 (35.2%) did not, and the perceived attributes of relative advantage ($p < 0.001$), complexity ($p = 0.04$), and observability ($p = 0.003$) predicted postsecondary faculty adoption of text expander technology, supporting Rogers' diffusion of innovation theory. The study results support positive social change by clarifying the employment of digital written feedback practices to improve student engagement in higher education.

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Dedication

I dedicate this study to my parents, to my son, and to my husband. My parents showed me that I had the strength and will to complete the dissertation process through their steady belief in my abilities. My son gave me the impetus to complete this study because of my desire for him to believe that he in turn has the ability to achieve as much as he chooses in academia and in his career. And finally, my husband gave me the ability to complete this dissertation. Without his unfailing support at home and work and his encouragement at the most difficult points in my program, I would not have completed this study. If I am standing tall, it is on the shoulders of my husband, who is a giant in every facet of his heart and mind.

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And finally, I would like to thank my friends Andi and Vicie for laughing with me, ranting with me, brightening my free moments, and reminding me that I too could complete a doctoral program. Your friendship continues to be a guiding light in darkness.

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Chapter 1: Introduction to the Study

Introduction

The feedback-focused interaction inherent to the online postsecondary education environment increases the importance of postsecondary faculty providing detailed, individualized, and timely digital written feedback (DITDWF) to students (Haughney et al., 2020; Martin et al., 2019). While there is no general consensus on the characteristics of effective feedback (Planar & Moya, 2016), multiple researchers have found that effective digital written feedback is detailed, individualized, and timely (Gredler, 2018; Ianos, 2017; Wisniewski et al., 2020). However, instructors often do not provide the detailed, individualized, and timely feedback that students prefer (Law, 2019). Although online instruction continues to expand in higher education, researchers have not determined methods of providing DITDWF to large numbers of students in online classrooms (Crimmins et al., 2016; Joyce, 2019).

One potential tool postsecondary faculty can use to provide DITDWF is text expander technology (Adams, 2017; Haughney et al., 2020). In addition, multiple researchers have argued that exploring faculty perspectives of feedback is important in the pursuit of providing effective feedback to learners (Clark-Gordon et al., 2019; Ene & Upton, 2018; Martin et al., 2019). In this study, the aim was to examine postsecondary faculty's perception of Rogers' (2003) attributes of innovation as related to the adoption of text expander technology to provide digital written feedback to students, which can contribute knowledge to the field by supporting instructor presence through the delivery of DITDWF. This study can contribute to positive social change through enhancing student motivation, engagement, and success in the online environment, as well as by lessening the gap between students' preferences for digital written feedback and postsecondary faculty's digital written feedback practices. In addition, this study will have implications for faculty training by helping administrators better understand faculty's needs for technological tools that can enhance digital written feedback.

This chapter provides pertinent information about the study's background, problem, purpose, research questions, theoretical framework, nature, definitions, assumptions, scope and delimitations, and significance. The chapter ends with a summary of the information and a preview of the next chapter.

Background

A review of the literature illustrates the need for generalizable quantitative studies that relate to the use of innovative technology to provide digital written feedback. While there are many studies surrounding feedback in higher education (Wisniewski et al., 2020), few feedback studies relate to the use of innovative technology to provide digital written feedback. There is a rich tradition of literature regarding student preferences for feedback, but there are fewer studies about postsecondary faculty approaches and preferences for feedback (Clark-Gordon et al., 2019). Multiple researchers have found that students and faculty can have conflicting views of the role and usefulness of digital written feedback (Douglas et al., 2016; Ianos, 2017). Students tend to prefer DITDWF, but instructors' delivery of digital written feedback often does not align with these preferences (Best et al., 2015; Gredler, 2018; Lowe & Shaw, 2019; Pitt & Norton, 2016). Likewise, Ianos (2017) found that students lost motivation to access digital written feedback because of the delay between submitting assignments and receiving feedback and recommended that instructors provide detailed digital written feedback within a reasonable time span. There is a need for more studies about feedback practices related to digital written feedback (Clark-Gordon et al., 2019).

While there are many studies supporting operationalization of effective feedback as detailed, individualized, and timely, the review of the literature also illustrates a student preference for digital written feedback. Although Nistor and Comanetchi (2019) found that both instructors and students believed that online feedback is not as useful as face-to-face communication in the classroom and viewed online feedback as complementary to face-to-face feedback, other researchers found that students preferred digital written feedback (Ene & Upton, 2018; Farshi & Safa, 2015; Johnson et al., 2018). In addition to students' preference for DITDWF, the few studies relating to faculty use of text expander technology to provide digital written feedback are positive, with faculty and researchers agreeing that this innovative tool can be used to streamline and enhance the feedback process in higher education (Campbell, 2016; Graham, 2015; Joyce, 2019; Mandernach, 2018). However, the studies existing about text expander technology are primarily contextual and qualitative, and there were no studies that addressed the frequency of postsecondary faculty adoption of text expander technology nor how the perceived attributes of innovation might predict adoption of text expander technology.

This study addressed the gap in knowledge about postsecondary faculty adoption of text expander technology to generalize information about the perceived attributes of innovation related to text expander technology. This study has the potential to positively affect instructors' ability to provide DITDWF.

Problem Statement

DITDWF drives student engagement and is an integral aspect of instructor presence in online instruction (Gredler, 2018; Martin et al., 2018), yet postsecondary faculty often do not provide DITDWF to students. Much of the research regarding digital feedback emphasizes the student perspective rather than faculty perspective, but existing research indicates faculty and student preference for digital written feedback over other types of feedback (Clark-Gordon et al., 2019). However, the high student numbers in online environments can create challenges in feedback delivery, particularly in providing detailed and individualized digital feedback (Cavalcanti, 2019). Furthermore, online instructors have reported providing formative feedback multiple times during a semester as too time-consuming (Baranczyk & Best, 2020). Text expander technology, which includes software programs that automatically convert snippets of predetermined text into longer phrases, can aid postsecondary faculty in providing DITDWF (Mandernach, 2018; Rios et al., 2018). In addition, while the use of comments from statement banks such as those within text expander programs can facilitate student learning (Denton & McIlroy, 2018), little research exists about the perceived attributes of diffusion of innovation theory that predict adoption of text expander technology.

Multiple researchers have indicated the need for research on digital feedback from the perspective of faculty (Clark-Gordon et al., 2019; Martin et al., 2019). Martin et al. (2019) found that timely responses and feedback are important to faculty, which illustrates the need for research into strategies that can enhance facilitation of online instruction. In addition, Fromme et al. (2020) found that feedback scripts, which are frameworks for feedback that can be integrated with text expander technology, can improve faculty feedback delivery. Research into the adoption of technology that enhances online feedback delivery can aid in bridging postsecondary faculty's intention and implementation of providing detailed, individualized, and timely feedback to students.

Purpose of the Study

The purpose of this quantitative study was to examine the perceived attributes of diffusion of innovation theory that predict postsecondary faculty adoption of text expander technology, which can support faculty in providing DITDWF to students. A quantitative approach aided in addressing the research gap, with a survey instrument used to examine perceived attributes of diffusion of innovation theory that predict postsecondary faculty adoption of text expander technology to provide DITDWF to students. The nominal independent variables for this study included relative advantage, compatibility, complexity, trialability, and observability, while the binary dependent variable for this study was postsecondary faculty adoption of text expander technology.

The covariates for this study included demographic characteristics such as gender, age, employment status, level of education, and years of experience.

Research Questions and Hypotheses

The research questions and hypotheses for the study were the following:

1. RQ1—Quantitative: At what frequency do postsecondary faculty adopt text expander technology to provide digital written feedback?
2. RQ2—Quantitative: What perceived attributes of innovation predict postsecondary faculty adoption of text expander technology?

H_02_A: The relative advantage attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_A: The relative advantage attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

H_02_B: The compatibility attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_B: The compatibility attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

H_02_C: The complexity attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_C: The complexity attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

H_02_D: The trialability attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_D: The trialability attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

H_02_E: The observability attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_E: The observability attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

All of the variables for this study were measured with a validated, reliable Likert scale developed by Moore and Benbasat (1991) to measure individuals' perception of adoption of information and communications technology. However, the covariates were recorded as demographic information.

Theoretical Framework for the Study

Rogers' (2003) diffusion of innovations theory provided the theoretical base for this study. While the theory originally stemmed from agricultural research, hundreds of education studies have included diffusion research, and Rogers cited the suitability of educational innovations for diffusion studies. Rogers determined that the perceived attributes of innovations include relative advantage, compatibility, complexity, trialability, and observability. The perception of greater relative advantage, or the perceived superiority of the innovation, compatibility, or how closely it aligns with an individual's current workflow and style, trialability, or the ease of trialing the innovation, and observability, or the extent to which others can see the innovation at work, lead to higher adoption rates, as does perception of lower complexity. According to Rogers, perception of relative advantage and compatibility are among the most important in increasing an innovation's adoption rate. For this study, the major theoretical proposition is that specific perceived attributes of innovation, such as compatibility and relative advantage, will predict postsecondary faculty adoption of text expander technology. A detailed explanation of the theory's connection to the current study is provided in Chapter 2, but the research questions related directly to the theory of innovation diffusion by continuing the line of research about the perceived attributes of an innovation that prompt individuals to adopt an innovation. The perceived attributes of diffusion of innovation theory provided information about the perceived characteristics of text expander technology that predict adoption by postsecondary faculty, and the study contributed to existing innovation diffusion research that relates to the adoption of technological innovations in higher education.

Nature of the Study

This nonexperimental quantitative study included binary logistic regression analysis in order to use multiple independent variables to predict a single binary dependent variable. Nonexperimental studies are helpful for establishing correlation between variables rather than indicating a causal relationship (Vellutino & Schatschneider, 2011). A quantitative survey design directly related to the study variables and research questions, as quantitative, descriptive, nonexperimental survey design allows a researcher to examine frequency and relationships between variables (Burkholder et al., 2016; Jhangiani et al., 2019). Because the goal was to answer specific questions regarding the adoption of text expander technology and to examine correlation rather than to determine causal relationships, a quantitative, nonexperimental survey design was appropriate for this study. Self-reported survey data provided insight into the frequency of text expander technology adoption, as well as into the perceived attributes of diffusion of innovation theory that predicted adoption.

To test the study hypotheses, I collected data using SurveyMonkey Audience, which allowed for random selection of individuals who use SurveyMonkey, are located in the United States, and currently teach in higher education. After collecting data, I employed binary logistic regression and χ^2 analysis, as well as the Hosmer-Lemeshow goodness-of-fit test. Before analyzing the data, I ensured that the data met the assumptions for using binary logistic regression, including that the dependent variable was dichotomous, that there was more than one independent variable, and that there was a linear relationship between continuous independent variables and the log odds of the dependent variable (Wagner, 2017). Besides the above tests, I also tested for linearity, tested for multicollinearity, calculated the variance inflation factor and variable tolerance, and examined the case-wise listing of residuals to detect whether all cases fit the model. Using random sampling of the population, ensuring that the data met the assumptions, and running multiple tests on the data aided in answering the research questions for this study.

Definitions

Feedback: Feedback is information provided by an agent meant to close a gap between actual and reference levels of performance (Hattie & Timperley, 2007; Sadler, 1989).

Effective feedback: Based on a review of the literature, effective feedback is operationalized as detailed, individualized, and timely feedback (Crisp & Bonk, 2018; Torres et al., 2020; Wisniewski et al., 2020).

Digital written feedback: Digital written feedback is written, as opposed to audio or video, feedback that is provided in a digital format (Clark-Gordon et al., 2019).

Innovation: An innovation is a practice, idea, or object that individuals perceive to be new (Rogers, 2003).

Diffusion: The term *diffusion* refers to the communication process of innovations that occurs within a social system (Rogers, 2003).

Relative advantage: The relative advantage of an innovation relates to how much individuals perceive the innovation as an improvement over existing ideas or technology (Rogers, 2003).

Compatibility: According to Rogers (2003), compatibility is “the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters” (p. 266).

Complexity: The perceived complexity of an innovation is how difficult it is perceived as being to use and comprehend (Rogers, 2003).

Trialability: The trialability of an innovation relates to how simple it is for an individual to use it on a trial basis (Rogers, 2003).

Observability: The observability of an innovation relates to how visible the results of the innovation are to others (Rogers, 2003).

Postsecondary faculty: For the purposes of this study, the term *postsecondary faculty* relates to educators who are located in the United States, who currently teach in a postsecondary, higher education setting, and who are over 18 years of age (National Center for Education Statistics, 2020).

Text expander technology: Text expander technology consists of software programs—or aspects of software programs—that automatically convert snippets of predetermined text into longer predetermined phrases (Mandernach, 2018; Rios et al., 2018).

Assumptions

The study included multiple assumptions related to the sample, survey, and method. Although the sample was randomly selected through SurveyMonkey Audience, I assumed that the population of SurveyMonkey has a sufficient representative population of postsecondary faculty for the study. In addition, the survey participation was voluntary and anonymous, and no personally identifiable data were collected, so additional assumptions were that participants are 18 years or older, that they had access to the Internet, that they understood and provided informed consent, and that they accurately and truthfully responded to the survey questions. Because there were no monetary incentives for completing the study—SurveyMonkey Audience provides a charity donation but no remuneration (SurveyMonkey, 2020)—I assumed that participants responded objectively to the survey questions. Another assumption was that the results of the study can be generalized to individuals located in the United States who are over 18 years of age and currently teach in higher education.

Assumptions are necessary when employing a quantitative survey design because it would be difficult to fully access a population that includes all postsecondary faculty. There were at least 1.5 million faculty teaching in higher education in the United States in 2018 (National Center for Education Statistics, 2020), and it would not be feasible to survey every faculty member or higher education institution in the United States. However, random sampling with a sample and method that aligns with best practices in quantitative survey design allows researchers to make certain assumptions about the sample and generalize the study results to the larger population (Creswell, 2009; Frankfort-Nachmias & Leon-Guerrero, 2016).

Scope and Delimitations

The research problem for this study was that postsecondary faculty do not provide DITDWF to students, even though feedback is an integral aspect of higher education according to both faculty and students (Martin et al., 2018, 2020). According to the new paradigm of feedback, assessment design is as important, if not more important, than feedback delivery, but innovative technology plays a role in the new paradigm of feedback (Winstone & Carless, 2020). This study’s scope extended to the adoption of innovative technology to provide digital written feedback, as it is more feasible to examine the adoption of innovative technology by individual postsecondary faculty than to examine assessment design at an institutional level.

The scope of the study population extended to postsecondary faculty who teach at undergraduate or graduate levels. Individuals within the SurveyMonkey Audience pool who are over 18, located within the United States, and currently teach in higher education were the target population. Because text expander technology can be used in either an online or face-to-face setting, no limitations were placed on whether the faculty teach in an online setting. Only individuals over 18 years of age were included in this study, as individuals younger than 18 would have needed guardian permission to complete the study. Only individuals located in the United States were included in this study.

This study featured Rogers' (2003) theory of innovation diffusion as the framework because this theory is well supported with multiple studies in higher education to undergird its application to the current study. In addition, this theory aligns innovation and adoption theory and allowed for use of a validated, reliable instrument. One model that is related to Rogers' theory of innovation diffusion but excluded from this study is the technology acceptance model, which relates to acceptance of technology within information systems (Davis, 1989). While the technology acceptance model can be used to predict use and acceptance of information systems and technology by individual users, it is most related to information systems rather than attributes of innovation. This study focused specifically on the attributes of innovation that predict adoption of text expander technology among users in decentralized systems rather than on user acceptance of innovative technology among users of centralized systems. Therefore, the technology acceptance model was excluded from investigation within this study.

The aim of this study was to examine the attributes of innovation that predict postsecondary faculty adoption of text expander technology. Because this study was cross-sectional rather than longitudinal, data were collected at only one point in time. The aim of this study was not to explore changes over time in postsecondary faculty adoption of text expander technology, which precluded a longitudinal design and affects generalizability, as responses in a longitudinal study may have had a different outcome. However, the findings of this study regarding which attributes of innovation predict adoption of text expander technology by postsecondary faculty may be generalizable to the population of postsecondary faculty who are located in the United States and currently teach in higher education.

Limitations

While the quantitative survey design aided in determining the relationships between variables, there were several methodological and design weaknesses involved. Quantitative designs aid in generalizing the results to a larger population, but the close-ended nature of survey questions limits the contextualization and detail of the findings (Burkholder et al., 2016; Cohen et al., 2018). A further weakness was that the design included an online survey; the data were self-reported and thus may not reflect objective reality, and issues with the Internet or bandwidth may have affected completion of the survey. In addition, although the sampling was random, it took place through a SurveyMonkey Audience panel rather than through the general population, which may limit the generalizability of the study. The sampling may also limit generalizability because the population of SurveyMonkey Audience may have had more access to the Internet or computers than the general population or may not have represented the general population in other ways. Another sampling issue was the inclusion of all postsecondary faculty as the population instead of delimiting to faculty who teach online; because postsecondary faculty who teach online may be more likely to use text expander program, the sample may have been skewed. However, as the use of digital written feedback occurs across face-to-face and online environments, all postsecondary faculty were targeted as a population. Quantitative survey designs have high external validity but low internal validity, and a nonexperimental design such as the current study design is on the lower end of internal validity within quantitative methodology (Jhangiani et al., 2019). However, the low internal validity was countered by following best practices in instrumentation and sampling.

