An Examination of Post Implementation Adoption of Business Intelligence Technologies and the Role of Training Programs during this Process

Juliana Gully
University of Central Florida

AN EXAMINATION OF POST IMPLEMENTATION ADOPTION OF BUSINESS INTELLIGENCE TECHNOLOGIES AND THE ROLE OF TRAINING PROGRAMS DURING THIS PROCESS

by

JULIANA L. GULLY
B.A. University of Central Florida, 2010
M.A. University of Central Florida, 2012

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ABSTRACT

This research study sought to determine if there was any difference in the perception of training modality delivery between participants who attended a face-to-face (F2F) training session or participated in blended training that supported business intelligence (BI) technology adoption. There is minimal information available identifying how training can influence an individual's intention to fully adopt BI technology into daily work processes. Identification of key factors influencing training modalities' effect on technology adoption promotes strategies that allow trainers to better facilitate and develop content that can help organizations to integrating BI technologies into their workflow. This study analyzed survey responses that captured the perceptions of end-users who completed training by attending a F2F or blended training and their readiness to utilize the BI technologies post-training. The sample for this study consisted of 62 individuals who completed both the training session survey (F2F or blended) and the client implementation survey; to qualify for this study, all participants completed both surveys; 33 participants attended the F2F training sessions, and 29 participants attended the blended training sessions.

Survey responses related to the training session and the training consultant were used to identify differences in perception when comparing the two different groups and their feelings of preparedness to accept responsibility for the technology. While there was an indication that the feeling of preparedness to adopt the BI technology was more heavily influenced by the blended training, it is important to consider methods for improving participant satisfaction in all areas related to blended training. Overall, this

study provides the basis for an executive summary indicating the need to implement more effective training strategies, policies, and training processes before and after implementing BI technologies within organizations.

This dissertation is dedicated to my children Jenaia Fowlkes, Freddie Robertson Jr., and Terell Robertson who have always been the reason I do anything in life. Thank you for being as proud of me as I am of you.

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CHAPTER 1
THE PROBLEM AND ITS CLARIFYING COMPONENTS

The ability to analyze provider performance (cost/quality) and population risk has have become increasingly important in recent years as these metrics are being tied to reimbursements for medical services ("Medicare," 2016). Historically, reimbursements were based on fee-for-service models that rewarded physicians for quantity, not quality. To support policy and reimbursement changes, organizations began to realize the value of claims and provider data. Health insurers traditionally processed claims using system-supported validation techniques to detect invalid billing items (Srinivasan & Arunasalam, 2013). These systems can identify erroneous billing practices but do not aid in discovering other healthcare service inefficiencies.

Sophisticated analytic systems that can identify cost overruns that constitute fraud, waste, and errors are essential for insurers and other healthcare payers (Srinivasan & Arunasalam, 2013). These analytic systems receive large amounts of data from sources that typically include medical claims, provider information, member information, and pharmacy claims. While this wealth of data offers significant opportunities for improving healthcare delivery, management, and policy making, new information systems and approaches are needed to make effective use of such "big data."

Healthcare analytics refer to the systematic use of health data and related business insights developed through applying analytical models (e.g., statistical, contextual, quantitative, predictive, cognitive) to drive fact-based decision-making for planning, management, measurement, and learning in healthcare (Cortada, Gordon, & Lenihan, 2012). Technologies exist that allow data to be retrieved and manipulated for these analytic purposes. Business intelligence (BI) is one area of the decision support systems (DSS) discipline and refers to information systems aimed at integrating structured and unstructured data, ultimately converting it into useful information and knowledge (Santos & Azevedo, 2015). However, the implementation and adoption of such technologies are often problematic. Regarding organizational barriers, prior studies have reported how organizations (Yang, Kankanhalli, Ng, & Lim, 2015) and healthcare professionals (Yang, Ng, & Kankanhalli, 2012) may resist the introduction of technologies that facilitate data capture for analytics but change their work processes.

Background of the Problem

Optum is a corporation specializing in developing software solutions that support healthcare analytics. Their information and technology-enabled health services platform serves a broad range of the healthcare marketplace. Optum is headquartered in Eden Prairie, Minnesota, with offices and facilities across various regions in the United States. They also maintain operations across the rest of North America, South America, Europe, Asia Pacific, and the Middle East. Clients engage Optum to assist with transforming health services in light of new healthcare information technologies. Clients represent a broad range of specialties within the field of healthcare, including insurance companies, health networks, and provider organizations. Optum combines data and analytics with technology and expertise to drive four core capabilities: (a) people, (b) technology, (c) data, and (4) action (Optum, 2017). Optum's organizational goal is to globally impact healthcare practices by implementing technological resources to aid partners in population data analytics (Optum, 2017).

One technology solution, Impact Intelligence, is at the forefront of providing clients with the capability to analyze data and implement actionable processes to maximize reimbursement potential. This solution was recently redeveloped using business intelligence (BI) technologies. Since the technology was redeveloped, Impact Intelligence end-users have lower-than-expected utilizations rates, which is indicative of poor overall adoption and dissimilation of the technology into daily workflow activities. The adoption of BI technologies presents challenges that organizations need to identify to achieve returns on investment. More specifically, the potential for increased profits by utilizing BI technologies is still not enough to promote employee acceptance and use.

Training has not been an integral component during the pre and post-implementation process of Impact Intelligence. A study on post-implementation perceptions and acceptance of technology provided data to support the conventional wisdom that training has a very strong influence on how a user not only perceives and accepts a technology system but also how the technology is utilized after it has been in training must not only focus on the functionality of the system but also on the content. Furthermore, the process of training must appeal to the psychological predisposition of the eventual users of the system. The emphasis of training on the psychological aspects of technology acceptance may reduce apathy and engender positive expectations that the technology will be valuable to the user (Amadi-Echendu & De Wit, 2015).

In an effort to measure client's satisfaction with the technology, Optum surveys clients twice a year using Net Promoter surveys. Net Promoter Scores measure satisfaction with the technology products (global survey) and implementation process (targeted survey). Net Promoter Scores (NPS) are an indicator of market growth. Research has shown that organizations with higher NPS scores than their competitors have better market share and business performance ("What Is Net Promoter," 2016). The Net Promoter Scoring system classifies clients into three distinct categories based on survey responses using a 0-10 scale ("What Is Net Promoter," 2016). This Net Promoter Scoring system places client responses into the following categories:

- Promoters (9-10): Loyalists who will keep buying services and referring others which stimulates business growth.
- Passives (7-8): Satisfied but unenthusiastic customers who are vulnerable to competitive offerings.
- Detractors (0-6): Unhappy customers who can damage your brand and impede market growth through negative word of mouth.

One survey question in particular focused on client readiness to use Optum's Impact Intelligence technology. In 2015, training consultants hosted 88 implementation training sessions. In those 88 sessions, 35% of the customers reported that they were unprepared to use the product (Optum. 2015). Based on the opened-ended responses to the NPS survey, several factors emerged as potential factors in customers' self-reported unease with the technology, including:

- Lack of a structured training program,
- Inconsistent training processes,
- Lack of clarity regarding pre and post-implementation training expectations, and
- Limited alignment of training goals and strategies with clients' business needs.

Training has not been an integral component of the pre and post-implementation of the Impact Intelligence technology. As the NPS survey feedback indicated, Optum's training process that historically supported Impact Intelligence lacked structure and were inconsistent. For end users to gain value from training, the process of training must appeal to the psychological predisposition of the eventual users of the system. Furthermore, placing the emphasis of training on the psychological aspects of technology use may reduce apathy and promote positive expectations that the technology will be valuable to the user (Amadi-Echendu & De Wit, 2015).

Statement of the Problem

Business intelligence is an essential technology for an organization with large amounts of data to purchase (Clavier, 2016). Nonetheless, organizations struggle to realize significant business value from their BI investments and existing solutions to address BI implementation failure and challenges are largely ineffective, highlighting the need for a new approach (Clavier, 2016). The potential for analyzing large amounts of data and gaining value from the results can be achieved through use the of BI technologies. Research studies have identified challenges associated with adoption of BI technologies (Clavier, 2016; Khan, Durrani, Khalid, & Aziz, 2016; Lee & Widener, 2016;

Shehzad & Khan, 2013); however, there is a paucity of information regarding behavior implications such as usage intention once technologies are introduced within organizations. Limited information is available identifying how training can influence an individual's intention to fully adopt BI technology into daily work habits. Identifying key factors that influence the effects of training on technology adoption may promote strategies that allow organizations to better integrate BI technologies.

One strategy implemented by Optum is the introduction of a blended training program to support BI technology training of their clients. Historically, clients were offered only face-to-face (F2F) training sessions that required participants to be in classroom settings for two days or more. The F2F training sessions come at a higher expense for clients. They are responsible for the cost of having a training consultant onsite, in addition to all incurred travel expenses. Also, there is a reduction in productivity levels of staff who are required to attend two days of classroom training. Incorporating blended or Web-based strategies into traditional delivery strategies for instruction offers enhanced training solutions for organizations with end-users in multiple locations and varying schedules (Boone, 2015). Reasons for the use of Web-based strategies for workplace instruction include:

- They are instrumental in the development of a global workforce,
- They facilitate the management of flat,
- They accommodate decentralized organizations,
- They adjust to learner needs, and
- They increase productivity and profitability (Boone, 2015).

A study on post-implementation perceptions and acceptance of technology provided data to support the conventional wisdom that training has a very strong influence on how a user not only perceives and accepts a technology system but also how the technology is utilized after it has been implemented (Amadi-Echendu & De Wit, 2015). Further research is needed to examine end-users' perception of the blended training model and its effect on how end-users adopt BI technology within organizations.

Purpose of the Study

This purpose of this research study was to explore the perceptions of end-users who attended either the F2F training session or completed a blended training program and how this training related to their feelings of preparedness to assume responsibility for the BI intelligence technology. The researcher used the unified theory of acceptance and use of technology (UTAUT) model as a guide in analyzing facilitating conditions, specifically the introduction of a blended training approach and its effect on end-users' feelings of preparedness to accept responsibility for the technology. The researcher used the results to identify opportunities for improvement within the blended training program curriculum. Improvement of the blended training curriculum better supports the training needs of end users in Optum's client organizations. Furthermore, blended training decreases the time spent onsite by training consultants which in turn reduces client cost. Changing the processes within the blended training program to include additional support once the implementation project concludes will increase the possibility of software technology renewals.

Research Questions

The following research questions were used to guide this study:

1. What are the differences in perception of the product training session as measured by the training survey between end-users who attended F2F training or end-users who attended blended training?
2. What are the differences in perception of the product training session facilitator as measured by the training survey between end-users who attended F2F training or end-users who attended blended training?
3. What are the differences in perception of the feeling of readiness to assume responsibility for the product as measured by the client implementation survey between end-users who attended F2F training or end-users who attended blended training?

Theoretical Framework

The UTAUT model was used as a theoretical framework to examine technology use in organizational settings (Venkatesh, Morris, Davis, & Davis, 2003). Venkatesh et al. (2003) developed the UTAUT model after reviewing well-known early studies of technology adoption models, such as the technology acceptance model (Davis, Bagozzi, & Warshaw, 1989) and the theory of planned behavior (Taylor & Todd, 1995). Ultimately, Venkatesh et al. (2003) settled on performance expectancy, effort expectancy, social influence, and facilitating conditions as the four primary determinants of user acceptance. The facilitating condition is the key determinant factor of focus with usage behavior identified as a dependent variable. The other determinants included performance expectancy, effort expectancy, and social influence; these determinants were not key factors because this study focuses on the impact of a blended training model (facilitating condition) on usage behavior (technology adoption).

Research has demonstrated the value of identifying how facilitating conditions affect the acceptance and use of technology in various organizational settings. For example, Alrawashdeh and Al-Mahadeen (2013) conducted a study using UTAUT to measure acceptance of Web-based training systems by public sector employees that concluded that facilitating conditions have a strong effect on employee's intention to use technology.

Population and Sample

The targeted population for this quantitative research study consisted of Optum clients who met the following criteria:

- Completed an Impact Intelligence project implementation project within the last six months,
- Participated in an end-user training session in one of two modalities (F2F or blended), and
- Completed end-of-training survey.

Surveys were electronically delivered to all key stakeholders after completion of both the implementation project and end-user training. The responses were limited to those participants associated with the researcher to ensure the validity of the study by ensuring all participants completed curriculum tasks assigned to either the F2F training or blended training program.

Significance of the Study

Organizations face many challenges when introducing new technologies into their existing work streams. Optum is an organization facing the problem of less-than-optimal adoption of their BI technology (Impact Intelligence). Reasons for this sub-optimal adoption of BI technology are associated with end-users' perception of how training modalities are delivered and feelings of preparedness to assume responsibility for the technology as exhibited by survey responses from clients who attended a F2F training session or blended training program. This is a common and foundational problem in many organizations regarding the acceptance of BI technologies into daily work processes. Although challenges associated with adoption of business intelligence have been identified through research (Khan et al., 2016; Lee & Widener, 2016; Shehzad & Khan, 2013; Clavier, 2016), there is little information regarding the implications of not accepting new technologies once technologies are introduced within organizations and if training modalities (F2F or blended training) have any influence in this regard. Without efficient training processes in place, the capacity to adopt new technologies within an organization may be hampered before it even begins. Not only does the lack of efficient training processes hinder the acceptance of new technologies within an organization, it may lead to eventual loss of clients as the motivation to renew technology licenses, due to lack of utilization, could affect Optum's revenue.

Addressing differences in perception of the current Optum training delivery models and the benefit of improving blended training processes will be beneficial for both Optum and its clients. For example, Broadbent (2017) noted that blended learning, if done well, combines the benefits afforded by online technologies with the structure and social aspects of F2F time, to give an overall richer experience. As technology advances, the mechanisms of blended delivery training would serve as an enhancement to Optum's clients who would benefit from asynchronous online training activities that would reduce the costs associated with onsite F2F time. Blended learning also promotes accessibility of content and is a mechanism to improve learning outcomes (Boone, 2015). Improvements in blended training will have a positive impact on Optum's clients as well as training consultants who manage the program. Moving to a more asynchronous method of delivering training reduces the pressure on training consultants to deliver large amounts of content within a small time frame without the ability to assess if any learning has transpired. Taken together, the important problem of improving blended training processes along with the positive impact these improvements will have on Optum's clients' feeling of preparedness to assume responsibility for adopting the technology makes this a significant problem to address.

Limitations

1. Validity is limited by the use of self-reported survey responses.
2. The sample population was obtained using Optum clients so results may only be applicable to the sampled population.

3. Generalization is limited to the client population with completed Impact Intelligence implementation projects.
4. Generalization is limited to the client population who either attended a F2F session or participated in a blended training program.