Another potential design weakness related to the use of Rogers' (2003) diffusion of innovation theory to identify constructs; perceived attributes of innovation are not the same as the attributes of an innovation, but multiple researchers have found that perception more accurately predicts adoption of an innovation because individuals have varying sets of personal circumstances and thus will view and adopt innovations differently (Moore & Benbasat, 1991). This study was limited to the study of perceived attributes of innovation rather than attributes. In addition, confounder variables related to demographic information were included to support the generalizability of the study.

Some biases that may have influenced the study outcomes of a quantitative nonexperimental survey design include missing confounders, volunteer bias, and nonresponse (Frankfort-Nachmias & Leon-Guerrero, 2016). Confounders were addressed by including demographic information that could be potential confounders in the survey; the demographic questions were from a validated research instrument that has been used to examine a similar phenomenon in a similar population. Nonresponse bias relates to missing information from individuals who might refuse to take part in the study. Nonresponse bias was addressed by using a validated, reliable instrument with no sensitive topics or information, which aided in the completion rate of the survey. Finally, volunteer bias relates to participants volunteering to take part in the study, which may set them apart from the general population in some way.

To address the study's limitations, I used random sampling through the SurveyMonkey Audience service, which also simplified the survey presentation and experience for participants. A validated, reliable instrument was employed that had been used to study a similar research problem and population. I also followed best practices in sampling for binary logistic regression by increasing the sample size to beyond the standard minimum (van Smeden et al., 2019). In addition, I ran multiple tests on the data and performed data checks as needed to support the generalizability of the results. These actions helped counter the limitations of the study.

Significance

This research filled a gap in the understanding of strategies that enhance online instruction facilitation by focusing on the adoption of tools that can aid postsecondary faculty in providing DITDWF to students. Digital written feedback tools are under researched within higher education (Clark-Gordon et al., 2019), and as online learning continues to expand (Martin et al., 2019), strategies and tools that enhance online feedback delivery will rise in importance. This study's results provided insight into the perceived attributes of diffusion of innovation theory that predict postsecondary faculty adoption of text expander technology, which can assist program- and institution-level administrators in amending and improving faculty training in digital feedback delivery. Online instruction continues to become more relevant and significant within higher education, and supporting instructor presence through DITDWF can contribute to positive social change through enhancing student motivation, engagement, and success in the online environment.

Summary

Feedback continues to be an integral aspect of both the student and faculty experience in higher education (Winstone & Carless, 2020; Wisniewski et al., 2020). While both students and faculty perceive feedback as important (Crisp & Bonk, 2018; Dawson et al., 2018), postsecondary faculty do not provide DITDWF to students. Adopting text expander technology can aid postsecondary faculty in providing digital written feedback to students (Mandernach, 2018; Rios et al., 2018), and specific perceived attributes of innovation may predict postsecondary faculty adoption of text expander technology. In this study, I examined the perceived attributes of innovation that predict postsecondary faculty adoption of text expander technology, which will advance the field by providing information about the alignment of adoption of text expander technology with Rogers' (2003) theory of innovation diffusion. The results of this study will aid faculty and administrators in better understanding the adoption of innovative technology to provide digital written feedback in higher education.

In this chapter, I provided the study's research problem and purpose, as well as the background, nature, scope and delimitations, limitations, and significance of the study. In Chapter 2, I provide insight into Rogers' (2003) theory of innovation diffusion, operationalize feedback as it applies to the current study, and review current studies related to the phenomenon.

Chapter 2: Literature Review

Introduction

Postsecondary faculty do not provide DITDWF to students, even though both students and faculty highlight these feedback qualities as integral to learning (Crisp & Bonk, 2018; Dawson et al., 2018; Rios et al., 2018). The purpose of this study was to examine the perceived attributes of diffusion of innovation theory that predict postsecondary faculty adoption of text expander technology, which can support faculty in providing DITDWF to students. As online enrollment in higher education institutions continues to increase, so does the need for research around online course facilitation (Martin et al., 2019), which contributes to the relevance of the problem. The importance of feedback to learning is well documented in the literature, but questions remain about the attributes of effective feedback (Ossenberg et al., 2019), whether that feedback is delivered in a face-to-face or online learning environment. In addition, little research exists about innovative tools that postsecondary faculty use to provide digital written feedback, and most research surrounding instructional feedback is focused on the student perspective rather than faculty perspective (Clark-Gordon et al., 2019). According to multiple researchers (Clark-Gordon et al., 2019; Martin et al., 2019; Winstone & Carless, 2020), problems related to improving feedback processes are both current and relevant in higher education.

In the following literature review, I develop a case for examining the attributes of diffusion of innovation theory that predict postsecondary faculty adoption of text expander technology, which can be used to support faculty in providing digital written feedback to students. The chapter opens with the literature search strategy, which contains a summary of the search process and sources for the study. Next, the theoretical foundation section includes an overview of Rogers' (2003) theory of innovation diffusion and its connection to the current study. Finally, a review of the literature related to feedback, digital feedback, technology adoption, and text expander technology is presented. Discussion of the role of feedback in online course facilitation, the attributes of effective feedback, student and faculty perceptions of feedback, the role of digital written feedback in online learning, and the use of text expander and comment bank technology to deliver feedback provide a foundation for the study.

Literature Search Strategy

I searched for relevant literature in the following Walden University Library databases: Academic Search Complete, APA PsycInfo, CINAHL Plus with Full Text, Cochrane Database of Systematic Reviews, Communication & Mass Media Complete, Computers & Applied Sciences Complete, Education Research Complete, ERIC, MEDLINE with Full text, ProQuest Dissertations and Theses Global, PsycARTICLES, PsycBOOKS, Research Starters Education, ScienceDirect, SocINDEX with Full Text, and Teacher Reference Center. Key words for the database search included *feedback, distance education*, *distance learning, online learning, online education, digital feedback, digital written feedback, electronic feedback, e-feedback, faculty perception, student perception, instructor presence*, *teaching presence, effective feedback, faculty adoption*, *faculty technology adoption, faculty innovation*, *text expander*, *text replacement, statement bank feedback, comment bank, feedback bank, Turnitin, GradeMark, QuickMark*, *SpeedGrader, semi-automatic marking, electronic marking,* and *digital marking*. The number of results varied from 796 for *effective feedback* to two for *statement bank*, and I identified seminal works dating to 1978. For some searches, I limited to full-text and peer-reviewed results, and for others I limited to works published since 2005 or works published since 2016. Aside from the Walden Library, I searched for relevant literature using Google Scholar as a search engine to identify seminal studies and studies outside of the Walden databases. I used citation chaining to identify seminal resources and further resources for review and closely read abstracts to determine the literature to be included in the review. Inclusion criteria included relation to higher education, college students, and postsecondary faculty.

Theoretical Foundation

The diffusion of innovation theory developed by Rogers (2003) exists to help explain and predict the spread of ideas through networks and organizations. Rogers originally published the theory in the early 1960s, following decades of diffusion research in anthropology and agriculture. Diffusion research is especially relevant to organizations such as educational institutions, as these are systems that often have clear communication channels and relation to innovation adoption. There are several branches of innovation diffusion theory, including the innovation-decision process, adopter categories, diffusion networks, change agents, and attributes of innovation and their relation to rate of adoption.

Innovation-Decision Process

The innovation-decision process revolves around the stages that individuals move through when adopting innovations. The knowledge stage involves awareness of the innovation or exposure to it, whereas the persuasion stage involves seeking out or being presented with information that leads to a positive stance regarding the innovation (Rogers, 2003). Individuals then move into the decision stage and the implementation stage, where they respectively decide whether or not to adopt the innovation and then adopt the innovation as is or attempt to adapt it to their needs (Rogers, 2003). Finally, individuals move into the confirmation stage, where they determine the usefulness of the innovation and whether using it should be sustained. A separate branch of the theory of innovation diffusion relates to adopter categories.

Adopter Categories

In addition to an individual decision-making process, Rogers (2003) also determined categories of adopters based on how soon they adopted an innovation. The categories of adopters include innovators, early adopters, early majority adopters, late majority adopters, and laggards. According to Rogers, the adoption of innovations within a given society follows an *s*-shaped curve with innovators and laggards at the respective ends of the *s*. While personal characteristics such as empathy, intelligence, and dogmatism affect adopter category, so do communication behavior and socioeconomic status. In general, research regarding adopter categories is used to inform innovation communication and marketing to various audiences.

Diffusion Networks

Besides detailing the individual characteristics of innovation adopters, Rogers (2003) identified elements of diffusion networks that encourage the diffusion of innovations. As an example, Rogers found that opinion leaders, who informally rather than formally motivate individuals to adopt innovations, can lead to increased adoption of innovations, particularly if the social norms and opinion leaders accommodate change. Another important aspect of diffusion networks is critical mass, which is the point when an innovation becomes self-sustaining because enough individuals within the system have adopted it. According to Rogers, analyzing and using the communication network within a system is essential to diffusing innovations within the system.

Change Agents

Rogers (2003) also identified change agents, who are agents from a change agency who attempt to influence individuals to change, as having important roles within the diffusion of innovation. While change agents' positions between clients and a change agency can be problematic in influencing change because change agents are often not fully part of a system, change agents can influence adoption by establishing the need for change to clients and helping clients change intentions into action, as well as by helping to prevent abandonment of the innovation (Rogers, 2003). In addition to individual and network characteristics, various attributes of an innovation can also influence adoption rates.

Attributes of Innovation

Attributes of innovation are characteristics of an innovation that predict the rate of adoption—or the rate at which individuals within a social system adopt an innovation. Rogers (2003) characterized five attributes of adoption, including relative advantage, compatibility, complexity, trialability, and observability. Individuals' perception of these attributes as they relate to an innovation affects the overall adoption rate of the innovation.

Relative Advantage

The relative advantage of an innovation relates to how much individuals perceive the innovation as an improvement over existing ideas or technology and positively relates to innovation adoption rate (Rogers, 2003).

Compatibility

According to Rogers (2003), the compatibility, or "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters" (p. 266), also positively affects the rate of adoption.

Complexity

In contrast to relative advantage and compatibility, the perceived complexity of an innovation—how difficult it is perceived as being to use and comprehend—relates negatively to the rate of the adoption.

Trialability

The trialability of an innovation relates to how simple it is for an individual to use it on a trial basis and relates positively to the rate of adoption.

Observability

Finally, the observability of an innovation, which relates to how visible the results of the innovation are to others, also relates positively to the rate of adoption for an innovation. While all the above branches of theory provide useful information about innovation adoption and diffusion, the focus of this study was on the perceived attributes of innovation and how they affect the adoption of text expander technology to provide digital written feedback.

Assumptions

Using the theory of innovation diffusion for a study led to several assumptions, including that analyzing the characteristics of an innovation can predict the adoption rate. Notably, an underlying assumption of the theory of innovation diffusion was that innovations solve problems once adopted. However, there are numerous examples of innovations adopted within a system through the work of change agents or other forces that resulted in unintentional harm to the system (Rogers, 2003). While innovations can solve some problems or some aspects of problems, it is important to fully understand the system and the system network when advocating for the adoption of an innovation to ensure that adoption of the innovation does not lead to unforeseen problems (Rogers, 2003).

Technology Adoption and Innovation Diffusion

Although there are no technology adoption studies that specifically relate to text expander applications, there are multiple such studies that relate to other e-learning systems and innovations. In a broad study of new technologies used for feedback and assessment, Deeley (2017) found that adoption of new technology can lead to more effective assessment and feedback. Furthermore, Sutton and DeSantis (2016) selected Rogers' (2003) innovation diffusion theory as one part of a three-part model for guiding faculty in adopting innovations, which aids in making the case for its use in studies of innovation adoption in higher education. More specifically, Chang et al. (2016) found that improvements in Rogers' perceived characteristics of innovation positively affected faculty's willingness to continue using an e-learning system. In the study of faculty adoption of text expander applications, the goal was to determine whether perceived attributes, or characteristics, of innovation positively affect faculty's adoption of text expander applications.

Different technologies have different determining attributes of innovation, but compatibility as a key attribute of innovation adoption is present throughout the literature. An early study of adoption of electronic editing highlighted compatibility and ease of use as determining factors in adoption (Dayton, 2004). A literature review of factors that influence information and communication technology adoption in higher education reinforced findings in an earlier study (Dintoe, 2018) and highlighted the importance of technology compatibility via Rogers' (2003) diffusion theory (Dintoe, 2019), which provides the impetus to examine whether or not the compatibility attribute of innovation also affects faculty adoption of text expander applications. Daouk and Aldalaien (2019) identified a gap in the research in understanding the Rogers' innovation diffusion factors that affect diffusion of technology through faculty in higher education and conducted a study to determine that relative advantage and compatibility had a positive impact on diffusion of instructional technology. In contrast, Chan et al. (2016) found that compatibility and trialability positively affected faculty adoption of audience response systems in higher education, which demonstrates that different technological innovations may have different innovation attributes that encourage adoption. A similar study was warranted to determine the attributes of innovation that predict faculty adoption of text expander applications.

Besides providing information about the attributes of innovation that encourage adoption for text expander applications, the study also provided information that will aid in training faculty in the use of innovative technology. In a literature review of 148 articles, Burch and Mohammed (2019) discovered a gap in faculty involvement in adoption processes in higher education, which confirms the need for more studies of technology adoption processes from the perspective of faculty. In addition, Reid (2017) argued that the current use of training and information supports faculty who have already decided to try a technology but not those who do not have general awareness of a technology and recommended walking faculty through Rogers' innovation attributes such as compatibility and relative advantage in relation to a technology innovation; this study aided in illustrating the perceived attributes of text expander applications and thus fills a gap in the literature about this innovative technology. While Shelton (2017) argued for the need to continue to study existing technologies as well as new technologies, the author confirmed the importance of continuing to study the adoption of new technologies in higher education. Overall, a study of innovation attributes that predict faculty adoption of text expander applications was warranted by a gap in the literature surrounding technology adoption in higher education.

Rationale

The field of education has been an important component of innovation diffusion research. The tradition of diffusion research in education trends toward the study of organizational decisions in adopting innovations, as organizational structures are often an aspect of adoption in an education setting (Rogers, 2003). Some seminal education diffusion studies include the study of the spread of modern math among school administrators, the diffusion of kindergarten, and local school control relation to innovation, and Rogers noted that diffusion studies are often used in the graduate education setting for doctoral dissertations.

There are four main elements of innovation diffusion theory, which include attributes of the innovation, communication channels, time, and the social system (Rogers, 2003). Many studies focus on one or two of the branches of innovation diffusion theory to provide avenues for future research in other branches. A study of the perception of innovation attributes aided in generalizing information about text expander technology that can be expanded in future studies of communication channels, time, and social systems related to the use of text expander technology. The attributes of innovation include relative advantage, compatibility, complexity, trialability, and observability, and perceptions of these attributes predict the adoption rate of an innovation (Rogers, 2003), which relates directly to an overarching research question for this study: What attributes of innovation predict postsecondary faculty adoption of text expander technology? This research question builds upon existing theory in determining whether the theory of innovation diffusion holds for the adoption of text expander technology, and answering the research question also aids administrators and other individuals in higher education in determining messaging approaches regarding text expander technology. Specific perceived attributes of the innovation may influence the rate of adoption, and these findings can be used to inform faculty messaging, training, and resources. Rogers' (2003) innovation diffusion theory is a theoretical foundation that allows for the study of innovative tools that postsecondary faculty use to provide digital written feedback.

Literature Review Related to Key Variables

Feedback is a sprawling category within the literature in higher education. A paradigm shift from focusing on the transmission of feedback to focusing on the interactions arising from feedback complicates the literature but does not lessen the need for more studies focused on tools and techniques to improve the feedback process in higher education (Winstone & Carless, 2020). Therefore, this literature review focuses on the overarching role of feedback, particularly within a community of inquiry (CoI) framework, as well as the new paradigm of feedback, and then funnels to the discussion of the attributes of effective feedback according to the literature. A discussion of the literature related to feedback perception and digital feedback follows. Finally, the review focuses on the discussion of text expander applications in feedback and highlights a gap in the literature.

Role of Feedback

Feedback plays an important role in the learning process of students in higher education. While the term can be defined in multiple ways, feedback is often described as information provided by an agent, whether that is a peer or teacher, regarding characteristics of understanding or performance (Hattie & Timperley, 2007). Sadler (1989) argued that feedback can only be considered feedback if it aims to close the gap between actual and reference levels of performance. According to Hattie and Timperley's (2007) seminal study, feedback has an outsized potential to affect student achievement. In a recent meta-analysis of 435 studies surrounding the effects of feedback on student learning, Hattie confirmed the importance of feedback for cognitive and physical outcome measures but found feedback less important for motivation and behavior (Wisniewski et al., 2020). In addition, Martin et al. (2019) interviewed eight award-winning U.S. faculty and highlighted the importance of feedback in outstanding instruction. Besides being important for student achievement (Black & William, 1998; Hattie & Timperley, 2007; Henderson et al., 2019; Sadler, 1989; Wisniewski et al., 2020), feedback is crucial to establishing instructor presence in a CoI.

Community of Inquiry

The CoI framework, despite having been developed in the early 2000s, is consistently hailed as the most recent, relevant, and commonly used framework in designing engaging experiences in online education (Bozkurt, 2019; Castellanos-Reyes, 2020; Valverde-Berrocoso et al., 2020). The CoI framework consists of three elements that are necessary to an educational experience, including cognitive presence, social presence, and teaching presence (Garrison et al., 2000). While cognitive presence aligns with the learning taking place in the environment, social presence relates to the ability to feel a connection in the environment, and teaching presence relates to the design of the experience and facilitation of the experience (Garrison et al., 2000). While teaching presence is sometimes split from instructor presence in the discussion of online course facilitation (Richardson et al., 2015), research indicates that feedback is important in both online and blended education (Arghode & Brieger, 2018; Martin et al., 2020; Thomas et al., 2017). Rios et al. (2018) listed prompt feedback as one of the determining factors of teaching presence in maximizing online student satisfaction. In addition, according to d'Alessio et al. (2019), instructors who provided less feedback led to students earning lower grades and led to decreased social presence, so feedback can affect social presence as well as teaching presence in a course. While Cole et al. (2017) found that a negative predisposition toward instructor feedback could negatively affect student motivation, the authors did not draw the conclusion that feedback is not important in the online setting but rather emphasized that care must be taken in assuming that students taking online courses actively desire a direct translation of an environment to an online environment. While the importance of feedback to student learning in higher education is not contested, perception of the role of feedback in higher education is undergoing a shift.

Feedback Paradigms

Many past studies have operationalized feedback as input—that is, the transmission of data from instructor to student or student to student (Sadler, 1989), but perception of the role of feedback is evolving from a transmission-focused old paradigm to an interaction-focused new paradigm (Winstone & Carless, 2020). In a seminal article, Boud and Molloy (2013) argued the importance of students driving learning and feedback instead of instructors. Focusing on what happens after feedback is provided rather than only on the transmission of feedback represents an important shift in the discussion surrounding the role of feedback in higher education. Multiple authors have found that students must be able to apply feedback to future tasks for it to be useful (Boud & Molloy, 2013; Sadler, 1989; Winstone et al., 2017), which makes feedback an important aspect of course design as well as instructional practice and aligns with the teaching presence aspect of the CoI framework. Use of innovative technology can contribute to implementation of the new paradigm, as long as the tool use is focused on facilitating student uptake of feedback rather than solely on transmission of feedback (Winstone & Carless, 2020). Wisniewski et al. (2020) also found that the effects of feedback vary based on the type of feedback transmitted, so operationalizing the term *effective* as it relates to feedback aids in laying a foundation for the use of innovative technology to design and deliver feedback.

Effective Feedback

While feedback in general has been established as an important component of the learning experience in higher education, questions remain about the attributes of feedback that encourage student uptake and application of feedback. While timeliness and individualization are consistently regarded as characteristics of effective feedback in the literature (Ossenberg et al., 2019), the inclusion of detail as an attribute of effective feedback is less supported (Wei & Yanmei, 2017). However, synthesizing the literature led to the adoption of *timely*, *individualized*, and *detailed* as attributes of effective feedback that demonstrate the need for use of innovative technology in feedback practices in higher education.

Detailed

Detailed feedback can aid students in understanding and applying instructor feedback. Based on the current literature, the term *detailed* is used to refer to both the specificity and outcome-based nature of feedback as well as the level of description in defining how students can improve rather than solely pointing out errors or issues. While the chosen term for this study is *detailed*, there are many other terms with similar descriptions that are used throughout the literature; for example, Qureshi (2017) argued that feedback in medical education should be positive, outcome based, measurable, relevant, and descriptive, and *descriptive* as a term is similar to *detailed* in that feedback should be specific and precise. Seden and Svaricek (2018) also described effective feedback as descriptive, which can be viewed as a parallel to detail in feedback. Another term that appeared in the literature that is similar to detail is *specific*. For example, Reimann et al. (2019) found that effective feedback—or feedforward—moves beyond the task at hand to other aspects of the program or projected role. Indeed, illustrating the application of feedback beyond a single module to other parts of the educational program and beyond the program is an important aspect of the new paradigm of feedback, but this type of feedback would require familiarity with programs and a specificity that could be difficult to capture consistently (Reimann et al., 2019). Winstone et al. (2016) also found that learners preferred specific feedback, although the authors believed that instructors should both provide specific feedback and encourage students in developing agency with dialogic feedback. In addition, Wisniewski et al. (2020) found that high-information feedback is most effective across 435 studies, and high information is closely related to detail as a descriptor. Overall, the term *detailed* is used as an umbrella term for different aspects of specificity, descriptiveness, and level of detail.

Despite the varying use of terms in the literature, multiple researchers described effective feedback as detailed (Cohen & Singh, 2020; Gredler, 2018; Helfaya, 2018; Lowe & Shaw, 2019; McGrath & Atkinson-Leadbeater, 2016; Mulliner & Tucker, 2017; Singh, 2016). Mauri et al. (2016) found the level of detail and the prompt delivery of feedback to be the most prevalent indicators of effectiveness. Petrović et al. (2017) found that providing detailed feedback improved learning outcomes more than providing the answer to a problem. In another study, students considered detailed feedback more important than timeliness, and for some students it was the only important aspect of feedback (Dawson et al., 2018). Rios et al. (2018) also listed detail and timeliness of feedback as two of the most important factors of agency and assessment within online course facilitation. Finally, Mulliner and Tucker (2017) found that detail was an important component of students' positive perception of feedback. While most of the research that included study of detailed feedback was positive, there were outliers. As an example, according to Wei and Yanmei (2017), instructors altered their feedback practice away from providing detailed comments because students did not apply it, but the authors cautioned that this may have been because the assessment design did not allow for application of feedback. While assessment design is also an integral part of the feedback process, the level of detail and specificity of feedback contribute to the effectiveness of feedback.

Individualized

The literature strongly supports the inclusion of *individualized* as an attribute of effective feedback (Cohen & Singh, 2020; Cox et al., 2015; Torres et al., 2020). In the context of this study, individualized feedback is specific to a learner's needs, goals, and questions (Crisp & Bonk, 2018). Dawson et al. (2018) found individualization of feedback to be important for both students and educators. Studies of English as a Foreign Language learners and English Second Language learners revealed that students preferred feedback that considered individual differences (Chong, 2020; Qutob & Madini, 2020).

Franc and Morton (2020) also found that feedback for language assessment should be personalized. In addition, Crisp and Bonk (2018) reviewed eight learner-centered instructional models and identified the six dimensions of feedback to be timeliness, frequency, distribution, source, individualization, and content. Cohen and Singh (2020) surveyed 179 students at a private higher education institute and found that effective feedback is individualized and expansive—i.e., detailed. Furthermore, in a scoping review of 61 studies, Ossenberg et al. (2019) found that effective feedback is responsive to the learner's needs and preferences, which can be interpreted as individualized to the learner. Finally, Torres et al. (2020) conducted a systematic review of 379 articles and found that personalized, contextual, dialogic feedback enhances students' self-perception; while the authors believed that specific quality indicators could not be determined, they identified tailoring feedback to students' needs as most important. While Henderson et al. (2019) argued that effective feedback practices cannot necessarily be transferred from one educational context to another, the authors specifically mentioned that feedback design should be tailored to the different needs of learners, which is in line with other findings that individualization of feedback as important. Planar and Moya (2016) also detailed the importance of personalizing feedback to students but mentioned as a barrier the current educational context of high student-instructor ratios, which aids in making the case for the use of innovative technology to individualize feedback.

Timely

Multiple researchers have discussed effective feedback as timely feedback (Al-Hattami, 2019; Crisp & Bonk, 2018; Helfaya, 2019; Ianos, 2017; Mauri et al., 2016; Mulliner & Tucker, 2017; Ossenberg et al., 2019; Rios et al., 2018; Seden & Svaricek, 2018; Zimbardi et al., 2016). In the context of this study, timely can refer to promptness and also to the appropriate timing within a learning cycle—that is, not too late to be applied to the next task (Winstone & Carless, 2020). For feedback to be usable, it must be presented before the student submits the next task in the same line of assessment. For example, feedback provided early in a learning cycle can be more effective than feedback provided at the end of the cycle (Wei & Yanmei, 2017). In a review of 70 studies, Haughney et al. (2020) determined that feedback should be specific, timely, positive, and encourage active engagement. In addition to finding that feedback should be understandable and outcome based, Graham (2015) argued that feedback should be delivered promptly. Few researchers discussed the timeliness of feedback as a negative trait. As a contrasting viewpoint, Lefevre and Cox (2017) found that delayed feedback can increase subsequent learner performance in some multiple-choice assessment learning contexts, but the authors also found that the overwhelming majority of students preferred immediate feedback and cautioned that delayed feedback without appropriate rationale would lead to decreased motivation. In sum, the importance of timeliness to effective feedback was a theme throughout the literature that intersected multiple studies.

Other Considerations

The three selected attributes of effective feedback intersected multiple studies in the current educational research landscape. However, other terms were closely considered but finally rejected. As an example, multiple researchers found that effective feedback is usable or understandable (Graham, 2015; Winstone et al., 2017), but *usable* is a broad term and is not as specific as *detailed*. For the purposes of this study, *detailed* is used, but *usable* may be considered as a broader umbrella that includes detail. In addition, *positive* as an attribute of effective feedback (Al-Bashir et al., 2016; Pitt & Norton, 2016; Richardson et al., 2016), wherein *positive* refers to tone and lack of evaluation or judgment, was present in some studies but not others (Mulliner & Tucker, 2017). There was enough disparity in the literature to prevent the inclusion of *positive* as an attribute in this study, although this term may be an area for further research and discussion. While providing consistently positive feedback can be achieved with the use of innovative technology, positive feedback was not the focus of this study.

The attributes of effective feedback, which include detail, individualization, and timeliness, set the stage for discussion of the perception of feedback by both faculty and students in higher education. The disparities in student and faculty perception of feedback, as well as the perceived barriers to providing detailed, individualized, and timely feedback, create a backdrop for discussion of innovative technology that can be used to improve feedback practices.

Perceptions of Feedback

While faculty and students generally agree on the importance of feedback (Al-Hattami, 2019; Menke & Anderson, 2019), they sometimes have differing perceptions of the use and quality of provided feedback (Mulliner & Tucker, 2017). Mulliner and Tucker (2017) found that while 93% of instructors were satisfied with the feedback provided, only 63% of students were satisfied with the feedback they received, and this general ratio held for student and faculty's perception of the usability of feedback, the specificity of feedback, and the fairness of the feedback. The most egregious gap between student and faculty perspective was that of providing detailed feedback (Mulliner & Tucker, 2017). In addition, students often prefer more feedback than instructors provide, while instructors provide less feedback to encourage learner agency (Atmaca, 2016). Moreover, while online students often believe that faculty do not provide feedback soon enough (Huss & Eastep, 2015; Mulliner & Tucker, 2017), instructors place the blame for poor online experiences on students neglecting their responsibilities in the online classroom (Huss & Eastep, 2015). There is consensus on the role of feedback in learning from both a student and faculty perspective, but there is a dearth of research on faculty perceptions of feedback and feedback processes.

Student preferences for feedback sometimes do not align with instructors' preferences or ability to provide feedback. Students tend to prefer detailed, individualized, and timely feedback (Best et al., 2015; Gredler, 2018; Lowe & Shaw, 2019) and also prefer detailed feedback both for strengths and areas of improvement (Pitt

& Norton, 2016). Torres et al. (2020) found that students considered on-time feedback as exceptional, which they identified as an issue to be addressed in further research. Both students and faculty see timeliness of feedback as *very important* (Mulliner & Tucker, 2017). However, providing the type of feedback that encourages learning is draining and time consuming for teachers (Crimmins et al., 2016; Joyce, 2019; Krishnan, 2016; Law, 2019; Planar & Moya, 2016; Sopina & McNeill, 2015). Instructors acknowledge difficulties with the marking process and desire training and new feedback processes (Norton et al., 2019). Finally, according to multiple researchers, there is not enough research addressing faculty perspectives of feedback (Chang et al., 2018; Clark-Gordon et al., 2019; Ene & Upton, 2018; Martin et al., 2019; Norton et al., 2019; Planar & Moya, 2016; Seden & Svaricek, 2018), and the research that does exist points to faculty's understanding of the need for detailed, individualized, and timely feedback but also to the reality of high workload and time constraints. Research on the use of innovative tools that faculty can use to provide DITDWF contributes to the literature surrounding feedback in higher education.

Digital Written Feedback

Another important aspect of feedback is whether the form of feedback affects its role or import in learning. Throughout the literature, researchers used the terms *digital* and *electronic* interchangeably in discussing digital written feedback, so the original term used by the researcher for each study has been preserved throughout. Overall, the literature points to a preference for digital written feedback over handwritten feedback, as well as improved learner outcomes with the use of digital written feedback.

Learner Outcomes

Based on the literature, the use of digital written feedback tends toward positive effects on student learning outcomes. Farshi and Safa (2015) and Johnson et al. (2018) found electronic feedback to be better at developing learners' skills than handwritten feedback. Ene and Upton (2018) discovered that asynchronous electronic feedback improved students' uptake of feedback compared to synchronous electronic feedback. Chong (2019) found that electronic feedback was more conducive to the type of dialogic feedback that increased feedforward and transfer and increased the motivation of students to read and apply instructor feedback. In addition, Wisniewski et al. (2020) found in a meta-analysis of 435 studies a tendency toward written feedback improving student outcomes but could not fully confirm it based on the parameters of the review. More research is needed in this area, but what research exists tends to point towards positive outcomes for the use of digital written feedback in higher education.

Preferences

Students preferring electronic written feedback was a theme in multiple studies and literature reviews (Chang et al., 2018; Chong, 2019; Ene & Upton, 2018; Qutob & Madini, 2020; Singh, 2016). According to Ene and Upton (2018), both instructors and students had positive perceptions of electronic feedback. Hast and Healy (2016) also found that students preferred electronic methods of submitting assignments, accessing feedback, and reading feedback, with convenience being a strong factor in their preferences. In a similar manner, McGrath and Atkinson-Leadbeater (2016) found a strong preference for electronic written feedback because students felt it was more legible, accessible, and convenient, and students liked that it encouraged more feedback from instructors. The convenience of electronic feedback was a strong factor for preference in Chong's (2019) study as well. Johnson et al. (2018) also found that instructors provided more feedback using electronic methods. McGrath and Atkinson-Leadbeater (2016) cautioned instructors against the use of Track Changes in Microsoft Word to simply edit the student's paper and instead encouraged detailed marginal comments, as editing in Track Changes did not encourage feedforward and application in future projects, which highlights the need for support in providing detailed feedback to large numbers of students. Sopina and McNeill (2015) found that with a few exceptions due to eye strain, both students and markers preferred digesting and providing electronic feedback. In another study that considered instructor preferences, Clark-Gordon et al. (2019) determined that instructors preferred digital written feedback because it allowed instructors to better personalize or individualize feedback—a hallmark of effective feedback—in addition to making the feedback more available and accessible to students.

Some studies of feedback type preference did not have clear takeaways. While Lowe and Shaw (2019) did not identify a strong preference for mode of delivery for feedback, students did value the legibility of written feedback. Another study concluded with mixed results, with some participants embracing the use of electronic feedback and others finding difficulty in implementation; however, the authors cautioned that this may be because optimizing a new feedback system takes time (Kennard & Arnold, 2016). Likewise, Ryan et al. (2019) determined that students preferred electronic annotations, but they most preferred receiving multiple modes of feedback. Sopina and McNeill (2015) found electronic marking to be a sufficient method of feedback delivery rather than identifying a strong preference and also found that use of electronic marking improved speed and consistency for faculty.