Assumptions

1. Survey responses were representative of all Optum clients with completed Impact Intelligence implementation projects.
2. Survey responses were completed by end-users who either attended a F2F session or participated in a blended training program (F2F, online, and Web conferencing).
3. The end-users answered the survey questions without assistance from other individuals.

Definition of Terms

Blended training: Refers to an educational experience that is conducted through a combination of F2F class meetings and online course activities (Zimmer, 2017).

Business intelligence (BI): One area of the Decision Support Systems (DSS) discipline and refers to information systems aimed at integrating structured and unstructured data to convert it into useful information and knowledge (Santos & Azevedo, 2015).

E-Learning: Takes place in an online, computer-based environment and covers a broad range of teaching techniques and practices. These include online instructional presentations, interactive lessons, and computer-supported in-class presentations (Lundin, 2017).

Facilitating conditions: Defined as the consumer perception of resources and support available to perform a behavior. Training is an example of a facilitating condition (Venkatesh et al., 2003).

Face-to-face (F2F): Traditional format of instruction with all participants in the same location (Allen & Seaman, 2013).

Human systems integration (HSI): A system design approach intended to ensure that human characteristics are considered throughout the entire design process with respect to selection and training, participation in the operation of the system, and safety

Impact Intelligence: Provides clients with the capability to analyze data and implement actionable processes to maximize reimbursement potential (Optum, 2016).

Learning organization: An organization that possesses intimate knowledge of the rapidly evolving global marketplace and its impact on the current planned sets of products and services (Mitra & Gupta, 2008).

Net promoter scores (NPS): An indicator of market growth. Research has shown that organizations with higher NPS scores than competitors have better market and business performance ("What Is Net Promoter," 2016).

Six-sigma methodology: A measurement of quality, processes for continuous improvement, and culture change enablement ("Six Sigma," 2016).

The Unified Theory of Acceptance and Use of Technology (UTAUT): Distills critical factors and contingencies related to predicting behavioral intention to use a technology and technology use, primarily in organizational settings (Venkatesh et al., 2003).

Usage behavior: Used to assess the validity of facilitating conditions, such as training in relation to technology adoption (Venkatesh et al., 2003).

CHAPTER 2
LITERATURE REVIEW

Introduction

There is an opportunity for healthcare organizations to identify areas where more efficient processes can be implemented by using claims data. Analytic systems can help identify cost overruns using claims data that can be attributed to fraud, waste and other billing errors (Srinivasan & Arunasalam, 2013). Large quantities of data offer significant opportunities for improvement; however, new information systems and approaches are needed to make effective use of the big data. Large and complex amounts of data that is difficult to analyze and manage by traditional computing tools can be defined as big data (Kamkanhalli, Hahn, Tan, & Gao, 2016). Technologies exist that allows data to be retrieved and manipulated for these analytic purposes. Business intelligence (BI) is one area of the Decision Support Systems (DSS) discipline and refers to information systems aimed at integrating structured and unstructured data to convert it into useful information and knowledge (Santos & Azevedo, 2015). Prior studies have reported how organizations (Yang et al., 2015) and healthcare professionals (Yang et al., 2012) may resist the introduction of technologies that facilitate data capture for analytics but change their work processes.

The purpose of this literature review is to establish the importance of processes that support BI, categorize issues that may affect technology adoption, identify theories used to support behavioral intentions and conditions that may influence use intent. This review begins by defining the origins of BI through describing Hans Peter Luhn's 1958 vision of a BI system and the evolution into a present-day version of digitally integrated processes to enhance organizational decision-making. The review then looks at issues that may influence adoption of new BI technologies from an organizational perspective. The literature identified various challenges that can positively or negatively influence end-user attitudes on technology adoption. Finally, this review examines models and theories used to study adoption and use of new technologies.

Business Intelligence

Business intelligence provides organizations with information to make informal decisions about their day to day business and long-term strategy. Business analysis is the act of tying business processes to actionable data and understanding how to use that data to make better decisions (Schrader, Swift, & Yonce, 2015). Hans Peter Luhn envisioned a "Business Intelligence System" back in 1958, but only recently has BI begun to deliver knowledge instead of numbers (Grimes, 2008). Specifically, this system would allow individuals to make business decisions by using disseminated data. Business intelligence systems present historical information to its users for analysis, query, and reporting to enable effective decision making and management support to increase the performance of business processes (Trieu, 2017).

In the medical and healthcare fields, BI systems are designed to deliver decision-support information and repeatedly have been shown to provide value to organizations. Evidence-based decision making relies on reliable access to timely and accurate information (Foshay & Kuziemsky, 2014). Clinical and business analytical tools are becoming a top priority for hospitals and health systems seeking real-time actionable surveillance data to optimize care (Hospitals & Health Networks, 2016). Business intelligence with healthcare analytics is an emerging technological approach that provides the analytical capability to help the healthcare industry improve service quality, reduce costs, and manage risks (Zheng, Zhang, & Li, 2014).

Business intelligence combines different data resources into information about processes in the company and provides this information in appropriate and timely ways to support company management (Horakova & Skalska, 2013). Bonasia (2006) described BI as a better way to define the analysis of quantitative information by a wide variety of users. Business intelligence can deliver information to end-users without needing them to be experts in operational research; furthermore, unstructured data is converted into structured data which supports problem-solving within organizations (Martens, 2006). Both definitions shared similar qualities in that the objective is to provide organizations with the resources to improve communication and manage data so business decisions can be made timelier. A further refined definition of BI added ideas and techniques that use computer-based systems to help drive managerial decision making (Deng & Chi, 2012).

Hocevar and Jaklic (2010) define BI as a comprehensive concept by which the whole organization supplies information systems with the most effective method to use timely and high-quality information. Jordan and Ellen (2009) state BI is a critical solution to help information-based organizations to make intelligent business decisions. The implementation of BI systems benefits organizations by providing the necessary tools to analyze large amounts of data, make informed decisions, and provide added value that supports business strategies. Business intelligence technology combines stored data within organizations from various sources to facilitate decision making by employees (Chaudhuri, Duval, & Narasayya, 2011).

The implementation of BI systems provides organizations with added value regarding data analysis. Research by Shehzad and Khan (2013) argued that a clear business vision and case is needed to establish a BI system. Benefits associated with analyzing big data effectively include up-to-date decision making and better-quality response rates to stakeholder inquiries. Business intelligence endows corporations with a competitive market advantage and stability in the long run (Shehzad & Khan, 2013). Although implementation of BI technologies has the potential to positively impact organizations return on investment, studies (Clavier, 2016; Khan et al., 2016; Lee & Widener, 2016; Shehzad & Khan, 2013) have identified issues associated with BI technology adoption.

Post Implementation Adoption of Business Intelligence Technology

There are varying issues affecting the post-implementation adoption of new BI technologies within organizations related to user perceptions and behaviors. Although viewed as a technological advancement, there are some challenges that affect adoption of a BI solution (Clavier, Lotriet, & van Loggerenberg, 2012). Some challenges influencing BI adoption include difficulty in understanding the terminology and end-users lacking the necessary skill set to use BI technology (Clavier et al., 2012). Martens (2006) suggested it is not typically technology that prevents adoption, but the culture within the organization. Organizational culture has been identified as one of the cornerstones of innovation and, in turn, innovativeness is viewed as one of the key factors that enable organizations to survive, grow, and compete in a competitive market (Kmieciak, Michna, & Meczynska, 2012). Research suggests that a lack of fit between an organization's BI technology, goals, and characteristics is one reason for lack of successful BI technology adoption (Isik, Jones, & Sidorova, 2013).

The individual intention to adopt technology is determined by two basic factors: personal interest (attitude toward adopting) and social influence (social pressure to adopt or not adopt) the technology (Karahanna, Straub, & Chervany,1999). Social context plays a role in triggering the automatic choice of using a given technology. This is especially true when more than one system is available to perform a given task. This choice may be based on recognizing superiors expect the technology to be used for a task to achieve predetermined organizational goals (Polites & Karahanna, 2013). There are also broader organizational challenges associated with adoption of BI technologies. Some examples of challenges include, low use, absence of the right sponsor, politics, culture, and unclear requirements. Deeper challenges related to technology adoption focus on skills. Business intelligence demands a broad skill set from end-users. The BI users must know more than just technology; business and soft skills are needed too. The BI user must know their data, how to use technology, the business, and have decision-making skills (Herschel, 2008). In terms of internal efficiency, research has shown that the adoption and use of technologies help redesign internal processes, enhancing efficiency by making them speedier, easier and more precise (Rowley, Baregheh, & Sambrook, 2011).

Studies have also identified critical or key factors to successfully implementing BI. Management post-implementation of these factors accelerates the process of technology adoption (Krsak, 2013). These factors include; strong sponsorship, open corporate culture, flexible architecture and BI tools, quality of the source data, close cooperation, the right team of BI workers, and enterprise-wide solution scope (Alonso-Almeida & Llach, 2013). Consequently, the adoption of new, not necessarily complex BI technologies can lead to small process changes that may vest the company with higher levels of efficiency (Alonso-Almeida & Llach, 2013). Many models and theories used to study adoption and use of new technologies. These constructs are represented in the theory of reasoned action, the theory of planned behavior, the extended TAM known as TAM2, and UTAUT as a direct determinant of behavioral intention (Lu, 2014).

Theory of Reasoned Action

Driven by two primary factors attitude and subjective norms, the theory of reasoned action is a psychological model that seeks to understand how individuals are persuaded to participate in a behavior or activity (Hahn & Popan, 2016). The TRA has been utilized by researchers to investigate human behavior in the disciplines of social psychology (Mishra, Akman, & Mishra, 2014). Teo (2012) used TRA to predict pre-service teacher’s intent to use technology. Hahn and Popan (2016) used TRA as the conceptual framework based on the behavioral intention model to analyze acceptance of green information technology by end-users. A study performed by Barman and Barman (2016) used TRA to understand factors in the adoption of a curriculum development system by lecturers. The study demonstrated the applicability of TRA in explaining technology adoption was influenced by lecturer's attitude, perceived belief control, and knowledge.

In the context of this study, prior knowledge included the lecturer's system awareness, definition of use, and understanding of system functionality (Barman & Barman, 2016). Behavior intention is a common framework shared between the theory of reasoned action (TRA) and the theory of planned behavior (TBB) in the analysis of technology adoption.

Theory of Planned Behavior

The theory of planned behavior (TPB) was developed in the 1980s by psychologist Icek Ajzen as an extension of the theory of reasoned action (TRA) that he co-developed in the 1970s (Boslaugh, 2013). The key refinement was the component of perceived behavioral control which acts as a proxy for actual behavioral intent (Boslaugh, 2013). With this theory Ajzen's claim is that execution of behavior is strongly related to intention which in turn is the best predictor of an individual's motivation and effort to use technology with the actual use demonstrating technology adoption (Butler Lamar, Samms-Brown, & Brown, 2016). A study conducted by Chu and Chen (2016) used TPB to analyze group influences on eLearning adoption. The research findings show significant effects of perceived behavioral control and other variables on intentions to adopt (Chu & Chen, 2016). The theory of planned behavior also influenced the development of the technology acceptance model (TAM).

Technology Acceptance Model

The study of "technology adoption" is not a new endeavor in science; research in this area began as early as the late 70s and early 80s in subjects related to agriculture and technologies, or economics and economic policies, with scholars being amongst the first to attempt theoretical modeling of the technology adoption phenomenon (Stanciu, 2017). The technology acceptance model (TAM) explores factors that affect behavioral intentions to use information or computer systems and suggests that two key variables—perceived usefulness and perceived ease of use—determine the intention to use systems (Yoon, 2016).

The TAM model has been widely used to identify the determinants of technology acceptance in many contexts, and especially for predicting people's acceptance of information technology (Yoon, 2016). Joo and Choi (2015) explored multiple factors affecting undergraduate students' online resource selection. The study found that both usefulness and ease of use positively influenced the undergraduates' behavioral intention to use online resources (Joo & Choi, 2015). The Technology Acceptance Model theorize individual (e.g., ease of use, usefulness) and organizational (e.g., social norms, facilitating conditions) antecedents to predict behavioral intention to use (i.e., acceptance) and/or actual use of a new technology in an organization (Ducey & Coovert, 2016).

Specifically, TAM posits that beliefs about the perceived usefulness (PU) and perceived ease of use (PEOU) of a piece of technology influence attitude toward a piece of technology and ultimately adoption proposing that external variables (e.g., organizational training, device characteristics, and supervisor support) impact PU and PEOU (Ducey & Coovert, 2016). Studies have been conducted by researchers (Liang et al., 2010; Tung, Chang, & Chou, 2008; Wu, Wang, & Lin, 2007) using TAM to analyze compatibility, self-efficacy, technical support and amount of training provided by individuals with relevant IT knowledge and how those variables relate to technology adoption.

Unified Theory of Acceptance and Use of Technology (UTAUT)

The unified theory of acceptance and use of technology (UTAUT) distills critical factors and contingencies related to predicting behavioral intention to use a technology and technology use, primarily in organizational settings (Venkatesh et al., 2003). The theory was developed through the review and integration of eight dominant theories and models, namely: The Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), the Motivational Model, the Theory of Planned Behavior (TPB), a combined TBP/TAM, the Model of PC Utilization, Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT; Williams, Rana, & Dwivedi, 2015).

These contributing theories and models have all been widely and successfully utilized by many previous studies of technology or innovation adoption and diffusionwithin a range of disciplines including information systems, marketing, social psychology, and management (Williams et al., 2015). This model has been the foundation in various studies to evaluate adoption and use of new technologies, new user populations, and new cultural settings (Venkatesh et al., 2003). Researchers have applied, integrated, and extended UTAUT to study individual technology acceptance and use across a variety of settings, different user types, different organization types, and different types of technologies, different tasks, different times, and different locations (Venkatesh, Thong, & Xin, 2016).