However, some researchers have identified a student preference for face-to-face feedback, even though electronic feedback improved uptake (Ene & Upton, 2018; Osterbur, 2015). Furthermore, while Nistor and Comanetchi (2019) found that students viewed electronic written feedback as complementary but not a substitute for face-to-face interactions, the instructor interviewees mentioned that electronic feedback can be better personalized and organized. Moreover, Alharbi (2017) found that 61% of students preferred video feedback, and 21% of students preferred written feedback. However, it is important to note that video feedback is time consuming for instructors and can lead to accessibility issues in the online classroom. In addition, Winstone and Carless (2020) warned against leaning too heavily on student preferences, as sometimes student preferences do not align with appropriate learning outcomes, so it is important to view these results against the current literature that supports digital written feedback as improving learning outcomes. Taken together, the literature shows that students both prefer and benefit from digital written feedback, and this finding highlights the need for more studies about innovative tools that instructors can use to improve digital written feedback processes.

Text Expander Applications

Text expander applications are software programs that allow the user to type predetermined snippets of text that are then expanded to longer phrases and resources. An example of a text snippet might be */thesis*, which once typed, would expand to a full-fledged comment with a definition of the thesis statement and resources to help with thesis statements that the instructor could then individualize for the specific context and learner needs. George-Williams et al. (2018) determined that using automatic marking decreased marking variation and simplified the marking process, and while text expanders are not fully automated feedback, the pre-written commentary can aid in achieving the same goals. Another issue with digital written feedback is the absence of the verbal cues present in face-to-face interaction (Clark-Gordon et al., 2018; Nistor & Comanetchi, 2019). Clark-Gordon et al. (2018) found that face-threat mitigation strategies such as a warm and encouraging tone in digital written feedback were more effective than nonverbal communication cues such as instructor profile pictures and text-based emojis. One benefit of text expander applications, aside from increased speed in marking, is that an instructor can develop feedback with a warm tone that can be deployed independently of other factors such as grading load and mood that might affect an instructor’s tone when providing digital written feedback.

Text expander applications, examples of which include aText, Breevy, PhraseExpress, and TextExpander, are distinct from comment bank applications such as Microsoft Word AutoText and QuickMark in that they can be used in most contexts and were not originally developed for educational purposes. AutoText only works within the Microsoft Word application and has several other important limitations in its use in an educational context (Mandernach, 2018), and QuickMark is part of Turnitin and not as useful outside of this context. However, text expander applications can expand text in word-processing applications, learning management systems, email, and other contexts, making them more flexible and adaptable to learner and instructor needs. There are no studies about specific text expander applications; instead, there are multiple studies about the general benefits of text expander applications. In addition, many of the studies relating to comment or statement banks are general or involve preset comment banks from plagiarism detection systems or grading systems such as Turnitin. Several gaps in the literature exist in relation to the topic of text expander applications.

Educational Comment Bank Applications

Some educational plagiarism detection software includes online marking assistance in the form of preset comment banks or automatic marking that instructors can use when providing feedback. According to the literature, these programs have both strengths and weaknesses. Reed et al. (2015) praised the use of GradeMark and QuickMarks in supporting learning analytics around student outcomes, as use of systems such as this can help ensure the consistency of marking. In addition, Krishnan (2016) recommended QuickMark as a time-saving and efficiency tool to provide comprehensive feedback that students prefer. Hast and Healy (2016) found that students preferred Turnitin feedback for submission, access, and reading of feedback over paper-based methods. In contrast, while Buckley and Cowap (2013) reported largely positive faculty experiences with implementing GradeMark and QuickMarks to provide feedback, faculty identified some assignments as easier to mark online than others and also mentioned other areas for improvement with the program. In a similar manner, Henderson (2016) recommended GradeMark for its automation of the marking process, reduction of repetitive processes, and time-saving functions, but also found that there were issues with the system timing out.

Similarly, while Penn and Wells (2017) argued that the use of QuickMarks, which are preset comments in the system, can connect explicitly to marking criteria, ensure that feedback is consistently neutral, and decrease idiosyncratic marking, in addition to supporting the provision of high-information feedback when there are limited resources, the authors cautioned against using the preset QuickMarks without individualizing them, as students tend to ignore generic comments. Watkins et al. (2014) found that use of GradeMark improved the timeliness and accessibility of feedback but could not confirm improvement in quality and consistency of feedback. Chang et al. (2018) also described the time-saving nature of e-feedback systems such as Markin and Emended but mentioned possible problems with these systems not being flexible and adaptable to instructor and student needs. These issues can be avoided by using text-expander applications that allow for flexibility and adaptability in how and where the applications are used. In contrast to other studies, Kostka and Maliborska (2016) argued that the arrangement of comment sets in QuickMarks can lead to lengthy timelines for instructors to find and employ QuickMarks to students. Overall, even with the use of QuickMarks, the time to grade student papers can be considerable (Law, 2019), which points to a need for further efficiencies in providing digital written feedback. Finally, Krishnan (2016) mentioned giving presentations to colleagues to encourage faculty adoption of QuickMarks as a feedback tool, which highlights the need to further explore faculty adoption of innovative tools to provide digital written feedback.

Comment Bank and Text Expander Applications

Multiple researchers recommended text expander applications to accelerate the grading process (Adams, 2017; Campbell, 2016). Haughney et al. (2020) reviewed 70 studies on feedback and determined that automated feedback could save both time for educators and money for institutions and reported a need to research untested tools. Based on the determination that effective feedback is individualized and timely and that instructors need to create efficiencies in providing effective feedback, Graham (2015) recommended the use of comment bank technology to reduce the amount of time required to provide feedback. Joyce (2019) specifically mentioned text expander applications when providing tips and tricks for providing efficient and effective feedback to students and argued that text expanders are an updated version of using comment banks in Microsoft Word. In addition, Al-Bashir et al. (2016) encouraged instructors to recycle comments that they find themselves repeatedly making and recommended specialized software such as text expander applications. Finally, Mandernach (2018) explicitly discussed the benefits of using text expander applications over Microsoft Word AutoText and pointed out both efficiency gains and the ability to quickly provide detailed and individualized feedback as benefits of faculty adopting text expander applications to provide feedback. Overall, while individualizing feedback is one benefit of text expanders, the literature mainly supports the use of text expander applications in higher education as a method of providing detailed and timely digital feedback to students.

There are few studies about how statement bank technology affects learning, but Denton and McIlroy (2018) found in a study of 161 students that students can learn from the feedback generated from statement banks. However, in order to do so, students must be assessment literate and the assessment design must allow for use of the feedback (Denton & McIlroy, 2018). In an earlier study, Denton and Rowe (2014) found that transmission-based statement bank feedback did not enhance the subject knowledge of student participants. These results are in line with Winstone's (2020) findings in regard to the need for students to be able to use feedback for it to be useful within the interaction-based new paradigm of feedback. Denton and McIlroy (2018) recommended a study with a broader scope regarding statement bank feedback, which relates to the current study's aims. Based on the literature, the use of text expander applications aligns with positive educational outcomes when used to create interaction-based and dialogic feedback, and text expander applications can be used to create efficiencies in providing DITDWF to students. While multiple researchers called for the use of text expander applications to create efficiencies in providing feedback, little is known about the frequency of adoption of text expander applications and perceived attributes of the tool that encourage adoption. Indeed, most research that exists within these parameters concerns tools that can only be deployed within specific contexts, such as QuickMark or other semi-automatic educational feedback systems. Therefore, there is a need for broader studies about the frequency of adoption of text expander applications and the attributes of the tool that encourage adoption.

Summary and Conclusions

Only six of the 98 studies in this literature review addressed the use of text expander applications to provide feedback in higher education (Adams, 2017; Al-Bashir et al., 2016; Campbell, 2016; Graham, 2015; Joyce, 2019; Mandernach, 2018). While these studies provided arguments and exemplars for the use of text expander applications to provide detailed, individualized, and timely digital feedback, none of the studies addressed frequency of adoption or attributes of innovation that predicted adoption. In addition, each of these studies arose from faculty practice and included qualitative data rather than quantitative data. Despite the encouragement by practitioners and researchers for faculty to adopt text expander applications to provide digital written feedback, little is known about the frequency of text expander adoption by postsecondary faculty or the attributes of innovation that predict adoption of text expander applications by postsecondary faculty. The review of the available literature illustrates the need for a generalizable quantitative study about the frequency of adoption of text expander applications by postsecondary faculty, as well as an examination of the perceived attributes of innovation of text expander technology that predict faculty adoption. In Chapter 3, I define and describe the research method for my study.

Chapter 3: Research Method

Introduction

The purpose of this study was to examine the perceived attributes of diffusion of innovation theory that predict postsecondary faculty adoption of text expander technology, which can support faculty in providing DITDWF to students. A quantitative approach addressed the research gap, with a survey instrument used to examine perceived attributes of diffusion of innovation theory that predict postsecondary faculty adoption of text expander technology to provide DITDWF to students. In this chapter, I first discuss the research design and rationale. Next, I discuss the methodology, including the population, sampling, recruitment procedures, and instrumentation. Threats to internal and external validity are also defined, as well as ethical procedures and concerns.

Research Design and Rationale

For the study, I employed a questionnaire survey research design and used an online survey to collect data regarding the relationship between postsecondary faculty adoption of text expander technology and the perceived attributes of innovation, which include relative advantage, compatibility, complexity, trialability, and observability, as they pertain to text expander technology. The binary dependent variable was postsecondary faculty adoption of text expander technology, and the nominal independent variables included relative advantage, compatibility, complexity, trialability, and observability. Using a quantitative survey design with the above dependent and independent variables aided in answering the research questions.

The study included two research questions. The first question related to the adoption rate of text expander technology by postsecondary faculty: At what frequency do postsecondary faculty adopt text expander technology? The second question probed the relationship between the rate of adoption and the perceived attributes of innovation: What attributes of innovation predict postsecondary faculty adoption of text expander technology? A quantitative survey design connected directly to these research questions, as quantitative descriptive, nonexperimental survey design allows a researcher to examine frequency and relationships between variables (Burkholder et al., 2016; Frankfort-Nachmias & Leon-Guerrero, 2016; Jhangiani et al., 2019). A quantitative survey design aided in answering the research questions.

There are multiple survey designs, and to answer the research questions regarding attributes of innovation and adoption frequency, a nonexperimental, cross-sectional, structured design was employed. Cross-sectional studies differ from longitudinal studies in that a researcher conducts them at one point in time rather than collecting data over time (Cohen et al., 2018). With the study I examined correlations between variables rather than establishing causal links between variables, which made a one-shot cross-sectional design appropriate. In addition, the study involved a nonexperimental design because there were no interventions associated with the study (Frankfort-Nachmias & Leon-Guerrero, 2016). Thus, there was no control group or experimental group, which indicated a nonexperimental design. Finally, the design was structured because the survey items included closed- rather than open-ended items, as answers on a scale are best suited to examining the relationship between variables. Because the research questions were specific and encompassed questions related to frequency and the relationship between specific variables, a quantitative design was more appropriate than a contextual, open-ended qualitative design.

Survey research aids researchers in measuring behaviors that cannot be observed directly (Burkholder et al., 2016), but there are some time and resource constraints associated with it. The time and resource constraints often relate to survey response rates; few participant responses may make the findings less generalizable to the population (Burkholder et al., 2016; Drew et al., 2008). In addition, developing a reliable and valid research instrument is a lengthy process that includes time developing scales and survey questions, as well as piloting the instrument (Burkholder et al., 2016). If a survey instrument that would provide answers to the research questions does not exist, a researcher would need to factor time to develop and pilot a survey instrument into the research process. An advantage of the study was the use of a validated survey instrument that has been successfully deployed in multiple studies.

Although quantitative survey design has some limitations, it was an appropriate design to study frequency and the relationship between variables and to advance knowledge in the field of higher education. According to Burkholder et al. (2016), a researcher can use a survey to explore previously unexamined topics. Text expander technology as an innovative use of technology in higher education is underexplored, and examining the relationship between variables related to innovation diffusion and the rate or frequency of adoption contributes new knowledge to the field. In addition, survey design allows a researcher to generalize to the population (Creswell, 2009; Jhangiani et al., 2019), which is helpful when little research exists on a given topic. Because use of text expander technology is generally not directly observable, survey research was ideal to examine the relationships between variables that relate to innovation diffusion and the adoption rate of text expander technology. Overall, quantitative survey design aided in answering the research questions and provided an opportunity to advance knowledge in the discipline.

Methodology

In-depth discussion of population, sampling, participant recruitment, instrumentation, and operationalization of constructs is important for transparency and may aid other researchers in replicating this study in future research.

Population

There were 1.5 million postsecondary faculty teaching part or full time in the United States in 2018 (National Center for Education Statistics, 2020). The number and variance in higher education institutions across the United States can create difficulties in random sampling of the population. Using a participant pool such as SurveyMonkey Audience can aid in securing a random sample of large populations. The population of this study included participants from the SurveyMonkey Audience pool who are located in the United States and who currently teach in higher education. Using SurveyMonkey Audience to recruit survey respondents provided access to a pool of over 80 million diverse people (SurveyMonkey, n.d.-a). The use of random sampling of a participant pool increased the generalizability of the study.

Sampling and Sampling Procedures

Probability sampling was used in this study to increase generalizability and ensure equal opportunity for participants to be selected from the population. Probability sampling improves the generalizability of a study because it allows a researcher to estimate how the sample findings will differ from the entire population and therefore reduces sampling error (Creswell, 2009; Frankfort-Nachmias & Leon-Guerrero, 2016). For this study, SurveyMonkey Audience used a random selection algorithm to randomly select participants who met the criteria to complete the study, and instead of being paid upon completion of the survey, SurveyMonkey Audience donated $0.50 to a participant's choice of charity, which helped reduce the number of surveys completed solely for recompense (SurveyMonkey, 2020). Participants were recruited from the two million people who complete SurveyMonkey surveys each day, which ensured current information for the participants, and SurveyMonkey Audience used a double opt-in system and limited survey invitations to respondents to ensure quality data; in addition, SurveyMonkey Audience runs panel calibration studies regularly (SurveyMonkey, 2020). The use of SurveyMonkey Audience aided in generating a quality sample for the study.

Sampling Frame

While the general population for SurveyMonkey Audience includes over 80 million individuals, the sampling frame for this study included only those participants from the participant pool who are located in the United States and currently teach in higher education, which includes college and university instructors. Inclusion criteria included being located in the United States and currently teaching in higher education.

Power Analysis

In order to increase the probability of finding an effect that exists within the population in a study, a researcher should conduct a statistical power analysis (Brysbaert, 2019; Cohen, 1992). Researchers will be less likely to detect true effects and more likely to detect false positives if a study is underpowered (Brysbaert, 2019). Because the statistical analysis for this study included binary logistic regression, there were multiple considerations for a power analysis. The traditional binary logistic regression models rely on an equation of events per variable (EPV) to determine minimal sample size (van Smeden et al., 2019). The EPV refers to the number of samples for each variable included, and researchers have long relied on the research of Peduzzi et al. (1996), who found that the EPV value should be at least 10. In addition, Vittinghoff and McCulloch (2007) found that lower EPVs can produce studies with adequate confidence interval coverage. However, recent research implies that an EPV value of 10 is too low (Bujang et al., 2018; van der Ploeg et al., 2014; van Smeden et al., 2019). Bujang et al. (2018) determined that an EPV of 50 should be used, as well as a formula where $n = 100 + 50i$, wherein i represents the number of independent variables. Likewise, van der Ploeg et al. (2014) found that researchers needed 20 to 50 EPV to provide more accurate predictions. This study includes five independent variables, and thus the sample size would be 50 with an EPV of 10 and 250 with an EPV of 50. Using the formula by Bujang et al. would necessitate a sample size of 350. However, these sample parameters for logistic regression were balanced against a statistical power analysis with G*Power 3.1.9.7.

G*Power can be used to determine sample size for logistic multiple regression (G*Power, 2017; Yenipinar et al., 2019), but the complexity of the analysis creates dependencies for statistical power analysis with G*Power. G*Power includes two procedures to calculate power, a large-sample approximation and an enumeration procedure (G*Power, 2017). For this study, I used an a priori power analysis, as this procedure aids in determining sample size before a study rather than after a study. There are many different methods of calculating sample size, but a general best practice is to balance the level of power, represented by $1 - \beta$, with the level of significance, or alpha, which is represented by α, and with the effect size, often measured using Cohen's *d*; standard deviation in the population can also affect sample size (Kadam & Bhalerao, 2010). The power of a statistical analysis determines the probability of correctly rejecting the null hypothesis and avoiding a Type II error, while the significance level determines the probability of a Type 1 error, or incorrectly rejecting the null hypothesis (Kadam & Bhalerao, 2010). The generally accepted alpha level and power level to determine statistical significance in behavioral science studies are 0.05 and 0.95, respectively (Brysbaert, 2019; Cohen, 1988). Therefore, these levels were adopted for this study.