Users can be categorized into different groups such as employees, consumers, and citizens. Hong, Thong, Chasalow, and Dhillon (2011) used a sample of employees at all organizational levels to study technology acceptance. Other studies have targeted specific users like teachers (Pynoo et al., 2011). Zhou, Lu, and Wang (2010) focused on user adoption of mobile banking whereas Venkatesh et al. (2016) included adoption, initial use, and post-adoptive use. Other studies have focused on specific economic sectors, such as education (Chiu & Wang, 2008), food service (Yoo, Han, & Huang, 2012), and medical services and healthcare (Akl, 2010. The original theory describes four key constructs that act as direct determinants of use intention and behavior: performance expectancy, effort expectancy, social influence, and facilitating conditions (Table 1; Venkatesh et al., 2003):

Table 1

Four Key Constructs that Act as Determinants of Use Intention and Behavior

Construct	Definition
Performance Expectancy	The degree to which using a technology will provide benefits to consumers' in performing certain activities (p. 447)
Effort Expectancy	The degree of ease associated with consumers' use of technology (p. 450)
Social Influence	The extent to which consumers perceive how important (p. 451)
Facilitating Conditions	The perception of resources and support available to consumers for them to perform a behavior (p. 453)

In addition, the theory proposes that the effect of these four determinants is mediated by individual difference variables, namely gender, age, and experience (Venkatesh et al., 2003). Venkatesh et al. (2016) expanded the UTAUT extensions to include: new exogenous mechanisms, new endogenous mechanisms, new moderating mechanisms, and new outcome mechanisms. New exogenous mechanisms refer to the impacts of external predictors on the four exogenous variables in UTAUT (i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions). According to Venkatesh et al. (2016) new endogenous mechanisms refer to (a) New predictors' impact on the two endogenous variables in UTAUT (i.e., behavioral intention and use behavior) and (b) the enrichment of the four exogenous variables and the two endogenous variables in the original UTAUT. Venkatesh et al. examined the impact of behavioral expectation on technology use. Similarly, Venkatesh et al. enriched the social influence construct with five dimensions based on the source of the influence. Venkatesh et al. provide an example of enriching the endogenous variables: they conceptualized and measured technology use by duration, frequency, and intensity. For example, Venkatesh et al. examined the moderating effect of experience on the relationship between behavioral intention and technology use, and the relationship between behavioral expectation and technology use.

New outcome mechanisms refer to the new consequences of behavioral intention and technology use added to the original UTAUT. Similarly, Chiu et al. (2009) studied the impact of technology use on individual performance. In a study conducted on acceptance of technology in building information modeling (Howard et al., 2017) the UTAUT model provided an appropriate insight of technology acceptance while proving their hypothesis of facilitating conditions having a positive influence on individual user behavior. Other research studies (Nistor, Gogu, and Lerche, 2013; Tosuntas, Karadag, and Orhan, 2015) using UTAUT have proven that the actual use of a technology is determined by facilitating conditions and the behavioral intention to use it. Research studies (Lian & Yen, 2014; Oliveiram, Faria, Thomas, and Popovič, 2014) have also integrated UTAUT with other theoretical models such as behavior intention to study technology acceptance and use (Venkatesh et al., 2016). For instance, Yoo et al. (2012) studied the impacts of extrinsic motivation and intrinsic motivation on employees' intention to use e-learning in the workplace. They conceptualized performance expectancy, social influences, and facilitating conditions as the components of extrinsic motivation, and effort expectancy as a component of intrinsic motivation (Yoo et al., 2012). Guo and Barnes (2012) also adopted the same theoretical foundation to examine consumers' purchase intention in the virtual world, but they viewed performance expectancy and effort expectancy as components of extrinsic motivation.

Facilitating Conditions and Usage

Venkatesh (2003) UTAUT model describes four key constructs that act as determinants of use intention and behavior. One of these constructs, facilitating conditions is defined as the consumer perception of resources and support available to perform a behavior (Venkatesh, 2003). Zhou (2012) later found there is extensive empirical evidence showing the significant effect of facilitating conditions on usage intentions. Chiu & Hofer (2015) hypothesized personal innovativeness positively moderates the impact of facilitating conditions on consumer intention to use technologies in emerging or advanced markets. This hypothesis was supported by data collected during a technology adoption study. Support for technology adopters may be one type of facilitating condition that influences system utilization (Alaiad & Zhou, 2014). Similarly, the UTAUT model predicts that the user behavior of an information system is impacted by behavioral intention constructs made up of performance expectancy, effort expectancy, social influence and facilitating conditions referring to the extent to which an individual believes the organization is there to support the use of the system through training (Howard et al., 2017).

Proper user training is an important factor in enhancing the perception of individual users; therefore, user training should be an important part in any system design and implementation (Alaiad & Zhou, 2014. For end-user training to be successful, organizations should identify their specific business and job tasks needs accurately. By training users and assisting them when they encounter difficulties some of the technical barriers to us can be alleviated or eliminated (Alaiad & Zhou, 2014).

Organizational Learning Culture

A fundamental component influencing the rate of technology adoption is the organizational culture of learning (Mitra and Gupta, 2008). The definition of a learning organization contains ideologies related to learning societies and economies of knowledge. Learning organizations most possess intimate knowledge of the rapidly evolving global marketplace and its impact on the current planned sets of products and services (Mitra & Gupta, 2008). Peter Senge proposed five fundamental disciplines essential for an organization to implement a culture of learning (Fillion, Koffi, & Ekionea, 2015). Senge viewed each discipline as a series of principles and practices studied, mastered, and integrated into our lives (Fillion et al., 2015). The fundamental disciplines encompass a system thinking approach, personal mastery, mental models, shared vision, and team learning (Fillion et al., 2015). These disciplines can be further broken down into three distinct levels of practice, principal, and essences (Fillion et al., 2015). As organizations become learning organizations building learning capability at the individual level is crucial (Kirwan, 2016).

P. J. Guglielmino and L. M Guglielmino (2001) proposed a distributed model comprising of the elements needed to promote learning throughout an organization:

- Learning is self-managed, not other managed. People take responsibility for their own learning and for sharing relevant learning with others.
- Content is individualized instead of predetermined. Learners can target their learning efforts where they are needed most increasing impact and improving learning transfer.
- Application of learning is primarily immediate, rather than delayed.
- Learning is primarily independent or interdependent rather than dependent. As independent learners seek others with similar learning needs for support interdependent small groups are likely to form.
- The cost to the organization is often reduced as more options and support for self-directed learning are provided.

Learning interventions can be integrated into daily organizational practices; however, implementation should be dynamic, sustainable, and scalable. Literature focusing on implementable learning interventional practices that advocate organizational change distinguishes between those classified as episodic and continuous improvements. Continuous change is described as ongoing and endless, involving constant modification, and stressing adaptability; while episodic changes are intentional, static, infrequent, goal seeking with a clear beginning and end (Henna et al., 2016).

Motivation

Motivation is an integral part of human behavior and an important determinant in why a person may pursue an activity. Intrinsic motivation is something internal, either primal or learned (Respovich, 2014). One example in relation to technology adoption would be an end-user taking supplemental courses to better understand the system. Extrinsic motivation is something external and may be both positive or negative (Respovich, 2014). Typically, end-users who attend BI training sessions are mandated by upper management to do so. The TAM model was refined within a motivational framework, which included both extrinsic and intrinsic motivations as predictors of behavioral intention to use technology (Abdujalil & Zainuddin, 2015).

For motivation theorists, the key factors determining both the intent to use and actual use of IT (Choi & Chung, 2013; Hajji, Jasouli, Mbarki, & Jaara, 2016; Khan et al., 2016; Wang & Feeney, 2016) include: (a) extrinsic factors, the performance of an activity because it is perceived to be instrumental in achieving valued outcomes that are distinct from the activity itself, such as improved job performance, pay, or promotions and (b) intrinsic factors, the performance of an activity for no apparent reinforcement other than the process of performing the activity. Intrinsic motivation comprises four dimensions, namely social support, self-concept, self- management, and self-compensation (Hsiche, Gong & Houn-Gee, 2017). Studies (Wu & Lu, 2013; Kwon & Noh, 2015) have found that perceived usefulness (an extrinsic motivator) is the strongest determinant of the use of utilitarian or productivity oriented systems, which aim to provide instrumental value to users.

Human Systems Integration

Human systems integration (HSI) is a system design approach intended to ensure that human characteristics are considered throughout the entire design process with respect to selection and training, participation in the operation of the system, and safety (Pew & Mavor, 2007). Endsley (2016) defines HSI as a disciplined, unified, and interactive systems engineering approach for integrating human considerations into system development, design, and life-cycle management. Too often acquisition system programs fail to consider the human capacity or requirements as part of the system (Boehm & Lane, 2007). How people perform with technology is a critical component of total systems performance. While our systems development processes often focus only on the mechanical performance, it is important to focus not only on technology but how well the technology supports the people who need it (Endsley, 2016). Human Systems Integration focuses attention on the human part of the total system equation by ensuring that human related considerations are integrated into the systems acquisition process (ACQNotes, 2016). The benefits of HSI are often indirect, such as reduction in users need for help with the system or an increase in user satisfaction (Stark & Kokini, 2010). Inclusion of those skilled in HSI practices during the research and development phases can aid in early identification of common system failures like underutilization or disuse due to difficult, inefficient designs (Pew & Mavor, 2007). Early integration of HSI philosophies can help identify and mitigate risks that may occur throughout the system life cycle. Human Systems Integration incorporates nine key areas: manpower, personnel, training, human factors engineering, environment, safety, occupational health and survivability (Endsley, 2016).

Blended Learning

Over the last few years blended learning has gained in popularity since being introduced during the late 1990s. Researchers have conducted studies in their pursuit to learn more about this mixed modality approach to learning in both educational and corporate environments. Fleck (2012) observed a growing interest in this method of instruction that combines face-to-face (F2F) teaching with other delivery methods including online interactions or eLearning. The increased evolution of technologies has also supported the acceptance of this learning model. For this reason, blended learning, if done well, may combine the benefits afforded by online technologies, with structure and social aspects of F2F time, to give an overall richer experience (Broadbent, 2017).

Since its introduction, the term has progressed to incorporate a more developed set of learning strategies. Several researchers have written articles that suggest similar definitions of blended learning. Hill (2017) identified that participants in a blended system of learning (F2F and online) 16-week field experiment specifically focusing on providing high content value in both settings had noticeable performance gains. Nair and Bindu (2016) proposed that blended learning provided a conceptual framework which resulted in sustained behavior changes. The studies hypotheses uncovered results that proved to be in favor of blended learning. Detractors of blended learning point to the merits of F2F classrooms regarding valuing the interactive experience (Donnelly, 2013).

Promoters believe online learning in combination with F2F instructor time has the potential to increase and improve the overall learning experience (Donnelly, 2013). Fleck (2012) agreed that blended learning, if used in a business education context, boosts learner-to-learner interaction through different activities. A study conducted by Vos, Dragovic, Jochimsen, Dirach, Foth, Wiese, and Bjerrum (2017) introduced a piloted blending learning program in addition to the standard F2F instruction in a post-graduate pharmacy program. The blended courses rated higher as compared to the standard F2F courses with participants in the blended piloted program preferring the online component in favor of traditional class attendance (Vos et al., 2017). Another study by Andruseac, Costeleanu, Boldureanu, Murgu, and Boldureanu (2017) analyzed blended learning in a medical environment to supplement facets of F2F traditional teaching. They found blended learning has a meaningful impact and consistently demonstrated their efficacy with learner satisfaction. However, it was noted online platforms should not replace, the F2F traditional teaching (Andruseac et al., 2017).

There is increasing acceptance of blended learning course delivery among learning organizations (Overbaugh & Nickel, 2011). The blended delivery has been found to be most effective, followed by online delivery formats, and traditional classroom delivery format, respectively. Incorporating blended or Web-based strategies into traditional delivery strategies for instruction is thought to be an advantageous training solution (Boone, 2015). It promotes accessibility of content and is a mechanism by which to improve learning outcomes (Boone, 2015).

CHAPTER 3
METHODOLOGY

Introduction

This research study utilized survey data to evaluate end-user perceptions of two training modalities: face-to-face (F2F) and blended learning. The training sessions were conducted in a training room setting or through a combination of online tools, Web conferencing sessions, and a training room setting from 2016 to 2017. The participants in this study belonged to organizations that completed implementation of a business intelligence (BI) technology project and attended either the F2F or blended learning training session during that same time frame. Impact Intelligence, an Optum technology, provides organizations with the capability to analyze large amounts of data. Some challenges influencing BI integration include difficulty in understanding the terminology and end-users' lack of the necessary skills to use BI technology (Clavier et al., 2012).

Although the implementation of BI technologies has the potential to impact positively organizations' returns on investment, studies have identified issues associated with BI and the willingness of users to integrate the technology (Clavier, 2016; Khan et al., 2016; Lee & Widener, 2016; Shehzad & Khan, 2013). Amadi-Echendu and de Wit (2015) studied employees' post-implementation perceptions and acceptance of technology that supported the conventional notion that training has a very strong influence on how a user (employee) perceives and accepts a new technological system as well as how the user utilizes the technology after it has been implemented. This study focused on the end-user perception of whether the F2F or blended learning training session had the strongest influence on their feelings to assume responsibility for the technology.

The purpose of this study was three-fold:

- To identify components of training session between two groups (one group completed training completely F2F and the other group training was blended modality) that influence user perceptions of the training;
- To implement and evaluate the delivery of a new blended learning program; and
- To further explore the differences in perceptions between participants who attended the F2F sessions versus the blended learning program and their feelings or readiness to assume responsibility for the technology.

In this chapter, the study design, study population, instrumentation, data collection, and data analysis are explained.

Research Questions

The following research questions were used to guide this study:

1. What are the differences in perception of the product training session as measured by the training survey between end-users who attended F2F training or end-users who attended blended training?
2. What are the differences in perception of the product training session facilitator as measured by the training survey between end-users who attended F2F training or end-users who attended blended training?

3. What are the differences in perception of the feeling of readiness to assume responsibility for the product as measured by the client implementation survey between end-users who attended F2F training or end-users who attended blended training?

Research Design

The selection of the appropriate research design and sampling method helps the researcher to develop a study that is highly deliberate and defensible (Vogt, Gardner, & Haeffele, 2012). There are three types of research studies that are typically used in causal-comparative analysis to investigate and explain perceptions between two groups: (a) exploration of effects, (b) exploration of causes, and (c) exploration of consequences (Curran, Reid, Fitzgerald, Heath, & Mullins-Richards, 2015). This researcher sought to compare differences of perception (effects) between individuals who participated in two different training programs and, accordingly, selected a causal-comparative research design. Specifically, the researcher focused on participants' perceptions of their assigned training and their feeling of readiness to assume responsibility for the selected BI technology

A causal-comparative research design involves the use of established or intact groups to explore the differences between groups that result from manipulating a dependent variable (or multiple dependent variables; Curran et al., 2015). A causal-comparative research design involving group comparisons is an appropriate design choice when study participants cannot be assigned randomly to groups and the researcher has limited control of outside factors that can influence the study outcomes (Shenker & Rumrill, 2004).

This causal-comparative analysis used secondary data (otherwise known as *ex post facto* data) to establish a correlation between the study's variables: (a) training and (b) end user technology readiness. The analysis of secondary data is used most commonly when pre-existing data are available (Goodwin, 2012). Secondary data exist in a variety of formats and can include any data that were collected originally to answer unrelated research questions (Vartanian, 2010). In this study, the analysis of the two groups' perceptions of readiness was retrospective as the training (BI technology) and survey completion had already occurred.

There are advantages and disadvantages to utilizing secondary data in research studies. One advantage is that the data collection process has already been completed, thus saving time and the costs incurred in collecting data. Another advantage of using secondary data is that the data may be more representative of a particular target population (Kozial & Arthur, 2014). Disadvantages of using secondary data include reliability and validity concerns that arise out of relying on previously selected data collection instruments or protocols. These threats to reliability and validity may result in survey items not aligning with validated survey instruments (Kozial & Arthur, 2014).

Description of the Population and Sample

The population for this study consisted of Optum clients whose Impact Intelligence technology was implemented between August 2016 and March 2017.

Because this training occurred in the past and the data had already been collected, the researcher used purposive sampling to target specific Optum clients. The main objective of purposive sampling is to choose elements that are meant for satisfying the research hypotheses. Of 88 possible participants in this study, 26 were ineligible because they did not complete the training session and client implementation survey. Thus, the sample for this study ultimately consisted of 62 individuals who completed both the training session (F2F or blended) and client implementation survey; 33 participants attended the F2F training sessions, and 29 participants attended the blended training sessions.

Face-to-Face Training Session

Face-to-face (F2F) is the standard modality of training for Optum clients who complete the implementation of the Impact Intelligence technology. The researcher served as a training consultant for the five clients identified as employing potential participants for this study. This relationship between the researcher and clients ensured that qualified participants were selected; these individuals had experienced the implementation of the BI technology product, completed the end-user training, and submitted post-training surveys between August 2016 and March 2017. For the participants who became part of this study, F2F end-user training occurred at the clients' headquarters and was facilitated by the researcher. To be eligible to participate in the study, participants (F2F group) must have attended the F2F sessions, participated in implementation activities, and been identified as an individual requiring system access.

The F2F training sessions were held over the course of two days, with each session lasting about 8 hours for a total of 16 hours of training. Participants were provided with an agenda that detailed the content covered during both sessions (Appendix A). The researcher used PowerPoint presentations to deliver all section content to end-users. Day 1 of the F2F training was broken out into four sections, each covering a specific functionality of the Impact Intelligence technology (Table 2).

Table 2

Day 1 of Face-to-Face Training: Description of Content Sections

Section	Duration (Hours)	Description of Sections
1	3	Focused on concepts and methodologies that supported the Impact Intelligence technology (3 hours)
2	1	Covered functionality that introduced end users to the functionality and technology navigation (1 hour)
3	1	Covered the analysis functionality and introduced the application data structure (1 hour)
4	3	Served as an extension of Module 1 covering the remaining concepts and methodological training (3 hours)

Day 2 followed a similar cadence, with the 8-hour session broken up into four sections (Table 3). There was no measurement of learning built into the 2-day training program. The researcher did not conduct any additional training activities outside of the 2-day F2F training session.

Table 3

Day 2 of Face-to-Face Training: Description of Content Sections

Section	Duration (Hours)	Description of Sections
1 - 2	4	Provided detailed guidance on report-building with the technology
3	2	Reviewed participant supplied use cases with the researcher using guided exercises to demonstrate how reporting gaps can be solved by the technology
4	1	Focused on using guided exercise to analyze physician performance
Discussion	1	Provided participants with opportunity to discuss the training activities and sections covered over both days

Blended Training Modality

The blended training program was introduced as an option in 2016 at the pilot stage to determine participants' perceptions regarding readiness to take responsibility for the technology. The program differs from the F2F format; a major difference in the blended training version is that its structure corresponds to the stages of the implementation project, starting at the implementation stage and continuing through completion of the project (Table 4).

Table 4

Comparison of Face-to-Face and Blended Training Formats

Format	Face-to-Face	Blended
Scheduling	Training conducted at end of project	Training was continuous throughout the project
Location	Onsite	Combination of onsite, online modules
Facilitation	In-person facilitation	Discussions via Web conferencing
Timeframe	2-3 days	1-day onsite
Delivery	PowerPoint	Client data and report building
Interaction	Report-building workshop	
Follow-Up	No formal follow-up after training	Web conferencing sessions 30 days after training to address questions or issues

During the first week of implementation, the researcher conducted an hour-long Web conferencing with identified participants to review expectations and the time commitment necessary to complete the blended training activities. During this Web conferencing session, participants also were introduced to the Optum content managing system (CMS). This step—setting expectations—is critical for instructors to explain their approach to blended learning, including the course schedule and structure, so students are clear concerning the distinction between classroom and online activities (Fetch, deNoyelles, Thomson, & Howard, 2016).

As part of the course orientation, participants received a curriculum summary document (Appendix B) that outlined the training tasks and detailed each step in the blended training. Following the Web conferencing session, participants were added to the Optum CMS and enrolled in 18 eLearning modules. The eLearning modules were cataloged by course number to provide guidance on the mastery levels. Participants were initially registered for 100 level modules (e.g., IIRP100 Introduction to Impact Intelligence). These modules were designed to build on the conceptual knowledge of the Impact Intelligence methodologies and aid in the development of skills needed to build reports within the application. The next level of modules—200 (e.g., IIRP221 Workspace Advanced Introduction- Creating a Report) level—were designed to improve the knowledge and skills acquired after completion of the 100 level courses. The completion for each eLearning module was an average of 15 minutes. The modules also contained an assessment component requiring 80% mastery before the next module can be accessed. The total time commitment for online activities for blended training was 20 hours, with eLearning modules accounting for 12 hours. The time commitment for the levels of eLearning modules was divided up into 4 hour increments based on 100 and 200 course levels. Web conferencing accounted for the remaining 4 hours of online commitment time.

In accordance with the curriculum review schedule (Appendix B), weekly synchronous web conferencing sessions were scheduled for five months. The scheduling of the web conferencing sessions was dependent upon participant's completion of weekly eLearning assignments. The researcher used the Optum CMS to generate eLearning reports as verification of participant module completion. The Web conferencing sessions counted towards 8 hours of the blended training program time and provided participants with the opportunity to ask questions and receive clarification regarding content covered in the modules. The second group of tasks was focused on classroom activities. The researcher scheduled a Web conferencing session with participants to determine business needs and use cases for the F2F portion before conducting classroom activities. The F2F classroom portion was reduced from 16 hours (Appendix B) to 8 hours. Participants spent 8 hours attending a workshop focused on building reports specific to the identified use cases. The researcher scheduled weekly follow-up sessions over the course of a month to focus on any issues or challenges clients may have been experiencing while using the technology.

Instrumentation

The client implementation survey and the training session survey were developed using Qualtrics survey software. Qualtrics is Web-based survey software used to create, distribute, and gather surveys data electronically and used to assist in analyzing results. The training session survey and client implementation survey were developed by selecting from a pool of questions available through the Qualtrics Website (Qualtrics, 2016). The researcher was not with the organization during development of these survey instruments and was unable to obtain information on the specific processes followed to determine which survey software was utilized and if a specific theoretical model was considered during the selection process. Because secondary data was utilized for this study, the researcher had no control over the development of survey instruments used to solicit responses and therefore cannot confirm the validity or reliability of the survey instruments. The primary source of data for this study consisted of survey data collected from groups of participants who participated in either F2F or a blended training program before the implementation of this study. Survey instruments measure the attitudes and beliefs of study participants by generating scores for statistical analysis (Venkatesh et al., 2012). Researchers have previously conducted causal-comparative studies using feedback from online survey data. One such study evaluated the feedback of different student groups after completing F2F and online components of selected healthcare practice learning modules (Curran et al., 2015). The training session survey (Appendix C), a quantitative instrument, was broken into two parts and used to measure perceptions of the F2F session or the blended training program. In the first section, participants were asked to consider their satisfaction when thinking about the F2F or blended training program and rate the sessions based on six additional sub-questions addressing the session overall, clarity of session objectives, session content, met session objectives, content value (I gained new knowledge and/or skills), quality of session materials, and amount of material covered. was used to measure perceptions of the training session and how training was delivered. Participants were then asked to consider their satisfaction when thinking about the instructor, in this case also the researcher, who conducted the F2F portion of either session. The instructor was rated using five additional sub-questions addressing the instructor overall, knowledge of session content, teaching methods, keeping me engaged in the session, providing ample opportunity to get answers to my questions. The client implementation survey (Appendix D) consists of four parts and used to quantitatively measure the perception of the overall Impact Intelligence technology implementation experience. In each section, participants were asked to consider their satisfaction about the implementation process, engagement/communication, quality, and overall satisfaction with the technology implementation project. In the context of this study, only the quality section, and sub-questions: successfully prepared staff to assume responsibility for the product at the end of the implementation was used for data analysis. Both instruments used in this study utilized a 10-point Likert scale, which has a range of 0 (Not at all Satisfied) to 10 (Extremely Satisfied). The surveys were delivered by the researcher in online format to participants upon completion of either the F2F or blended training sessions. The project manager delivered the client implementation survey used for this study in an online format to individuals who participated in all activities associated with the technology project implementation. The processes and format by which these surveys are delivered to individuals were pre-developed outside of the researcher and not for the intent or purposes of this study.

Data Collection

Because secondary data was utilized in this study, the researcher was not required to solicit participants to complete online surveys or require consent to use the data. Participants in the original training program had received electronically delivered surveys after completing F2F or blended training components. Because the researcher was also a training consultant, survey responses were routinely delivered via email to the researcher (for informational purposes) by a colleague who uses the data to report training metrics. The researcher used the collected responses to identify perceptions of participants who attended a F2F training session and those who engaged in the blended training program. The possibility of sampling bias exists, as the researcher was assigned as the training consultant for those clients selected for the study. Findings may not fully represent the training experiences of other Optum consultants and those clients who participated in modified versions of the training activities.

The researcher used the following steps to collected data:

Step 1: The researcher received approval from the University of Central Florida's Institutional Review Board (Appendix E).

Step 2: Each month, the researcher received a monthly email containing survey responses (Microsoft Excel format); these responses were maintained by the researcher in a personal folder on a virtual private network.

Step 3: The researcher used data collected from the surveys to identify clients who completed projects during a specific period of time: August 2016 to March 2017.

Step 4: The researcher accessed the client implementation-training database to identify (from the data collected in Step 3) which clients were assigned to the researcher;

Step 5: The researcher downloaded and imported into a Microsoft Excel spreadsheet survey responses from those clients to whom the researcher was assigned as a training consultant.

Step 6: The researcher downloaded and imported into Microsoft Excel all training session survey responses from those clients identified in Step 4.

Step 7: The researcher used the training session survey to identify responses of participants who participated in the F2F training or blended training program.

Step 8: The researcher identified 88 possible participants and found that 26 were ineligible to participate in this study because they did not complete the training session and client implementation survey; thus, the sample for this study consisted of 62 individuals who participated in either a F2F or blended training session and completed both the training session and client implementation survey.

Step 9: The data was reviewed and any identifiable client or participant information was removed.

Step 10: The researcher checked for duplicate entries using the IP address field on the Microsoft Excel export—there were no duplications.

Step 11: The researcher created two new Microsoft Excel spreadsheets representing survey responses of clients who participated in F2F training sessions and those who participated in the blended training session.

Step 12: The data was coded and imported into SPSS for further analysis.

Step 13: The researcher used SPSS software to categorize and analyze quantitative survey response data.

Data Analysis

In its broadest sense, the analysis of secondary data involves looking at data collected by another source (Boslaugh, 2007). Because this study used secondary data, the researcher had no control over the development of survey instruments used to solicit responses. The researcher used SPSS software to categorize and analyze quantitative survey response data. Data are reflective of responses capturing the experiences of each group who participated in either a F2F training session or blended training program.

To answer the research questions, a Mann-Whitney *U* test to was used identify the differences in responses between the F2F and blended training comparison groups regarding their training experiences. The Mann-Whitney *U* test is a non-parametric measurement of analysis that identifies differences in ranking or distribution of rank and constitutes an alternative non-parametric test to the independent *t*-test.

The Mann-Whitney *U* test is used in every field but is frequently used in psychology, healthcare, nursing, and business (Fay & Proschan, 2010). This test is appropriate when the independent variable is either ordinal or continuous, and the data are not normally distributed. While a *t*-test is preferred when identifying statistical differences (Fay & Proschan, 2010), the data collected for this study were not normally distributed, which is an assumption of a *t*-test. There are many situations where the use of a Mann-Whitney *U* test is more powerful and efficient than the preferred *t*-test method when identifying differences unrelated to statistical measures (Fay & Proschan, 2010). For example, for distributions with heavy tails or very skewed distributions, one can increase the power of results by using the Mann-Whitney procedure rather than the *t*-test (Fay & Proschan, 2010).

Summary

This causal-comparative study explored the effect of technology-related training on the readiness of end-users who participated in either a F2F session or a blended training program. This study analyzed secondary data imported from a client implementation survey and training session survey. Sixty-two end-users met the criteria to participate in this study (N = 88). Sample groups were created based on their participation in one of two training modalities: F2F training (33 participants) or a blended training program (29 participants). To answer the research questions, a Mann-Whitney U test was performed to determine whether differences in perceptions of the training programs (F2F or blended) emerged based on group membership. The researcher chose this type of analysis due to the small size of the sample population and non-normality of data. The researcher’s analysis focused on identifying what variation exists, if any, between the perceptions of F2F and blended training comparison groups’ training experience. Analysis of the survey responses was conducted using the IBM Statistics Premium Grad Pack Version 24.0 software. Chapter 4 provides the results of the quantitative analysis conducted to answer the research questions guiding this study.

CHAPTER 4
ANALYSIS AND RESULTS

Introduction

The purpose of this research study was to create a case for developing processes to improve delivery of blended training by analyzing end-user perceptions of training conducted to support the use of business intelligence (BI) technologies. The unified theory of acceptance and use of technology (UTAUT) served as a theoretical guide to examine the end-user perceptions of technology use in organizational settings (Venkatesh, 2003). Facilitating conditions, a construct of UTAUT, is defined as the perception of resources and support (e.g., training) available to end-users to perform a behavior. Quantitative data was collected using the training session and client implementation survey from two comparison groups who participated in a learning program in one of two modalities (face-to-face or blended). This chapter provided the results of the quantitative analysis conducted to answer the following research questions:

1. What are the differences in perception of the product training session as measured by the training survey between end-users who attended face-to-face (F2F) training or end-users who attended blended training?
2. What are the differences in perception of the product training session facilitator as measured by the training survey between end-users who attended F2F training or end-users who attended blended training?
3. What are the differences in perception of the feeling of readiness to assume responsibility for the product as measured by the client implementation survey

between end-users who attended F2F training or end-users who attended blended training?

Demographic Data

This causal comparative analysis used secondary data to establish a correlation between the study's variables: (a) training and (b) end user technology readiness. The analysis of secondary data is most commonly used when pre-existing data are available (Goodwin, 2012). As such, the researcher had no control over the development of survey instruments used to solicit responses for this study. Finally, these secondary data did not contain demographic details (e.g., gender, age, ethnicity) normally available for categorization or analysis.

Research Question 1

What are the differences in perception of the product training session as measured by the training survey between end-users who attended F2F training or end-users who attended blended training?