Using Wald-type enumeration in G*Power, I determined that a sample size of 199 is appropriate for two tails, where $\alpha = 0.05$ and $1 - \beta = 0.95$, for a *z* test, and a sample size of 177 is appropriate for a Demidenko large sample approximation with the same parameters as for Wald-type enumeration for a *z* test. However, the enumeration sample data were used for this study because it increases accuracy for smaller sample sizes. One issue with using G*Power to determine sample size for logistic regression is that the odds ratio, or probabilities of the outcome from two different events, must be defined (Yenipinar et al., 2019), and researchers generally base this statistic on past similar studies. However, text expander program applications have not been measured quantitatively with binary logistic regression, and thus this statistic is an estimate that cannot be fully supported by prior research. For this study, I used an odds ratio of 2.01, which is the average odds ratio that Chan et al. (2016) determined from the statistically significant variables of compatibility (2.45) and trialability (1.57) in predicting faculty adoption of an audience response system using the perceived attributes of innovation. However, because this is an average and estimation, it was important to balance the G*Power analysis for this test against the EPV calculation when determining sample size. Another test that was applied was the χ^2 goodness-of-fit test to determine how well the logistic regression model fit the data; for a medium effect size of .3 with $\alpha = 0.05$ and $1-\beta = 0.95$, a sample size of 220 would have been appropriate. Considering the current EPV best practices and the G*Power analysis for the *z* test and χ^2 test, a sample size of 305 was the mean of the estimates rounded up from 254.75 to 255 plus an additional 50 participants and thus aided in ensuring that the study was not underpowered. According to Brysbaert (2019), researchers should consider sample size estimation as the minimum sample size required rather than the maximum to avoid underpowered studies, and this assertion undergirded the study's sample size.

Procedures for Recruitment, Participation, and Data Collection

Rather than personally collecting data, I relied on the data collection service of SurveyMonkey Audience to complete the study. SurveyMonkey Audience employed a screening process that matched survey participants to study inclusion criteria and then applied a random selection algorithm to send email survey participation invitations; for this study, the participants were located in the United States and currently teaching in higher education. The recruitment procedure involved SurveyMonkey Audience sending email invitations to the millions of people who complete SurveyMonkey surveys daily; there was a double-opt in procedure for consent, and the incentive for completing the survey was donation to a chosen charity rather than payment (SurveyMonkey, n.d.-b). SurveyMonkey Audience automatically collected demographic data, including data about device used to complete the survey, U.S. census region, gender, age, and household income (Lieu, n.d.). When participants complete a survey with SurveyMonkey audience, they do so by clicking a link in the invitation email, opting into the survey to provide informed consent, and then selecting an answer to each survey question; participants were able to exit the survey directly after completing it or at any time during the process. Participants who did not provide informed consent before beginning the survey were not able to take the survey. There were no follow-up procedures for the study, and it was not a pilot study nor an intervention study. In addition, no archival data were used during this study.

Instrumentation and Operationalization of Constructs

Designing a survey instrument involves multiple steps and includes pilot testing, so researchers should always carefully review the literature for an existing instrument that would aid in answering the research question (Burkholder et al., 2016). A validated research instrument exists to examine the perceived attributes to innovation as they apply to innovative technology. Moore and Benbasat (1991) developed an instrument that would measure an individual's perceptions of adopting an information technology innovation. As Rogers (2003) stated, the scale items developed by Moore and Benbasat "can be applied to any particular innovation that is adopted by any set of individuals" (p. 224). Rogers cited the use of the instrument in studies regarding adoption of computer-based delivery of a university course and a computer-assisted counseling innovation to illustrate the wide range of possibilities for use of the instrument. In addition, Chan et al. (2016) used an adapted version of the Moore and Benbasat instrument to determine the perceived attributes of innovation that predict faculty adoption of an audience response system at a nonprofit, private university in the southeastern United States. For this study, Benbasat provided permission to use the Perceived Attributes of Innovation instrument (see Appendix A), and Chan provided permission to use the adapted version of the Perceived Attributes of Innovation instrument, as well as the demographic questions for the study (see Appendix B). The adapted Moore and Benbasat Perceived Attributes of Innovation instrument aided in answering the research questions for this study.

Reliability and Validity

Both the original Moore and Benbasat (1991) instrument and the adapted version of the instrument in the study by Chan et al. (2016) have been validated. Moore and Benbasat originally developed the instrument to focus on perceived attributes rather than primary attributes because perceptions of attributes affect individual behavior; for example, the cost of an item may be a primary attribute, but an individual's perception of the cost of the item related to their salary and disposable income will determine their behavior. The Perceived Attributes of Innovation instrument measures relative advantage, compatibility, complexity, observability, and trialability, and the operationalization of these constructs stemmed from Rogers' theory of innovation diffusion. In addition, the authors added *image*—or enhancement of status—and *voluntariness of use*—or how voluntary use of the innovation is—as constructs for the original study (Moore & Benbasat, 1991). Another important aspect of the Moore and Benbasat instrument is that the constructs relate to perception of use of the innovation rather than just perception of the innovation itself; this is because perceptions of using the innovation are most important to encouraging diffusion. Moore and Benbasat based the development of their instrument on prior research instruments used to examine the perceived attributes of innovation, as well as on instruments based on the technology acceptance model, which has roots in the diffusion of innovations model. Based on past research, Moore and

Benbasat focused on developing valid and reliable scales to measure observability, trialability, relative advantage, and compatibility.

Moore and Benbasat (1991) developed the instrument in three stages to ensure validity, including an item creation stage, a scale development stage, and an instrument testing stage. The instrument testing stage also contained three steps, beginning with a small sample analysis, a second round of pilot testing with more subjects, and then further refinement and field testing. Moore and Benbasat focused on content validity in the first stage by evaluating and eliminating redundant or ambiguous items and construct validity in the second stage by removing the construct labels and having judges develop their own labels for the construct definitions, as well as having judges sort items into construct categories. Much of the second stage was informed by the technology acceptance model's test of construct validity (Moore & Benbasat, 1991). After multiple sorting rounds, Moore and Benbasat divided observability into two different constructs—result demonstrability and visibility—in order to ensure validity and reliability. Moore and Benbasat also tested the inter-rater reliability of the judges' level of agreement and found an average Cohen's Kappa of 0.82 by the fourth sort, which is well over the acceptable threshold of 0.65. In addition, the overall placement ratio of items within the target construct was 92%, which indicates high construct validity and reliability (Moore & Benbasat, 1991).

In the pilot tests, Moore and Benbasat (1991) measured the Cronbach α, which is standard in social science research. The Cronbach α aids in assessing the reliability of scales; the scale ranges from 0 to 1, with higher scores indicating more reliability, and the lowest acceptable reliability coefficient in social science research is generally considered to be 0.70 (Santos, 1999). After two pilot tests and a field test, the authors determined the average Cronbach α as 0.83, which is well within the acceptable range for a reliable instrument. In addition to determining Cronbach's α, Moore and Benbasat conducted a factor analysis and dropped items from the scale that were too complex or did not load strongly on any factor, ending with a factor pattern with most loadings in excellent range and none lower than "fair" range. While there was one area of concern with relative advantage and compatibility not emerging as separate factors, the scales were separated in the sorting and thus indicated conceptual differences in the constructs (Moore & Benbasat, 1991). Finally, Moore and Benbasat further examined validity by testing the instrument on a split sample of adopters and non-adopters and found significant differences for all variables between the two groups, which aligns with Rogers' (2003) theory of innovation diffusion. In sum, this instrument provided valid and reliable measurements of the perceived attributes of innovation.

Chan et al. (2016) slightly modified the Perceived Attributes of Innovation instrument to better align with the context of adopting an innovation in higher education. The revised instrument included 10 demographic questions and a question to determine whether a faculty member was an adopter or non-adopter, and also dropped the image and voluntariness constructs (Chan et al., 2016). Chan et al. conducted a pilot study to confirm the face and content validity of the modified instrument and also conducted a factor analysis. The factor analysis provided similar results to the Moore and Benbasat (1991) study, and the Cronbach α for the revised instrument was above 0.80. Therefore, the revised instrument has acceptable levels of reliability and internal consistency. Because the population for the current study is also postsecondary faculty in higher education, I used the revised instrument adapted by Chan et al.

Previous Populations

The Perceived Attributes of Innovation instrument has often been used within the context of higher education, which illustrates its use in the proposed study. Moore and Benbasat (1991) tested the instrument on business faculty members from two universities, as well as on utility company office workers, two government departments, and two resource-based companies. In addition, Chan et al. (2016) used the instrument at a private, nonprofit university with a sample of 204 faculty members. Rogers (2003) also noted the usefulness of the Perceived Attributes of Innovation instrument in higher education and remarked that any innovation could be substituted for use with the instrument.

In this study, I examined the relationship between postsecondary faculty adoption of text expander programs to provide digital written feedback and the perceived attributes of innovation, which include relative advantage, compatibility, trialability, complexity, and observability. All of these variables were measured using the modified and shortened version of the Perceived Attributes of Innovation instrument, which was adapted by Chan et al. (2016). The survey for the study included 7 demographic questions related to current employment status, education, and years teaching—SurveyMonkey Audience automatically collected gender and age demographic data (Lieu, n.d.)—and 20 items related to the perceived attributes of innovation. There were six constructs overall, with five items relating to relative advantage, three items relating to compatibility, three items relating to ease of use, four items relating to results demonstrability, three items relating to visibility, and two items related to trialability (Moore & Benbasat, 1991). The modified version of the Perceived Attributes of Innovation instrument, which was adapted for use in a higher-education context, aided in answering the research questions for the study.

Operationalization

The binary dependent variable for this study was postsecondary faculty adoption of text expander technology, and the nominal independent variables included relative advantage, compatibility, complexity, trialability, and observability. The operational definitions of the variables are below:

1. Postsecondary faculty adoption of text expander technology is the rate at which postsecondary faculty adopt text expander technology to provide digital written feedback. For the purpose of this study, an adopter is an individual who has decided to use text expander technology to provide digital written feedback to learners.

2. The relative advantage of an innovation relates to how much individuals perceive the innovation as an improvement over existing ideas or technology (Rogers, 2003).
3. According to Rogers (2003), compatibility is “the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters” (p. 266).
4. The perceived complexity of an innovation is how difficult it is perceived as being to use and comprehend (Rogers, 2003).
5. The trialability of an innovation relates to how simple it is for an individual to use it on a trial basis (Rogers, 2003).
6. The observability of an innovation relates to how visible the results of the innovation are to others (Rogers, 2003).

The binary dependent variable was measured through a *yes/no* survey question: At this time, do you consider yourself an adopter of text expander technology to provide digital written feedback to students? In contrast, the faculty’s perception of the attributes of innovation variables, which include relative advantage, compatibility, complexity, trialability, and observability, was measured on a seven-point Likert scale that ranges from 1—strongly disagree—to 7—strongly agree. An example item for relative advantage was the following: Using text expander technology allows me to accomplish tasks more quickly. An example item for compatibility was the following: Using text expander technology fits into my work style. An example item for complexity was the following: Using text expander technology is often frustrating. An example item for trialability was the following: Before deciding to use text expander technology, I was able to properly try it out. Finally, an example item for observability was the following: I have seen what others do using text expander technology. Examining these variables aided in answering the study's research questions.

Data Analysis Plan

I quantitatively analyzed the data collected for the study through SurveyMonkey Audience using the Statistical Package for Social Sciences (SPSS), version 27. SurveyMonkey Audience provided some automatic options for screening, particularly for demographic variables (SurveyMonkey, n.d.-a); SurveyMonkey Audience screening procedures ensured that the participants were located in the United States and that they were currently working in higher education. In addition, I added a further screening question to ensure that the participants were currently teaching in higher education: Do you currently teach in a college or university setting? After collecting responses, I cleaned the data by excluding participants who did not fully complete the survey, excluding participants who were outliers in survey completion speed, filtering inconsistent responses, and removing straight-lined survey responses (Gitlin, n.d.). The screening and data cleaning procedures helped ensure the validity of the survey results.

Research Questions and Hypotheses

The research questions and hypotheses for the study were the following:

3. RQ1—Quantitative: At what frequency do postsecondary faculty adopt text expander technology to provide digital written feedback?
4. RQ2—Quantitative: What perceived attributes of innovation predict postsecondary faculty adoption of text expander technology?

H_02_A: The relative advantage attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_A: The relative advantage attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

H_02_B: The compatibility attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_B: The compatibility attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

H_02_C: The complexity attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_C: The complexity attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

H_02_D: The trialability attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_D: The trialability attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

H_02_E: The observability attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_E: The observability attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

To test the above hypotheses, I used binary logistic regression and χ^2 analysis. Binary logistic regression can be used to help develop a prediction model because it allows a researcher to evaluate a logistic model against a constant only model (van Smeden et al., 2019). In addition, the Hosmer-Lemeshow goodness-of-fit test was used to confirm that the model fit the data. Before analyzing the data, I checked for negatively keyed items on the instrument to ensure consistency in the levels of agreement scores. I also ensured that the data met all of the assumptions for using binary logistic regression, including that the dependent variable was dichotomous, that there was more than one independent variable, and that there was a linear relationship between continuous independent variables and the log odds of the dependent variable (Wagner, 2017). I determined the variation in the dependent variable based on the Nagelkerke R^2 value, as well as the statistical significance for each independent variable through the Wald test (Laerd Statistics, 2018). While the Wald test determined the statistical significance of each variable, I also reviewed the significance of the test to determine whether it met the *p*-value threshold of 0.05. In addition, I tested to rule out multicollinearity, which relates to highly related predictor variables. One procedure to help to ensure that there were no issues with multicollinearity was to calculate the variance inflation factor and variable tolerance and to ensure that the variable tolerance was more than 0.10 and that the variance inflation factor was less than 10 (Katz, 2011). I also examined the case-wise listing of residuals to determine if there were any cases that did not fit the model, and taken together, these tests allowed me to determine whether the model predicted the probability of postsecondary faculty adopting text expander technology to provide digital written feedback.

Potential covariates for this study included demographic characteristics such as gender, age, household income, employment status, level of education, and years of experience. Including these covariates and possible confounding variables helped to ensure that the perceived attributes of innovation predicted the probability of adoption of text expander technology, rather than years of experience in teaching or another confounding variable. Finally, to interpret results, I closely reviewed the strength of the logistic model—that is, how well it predicted postsecondary faculty adoption of text expander technology—in addition to the overall fit of the model. Furthermore, examining the odds ratio for each variable aided in determining which variable or variables significantly increased the odds of adoption. This data analysis plan was employed to ensure that the appropriate SPSS tests and modelling were applied to answer the research questions.

Threats to Validity

Ensuring internal and external validity is an important aspect of developing a generalizable quantitative design. Validity considerations include whether or not the data collection leads to an answer to the research question, whether the type of data collection helps in answering the research question, whether the appropriate subjects are tested, and whether enough participants are included (Burkholder et al., 2016; Jhangiani et al., 2019). Researchers must design studies that are likely to add to the body of knowledge about a topic, which illustrates the importance of study results being valid and generalizable to a broad population. This study included a nonexperimental survey design to examine the relationship between variables. This section includes a discussion of threats to validity and mitigation strategies related to nonexperimental survey research.

External Validity

External validity relates to the generalizability of a study across multiple contexts (Burkholder et al., 2016; Creswell, 2009). For a survey research design, the main threats to external validity include setting, outcome measures, and sampling (Burkholder et al., 2016; Drew et al., 2008). The setting threat relates to differences between the setting of the study and other contexts, and the outcome measures threat relates to what tests are used to test the outcomes, as some might be more valid and reliable than others (Burkholder et al., 2016). In contrast, the sampling threat relates to the size and representativeness of the sample—a sample that is too small or not representative could not be generalized to a broad population (Drew et al., 2008). Because this study relied on SurveyMonkey Audience to randomly select participants who voluntarily participate in the service, there may be threats to external validity through the representativeness of the sample, as participants who voluntarily participated may differ from the general population in some way, particularly in their access to the Internet and computers.

There were several methods of addressing the external threats to validity for this study. Because the research included a nonexperimental survey design, the context of a natural setting aided in external validity (Drew et al., 2008; Jhangiani et al., 2019). In addition, according to Burkholder et al. (2016), a thorough literature review and carefully considering in what contexts the findings can generalize to other settings can minimize threats to external validity. The literature review for this study provided a basis for generalization of the study results, based on the use of the instrument and design in a similar context. The study results are not generalizable to contexts outside of higher education; instructors in K-12 were not addressed in this study, as teaching in higher education is part of the inclusion criteria. In addition, the results are not generalizable outside of the United States, as location in the United States was a characteristic of the inclusion criteria for this study. The results are also not generalizable to other innovations used to provide digital written feedback—for example, Turnitin Feedback Studio, which contains integrated, pre-filled comment banks. The focus of this study was solely on text expander technology and thus limits the generalizability of the findings to other related technologies.