Using an 11-point Likert scale (0 = Not at All Satisfied, 5 = Neutral, 10 = Extremely Satisfied), respondents selected for this research study were asked to rate their perceptions concerning the product training session they completed (F2F or blended modality). On this scale, only Ratings 0, 5, and 10 have an associated label (e.g., Not at All Satisfied). Normally distributed data will have a skewness of zero. The researcher analyzed each of the survey sub-questions associated with Research Question 1 to determine whether there was a difference in perception between the respondents who participated in the F2F training session compared to individuals who participated in the blended training program.

Clarity of Session Objectives

Participants in both groups (F2F and blended) were asked to rate their perception regarding the clarity of session objectives included in their training session (Table 5). Participants selected Rating 10 (Extremely Satisfied) most frequently (29%), followed by Ratings 8 and 9 that were tied at 24%. On the lower end of the scale, 3% of participants selected Rating 1 while 8% selected Rating 2.

Table 5

Results: Clarity of Session Objectives

Scale	Frequency	Percent
0 Not at All Satisfied	0	0
1	2	3.2
2	5	8.1
3	1	1.6
4	1	1.6
5 Neutral	1	1.6
6	0	0
7	4	6.5
8	15	24.2
9	15	24.2
10 Extremely Satisfied	18	29.0
Total	62	100.0

For both training sessions (F2F and blended), the distribution of responses on this item (Clarity of Session Objectives) was similar but not normally distributed. The mean

(*M* = 7.85) was smaller than the median (*Mdn* = 9.00), which indicates a negative skew. The results of this analysis indicate a skewness of -1.555 that is indicative of non-normally distributed data (Table 6).

Table 6

Participant Perceptions: Clarity of Session Objectives

		Statistic	Standard Error
Mean		7.85	.332
95% Confidence Interval for Mean	Lower Bound	7.19	
	Upper Bound	8.52	
5% Trimmed Mean		8.10	
Median		9.00	
Variance		6.847	
Standard Deviation		2.617	
Minimum		1	
Maximum		10	
Range		9	
Interquartile Range		2	
Skewness		-1.555	.304
Kurtosis		1.300	.599

Because the data were not normally distributed, a Mann-Whitney *U* test was performed, and the mean ranks for each group were determined (Figure 1).

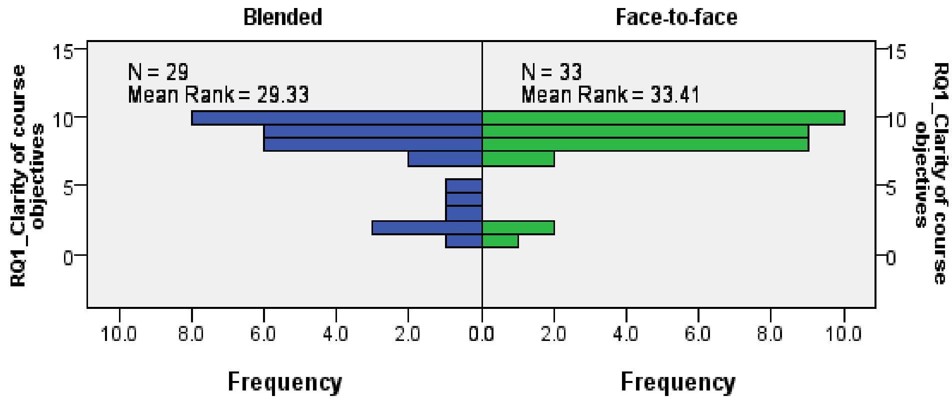

Figure 1. Mean rank comparison: Clarity of session objectives.

Responses of participants in the F2F sessions (Mean Rank = 33.41) and the blended sessions (Mean Rank = 29.33) were not different to a statistically significant degree (U = 415.50, z = -.914, p = .361), using an exact sampling distribution for U (Table 7). Based on the mean ranks of the survey responses, participants who attended the F2F training sessions were more likely to report that the training sessions objectives were clear compared to those participants who attended the blended training.

Table 7

Clarity of Session Objectives: Mann-Whitney U Test

	Rank Sum
Mann-Whitney U	415.500
Wilcoxon W	850.500
Standardized Test Statistic (Z)	-.914
Asymptotic Sig. (2-sided test)	.361

Course Content Met Course Objectives

Participants in both groups (F2F and blended) were asked to rate their perception regarding the degree to which course content met the course objectives included in their training session (Table 8). Participants selected Rating 10 (Extremely Satisfied) most frequently (34%), followed by Ratings 8 and 9 that were tied at 23%. On the lower end of the scale, 5% of participants selected Rating 3 while 2% selected Rating 4.

Table 8

Results: Course Content Met Course Objectives

Scale	Frequency	Percent
0 Not at All Satisfied	0	0
1	0	0
2	3	4.8
3	0	0
4	1	1.6
5 Neutral	4	6.5
6	0	0
7	5	8.1
8	14	22.6
9	14	22.6
10 Extremely Satisfied	21	33.9
Total	62	100.0

For both training sessions (F2F and blended), the distribution of responses on this item (Course Content Met Course Objectives) was similar but not normally distributed. The mean (M = 8.27) was smaller than the median (Mdn = 9.00), which indicates a negative skew. The results of this analysis indicate a skewness of -1.665 that is indicative of non-normally distributed data (Table 9).

Table 9

Participant Perceptions: Course Content Met Course Objectives

		Statistic	Standard Error
Mean		8.27	.261
95% Confidence Interval for Mean	Lower Bound	7.75	
	Upper Bound	8.80	
5% Trimmed Mean		8.52	
Median		9.00	
Variance		4.235	
Standard Deviation		2.058	
Minimum		2	
Maximum		10	
Range		8	
Interquartile Range		2	
Skewness		-1.665	.304
Kurtosis		2.540	.599

Because the data were not normally distributed, a Mann-Whitney *U* test was performed, and the mean ranks for each group were determined (Figure 2).

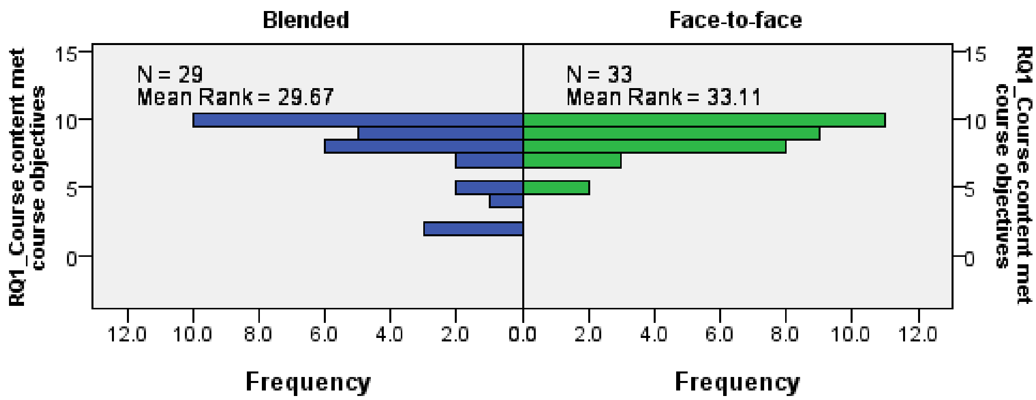

Figure 2. Mean rank comparison: Course content met course objectives.

Responses of participants in the F2F sessions (Mean Rank = 33.11) and the blended program (Mean Rank = 29.67) were not different to a statistically significant degree (U = 425.50, z = -.772, p = .440), using an exact sampling distribution for U (Table 10). Based on the mean ranks of the survey responses, participants who attended the F2F training sessions were more likely to report that the training sessions met course objectives compared to those participants who attended the blended training.

Table 10

Course Content Met Course Objectives: Mann-Whitney U Test

	Rank Sum
Mann-Whitney U	425.500
Wilcoxon W	860.500
Standardized Test Statistic (Z)	-.772
Asymptotic Sig. (2-sided test)	.440

Content Value

Participants in both groups (F2F and blended) were asked to rate their perception regarding the degree to which the course content had value in their training session (Table 11). Participants selected Rating 10 (Extremely Satisfied) most frequently (45.2%), followed by Ratings 8 and 9 at 11.3% and 27.4%, respectively. On the lower end of the scale, 4.8% of participants selected Rating 1 while 1.6% selected Rating 4.

Table 11

Results: Content Value

Scale	Frequency	Percent
0 Not at All Satisfied	0	0
1	3	4.8
2	0	0
3	0	0
4	1	1.6
5 Neutral	3	4.8
6	2	3.2
7	1	1.6
8	7	11.3
9	17	27.4
10 Extremely Satisfied	28	45.2
Total	62	100.0

For both training sessions (F2F and blended), the distribution of responses on this item (Content Value) was similar but not normally distributed. The mean (M = 8.55) was smaller than the median (Mdn = 9.00), which indicates a negative skew. The results of this analysis indicate a skewness of -2.179 that is indicative of non-normally distributed data (Table 12).

Table 12

Participant Perceptions: Content Value

		Statistic	Standard Error
Mean		8.55	.286
95% Confidence Interval for Mean	Lower Bound	7.98	
	Upper Bound	9.12	
5% Trimmed Mean		8.88	
Median		9.00	
Variance		5.071	
Standard Deviation		2.252	
Minimum		1	
Maximum		10	
Range		9	
Interquartile Range		2	
Skewness		-2.179	.304
Kurtosis		4.484	.599

Because the data were not normally distributed, a Mann-Whitney *U* test was performed, and the mean ranks for each group were determined (Figure 3).

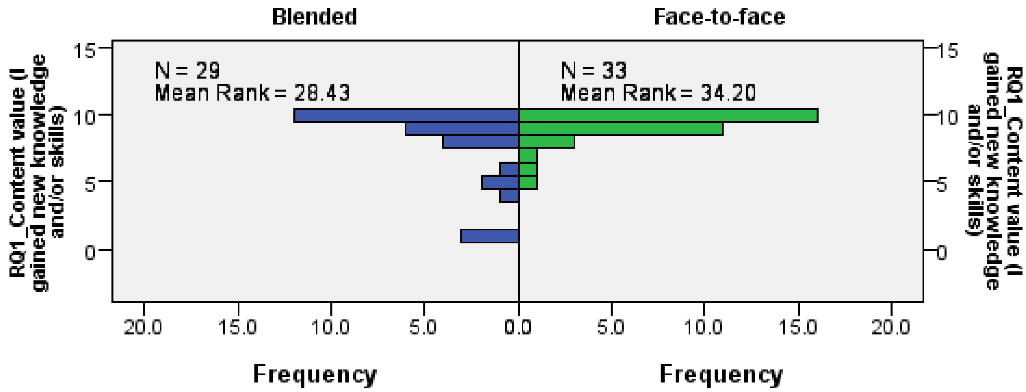

Figure 3. Mean rank comparison: Content value.

Responses of participants in the F2F sessions (Mean Rank = 33.20) and the blended training program (Mean Rank = 28.43) were not different to a statistically significant degree (U = 389.50, z = -1.334, p = .182), using an exact sampling distribution for U (Table 13). Based on the mean ranks of the survey responses, participants who attended the blended training session—including the use of online learning modules—viewed the course content as less valuable compared to those participants who participated in the F2F training sessions.

Table 13

Content Value: Mann-Whitney U Test

	Rank Sum
Mann-Whitney U	389.500
Wilcoxon W	824.500
Standardized Test Statistic (Z)	-1.334
Asymptotic Sig. (2-sided test)	.182

Quality of Course Materials

Participants in both groups (F2F and blended) were asked to rate their perception regarding the quality of course materials included in their training session (Table 14). Participants selected Rating 9 most frequently (37.1%), followed closely by Rating 10 (33.9%; Extremely Satisfied). Ratings 7 (11.3%) and 8 (9.7%) were the next most frequently selected answers. On the lower end of the scale, 3.2% of participants selected Ratings 1 and 2 while 1.6% selected Rating 3.

Table 14

Results: Quality of Course Materials

Scale	Frequency	Percent
0 Not at All Satisfied	0	0
1	2	3.2
2	2	3.2
3	1	1.6
4	0	0
5 Neutral	0	0
6	0	0
7	7	11.3
8	6	9.7
9	23	37.1
10 Extremely Satisfied	21	33.9
Total	62	100.0

For both training sessions (F2F and blended), the distribution of responses on this item (Quality of Course Materials) was similar but not normally distributed. The mean (*M* = 8.44) was smaller than the median (*Mdn* = 9.00), which indicates a negative skew. The results of this analysis indicate a skewness of -2.287 that is indicative of non-normally distributed data (Table 15).

Table 15

Participant Perceptions: Quality of Course Materials

		Statistic	Standard Error
Mean		8.44	.280
95% Confidence Interval for Mean	Lower Bound	7.87	
	Upper Bound	9.12	
5% Trimmed Mean		8.74	
Median		9.00	
Variance		4.873	
Standard Deviation		2.207	
Minimum		1	
Maximum		10	
Range		9	
Interquartile Range		2	
Skewness		-2.287	.304
Kurtosis		4.902	.599

Because the data were not normally distributed, a Mann-Whitney *U* test was performed, and the mean ranks for each group were determined (Figure 4).

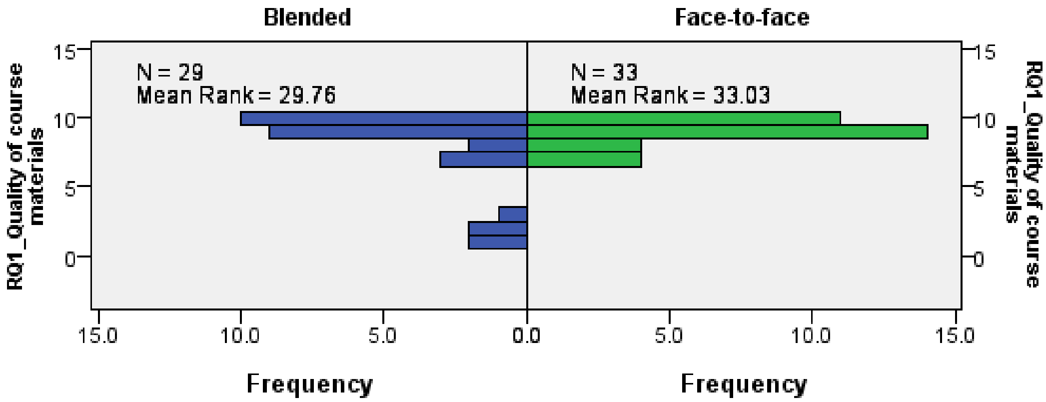

Figure 4. Mean rank comparison: Quality of course materials.

Responses of participants in the F2F sessions (Mean Rank = 33.03) and the blended sessions (Mean Rank = 29.76) were not different to a statistically significant degree (U = 428.00, z = -.748, p = .455), using an exact sampling distribution for U (Table 16). Based on the mean ranks of the survey responses, there was a difference in the perceived quality of course materials between those participants who attended the F2F session compared to those participants who attended the blended training.