Adhering to best practices in the sampling strategy can also increase external validity. Furthermore, sampling across multiple contexts can improve the external validity, as can ensuring that the sample is large enough to avoid statistical errors. For this study, the use of a validated and reliable instrument that has successfully measured the outcomes in a similar context was key, as was using SurveyMonkey Audience, which randomly selected participants across multiple contexts. Finally, the random selection of participants and a sample size that was larger than the minimum based on the statistical power analysis will also aided in increasing the study's generalizability.

Internal Validity

The internal validity of a study, in contrast to external validity, improves researchers' confidence that they studied what they intended to study and that they can attribute the outcome of the research to the independent variable (Creswell, 2009; Jhangiani et al., 2019). This study design was nonexperimental, which is lower in internal validity than an experimental study that would identify a causal relationship between variables because the variables are measured rather than manipulated (Jhangiani et al., 2019). However, according to Jhangiani et al. (2019), nonexperimental design is appropriate when the goal is to describe or predict rather than to establish a causal relationship, which aligns with the goals of the study. In addition, the threats to internal validity in nonexperimental research are counterbalanced by their strengths in external validity (Jhangiani et al., 2019). Some general threats to internal validity for nonexperimental research include instrumentation, researcher bias, selection, and attrition (Burkholder et al., 2016). The instrumentation threat and researcher bias were addressed by using a valid and reliable instrument that has provided generalizable results with a similar population, which ensured that survey items are not worded in a manner that exposes researcher bias. The selection threat, which relates to sampling methods (Burkholder et al., 2016), was mitigated through the use of SurveyMonkey Audience, which used random sampling on a large population. Furthermore, the sample size was larger than the minimum according to the statistical power analysis, which further mitigated threats to internal validity. Finally, attrition relates to study participants dropping out or failing to complete the study; the survey for the proposed study could be completed in approximately 5 minutes, and participants were able to complete the survey at their convenience in a natural setting, which lessened the attrition threat. Overall, the threats to internal validity were addressed through stringent sampling and the use of a valid and reliable instrument.

Construct and Statistical-Conclusion Validity

In addition to external and internal validity, construct validity, operationalization, and statistical validity contribute to the generalizability of study results. While construct validity relates to how concepts associated with the study are conceptualized and operationalized, statistical-conclusion validity relates to researchers' understanding of the research question, data set, and appropriate tests and models to address the research question (Burkholder et al., 2016; Creswell, 2009; Jhangiani et al., 2019). For nonexperimental survey research design, threats to construct and statistical-conclusion validity include the operationalization of the constructs, the tests used and assumptions for those tests, and the sample size (Jhangiani et al., 2019). For this study, the construct and operationalization validity threats were addressed by using Rogers' operationalization of constructs related to innovation diffusion. This well-understood theory has been tested and refined since the early 1960s (Rogers, 2003), and the use of these constructs and their operationalization aligned with the ways in which researchers have applied the constructs and theory in the past. More importantly, the operationalization included the perceived attributes of an innovation rather than the main attributes, as how individuals perceive an attribute can more readily predict an individual's actions regarding it.

The statistical-conclusion threat to validity was addressed by applying tests that are reliable in testing the specific population with the specific instrument. I used binary logistic regression to examine the relationship between multiple independent variables and a binary dependent variable, in addition to the χ^2 test to determine the fit of the regression model. Using multiple tests and checking the assumptions of binary logistic regression are both methods to ensure statistical-conclusion validity. Tests of multicollinearity and log odds were used to ensure that the data meets the statistical assumptions, as well as comparing the odds ratio to prior studies using the same instrument and a similar population. Finally, because logistic regression requires a larger sample size, the sample size was larger than the minimum according to the statistical power analysis and EPV parameters. These techniques aided in addressing the threats to construct and statistical-conclusion validity.

Ethical Procedures

Besides controlling for threats to validity, quantitative researchers must also ensure that they conduct ethical research. The standard for social research is to ensure that participation is voluntary and confidential and to ensure that participation does not result in harm (Babbie, 2016). After receiving institutional review board (IRB) approval (01-22-21-0757911), I collected and analyzed the study data. I was the sole researcher for the study, and I only used the collected data for research.

Institutional Review Board Approval

For this study, the data were not collected or accessed outside of the United States, and there were no partner organizations providing support roles. No pilot testing or instrument validation was necessary for this study, as a reliable, valid instrument used on a similar population was employed. To ensure ethical procedures for the study, I completed the Walden University Institutional Review Board process, which aligns with U.S. federal regulations, and did not gather data until I received approval.

Recruitment Material and Processes

I used the SurveyMonkey Audience service to recruit participants and collect data, which aided in ensuring ethical procedures for the study. Use of this service precluded relationship risk in the study, as I had no relationship to the participants. In addition, participants were over 18 years of age and were able to provide informed consent in completing the survey. Participation in the survey was entirely voluntary and included a double opt-in procedure. Therefore, there was no professional, legal, or economic risk to participants, which alleviated the need to disclose legal, economic, or professional information related to participants. Because this study included a nonexperimental design, participants completed the survey in a natural setting rather than a laboratory environment. The survey instrument is valid and reliable and has been employed with a similar population; none of the constructs was offensive or sensitive, which mitigated risks related to human treatment. The instrument developers provided permission to use the instrument (see Appendix A and Appendix B). In addition, using the SurveyMonkey Audience service supported the anonymous recruitment of participants; I was not involved in the recruitment process, nor was I able to view or download any identifying information about participants. Rather than having direct payment as an incentive, SurveyMonkey Audience survey participants can choose a charity to which to donate $0.50, which aided in ensuring that participants chose to participate for humanitarian purposes rather than for remuneration (SurveyMonkey, 2020). The recruitment material and processes ensured appropriate treatment of human subjects.

Data Collection

The SurveyMonkey Audience service sent separate invitations to randomly selected participants, and before participating, participants completed an informed consent form that was written in English and that included information about the research background, data collection, potential benefits and risks, estimated time to completion, and researcher contact information, in addition to information about voluntary participation, privacy, anonymity, and the right to decline participation at any time. Participants selected “Next” to continue to the survey, and if they did not agree to the informed consent, were able to exit the consent form without completing the survey. The same survey was provided to each participant, and the survey took approximately 5 minutes to complete. There were no open-ended questions on the survey, which reduced discomfort and the time necessary for completion. Participants were able to complete the survey at their convenience in a natural setting, which also reduced discomfort and risk. The survey design did not permit identification of participants, as this information was not requested. Toward this goal, demographic information was presented on a scale to further anonymize the data. Finally, participants were able to withdraw consent at any time and exit the survey without completing it.

Treatment of Data

The data collected were anonymous and confidential; the survey design did not allow collection of personally identifiable information or contact information. I did not have access to survey participants’ SurveyMonkey profile information and thus was not able to identify participants during or after the data collection process. When I completed the data collection phase, I downloaded the survey responses from SurveyMonkey, and this data did not include personally identifiable information. Storage of the data will include securing the data in a password-protected laptop for five years, and after that time I will destroy the data. Only I have access to the data, which will aid in ensuring anonymity and confidentiality for the study.

Summary

With this study, I examined the perceived attributes of innovation that predict postsecondary faculty adoption of text expander technology to provide DITDWF to students. In this chapter, I first discussed the research design and explained the rationale for using a quantitative nonexperimental survey research design. In the methodology section, I discussed the population of the study, which included SurveyMonkey Audience panel members who are over 18 years old and who currently teach in higher education, and the sampling, recruitment procedures, and instrumentation. In addition, I combined EPV parameters and G*Power statistical analysis to determine the minimum sample size. I next explained the use of a validated, reliable survey instrument for the data collection phase and provided details about instrument use permission. I also defined threats to internal and external validity and discussed mitigation strategies, such as increased sample size and accurate description of the contexts to which the study may be generalized. Finally, I discussed the ethical procedures and human treatment of subjects for the study. In Chapter 4, I will answer the research question with a detailed description of the perceived attributes of innovation that predict postsecondary faculty adoption of text expander technology and support the conclusions with the statistical analysis.

Chapter 4: Results

Introduction

The purpose of this study was to examine the perceived attributes of diffusion of innovation theory that predict postsecondary faculty adoption of text expander technology, which can support faculty in providing DITDWF to students. Employing a questionnaire survey research design and using an online survey to collect data allowed examination of the relationship between postsecondary faculty adoption of text expander technology and the perceived attributes of innovation, which include relative advantage, compatibility, complexity, trialability, and observability. The first research question for this study was the following: At what frequency do postsecondary faculty adopt text expander technology to provide digital written feedback? The second research question, which required hypotheses, was the following: What perceived attributes of innovation predict postsecondary faculty adoption of text expander technology? The null and alternative hypotheses for the second research question are below:

$H_0 2_A$: The relative advantage attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

$H_A 2_A$: The relative advantage attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

$H_0 2_B$: The compatibility attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_B: The compatibility attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

H_02_C: The complexity attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_C: The complexity attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

H_02_D: The trialability attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_D: The trialability attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

H_02_E: The observability attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_E: The observability attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

The binary dependent variable was postsecondary faculty adoption of text expander technology, and the nominal independent variables included relative advantage, compatibility, complexity, trialability, and observability. Using a quantitative survey design with the provided dependent and independent variables aided in answering the research questions.

This chapter contains a description of the data collection process and the results of the data analysis. First, I discuss the data collection process, including the data collection time frame, baseline descriptive and demographic sample characteristics, and covariates. Next, I report the results of the study—including descriptive statistics, statistical assumptions, and statistical analysis findings—using narrative text and tables. Finally, I provide a summary of the study results.

Data Collection

Data collection took place in SurveyMonkey Audience following IRB approval (01-22-21-0757911). Using SurveyMonkey Audience allowed for random selection of participants who were over 18 years of age, located in the United States, and currently teaching in higher education from a diverse pool of over 80 million individuals (SurveyMonkey, n.d.-b). The SurveyMonkey Audience service sends survey invitations to individuals who meet a study's inclusion criteria; in addition to using the SurveyMonkey Audience targeting options to invite only participants over 18 years of age located in the United States and within the education industry, I also added a screening question to the survey after the informed consent: Do you currently teach in higher education? If participants responded "no," they exited the survey. The survey was a reliable, validated instrument developed by Moore and Benbasat (1991). The online survey remained open until SurveyMonkey Audience returned the requested 305 responses—a number generated from G*Power analysis and EPV best practices.

The data collection process lasted 4 days. Overall, 799 respondents accessed the survey, and 350 participants completed the survey after screening. There was a 34% abandon rate and a 43% response rate, which are both acceptable rates for an online survey (Sauermann & Roach, 2013). Throughout the data collection process, there were no discrepancies from the data collection plan.

Sample Characteristics

Although there were 350 responses overall, after data cleaning 321 responses were included in the analysis. During the data cleaning process, I removed speed outliers, straight-lined responses, and responses with more than three missing cases, as well as missing cases related specifically to the research questions (see Appendix C). In addition, I investigated eight cases in the casewise listing of residuals and removed six outlier cases. The remaining 321 cases exceeded the minimum sample size established through G*Power and EPV analysis.

The sample after data cleaning included 102 (31.8%) male respondents and 219 (68.2%) female respondents. Most of the respondents were in the 18-29 (38%) and 30-44 (39.9%) age range, as shown in Table 1.

Table 1

Age Demographics

		Frequency	Percent	Valid percent	Cumulative percent
Valid	18-29	122	38.0	38.0	38.0
	30-44	128	39.9	39.9	77.9
	45-60	57	17.8	17.8	95.6
	> 60	14	4.4	4.4	100.0
	Total	321	100.0	100.0	

The respondents overwhelmingly held master's degrees (50.8%) and bachelor's degrees (32.4%), as illustrated in Table 2.

Table 2

Degree Demographics

		Frequency	Percent	Valid percent	Cumulative percent
Valid	Other (please specify)	10	3.1	3.1	3.1
	Doctorate	44	13.7	13.7	16.8
	Masters	163	50.8	50.8	67.6
	Bachelors	104	32.4	32.4	100.0
	Total	321	100.0	100.0	

Most of the respondents taught full time (60.1%), as represented in Table 3.

Table 3

Employment Status Demographics

		Frequency	Percent	Valid percent	Cumulative percent
Valid	Full-time	193	60.1	60.5	60.5
	Part-time/adjunct	126	39.3	39.5	100.0
	Total	319	99.4	100.0	
Missing	System	2	.6		
Total		321	100.0		

Most respondents defined themselves as instructors (46.7%), although there was representation for each listed rank, as shown in Table 4.

Table 4

Academic Rank Demographics

		Frequency	Percent	Valid percent	Cumulative percent
Valid	Full professor	32	10.0	10.0	10.0
	Associate professor	41	12.8	12.9	22.9
	Assistant professor	53	16.5	16.6	39.5
	Instructor	150	46.7	47.0	86.5
	Lecturer	43	13.4	13.5	100.0
	Total	319	99.4	100.0	
Missing	System	2	.6		
Total		321	100.0		

Finally, many of the survey participants had been teaching 0-4 years (46.7%) or 5-9 years (24.3%), as depicted in Table 5.

Table 5

Years Teaching Demographics

		Frequency	Percent	Valid percent	Cumulative percent
Valid	40 years or more	4	1.2	1.2	1.2
	35-39 years	6	1.9	1.9	3.1
	30-34 years	10	3.1	3.1	6.2
	25-29 years	7	2.2	2.2	8.4
	20-24 years	16	5.0	5.0	13.4
	15-19 years	15	4.7	4.7	18.1
	10-14 years	35	10.9	10.9	29.0
	5-9 years	78	24.3	24.3	53.3
	0-4 years	150	46.7	46.7	100.0
	Total	321	100.0	100.0	

A final important descriptive characteristic is faculty text expander adoption; within the sample, 208 (64.8%) participants identified as adopters and 113 (35.2%) did not identify as adopters of text expander technology.

The sample was gathered through random sampling of a large participant pool, which aids in making it more representative of postsecondary faculty in the United States. According to the National Center for Education Statistics (2020), 54% of postsecondary faculty were full time and 46% of postsecondary faculty were part time in 2018, whereas in this sample, 60.5% of the respondents were employed full time and 39.5% were employed part time. In 2018, 50% of faculty were female and 50% of faculty were male (National Center for Education Statistics, 2020). This percentage varies from this study's participants, which included 68.2% female respondents and 31.8% male respondents. However, this discrepancy may arise in part from the respondents' academic rank characteristics. Separately from the overall gender frequency, lecturers and instructors tend to be women, with 56% female lecturers and 57% female instructors in 2018 (National Center for Education Statistics, 2020). Sixty percent of the respondents were either instructors or lecturers, which may have affected gender frequency in the responses. Likewise, the median age of all faculty in 2018 was 55 (McChesney & Bichsel, 2020), but the median age is lower for instructors, which may aid in explaining the high representation of faculty between the ages of 18-29 and 30-44. This sample aligns in general with the population of interest, and because the focus is on regression analysis rather than descriptive analysis, no cases were weighted.

Simple Logistic Regression

Before modeling the data, I performed a Chi-square test of independence and simple logistic regression in SPSS to verify whether covariates should be included in the model. First, I conducted a Chi-square test of independence using the crosstab function in SPSS to examine the relationship between gender and text expander adoption, which reported an insignificant result and a *p* value greater than 0.05, with χ^2 (1, N = 321) = 0.98. Therefore, gender did not have a significant effect on postsecondary faculty adoption of text expander technology. Next, I examined the remaining covariates and variables using the Chi-square test of independence to determine whether covariates should be included in the model, and I then used simple logistic regression for further analysis of variables. First, I transformed the variables related to the perceived attributes of innovation to the mean of each set of questions related to the variable, which created five transformed variables, including relative advantage, compatibility, complexity, observability, and trialability. The χ^2 results for household income (p = 0.77), region (p = 0.12), highest degree held (p = 0.97), employment status (p = 0.29), and academic rank (p = 0.12) were insignificant. In contrast, the results for age (p = 0.01), relative advantage (p < 0.001), compatibility (p < 0.001), complexity (p < 0.001), observability (p < 0.001), and trialability (p < 0.001) were significant. Further analysis of the age covariate using simple logistic regression garnered an insignificant result (p = 0.40), while simple logistic regression results were significant for relative advantage (p < 0.001), complexity (p <

0.001), compatibility ($p < 0.001$), observability ($p < 0.001$), and trialability ($p < 0.001$). Therefore, the inclusion of covariates in the model was not justified.

Results

I analyzed the data for this study using binary logistic regression. Before analyzing the data using regression, I cleaned and transformed the data and verified that the statistical assumptions were met. The sample of 321 participants used in the data analysis included 102 (31.8%), male respondents and 219 (68.2%) female respondents. Most of the respondents were in the 18-29 (38%) and 30-44 (39.9%) age range, with 17.8% in the 45-60 age range and 4.4% over 60, which is illustrated in the following table.