Table 16

Quality of Course Materials: Mann-Whitney U Test

	Rank Sum
Mann-Whitney U	428.000
Wilcoxon W	863.000
Standardized Test Statistic (Z)	-.748
Asymptotic Sig. (2-sided test)	.455

Research Question 2

What are the differences in perception of the product training session facilitator as measured by the training survey between end-users who attended F2F training or end-users who attended blended training?

Using an 11-point Likert scale (0 = Not at All Satisfied, 5 = Neutral, 10 = Extremely Satisfied), respondents selected for this research study were asked to rate their perceptions concerning the product training session facilitator (F2F or blended modality). On this scale, only Ratings 0, 5, and 10 have an associated label (e.g., Not at All Satisfied). Normally distributed data will have a skewness of zero. The researcher analyzed each of the survey sub-questions associated with Research Question 2 to determine whether there was a difference in perception between the respondents who participated in the F2F training session compared to individuals who participated in the blended training program.

Product Training Session Facilitator: Knowledge of Session Content

Participants in both groups (F2F and blended) were asked to rate their perception regarding the product training session facilitator's knowledge of session content (Table 17). Participants selected Rating 10 (Extremely Satisfied) most frequently (37.1%), followed closely by Rating 9 (33.9%). Rating 8 ranked as the third most frequently selected answer (16.1%). On the lower end of the scale, 3.2% of participants selected Ratings 1 and 4 while 1.6% selected Ratings 2 and 4.

Table 17

Results: Product Training Session Facilitator's Knowledge of Session Content

Scale	Frequency	Percent
0 Not at All Satisfied	0	0
1	2	3.2
2	1	1.6
3	2	3.2
4	1	1.6
5 Neutral	1	1.6
6	0	0
7	1	1.6
8	10	16.1
9	21	33.9
10 Extremely Satisfied	23	37.1
Total	62	100.0

For both training sessions (F2F and blended), the distribution of responses on this item (Product Training Session Facilitator's Knowledge of Session Content) was similar but not normally distributed. The mean (M = 8.47) was smaller than the median (Mdn = 9.10), which indicates a negative skew. The results of this analysis indicate a skewness of -2.194 that is indicative of non-normally distributed data (Table 18).

Table 18

Participant Perceptions: Product Training Session Facilitator's Knowledge of Session Content

		Statistic	Standard Error
Mean		8.47	.286
95% Confidence Interval for Mean	Lower Bound	7.90	
	Upper Bound	9.04	
5% Trimmed Mean		8.78	
Median		9.10	
Variance		5.073	
Standard Deviation		2.252	
Minimum		1	
Maximum		10	
Range		9	
Interquartile Range		2	
Skewness		-2.194	.304
Kurtosis		4.181	.599

Because the data were not normally distributed, a Mann-Whitney *U* test was performed, and the mean ranks for each group were determined (Figure 5).

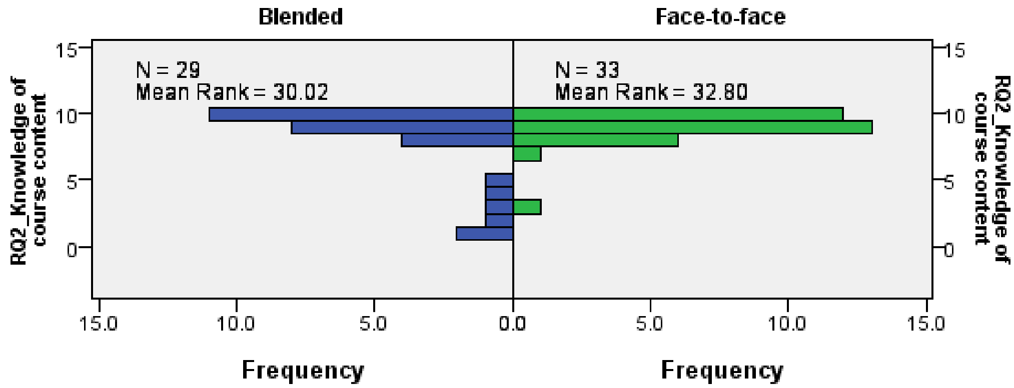

Figure 5. Mean rank comparison: Product training session facilitator's knowledge of session content.

Responses of participants in the F2F sessions (Mean Rank = 32.80) and the blended sessions (Mean Rank = 30.02) were not different to a statistically significant degree (U = 435.50, z = -.637, p = .524), using an exact sampling distribution for U (Table 19). Based on the mean ranks of survey responses, participants who attended the F2F session reported that the training session facilitator was more knowledgeable in the delivery of course content compared to those participants who attended the blended training.

Table 19

Product Training Session Facilitator's Knowledge of Session Content: Mann-Whitney U

	Rank Sum
Mann-Whitney U	435.000
Wilcoxon W	870.500
Standardized Test Statistic (Z)	-.637
Asymptotic Sig. (2-sided test)	.524

Product Training Session Facilitator: Teaching Methods

Participants in both groups (F2F and blended) were asked to rate their perception regarding the product training session facilitator's teaching methods (Table 20). Participants selected Rating 10 (Extremely Satisfied) most frequently (40.3%), followed closely by Rating 9 (38.7%). Rating 8 ranked as the third most frequently selected answer (9.7%). On the lower end of the scale, 4.8% of participants selected Rating 3, 3.2% selected Rating 2, and 1.6% selected Rating 1.

Table 20

Results: Product Training Session Facilitator's Teaching Methods

Scale	Frequency	Percent
0 Not at All Satisfied	0	0
1	1	1.6
2	2	3.2
3	3	4.8
4	0	0
5 Neutral	1	1.6
6	0	0
7	0	0
8	6	9.7
9	24	38.7
10 Extremely Satisfied	25	40.3
Total	62	100.0

For both training sessions (F2F and blended), the distribution of responses on this item (Product Training Session Facilitator's Teaching Methods) was similar but not normally distributed. The mean (*M* = 8.60) was smaller than the median (*Mdn* = 9.00), which indicates a negative skew. The results of this analysis indicate a skewness of -2.275 that is indicative of non-normally distributed data (Table 21).

Table 21

Participant Perceptions: Product Training Session Facilitator's Teaching Methods

		Statistic	Standard Error
Mean		8.60	.285
95% Confidence Interval for Mean	Lower Bound	8.03	
	Upper Bound	9.17	
5% Trimmed Mean		8.90	
Median		9.00	
Variance		5.031	
Standard Deviation		2.243	
Minimum		1	
Maximum		10	
Range		9	
Interquartile Range		1	
Skewness		-2.275	.304
Kurtosis		4.226	.599

Because the data were not normally distributed, a Mann-Whitney *U* test was performed, and the mean ranks for each group were determined (Figure 6).

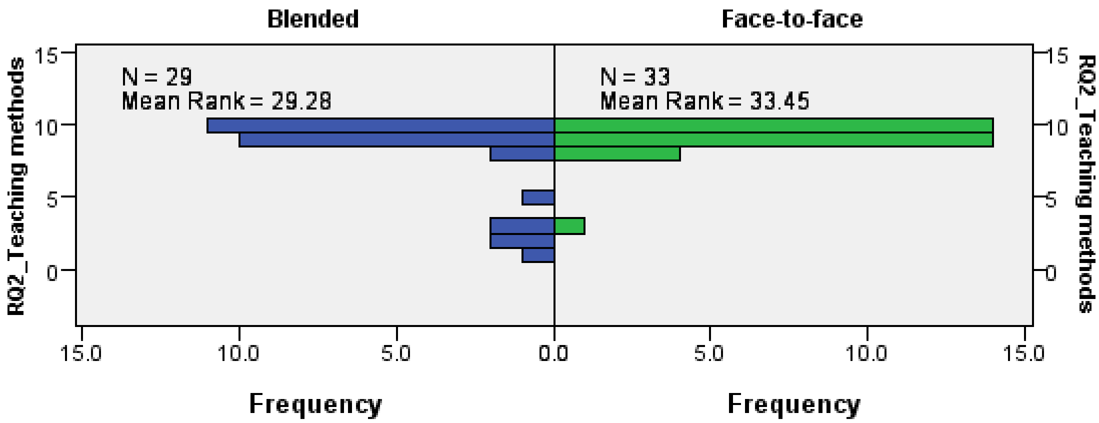

Figure 6. Mean rank comparison: Product training session facilitator's teaching methods.

Responses of participants in the F2F sessions (Mean Rank = 33.45) and the blended sessions (Mean Rank = 29.28) were not different to a statistically significant degree (U = 414.00, z = -.972, p = .5331), using an exact sampling distribution for U (Table 22). Based on the mean ranks of the survey responses, participants who attended the F2F session perceived the product training session facilitator's teaching methods to be of higher quality compared to those who participated in the blended training.

Table 22

Product Training Session Facilitator's Teaching Methods: Mann-Whitney U Test

	Rank Sum
Mann-Whitney U	414.000
Wilcoxon W	849.000
Standardized Test Statistic (Z)	-.972
Asymptotic Sig. (2-sided test)	.331

Product Training Session Facilitator: Opportunities for Questions

Participants in both groups (F2F and blended) were asked to rate their perception regarding how well the product training session facilitator provided opportunities to ask questions (Table 23). Participants selected Rating 10 (Extremely Satisfied) most frequently (43.5%), followed closely by Rating 9 (38.7%). Rating 8 ranked as the third most frequently selected answer (6.5%). On the lower end of the scale, 6.5% of participants selected Rating 1 while 3.2% selected Rating 3.

Table 23

Results: Product Training Session Facilitator's Opportunities to Ask Questions

Scale	Frequency	Percent
0 Not at All Satisfied	0	0
1	4	6.5
2	0	0
3	2	3.2
4	0	0
5 Neutral	0	0
6	0	0
7	1	1.6
8	4	6.5
9	24	38.7
10 Extremely Satisfied	27	43.5
Total	62	100.0

For both training sessions (F2F and blended), the distribution of responses on this item (Product Training Session Facilitator Provided Opportunities to Ask Questions) was similar but not normally distributed. The mean (M = 8.63) was smaller than the median (Mdn = 9.00), which indicates a negative skew. The results of this analysis indicate a skewness of -2.500 that is indicative of non-normally distributed data (Table 24).

Table 24

Participant Perceptions: Product Training Session Facilitator's Opportunities to Ask Questions

		Statistic	Standard Error
Mean		8.63	.306
95% Confidence Interval for Mean	Lower Bound	8.02	
	Upper Bound	9.24	
5% Trimmed Mean		8.98	
Median		9.00	
Variance		5.811	
Standard Deviation		2.411	
Minimum		1	
Maximum		10	
Range		9	
Interquartile Range		1	
Skewness		-2.500	.304
Kurtosis		5.236	.599

Because the data were not normally distributed, a Mann-Whitney *U* test was performed, and the mean ranks for each group were determined (Figure 7).

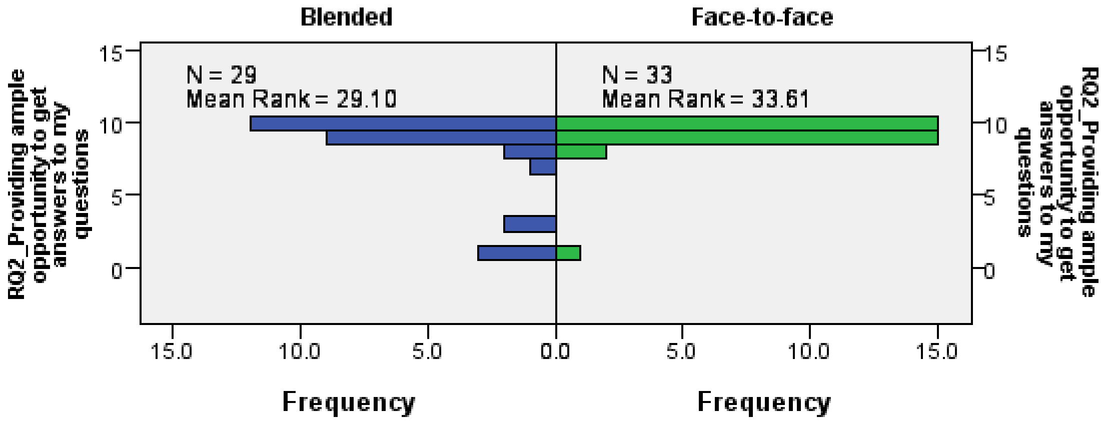

Figure 7. Mean rank comparison: Product training session facilitator provided opportunities to ask questions.

Responses of participants in the F2F sessions (Mean Rank = 33.61) and the blended program (Mean Rank = 29.10) were not different to a statistically significant degree (U = 409.00, z = -1.058, p = .290), using an exact sampling distribution for U (Table 25). Based on the mean ranks of the survey responses, participants who attended the F2F training session reported a greater number of opportunities to ask questions (as provided by the product training session facilitator) during the session compared to those participants who attended the blended training.

Table 25

Product Training Session Facilitator's Opportunities to Ask Questions: Mann-Whitney U Test

	Rank Sum
Mann-Whitney U	409.000
Wilcoxon W	844.000
Standardized Test Statistic (Z)	-1.058
Asymptotic Sig. (2-sided test)	.290

Research Question 3

What are the differences in perception of the feeling of readiness to assume responsibility for the product as measured by the client implementation survey between end-users who attended F2F training or end-users who attended blended training?

Using an 11-point Likert scale (0 = Not at All Satisfied, 5 = Neutral, 10 = Extremely Satisfied), respondents selected for this research study were asked to rate their perceptions concerning the degree to which they felt prepared to assume responsibility for the technology after implementation (F2F or blended modality). On this scale, only Ratings 0, 5, and 10 have an associated label (e.g., Not at All Satisfied). Normally distributed data will have a skewness of zero. The researcher analyzed each of the survey sub-questions associated with Research Question 3 to determine whether there was a difference in perception between the respondents who participated in the F2F training session compared to individuals who participated in the blended training program.

Staff Preparation

Participants in both groups (F2F and blended) were asked to rate how well prepared they felt to assume responsibility for the product (Table 26). Participants selected Rating 9 most frequently (33.9%), followed by Ratings 10 (25.8%) and 8 (19.4%). On the lower end of the scale, 1.6% of participants selected Rating 2.

Table 26

Results: Staff Preparation

Scale	Frequency	Percent
0 Not at All Satisfied	0	0
1	0	0
2	1	1.6
3	0	0
4	0	0
5 Neutral	1	1.6
6	3	4.8
7	8	12.9
8	12	19.4
9	21	33.9
10 Extremely Satisfied	16	25.8
Total	62	100.0

For both training sessions (F2F and blended), the distribution of responses on this item (Staff Preparation) was similar but not normally distributed. The mean (M = 8.48) was smaller than the median (Mdn = 9.00), which indicates a negative skew. The results of this analysis indicate a skewness of -1.687 that is indicative of non-normally distributed data (Table 27).