Table 6

Age Demographics

		Frequency	Percent	Valid percent	Cumulative percent
Valid	18-29	122	38.0	38.0	38.0
	30-44	128	39.9	39.9	77.9
	45-60	57	17.8	17.8	95.6
	> 60	14	4.4	4.4	100.0
	Total	321	100.0	100.0	

The respondents mostly held master's degrees (50.8%), but 32% held bachelor's degrees, 13.7% held doctorate degrees, and 10% selected "Other," shown in Table 7.

Table 7

Degree Demographics

		Frequency	Percent	Valid percent	Cumulative percent
Valid	Other (please specify)	10	3.1	3.1	3.1
	Doctorate	44	13.7	13.7	16.8
	Masters	163	50.8	50.8	67.6
	Bachelors	104	32.4	32.4	100.0
	Total	321	100.0	100.0	

In addition, most of the respondents were employed full time (60.5%), with 39.5% employed part time. The academic rank of most respondents was instructor (46.7%), but 13.4% were lecturers, 16.5% were assistant professors, 12.8% were associate professors, and 10% were full professors, as shown in Table 8.

Table 8

Academic Rank Demographics

		Frequency	Percent	Valid percent	Cumulative percent
Valid	Full professor	32	10.0	10.0	10.0
	Associate professor	41	12.8	12.9	22.9
	Assistant professor	53	16.5	16.6	39.5
	Instructor	150	46.7	47.0	86.5
	Lecturer	43	13.4	13.5	100.0
	Total	319	99.4	100.0	
Missing	System	2	.6		
Total		321	100.0		

In addition to mostly being instructors or lecturers, most of the survey participants had been teaching 0-4 years (46.7%) or 5-9 years (24.3%), as shown in the table below.

Table 9

Years Teaching Demographics

		Frequency	Percent	Valid percent	Cumulative percent
Valid	40 years or more	4	1.2	1.2	1.2
	35-39 years	6	1.9	1.9	3.1
	30-34 years	10	3.1	3.1	6.2
	25-29 years	7	2.2	2.2	8.4
	20-24 years	16	5.0	5.0	13.4
	15-19 years	15	4.7	4.7	18.1
	10-14 years	35	10.9	10.9	29.0
	5-9 years	78	24.3	24.3	53.3
	0-4 years	150	46.7	46.7	100.0
	Total	321	100.0	100.0	

Finally, within the sample 208 (64.8%) participants considered themselves adopters of text expander technology and 113 (35.2%) did not, as depicted in Table 10.

Table 10

Text Expander Adoption Frequency

		Frequency	Percent	Valid percent	Cumulative percent
Valid	Yes	208	64.8	64.8	64.8
	No	113	35.2	35.2	100.0
	Total	321	100.0	100.0	

Statistical Assumptions

There are multiple assumptions related to binary logistic regression. The first assumption, that there is one dichotomous dependent variable (Laerd Statistics, 2018), was met, as postsecondary faculty adoption of text expander technology is a nominal dichotomous variable. The second assumption of binary logistic regression was also met, as there were five independent nominal variables included in the study—relative advantage, compatibility, complexity, observability, and trialability. In addition to the first two assumptions, the third assumption, that there is independence of observations and that all nominal independent variables are exhaustive and mutually exclusive (Laerd Statistics, 2018), was also met. There are no relationships between observations in the dependent variable categories, which include "yes" and "no." Furthermore, all the independent variables are mutually exclusive and exhaustive, with no observations able to be placed in multiple categories. The fourth assumption for binary logistic regression, that there are a minimum of 15 cases per independent variable (Laerd Statistics, n.d.; van Smeden et al., 2019), was also met; there were 62 cases per independent variable in this study. In sum, the assumptions for performing binary logistic regression were met for this study for the collected data.

There are also assumptions for the output of binary logistic regression that must be met. These assumptions include a linear relationship between continuous independent variables and the dependent variables, a lack of multicollinearity, and a lack of significant outliers. Because all the independent variables were nominal, there was no need to create natural log transformed variables and analyze using the Box-Tidwell procedure. However, I calculated the tolerance and variance inflation factor (VIF) for each independent variable to test for multicollinearity. A tolerance of less than 0.10 and a VIF above 5 should be investigated, as multicollinearity might be indicated (Frankfort-Nachmias & Leon-Guerrero, 2016). For this study, the tolerance ranged from 0.31 to 0.64, with a mean of 0.41, and the VIF ranged from 1.54 to 3.22, with a mean of 2.56. None of the values indicated the presence of multicollinearity, as illustrated in Table 11.

Table 11

Multicollinearity Statistics

	B	Std. Error	Beta	*t*	*p*	Tolerance	VIF
Relative advantage	.143	.038	.305	3.765	.000	.334	2.992
Compatibility	-.038	.036	-.089	-1.050	.294	.310	3.229
Complexity	.071	.035	.154	2.015	.045	.377	2.655
Observability	.112	.043	.191	2.597	.010	.408	2.449
Trialability	.029	.022	.078	1.343	.180	.648	1.542

Note. Dependent variable: Text expander adoption. Independent variables: Relative advantage, compatibility, complexity, observability, and trialability.

Similarly, none of the variance proportion values indicated multicollinearity. As shown in Table 12, there were no variance proportion values above 0.90 and no multiple high variance proportion values on the same row, which also indicates no multicollinearity in the results.

Table 12

Collinearity Diagnostics

Condition index	Variance proportions					
	Constant	Relative advantage	Compatibility	Complexity	Observability	Trialability
1.000	.00	.00	.00	.00	.00	.00
11.445	.01	.02	.05	.01	.00	.82
13.944	.66	.03	.10	.01	.01	.04
19.278	.07	.21	.07	.60	.07	.05
24.080	.26	.13	.16	.17	.75	.09
24.922	.00	.61	.63	.21	.17	.00

To test whether the data met the final statistical assumption of binary logistic regression, I examined the casewise list of standardized residuals, which contains cases that have a poor fit for the model. The casewise list contained information for seven cases with standardized residuals greater than 2, including case 33, case 79, case 140, case 157, case 262, case 310, and case 319. Outlier cases with standardized residuals greater than 2.5 should be examined individually and removed if necessary, as they may affect the strength of the model (Laerd Statistics, n.d.). All seven cases listed had standardized residual values below 2.5, with the values ranging from -2.00 to 2.22. I individually investigated each case in addition to examining the standardized residual values, and all seven cases were kept in the analysis after investigation. The standardized residuals of outlying cases are presented in Table 13.

Table 13

Casewise List of Residuals

Case	Selected status	Observed Text expander adoption	Predicted	Predicted group	Temporary variable Resid	ZResid	SResid
33	S	0**	.861	1	-.861	-2.489	-2.006
79	S	0**	.940	1	-.940	-3.942	-2.384
140	S	0**	.909	1	-.909	-3.154	-2.203
157	S	1**	.134	0	.866	2.541	2.027
262	S	1**	.124	0	.876	2.659	2.068
310	S	1**	.089	0	.911	3.205	2.226
319	S	0**	.875	1	-.875	-2.648	-2.058

Note. S = Selected, U = Unselected cases, and ** = Misclassified cases.

The combined test results indicate that all the assumptions for binary logistic regression were met for this study.

Statistical Analysis Findings

In this study, I examined whether variables related to the perceived attributes of innovation predicted postsecondary faculty adoption of text expander technology. Toward this end, I analyzed the data using binary logistic regression in SPSS 27. The first research question for this study was descriptive: At what frequency do postsecondary faculty adopt text expander technology to provide digital written feedback? For this study (N = 321), 208 (64.8%) postsecondary faculty considered themselves adopters of text expander technology, while 113 (35.2%) did not consider themselves adopters of text expander technology. The frequency of postsecondary faculty text expander adoption is presented in Table 14.

Table 14

Postsecondary Faculty Text Expander Adoption Frequency

		Frequency	Percent	Valid percent	Cumulative percent
Valid	Yes	208	64.8	64.8	64.8
	No	113	35.2	35.2	100.0
	Total	321	100.0	100.0	

The second research question for this study was relational: What perceived attributes of innovation predict postsecondary faculty adoption of text expander technology? The null and alternative hypotheses for the second research question are below:

H_02_A: The relative advantage attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_A: The relative advantage attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

H_02_B: The compatibility attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_B: The compatibility attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

H_02_C: The complexity attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_C: The complexity attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

H_02_D: The trialability attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_D: The trialability attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

H_02_E: The observability attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.

H_A2_E: The observability attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

To answer the second research question, I performed binary logistic regression to determine whether the perceived attributes of innovation, including relative advantage, compatibility, complexity, observability, and trialability, predict postsecondary faculty of text expander technology. The logistic regression model was statistically significant, with χ^2 (5) = 128.85 and $p < 0.001$. In addition, the Hosmer-Lemeshow test was not statistically significant, with χ^2 (8) = 4.64 and $p = 0.79$, which indicates a model that is a good fit. The logistic regression model significance is illustrated in Table 15.

Table 15

Omnibus Tests of Model Coefficients

		Chi-square	*df*	*p*
Step 1	Step	128.852	5	.000
	Block	128.852	5	.000
	Model	128.852	5	.000

The result of the Hosmer-Lemeshow test is presented in Table 16.

Table 16

Hosmer-Lemeshow Test

Step	Chi-square	*df*	*p*
1	4.640	8	.795

In addition to an overarching significant result, the model explained 45% (Nagelkerke R^2) of the variance in postsecondary faculty adoption of text expander technology. The model correctly classified 80.1% of cases, as illustrated in Table 17.

Table 17

Classification Table

			Predicted		
			Text expander adoption		Percentage
	Observed		.00	1.00	correct
Step 1	Text expander adoption	.00	82	31	72.6
		1.00	33	175	84.1
	Overall percentage				80.1

Note. The cut value is .500

Three of the five predictor variables were significant, including relative advantage ($p < 0.001$), complexity ($p = 0.04$), and observability ($p = 0.003$). Postsecondary faculty who perceived text expander technology as having a relative advantage had 2.76 times higher odds of adopting text expander technology, and each unit increase in perception of this attribute increased the likelihood of adoption by 1.01. Postsecondary faculty who viewed text expander technology as being less complex had 1.57 times higher odds of adopting text expander technology, and each unit increase in perception of this attribute increased the likelihood of adoption by 0.45. Similarly, postsecondary faculty who were able to observe others using text expander technology—that is, observability—had 2.66 times higher odds of adopting text expander technology, and each unit increase in the observability attribute increased the likelihood of adoption by 0.97. The individual variable analysis, which included a confidence interval of 95%, is presented in Table 18.

Table 18

Logistic Regression Predicting Likelihood of Postsecondary Faculty Adoption

							95% C.I. for Exp(*B*)	
	B	S.E.	Wald	*df*	*p*	Exp(*B*)	Lower	Upper
Relative advantage	1.018	.271	14.149	1	.000	2.769	1.629	4.707
Compatibility	-.254	.233	1.190	1	.275	.776	.491	1.224
Complexity	.456	.231	3.905	1	.048	1.578	1.004	2.481
Observability	.979	.328	8.910	1	.003	2.661	1.399	5.059
Trialability	.259	.140	3.423	1	.064	1.295	.985	1.703
Constant	-10.328	1.338	59.594	1	.000	.000		

Based on the statistical analysis, relative advantage, complexity, and observability predict postsecondary faculty adoption of text expander technology. The individual accepted hypotheses are below:

1. I rejected the null hypothesis and accepted H_A2_A: The relative advantage attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.
2. I accepted the null hypotheses for H_02_B: The compatibility attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.
3. I rejected the null hypothesis and accepted H_A2_C: The complexity attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.
4. I accepted the null hypotheses for H_02_D: The trialability attribute of innovation as perceived by postsecondary faculty does not predict text expander technology adoption.
5. I rejected the null hypothesis and accepted H_A2_E: The observability attribute of innovation as perceived by postsecondary faculty predicts text expander technology adoption.

In conclusion, the binary logistic regression analysis of the data produced a significant result that has implications for the field of education.

Summary

This chapter contained a description of the data collection process and data analysis for the study regarding whether the perceived attributes of innovation predict postsecondary faculty adoption of text expander technology. After cleaning and transforming the data, I analyzed a data set that included 321 responses gathered through SurveyMonkey Audience. I conducted binary logistic regression using SPSS 27 to test the research hypotheses and answer the research questions. I tested the data both before and during the statistical analysis to ensure that it met the statistical assumptions of binary logistic regression. According to the test results, the assumptions were not violated.

The first research question was the following: At what frequency do postsecondary faculty adopt text expander technology to provide digital written feedback? For this study, 208 (64.8%) postsecondary faculty considered themselves adopters of text expander technology, while 113 (35.2%) did not consider themselves adopters of text expander technology. The second research question was the following: What perceived attributes of innovation predict postsecondary faculty adoption of text expander technology? In answer to this research question, relative advantage ($p < 0.001$), complexity ($p = 0.04$), and observability ($p = 0.003$) predict postsecondary faculty adoption of text expander technology.

In Chapter 5, I interpret the statistical analysis results and relate them to prior studies related to innovation diffusion and adoption. I also discuss study limitations and recommendations for future research. Lastly, I explore the implications of this study related to positive social change.

Chapter 5: Discussion, Conclusions, and Recommendations

Introduction

The purpose of this quantitative study was to examine the perceived attributes of diffusion of innovation theory that predict postsecondary faculty adoption of text expander technology, which can support faculty in providing DITDWF to students. This nonexperimental quantitative study included binary logistic regression analysis in order to use multiple independent variables to predict a single binary dependent variable. Because the goal was to answer specific questions regarding the adoption of text expander technology and to examine correlation rather than to determine causal relationships, a quantitative, nonexperimental survey design was appropriate for this study. Self-reported survey data provided insight into the frequency of text expander technology adoption, as well as into the perceived attributes of diffusion of innovation theory that predict adoption. The study was conducted to fill a gap in the understanding of strategies that enhance online instruction facilitation by focusing on the adoption of tools that can aid postsecondary faculty in providing DITDWF to students.

This study included two research questions, which were answered with descriptive statistical analysis and binary logistic regression. The first research question was the following: At what frequency do postsecondary faculty adopt text expander technology to provide digital written feedback? According to the study results, 208 (64.8%) postsecondary faculty considered themselves adopters of text expander technology, while 113 (35.2%) did not consider themselves adopters of text expander technology. The second research question was the following: What perceived attributes of innovation predict postsecondary faculty adoption of text expander technology? According to the study results, the perceived attributes of relative advantage ($p < 0.001$), complexity ($p = 0.04$), and observability ($p = 0.003$) predicted postsecondary faculty adoption of text expander technology. The five independent variables predicted 45% of the variance in postsecondary faculty adoption of text expander technology, and the model correctly classified 80.1% of cases. The model's fit was good, and the study results were significant.

In Chapter 5, I interpret the findings in relation to the existing literature and discuss the limitations of the study. I also recommend future research avenues and explore the implications for positive social change in the field of education that stem from this study. Finally, I provide the overarching takeaways from this study.

Interpretation of the Findings

The findings for this study extend knowledge in the field of innovation diffusion research and research surrounding innovative tools used to enhance digital written feedback. The theoretical framework for this study was Rogers' (2003) theory of innovation diffusion—specifically, perceived attributes of innovation and their relation to adoption frequency. Perceived attributes of innovation are characteristics of an innovation that predict the rate of adoption—or the rate at which individuals within a social system adopt an innovation (Rogers, 2003). Rogers characterized five attributes of adoption, including relative advantage, compatibility, complexity, trialability, and observability. Individuals' perception of these attributes as they relate to an innovation affects the overall adoption rate of the innovation. The current study confirmed prior findings that different technological innovations may have different innovation attributes that encourage adoption. For example, while Daouk and Aldalaien (2019) found that perception of relative advantage and compatibility positively affected the diffusion of instructional technology, Chan et al. (2016) found that perception of compatibility and trialability positively affected faculty adoption of audience response systems in higher education. For adoption of electronic editing, Dayton (2004) found that perception of complexity and compatibility determined adoption. The results of this study were that specific perceived attributes of innovation predicted the rate of adoption: The perceived attributes of relative advantage ($p < 0.001$), complexity ($p = 0.04$), and observability ($p = 0.003$) predicted postsecondary faculty adoption of text expander technology.

Although few quantitative studies exist about text expander technology, the study results can be situated within the qualitative literature on the topic. Relative advantage relates to how much the individuals view an innovation as an improvement over existing technology (Rogers, 2003). Penn and Wells (2017) argued that innovative technology such as the learning management system-based text expander application QuickMarks aids postsecondary faculty in improving learner access to feedback, and this technology also aids faculty in using feedback methods that would be too resource intensive otherwise, which reconciles "the need for high value feedback with resource constraints" (p. 64). The relative advantage of text expander technology over other digital marking methods is prevalent in the literature; multiple researchers mentioned the relative speed advantage that using text expander technology has over other methods of providing digital written feedback (Adams, 2017; Al-Bashir et al., 2016; Campbell, 2016; Haughney et al., 2020; Joyce, 2019; Mandernach, 2018; Rios et al., 2018). Therefore, perception of relative advantage having the greatest influence on postsecondary faculty adoption ($p < 0.001$) aligns with the literature on text expander technology.