Table 27

Participant Perceptions: Staff Preparation

		Statistic	Standard Error
Mean		8.48	.189
95% Confidence Interval for Mean	Lower Bound	8.11	
	Upper Bound	8.86	
5% Trimmed Mean		8.63	
Median		9.00	
Variance		2.221	
Standard Deviation		1.490	
Minimum		2	
Maximum		10	
Range		8	
Interquartile Range		2	
Skewness		-1.687	.304
Kurtosis		4.746	.599

Because the data were not normally distributed, a Mann-Whitney *U* test was performed, and the mean ranks for each group were determined (Figure 8).

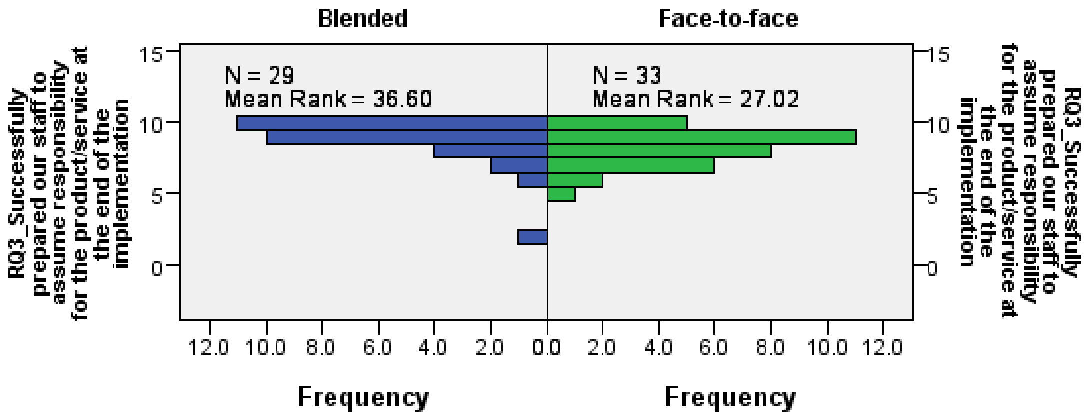

Figure 8. Mean rank comparison: Staff preparation.

Responses of participants in the F2F sessions (Mean Rank = 27.02) and the blended program (Mean Rank = 36.60) were different to a statistically significant degree (U = 626.50, z = 2.160, p = .031), using an exact sampling distribution for U (Table 28). The statistically significant p-value is unspecific as to what has been found when considering perceptions of preparedness to assume responsibility for the technology. There is evidence that contradicts the null hypothesis of identical distributions in the two comparison groups. However, the researcher cannot be more specific as to why the perception of preparedness was different between those who participated in the blended training compared to those who participated in the F2F session without doing further analysis.

Table 28

Staff Preparation: Mann-Whitney Test

	Rank Sum
Mann-Whitney U	626.500
Wilcoxon W	1,061.500
Standardized Test Statistic (Z)	2.160
Asymptotic Sig. (2-sided test)	.031

Summary

The purpose of this research study was to identify factors that hindered the use of BI technologies within organizations and create a case for developing processes to improve delivery of blended training. The researcher used survey responses collected from two comparison groups to further explore the differences in end-user perceptions by individuals who attended F2F or blended training sessions as part of BI implementation projects. The researcher used SPSS software to categorize and analyze responses to a quantitative survey. These data capture the experiences of each group who participated in either a F2F training session or blended training program. Responses were analyzed using descriptive statistics to determine the normality of distributed data. A Mann-Whitney *U* test—the preferred test when data are not normally distributed—was used identify any differences in perception based on modality (F2F and blended) and the survey responses. While a *t*-test is preferred when identifying statistical differences (Fay & Proschan, 2010), the data collected for this study were not normally distributed, which is an assumption of a *t*-test.

Analysis of results for Research Questions 1 and 2 indicated a preference for F2F training session methods. Analysis of results for Research Question 3 indicated that participants did have a feeling of preparedness to assume responsibility for the technology, results that also favored the blended training methods. The researcher cannot be more specific as to why the perception of preparedness was greater for those who participated in the blended training program in comparison to those who participated in F2F. The results can be used to extend this study by doing further analysis to establish causation.

CHAPTER 5
DISCUSSION AND CONCLUSION

Chapter 5 presents the results of the data analysis presented in Chapter 4, along with recommendations for future research. The purpose of this study was to identify components of training sessions, face-to-face (F2F) or blended modality, that influence end-user perceptions of the training. In addition, this study sought to evaluate the implementation of the new blended version of the training program. Also, this study explored the differences in end-user perceptions (F2F versus blended training group) and their feelings of readiness to assume responsibility for the Impact Intelligence technology. Quantitative data was collected using responses from the training session survey client implementation surveys electronically delivered to end users that participated in either F2F or blended training program.

Research Question 1

What are the differences in perception of the product training session as measured by the training survey between end-users who attended F2F training or end-users who attended blended training?

The results of the Mann-Whitney *U* test demonstrated a difference between the responses of F2F training session participants when compared with those in the blended program. The difference in mean ranking scores may be a result of how the F2F training session was structured and how the online modules were developed and organized.

The F2F training sessions were held over the course of two days, with each session lasting approximately eight hours. Classroom activities were pre-scheduled, a 2-day agenda was provided, and the facilitator was present during all instructional activities. Course content focused on concepts and methods that supported the Impact Intelligence technology, navigating through pre-defined dashboards and building reports based on clients' use cases. All sections were delivered via PowerPoint, with some guided exercises occurring on Day 2 of the agenda. The mean ranked survey responses of F2F participants were higher than the blended training participants when asked to consider the training sessions' clarity, course content, content value, and quality of course materials. These results were possibly driven by the presence of the instructor (who was also the researcher) and her ability to engage and effectively deliver content.

Conversely, the blended training program included an asynchronous learning component with a robust catalog of eLearning modules that supported the Impact Intelligence technology. The blended training modules were designed to build upon the conceptual knowledge of the Impact Intelligence methodologies and aid in developing skills needed to build reports within the application. Survey questions (discussed in Chapter 4) were not conclusive in determining if those who participated in traditional F2F sessions gained more knowledge and/or skills, reported greater clarity regarding session objectives, or reported greater overall value from the delivered content than those who participated in the blended training program.

Improving the blended training program will be beneficial in many ways within my organization. The blended training program promotes self-paced learning, reducing the need for F2F time, and provides ample opportunity for the instructor to address and focus on client specific strategies to increase technology usage. Blended training solutions have the potential to decrease the expense of instruction through the use of technology, while promoting student engagement and providing some face-to face interaction with faculty (Boone, 2015).

Clients of Optum are responsible for all expenses incurred by training consultants who facilitate the two days of F2F training, including airfare, hotel, and incidentals. In addition, a contracted rate of $175.00 per hour is charged for the facilitator-conducted training sessions, with a minimum charge of $2,800 for two days of training. The blended training program reduced the need for consultants to be onsite, condensing the 2-day onsite facilitated training session into a single day and generating a cost savings of $1,400 for the client. Further evaluation of the blended training program should be conducted to determine what, if any, additional cost savings may be associated with moving to a fully-blended training program.

Research Question 2

What are the differences in perception of the product training session facilitator as measured by the training survey between end-users who attended F2F training or end-users who attended blended training?

In looking at survey responses, the mean rankings of participants' perceptions related to the training consultant's knowledge of course content, teaching methods, and provision of ample opportunities for questions revealed differences in perception. The perception of those surveyed for this study appeared to indicate a preference for the F2F modality of training when considering the training consultants' knowledge of session content, teaching methods, and opportunities for questions regarding the content to be addressed.

During the F2F sessions, training consultants used PowerPoint presentations to deliver the modules to end-users. Participation in the navigation and report-building module was optional for end-users attending F2F training session. Upon conclusion of the 2-day F2F training, consultants were not involved in additional training activities unless the client requested a follow-up session. The blended training modules were delivered online and contained training content developed specifically for delivery through the content management systems (CMS). In addition, the blended training onsite module was delivered as a focused hands-on workshop that participants were required to attend. These new blended training processes also incorporated Web-conferencing sessions to address any questions, verifying the completion of online modules through CMS reports, and holding weekly follow-up sessions after training was completed. Finally, in the F2F training modality, 100% of learner engagement occurred during the onsite sessions. In comparison, the blended training program consisted of distributed interaction: F2F activities (50%), online learning activities (25%), and activities focused on Web-conferencing presentations and group discussion (25%).

While the primary focus of this study was to identify participant participation in the F2F and blended training sessions, one recommendation is to ensure the right individuals are conducting the appropriate training in all stages of project implementation. For example, if the training consultant does not have the skill set to conduct a data analysis workshop, then a more skilled resource (e.g., a trained data analyst) should be engaged. In this instance, a closer look at how human systems integration (HSI) could be applied to improve the blended training program is the recommendation. Human systems integration is a system design approach intended to ensure that human characteristics are considered throughout the entire design process with respect to selection and training, participation in the operation of the system, and safety (Pew & Mavor, 2007). Criteria for an HSI framework include simplifying the processes requiring technology readiness, evaluating human-to-technology interactions and examining the risks of poor system performance (O'Neil, Shattuck, & Sciarini, 2015). This framework typically is used in product development lifecycles; however, training is a system of development and the blended training program would benefit from implementing the HSI methodology.

Research Question 3

What are the differences in perception of the feeling of readiness to assume responsibility for the product as measured by the client implementation survey between end-users who attended F2F training or end-users who attended blended training?

The results of the Mann-Whitney *U* test demonstrated a difference in responses between the F2F and blended training groups regarding their feelings of readiness to assume responsibility for, or adoption of, the technology product that was the focus of the training. More specifically, there was a statistically significant difference between the F2F and blended training groups' feelings of preparedness to accept responsibility for the technology. Specifically, the blended training participants reported feeling more prepared to accept responsibility for the technology compared to the F2F training participants.

One reason for this difference in perception may be a result of the researcher serving as the training consultant in the F2F training sessions as well as the blended training. The researcher's scores for the training session survey and client implementation survey are, on average, higher than other training consultants who facilitate the F2F training sessions. The researcher chose to limit the scope of this study and exclude the surveys of other training consultants in an effort to increase validity by ensuring survey participants completed all curriculum tasks associated with both the F2F and blended training programs. Additional analysis of the excluded consultants' training surveys is recommended to determine if the difference in perception is due to the training programs or the instructor, who for the purposes of this study was also the researcher.

Significance of the Study

Organizations face many challenges when introducing new technologies into their existing work streams. Research studies have identified challenges associated with the adoption of business intelligence (BI) technologies (Clavier, 2016; Khan et al., 2016; Lee & Widener, 2016; Shehzad & Khan, 2013); however, there is limited information available regarding associated behavioral implications, including usage intention, once technologies are introduced within organizations. Technological compatibility reflects the degree to which an innovation is perceived as consistent with existing values, needs, and experiences of potential adopters (Venkatesh, 2003). The identification of key factors related to the types of training that influence technology adoption may inspire the development of strategies that allow organizations to better integrate BI and realize the return on technological investment.

This study utilized on secondary data collected through surveys to identify if there was any difference in perception of training during the implementation of Impact Intelligence technology between participants who engaged in F2F verses a blended training program in a specific organization. The specificity of this scope was intended by the researcher to demonstrate an organizational need for further analysis of the piloted blended training program to identify process improvements that would increase the rate of Impact Intelligence technology adoption through training. The results of this study can be used to support ongoing initiatives focused on Optum's current initiative to improve Net Promoter Scores (NPS). Research has shown that organizations with higher NPS scores than their competitors enjoy better market and business performance ("What Is Net Promoter," 2016).

Conclusion

Business intelligence technology, if leveraged correctly, helps organizations to make decisions that can favorably impact their return on investment of the technology. Business intelligence systems present historical information to its users for analysis, query, and reporting, thus enabling effective decision making and management support to increase the performance of business processes (Trieu, 2017). In the medical and healthcare fields, BI systems are designed to deliver decision-support information and have been repeatedly shown to provide value to organizations. Evidence-based decision making relies on reliable access to timely and accurate information (Foshay & Kuziemsky, 2014). Some challenges influencing BI adoption include difficulty in understanding the terminology and end-users' lack of the necessary skills to use BI technology (Clavier et al., 2012).

This research study sought to determine if there was any difference in the end-users' perceptions of training experiences between participants who participated in F2F training versus a blended training program. The review of literature related to BI helped to establish a foundation to explore the research questions. Although implementation of BI technologies has the potential to positively impact organizations' return on investment, research studies have identified issues associated with BI technology adoption (Clavier, 2016; Khan et al., 2016; Lee & Widener, 2016; Shehzad & Khan, 2013). Clavier (2016) identified some of those issues as including: (a) end-users' struggle with understanding BI terminology, (b) interruption of daily tasks when end-users are required to integrate BI into their daily work streams, and (c) limited skill sets necessary for end-users to utilize the technology. This study was guided by the facilitating conditions construct of UTAUT specifically looking at the perception of the F2F or blended training participants training experience. Future research should address the constructs in UTAUT and determinant factors of technology adoption outside of usage behavior.

Survey responses of blended training participants were associated with a higher mean rank in terms of satisfaction regarding feelings about the training experience and the effect of training on readiness to assume responsibility for the technology.

While there was an indication that the feeling of preparedness to adopt technology was more highly influenced by the blended training program, it is important to consider methods for improving participant satisfaction in all areas related to blended learning. Blended learning, if done well, combines the benefits afforded by online technologies with structure and social aspects of F2F facilitation, to provide an overall richer experience (Broadbent, 2017). Furthermore, blended delivery has been found to be the most effective delivery format, followed by online delivery formats, and traditional classroom delivery format, respectively (Boone, 2015). Incorporating blended or Web-based strategies into traditional delivery strategies for instruction constitutes an advantageous training solution for-end users of technology (Boone, 2015). To accomplish this, a further review of literature should focus on HSI. The blended training program incorporated certain aspects of HSI, gathering requirements for training throughout the implementation project instead of at the end, when training occurs. The benefits of HSI are often indirect, such as reduction in users' need for help with the system or an increase in user satisfaction (Stark & Kokini, 2010). Introducing a more in depth blended training approach during pre-technology implementation and measuring instructor's ability to effectively engage, motivate, and influence end-users rate of technology adoption can be supported through implementation of HSI processes. Overall, this study can provide the basis for an executive summary indicating the need to implement more effective training strategies, policies, and developed processes prior to implementing BI technologies within organizations.

Recommendations for Further Research

Based on this research study and review of the current academic literature on these topics, the following suggestions are made for future research:

1. Further research should be conducted on the additional constructs of UTAUT to identify other determinants that could contribute to technology acceptance.
2. Further research should be conducted to examine student motivation and learning in relation to participation in blended training.
3. Further research needs to be conducted to test the validity of the content developed for these training modalities and determine content delivery methods that would assist in this type of training.
4. Additional research should be conducted to determine the cost benefit of a blended training program versus F2F training sessions.
5. Further research should be conducted to include other training consultants and their clients' session surveys to see if the statistical significance is changed.
6. Further research should be conducted using a validated instrument to better gauge survey responses based on demographic factors.
7. Further research should be conducted to determine if the impact of implementing more structured training programs has an influence on NPS scores.

APPENDIX A

FACE-TO-FACE TRAINING AGENDA

*Cadence	Description	Length	Title/Task	Delivery
Day 1	Concepts and Methodology Training, Part 1	3 hours	Provide a detailed understanding of the concepts and methods embedded in Impact Intelligence.	**Power Point**
	Quick Lists	1 hour	Introduce the quick list functionality, categories and navigation	**Power Point**
	Online Analysis	1 hour	Introduce the cube structure and functionality	**Power Point**
	Concepts and Methodology Training, Part 2	3 hours	Provide a detailed understanding of the concepts and methods embedded in Impact Intelligence.	**Power Point**
*Cadence	Description	Length	Title/Task	Delivery
Day 2	Navigation- Quick Lists	2 hours	Review all quick list functionality with hands on practice	**Power Point/Guided exercises**
	Navigation- Online Cubes	2 hours	Review all cube structure and functionality with hands on practice	**Power Point/Guided exercises**
	Use Cases	2 hours	Discuss client supplied use cases and demonstrate how to solve reporting needs in the application	**Power Point/Guided exercises**
	Provider Measurements	1 hour	Review provider measurement concepts and available reports.	**Power Point/Guided exercises**
	Q&A	1 hour	Wrap up of the 2-day training activities.	**Discussion**
	Hours commitment	16 hours		

APPENDIX B
BLENDED TRAINING CURRICULUM

*Cadence	Description	Length	Title/Task	Administrator	Report Author	Business Author	Consumer
Day 1	Onsite	8 hours	Initial Project Kick-off	X	X	X	X
Week 1-2	WebEx	60 mins	Curriculum Intro and Review with Project Team	X	X	X	X
Week 1-2	WebEx	60 mins	Curriculum Intro and Review with End Users and Managers	X	X	X	X
Week 1-2	eLearning/Video	5 mins	Introduction to Impact Suite of Products #001 Impact	X	X	X	X
Week 1-2	eLearning	15 mins	Introduction to Impact Intelligence #II 100	X	X	X	X
Week 1-2	eLearning	15 mins	Impact Intelligence Reporting Portal (IIRP) Overview -# IIRP 100	X	X	X	X
Month 2	eLearning/Video	5 mins	Population Dashboards Video #IIRP Demo: Population	X	X	X	X
Month 2	eLearning/Video	5 mins	Admissions Dashboards Video #IIRP Demo: Admissions	X	X	X	X
Month 2	eLearning/Video	5 mins	CPA and Provider Performance Video - #Demo: CPA	X	X	X	X
Month 3-4	eLearning	20 mins	Population Dashboards # IIRP 131	X	X	X	X
Month 3-4	eLearning	20 mins	Population Group Reporting # IIRP 132	X	X	X	X
Month 3-4	eLearning	20 mins	Admissions Dashboards # IIRP 121	X	X	X	X
Month 3-4	eLearning	15 mins	Provider Performance #IIRP 111	X	X	X	X

*Cadence	Description	Length	Title/Task	Administrator	Report Author	Business Author	Consumer
Month 3-4	eLearning	1615 mins	Care Pattern Analyzer (CPA) #IIRP 112	X	X	X	X
Month 3-4	eLearning	15 mins	ETG Opportunity Identification #IIRP 113	X	X	X	X
Month 3-4	eLearning	15 mins	Facility Attribution #IIRP 114	X	X	X	X
Month 1-4	WebEx Check-ins	30 mins	Meet with Optum Learning Consultant Q&A	X	X	X	X
Month 4-5	eLearning/Video	5 mins	IIRP Audit Reports and Data Security	X			
Month 4-5	Job aid	15 mins	User Roles & Management	X			
Month 4-5	WebEx	20 mins	System Administrator	X			
Month 4-5	eLearning	25 mins	Physician Profile Reports: #IIRP 141	X	X	X	
Month 4-5	eLearning	20 mins	Workspace Advanced Intro- Creating a Report #IIRP 221		X	X	
Month 4-5	eLearning	20 mins	Workspace Advanced Intro- Adding Advanced Features #IIRP 222		X	X	
Month 4-5	eLearning	20 mins	Report Studio Intro #IIRP 231		X		
Month 4-5	eLearning	20 mins	Report Studio Custom Queries & Table Joins #IIRP 232		X		

*Cadence	Description	Length	Title/Task	Administrator	Report Author	Business Author	Consumer
Month 4-5	WebEx Check-ins	60 mins	Meet with Optum Learning Consultant Q&A	X	X	X	
Month 1-5	**Hours Commitment**	**20**		**20**	**19**	**19**	**15**

*Cadence	Description	Length	Title/Task	Administrator	Business Author	Report Author	Consumer
Month 5-6	Onsite Training	8 hours	First Deliverable Training to prepare for UAT of data	X	X	X	X
Month 5-6	Onsite/ WebEx Training	90 mins	System Administrator Training with practice	X			
Month 5-6	WebEx Check-ins	30 mins	UAT Check-ins with Optum Learning Consultant	X	X	X	X
Month 8-9	Onsite Training	8 hours	Second Deliverable Training **Optional Training session	X	X	X	X
Month 8-9	WebEx Check-in	30 mins	Check-ins with Optum Learning Consultant	X	X	X	X
Month 5-9	**Hours Commitment**	**11**	**Not including Second Deliverable Training	**11**	**9.5**	**9.5**	**9.5**

APPENDIX C
TRAINING SESSION SURVEY

Thank you for taking the time to complete our brief post-session evaluation.

Date of Session(s)

Date (mm/dd/yyyy)

Please select the instructor(s) of the session from the list below (*check all that apply*):

Other (Please provide name)

Product training session(s) completed (*check all that apply*)?

Impact Pro

Impact Intelligence

Connect Portal

Symmetry (ETG, ERG, PEG, EBM)

Other (Please provide name of session)

Product training session(s) type completed (*check all that apply*)?

F2F

ELearning modules

Web conferencing

Blended Session (F2F, ELearning, Web conferencing)

Other (Please provide name of session)

Thinking about the **session(s)** you just completed, please rate your satisfaction with the following using a scale where 0 is “Not at all satisfied” and 10 is “Extremely satisfied”:

	0 - Not at all satisfied		2	3	4	5	6	7	8	9	10 - Extremely satisfied	
The session overall	○	○	○	○	○	○	○	○	○	○	○	○
Clarity of session objectives	○	○	○	○	○	○	○	○	○	○	○	○
	○	○	○	○	○	○	○	○	○	○	○	○
Session content met session objectives	○	○	○	○	○	○	○	○	○	○	○	○
Content value (I gained new knowledge and/or	○	○	○	○	○	○	○	○	○	○	○	○

	0 - Not at all satisfied		2	3	4	5	6	7	8	9	10 - Extremely satisfied	
Amount of material covered	○	○	○	○	○	○	○	○	○	○	○	○
	○	○	○	○	○	○	○	○	○	○	○	○

Next, please rate your satisfaction with your **instructor(s)** using the same scale where 0 is “Not at all satisfied” and 10 is “Extremely satisfied”:

	0 - Not at all satisfied		2	3	4	5	6	7	8	10 - Extremely 9	satisfied	
The instructor overall	○	○	○	○	○	○	○	○	○	○	○	○
Knowledge of session	○	○	○	○	○	○	○	○	○	○	○	○
content Teaching	○	○	○	○	○	○	○	○	○	○	○	○
methods	○	○	○	○	○	○	○	○	○	○	○	○
Keeping me engaged in the	○	○	○	○	○	○	○	○	○	○	○	○

If you would like to share any additional comments or experiences about the training session(s) please enter them below.

APPENDIX D
CLIENT IMPLEMENTATION SURVEY

OPTUMInsight™

Client Implementation Survey

Thank you for participating in our short survey regarding your recent OptumInsight implementation experience. Your feedback will be used to improve the process, communication and quality of future implementations.

Overall Satisfaction

How satisfied are you with your recent implementation experience?

0 - Not at all satisfied	1	2	3	4	5	6	7	8	9	10 - Extremely satisfied
○	○	○	○	○	○	○	○	○	○	○

Please provide feedback about the implementation experience that resulted in the rating you provided above.

Continue

OPTUMInsight™

Implementation Process

(Please rate your satisfaction with OptumInsight for the following):

	0 - Not at all satisfied	1	2	3	4	5	6	7	8	9	10 - Extremely satisfied	n/a
Clarity of expectations established at project kick-off	○	○	○	○	○	○	○	○	○	○	○	○
Success at meeting agreed upon delivery dates	○	○	○	○	○	○	○	○	○	○	○	○
Ability to stay within budget	○	○	○	○	○	○	○	○	○	○	○	○
Delivery of agreed upon requirements	○	○	○	○	○	○	○	○	○	○	○	○
Implementing the product/service to the Statement of Work	○	○	○	○	○	○	○	○	○	○	○	○

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Quality

(Please rate your satisfaction with OptumInsight for the following):

	0 - Not at all satisfied	1	2	3	4	5	6	7	8	9	10 - Extremely satisfied	n/a
Demonstrated understanding of our organization, business needs and culture												
Depth of technical understanding and technical assets												
Key deliverables met predefined acceptance criteria (e.g., conformed to standards, met requirements, free of defects)												
Effectively identifed and resolved issues												
Partnered to control scope												
Successfully prepared our staff to assume responsibility for the product/service at the end of the implementation												

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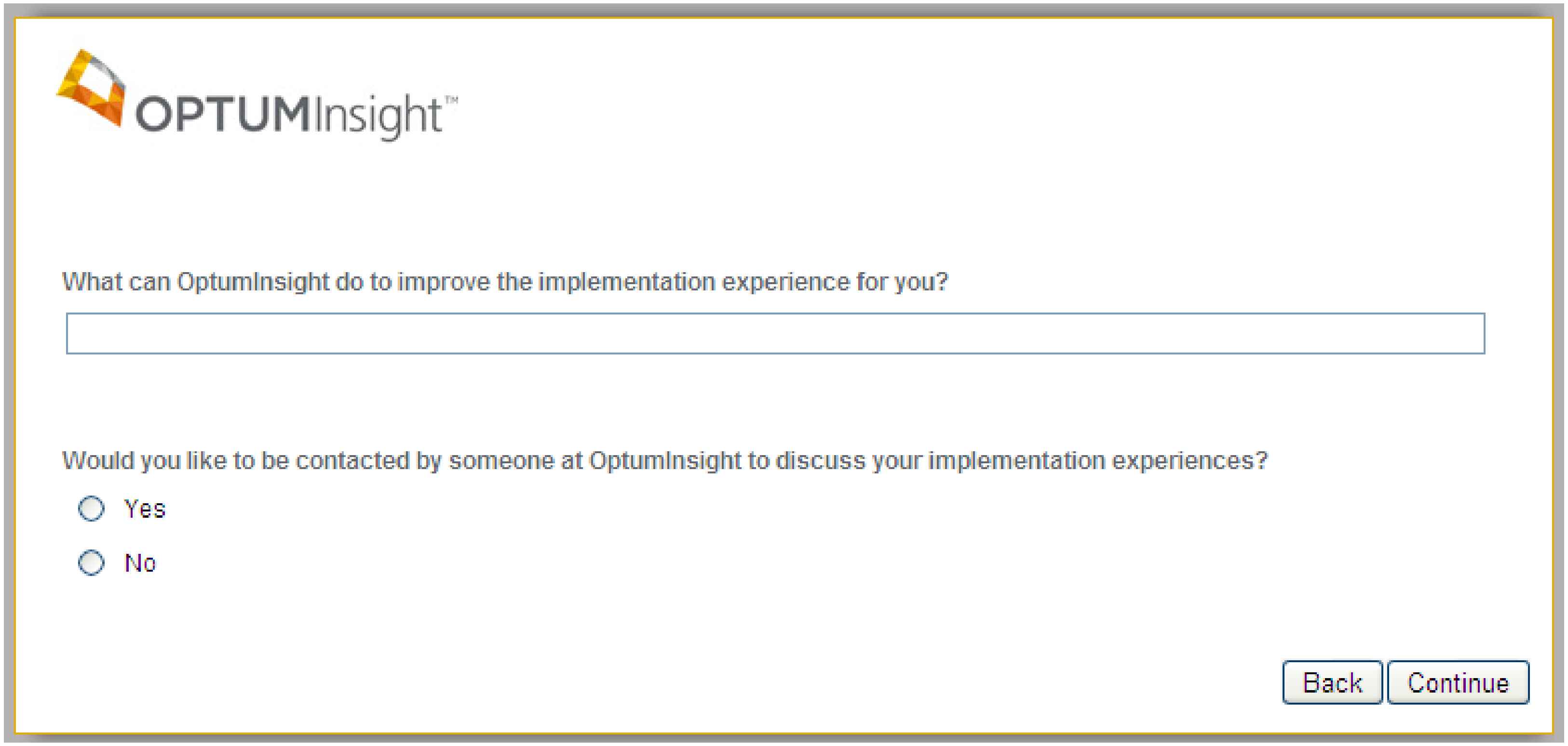

OPTUMInsight™

What can OptumInsight do to improve the implementation experience for you?

Would you like to be contacted by someone at OptumInsight to discuss your implementation experiences?

Yes

No

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APPENDIX E
UCF IRB APPROVAL LETTER

University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901, 407-882-2012 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

NOT HUMAN RESEARCH DETERMINATION

From : **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To : **Juliana Robertson**

Date : **April 20, 2017**

Dear Researcher:

On 04/20/2017 the IRB determined that the following proposed activity is not human research as defined by DHHS regulations at 45 CFR 46 or FDA regulations at 21 CFR 50/56:

Type of Review:	Not Human Research Determination
Project Title:	AN EXAMINATION OF POST IMPLEMENTATION ADOPTION OF BUSINESS INTELLIGENCE TECHNOLOGIES AND THE ROLE OF TRAINING PROGRAMS DURING THIS PROCESS.
Investigator:	Juliana Robertson
IRB ID:	SBE-17-13084
Funding Agency:	
Grant Title:	
Research ID:	N/A

University of Central Florida IRB review and approval is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are to be made and there are questions about whether these activities are research involving human subjects, please contact the IRB office to discuss the proposed changes.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Renea Carver

Signature applied by Renea C Carver on 04/20/2017 11:55:57 AM EDT

IRB Coordinator

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