Perception of complexity, or ease of use, also predicted postsecondary faculty adoption of text expander technology ($p = 0.04$). This finding also fits within the existing literature; Burrows and Shortis (2011) reviewed multiple feedback and marking systems and found that the perception of worst features of these systems included needed training for the system, the system being difficult to use, and the system not being user friendly. In addition, Campbell (2016) acknowledged the time it takes to create text snippets and the difficulty remembering abbreviations for snippets. Mandernach (2018) provided an overall positive review and explanation of text expanders, but the explanation included instructions for how to simplify the complex abbreviation naming systems needed for text expander technology. Postsecondary faculty who consider adopting text expander technology must balance their perception of the relative advantage of the technology with their perception of the complexity of learning and using the technology, which likely contributes to perception of complexity affecting the rate of adoption of text expander technology.

Finally, perception of observability, or how visible the results are of the innovation, predicted postsecondary faculty adoption of text expander technology (p = 0.003). According to Rogers (2003), potential adopters must be aware of an innovation in order to adopt it. The literature surrounding text expander technology confirms the importance of observability in adopting innovative technology; most of the literature revolves around researchers extoling the features of text expander technology to encourage its adoption (Campbell, 2016; Mandernach, 2018; Rios et al., 2018). The nature of text expander technology also contributes to observability's importance to adoption of this innovation—as Mandernach (2018) explained, the output of text expander technology should look identical to strong feedback provided by other methods; the difference lies in how that feedback is stored and transmitted. The perception of observability, whether through faculty training or personal networks, positively contributes to the adoption of innovations such as text expander technology.

Another key finding of this study was the frequency of postsecondary faculty adoption of text expander technology. Within the parameters of this study, 208 (64.8%) postsecondary faculty considered themselves adopters of text expander technology, while 113 (35.2%) did not consider themselves adopters of text expander technology. There are no descriptive analyses of text expander technology in the literature, but Chan et al. (2016) conducted a similar study of postsecondary faculty adoption of audience response systems and found that 18.4% of 201 respondents considered themselves adopters of audience response systems, in addition to determining that compatibility and trialability affected the adoption frequency. The percentage of adoption for the current study was higher than the study by Chan et al. (2016), which may be explained by multiple factors, including the context—Chan et al. used an internal survey—and the specific innovation—the audience response system has different functions and use cases than text expander applications. The adoption rate for text expander technology by postsecondary faculty was 64.8% for this study, which is a relatively high percentage considering the dearth of literature on text expander technology. This finding may have roots in the perceived observability attribute of text expander technology and how willing adopters are to champion the innovation; if participants in this study were early adopters, then they may have been more willing to discuss adoption of text expander technology and participate in the study. This interpretation is in line with Rogers' (2003) categories of innovation adopters. In contrast, Chan et al. found similar odds ratios to the current study, with the mean odds ratio for the significant predictor variables of compatibility and trialability being 2.01 and the mean of the odds ratio for the significant predictor variables for this study being 2.34, which illustrates the similarity between the studies' findings that the perceived attributes of innovation predict postsecondary faculty adoption of innovative technology. In sum, different innovations have varying adoption rates and significant predictors of adoption in the education literature, which warranted a study examining postsecondary faculty adoption of text expander technology.

Limitations of the Study

The limitations of this study relate to its generalizability to the general population of postsecondary faculty in the United States. Although SurveyMonkey Audience provides access to an extensive participant pool (SurveyMonkey, n.d.-a), the sample from this participant pool may not reflect the general population. Because the data for this study were self-reported and involved a Likert scale, the survey responses may not reflect objective reality. There was no follow up to the survey responses for this study, which limits the generalizability of the results. In addition, using SurveyMonkey Audience to collect data may also limit generalizability; the population of SurveyMonkey Audience may have more access to the Internet or computers than the general population and thus may not reflect general population of postsecondary faculty. This limitation has added relevance because this study did not delimit to postsecondary faculty who teach online, which means that the sample may have been skewed. Survey research in general has high external validity but low internal validity (Jhangiani et al., 2019), which means that future researchers should be cautious in generalizing these study results.

Another limitation of this study is the characteristics of the sample and biases that may have influenced the outcome. While the sample in general aligned with postsecondary faculty characteristics in the United States, there were more female respondents than male respondents, the respondents skewed younger than the median postsecondary faculty age, and instructors and lecturers were the most common academic ranks of the respondents. Therefore, the sample characteristics may not fully align with the general population, which limits the study’s generalizability. There are also several biases that may have influenced the study outcome, including missing confounders, volunteer bias, and nonresponse bias. Although this study included multiple covariates, such as gender, age, region, experience, and academic rank, there may be unidentified confounders that skewed the study results. Nonresponse bias, which is when individuals refuse to take part in the study, may also have affected this study; people who had adopted text expander technology may have been more willing to complete the survey than people who had not adopted text expander technology, which could have skewed the adoption rate determined through the statistical analysis. Similarly, volunteer bias could have been present, as the volunteers for this study may have been different from the general population some way, either in the adoption of text expander technology or in other areas. While random sampling and a validated, reliable instrument may have mitigated these issues, nonresponse bias, volunteer bias, and self-reported data limit the generalizability and value of the results.

Recommendations

Recommendations for future research include expanding generalizability by replicating this study through other means than SurveyMonkey Audience, exploring text expander technology through other research approaches and traditions, and creating intervention studies related to text expander technology.

One recommendation for future research is to replicate this study but to use other means than SurveyMonkey Audience to collect data; this could aid in generalizing this study's results to the general population of postsecondary faculty. For example, replicating this study in a specific organization as in Chan et al.'s (2016) study of postsecondary faculty adoption of audience response systems might lead to different results or might confirm this study's results. In addition, this study's approach was quantitative and relational, so other avenues of research could contextualize this study's results. For example, traditional diffusion research that uses snowball sampling to trace innovation diffusion among networks (Rogers, 2003) would add useful information regarding how text expander technology use diffuses within personal and organizational networks. In addition, a basic qualitative approach that includes interviews would allow for depth and richness in exploring postsecondary faculty's perception of innovation attributes as they apply to text expander technology. Another avenue of research might be a case study of an organization or department that includes training in text expander technology within its new faculty orientation and how this training affects adoption of text expander technology within the organization.

A final recommendation would be to examine cause-and-effect relationships related to text expander technology. While this study was relational, an intervention study that includes studying postsecondary faculty digital written feedback before and after adopting text expander technology would be a valuable addition to the literature, as it would aid in confirming the importance of researching innovative tools that can be used to provide digital written feedback in higher education.

Implications

This study filled a gap in the understanding of strategies that enhance online instruction facilitation by focusing on the adoption of tools that can aid postsecondary faculty in providing DITDWF to students. Providing insight into the frequency of postsecondary faculty text expander adoption and the perceived attributes of innovation that predict postsecondary faculty adoption of text expander technology can positively affect faculty and administrators at the individual and organizational level.

This study's results were that postsecondary faculty's perception of relative advantage, complexity, and observability predict adoption of text expander technology. At the individual level, this study increases the visibility of text expander technology and its features and benefits. At the organizational level, understanding the perceived attributes of an innovation that increase adoption can inform and enhance faculty training, as administrators can adapt faculty training programs to specifically utilize and discuss the specific perceived attributes of innovation as they relate to the innovative technology (Reid, 2017). In addition, the finding that 64.8% of this study's respondents considered themselves adopters of text expander technology—while it may not be generalizable across all contexts—has implications for faculty training. If a significant number of postsecondary faculty use text expander technology to provide digital written feedback, administrators should consider developing or modifying training to support use of the technology and to ensure that postsecondary faculty use of text expander technology aligns with best practices related to the new paradigm of feedback. Although this study's implications are mostly at the individual and organizational level, there may also be an indirect societal benefit from this research related to the adoption of text expander technology. Digital written feedback continues to become more relevant to higher education, and supporting instructor presence through the DITDWF that can result from the adoption of text expander technology can contribute to positive social change through enhancing student motivation, engagement, and success in the online environment.

This study also has theoretical implications in its support of Rogers' (2003) theory of innovation diffusion. The perceived attributes of innovation, which include relative advantage, compatibility, complexity, observability, and trialability, were significant predictors of postsecondary faculty adoption of text expander technology in this study and thus imply the continued importance of thoroughly understanding the perceived attributes of innovation as they relate to specific innovations when championing an innovative technology within an organization. Further recommendations for practice include emphasizing relative advantage and ease of use when developing faculty training around text expander technology, as well as increasing the observability of use cases related to text expander technology where appropriate. These recommendations may aid in influencing postsecondary faculty to adopt text expander technology to provide digital written feedback and may ensure that postsecondary faculty who use text expander technology align its use with the new paradigm of feedback, which may positively affect individual and organizational efficiency in digital written feedback practices, as well as student motivation and engagement.

Conclusion

While both students and faculty perceive feedback as important (Crisp & Bonk, 2018; Dawson et al., 2018), postsecondary faculty do not provide detailed, individualized, and timely feedback to students. Adopting text expander technology can help postsecondary faculty provide DITDWF to students (Mandernach, 2018; Rios et al., 2018), and according to this study's results, specific perceived attributes of innovation, including relative advantage, complexity, and observability, predicted postsecondary faculty adoption of text expander technology. The alignment of adoption of text expander technology with Rogers' (2003) theory of innovation diffusion can aid faculty and administrators in better understanding the adoption of innovative technology to provide digital written feedback in higher education, which can positively affect digital written feedback practices at the individual and organizational level. Continued research into the adoption of technology that enhances online feedback delivery can aid in bridging postsecondary faculty's intention and implementation of providing detailed, individualized, and timely feedback to students in online learning environments, which can in turn enhance student motivation and engagement in higher education.

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Appendix A: Permission to Use Perceived Attributes of Innovation Instrument

Benbasat, Izak [redacted]
Sun 6/14/2020 12:28 PM
Dear Katherine:

Yes, please feel free to use the instrument for your research.

Best wishes for success in your academic work.

Sent from my iPhone

On Jun 14, 2020, at 06:05, Katherine Mckinney <[redacted]
wrote:

Dear Dr. Benbasat,

My name is Katherine McKinney, and I am a student in the PhD in Education program at Walden University. I have recently entered the dissertation stage of my program, and I am interested in studying the adoption of text expander programs by college-level instructors to provide online feedback to students. I greatly admire your 1991 perceptions of adoption survey instrument and am wondering if I would be able to use it for my study. I would be glad to provide more information about my study and the possible use of the instrument as needed.

Kind regards,

Katherine R. McKinney

Appendix B: Permission to Use Adapted Perceived Attributes of Innovation Instrument

Chan, Tan Fung <[redacted]>
Sun 8/30/2020 11:20 AM
Ms. Mckinney,

Absolutely. Please feel free to adapt those demographic questions. Good luck with your study.

Ivan

Tan Fung (Ivan) Chan, EdD, OTD, OTR/L
Associate Professor and Assistant Program Director
Chair, Institutional Review Board (IRB)

College of Nursing and Health Sciences
Occupational Therapy Programs
Barry University
[redacted]

Katherine Mckinney
Sun 7/26/2020 4:17 PM
Good afternoon,

My name is Kat McKinney, and I am a PhD candidate within the Riley College of Education and Leadership at Walden University. Dr. Arome is my chair, and Dr. Griffiths-Prince is my methodologist. I am currently writing Chapter 2, and I found your study and have determined that it closely aligns with my own proposed study, which is to use Rogers' attributes of innovation to predict postsecondary faculty adoption of text expander programs to provide digital feedback.

I have already received approval from Dr. Benbasat to use the Attributes of Innovation survey instrument for my study, but I am also planning to add questions about faculty adoption of the innovation (e.g., Do you consider yourself an adopter of text expander programs?). I am wondering if it would be possible to adapt your demographic/adoption questions for use in my dissertation study.

I would appreciate any guidance you could provide, either about your instrument or about any part of my study, and will gladly provide more information about my study if you would like.

Kind regards,

Kat R. McKinney
Learning, Instruction, and Innovation PhD Candidate
Learning Designer - John Wiley & Sons

[redacted]

Perceptions of Adopting an Information Technology Innovation

Adapted from "Development of an instrument to measure the perceptions of adopting an information technology innovation" by G. C. Moore and I. Benbasat, 1991.
The objective of this survey is to identify factors that influence faculty's use of instructional technology, specifically the audience response system (ARS) in the delivery of instruction.

The audience response system appears in the literature under different names, some examples of which are classroom response system (CRS), student response system (SRS), clicker, and classroom polling system. These commercially available systems are remarkably similar in form and in function. They are generally made up of a combination of software and hardware for the purpose of presenting questions, recording responses, and providing immediate feedback (Kay & LeSage, 2009a).

Your participation in this research is strictly voluntary. Your completion and submission of the questionnaire indicate your consent to participate in the study.

PLEASE DO NOT IDENTIFY YOURSELF ON THIS SURVEY. ALL INDIVIDUAL RESPONSES WILL REMAIN CONFIDENTIAL. ONLY THE AGGREGATE RESULTS WILL BE REPORTED.

Thank you for participating in this survey.

Part I. Demographic Information

Q1. Have you been teaching any on-campus class within the past 12 months?
- o Yes
- ¨ No (If your answer is no, you will not be included in this study. Thank you for your time.)

Q2. Gender
- o Male
- ¨ Female

Q3. Age
- o 75 or older
- o 65-74
- o 55-64
- o 45-54
- o 35-44
- o 25-34

o Under 25 years old

Q4. Highest degree held:
o Doctorate
o Masters
o Bachelors
o Other (please specify) _______________

Q5. Please indicate your current employment status:
o Full-time
o Part-time/adjunct

Q6. Please indicate your current academic rank:
o Full Professor
o Associate Professor
o Assistant Professor
o Instructor

Q7. How many years have you taught at university level?
o 40 years or more
o 35-39 years
o 30-34 years
o 25-29 years
o 20-24 years
o 15-19 years
o 10-14 years
o 5-9 years
o 0-4 years

Q8. How many years have you taught at your current department?
o 40 years or more
o 35-39 years
o 30-34 years
o 25-29 years
o 20-24 years
o 15-19 years
o 10-14 years
o 5-9 years
o 0-4 years

Q9. At this time, do you consider yourself an adopter of the ARS?

(For the purpose of this study, an adopter is defined as a faculty member who has made the decision to make use of ARS in his/her teaching when the use of it is deemed appropriate. Please note that the current study is not designed to investigate the actual implementation of ARS; therefore, an adopter is not necessarily a current user of the technology.)
o Yes
¨ No

Q10. Please select which of the following statements best describes your disposition toward the adoption of change:
- o I consider myself traditional. I often refer to past for your guidance and resist innovations until certain that it will not fail.
- o I consider myself cautious about change. I often require convincing of the economic necessity of a change, and I am uncomfortable with uncertainty.
- o I consider all consequences fully and frequently interact with my peers. I am willing to change to a new way or method, but not willing to be a leader in the process.
- o I consider myself judicious when it comes to innovation decisions. I decrease uncertainty by fully evaluating something new, and I often use interpersonal networks within my immediate area to gain more information.
- o I consider myself venturesome. I am often obsessed with trying new things and seeking information outside of the immediate area.

Ms. Mckinney,

Here were the demographic questions I used. Please feel free to modify them to fit your needs.

Best,

Tan Fung (Ivan) Chan, EdD, OTD, OTR/L
Associate Professor and Assistant Program Director
Chair, Institutional Review Board (IRB)

College of Nursing and Health Sciences
Occupational Therapy Programs
Barry University
[redacted]

Appendix C: Data Cleaning Steps

During the data cleaning process, I followed the steps below:

1. I first cleaned the data using SurveyMonkey's filter tools. To begin, I filtered for completeness and removed respondents who only answered a fraction of the survey questions.
2. Next, I reviewed the average response time for the survey, and I then filtered responses by time and removed responses that greatly deviated from the average.
3. I then checked the responses for straightlining by applying filters related to each question and each answer on the Likert scale. By filtering each question, I was able to remove responses that were straightlined—i.e., responses with the same answer chosen for each question. I repeated this filtering process for each item on the Likert scale.
4. I also applied multiple filters to check for inconsistent responses. For example, I looked for responses that included opposite answers for the same question asked in a different way.
5. After cleaning the responses in SurveyMonkey, I then exported the data to SPSS and continued data cleaning. First, I checked each response individually and removed responses with more than three missing cases.
6. Then, I removed responses with missing cases related to my first research question—i.e., I removed responses where the respondents did not identify whether or not they identified as adopters of text expander technology.
7. I finally examined the casewise listing of residuals during the data analysis process. After producing the table, I individually examined each case with a standardized residual over 2.5. I reviewed each case and removed responses with a pattern of inconsistent answers.