2020

Leveraging Augmented Reality for Real-time Operational Performance Management

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LEVERAGING AUGMENTED REALITY FOR REAL-TIME OPERATIONAL PERFORMANCE MANAGEMENT

by

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A dissertation submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
in the Department of Industrial Engineering and Management Systems
in the College of Engineering and Computer Science
at the University of Central Florida
Orlando, Florida

Fall Term
2020

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ABSTRACT

Augmented Reality (AR) projects a virtual overlay onto real space so that the user can see a superimposed image over the real-world background. Although AR has advanced recently and a breadth of applications can be found in practice, they are focused on simple tasks with few examples of more complex work tasks. One area that could benefit from advancing AR technology is operations management, specifically operational performance measurement (OPM); however, a brief review of the literature reveals that this potential application area has not yet been explored. Therefore, the purpose of this work is to investigate the application of AR technology to OPM to improve real-time decision-making and management practice. A systematic literature review was conducted to evaluate the current application areas related to management practices. This review did not identify any studies related to using AR to support OPM, but did identify many applications relevant to management activities that empirically demonstrate the benefit of adoption. The review analyzed the current development in this research area and how it has matured including evaluating the applications discussed in the identified publications to demonstrate the existing gap in the research related to OPM applications. An expert study was then conducted to explore potential challenges and benefits of such a device as well as to operationally define effective decision-making for operations managers. The results of the expert study were leveraged to develop a Design of Experiments based laboratory study to empirically test the effects of an AR supported environment on decision-making effectiveness and operational performance. The results showed that the AR device supported improved operational performance, but did not show a significant effect on participants' perceived decision-making effectiveness. This study contributes to the academic literature on technology-enabled OPM and managerial decision-making as well as

providing insights for industry professionals interested in adopting AR to support management functions.

ACKNOWLEDGMENTS

This dissertation was created with the contribution of committee members and a special thank you to Dr. Heather Keathley as the dissertation's primary advisor.

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LIST OF ACRONYMS (or) ABBREVIATIONS

AI	Artificial Intelligence
AR	Augmented Reality
DOE	Design of Experiments
EFA	Exploratory Factor Analysis
IRB	Institutional Review Board
OPM	Operational Performance Measurement
TAM	Technology Acceptance Model
VR	Virtual Reality

CHAPTER ONE: INTRODUCTION & BACKGROUND

Augmented Reality (AR) is a technology that combines a virtual image with a real-world setting (Raghavan et al., 1999; Zollmann & Poglitsch, 2014). This technology has been used for many different applications across a wide range of industries. For example, AR has been shown to aid in the assembly of parts in a production environment and has been demonstrated to be effective as a training tool for workers by portraying assembly instructions overlaid at their workspace (Mura et al., 2016). AR has also been shown to improve human performance by carrying out maintenance tasks with step by step assembly and disassembly instructions overlaid (Palmarini, Erkoyuncu, Roy, & Torabmostaedi, 2018). AR has traditionally been used for simpler tasks such as augmenting human vision or procedural guidance, with fewer examples of more complex tasks such as managerial support tools. More recent applications of AR technologies have begun to focus on more complex tasks. For example, AR is being used in the construction industry for project-management tasks such as overlaying metrics onto the construction site regarding whether particular tasks are on time (Kim, Park, Lim, & Kim, 2013). Though the use of AR is well-established in the literature, the technologies used vary greatly across application areas and users with a distinct lack of best practices to guide adoption of AR tools in practice (Ojer et al., 2020). Additional applications for complex tasks need to transfer from the operator level to the managerial or supervisorial level to support operations management activities.

Operations management includes making data-based decisions while incorporating continuous improvement into an organization. Operational performance measurement (OPM) uses processes and systems to monitor metrics or measures over time (Mathur et al., 2011). This dissertation explores AR applications for higher-order tasks with specific interest in operations management and, more specifically, operational performance measurement. The research consists of three distinct sub-studies and documented as a manuscript style dissertation. This research design leverages a literature review, OPM & AR expert, and an empirical lab study as a mixed-methods research approach. The results of this study contribute both academically and practically by evaluating a novel technology used with principles of operations management. Academically, this research provides a new perspective on accessing information to assist real-time decision-making. Implications for practice include providing key insights to industry professionals interested in adopting AR to support management functions.

1.1 Augmented Reality in Industry

As Augmented Reality (AR) technology rapidly develops, a wide variety of practical applications have emerged across many industries including the medical field, manufacturing, and education (Baran et al., 2019; Liebert et al., 2016; Novak et al., 2014). The AR technology and hardware being used varies across application areas and continues to grow year after year. The entertainment industry has many AR examples which started to attract attention from academia and industry. Such examples include engaging users in different types of educating and entertaining experiences (Baran et al., 2019; Caggianese et al., 2015). What was once considered a novelty is now becoming a practical tool to improve work practices. While there have been many interesting and effective examples of AR applications in industry, these are mainly limited to simple tasks or human performance augmentation and rarely focus on complex tasks such as operational performance management.

The medical field has been using Augmented Reality in various applications. One significant benefit from using AR in the medical field is relation to having 'X-ray Vision." The system can augment data directly onto the patient providing an important visualization tool for medical professionals when conducting sensitive procedures to see things that are typically obscured such as organs or skeletal information below the skin. (Sielhorst, Feuerstein, & Navab, 2008). Advantages of this include seeing traditionally obscured details and physiology as well as the ability of the image being seen by multiple users simultaneously.

Augmented Reality is currently being used in the construction industry to over lay work tasks virtually over the real world. The construction worker loads their geographical location and locations of work tasks are superimposed to the real world showing the construction worker what tasks need to be accomplished. When the user faces their mobile device in different directions, different tasks are be superimposed onto the real construction site (Kim, Park, Lim, & Kim, 2013).

Another application of AR is education and training. In education, Augmented Reality is being used to promote learning motivation and increase better learning performance. AR also led to increased student engagement and enjoyment (Chen, Liu, Cheng, & Huang, 2017). It is used to generate more student learning scenarios and to train students on new activities and learning strategies. Augmented Reality has also been used to measure human perceived distance both in the real world and in comparison using Virtual Reality (Swan, Kuparinen, Rapson, & Sandor, 2017). These applications are used in the effectiveness of using AR map and navigation applications.

Although many practical AR applications have emerged, a review of the literature shows that managerial-focused applications of AR are currently lacking. There is research that supports AR being used for simple tasks such as human vision augmentation and procedural support tools. However, applications for more complex works tasks are limited. Examples of more complex tasks exist in project management and production line monitoring, but are limited. Another example of a more complex task includes surgeons using AR to support procedures in the operating room to avoid needing to look at a monitor to view patient information, which may not be right in front of them. This information could also be setup for multiple users to create a shared experience.

Most current examples of industrial applications are at the operator level and the transition from that to supervisorial level is needed. There appears to be a gap in the research on using AR for more complex tasks that could assist in managerial work such as in operations management and decision-making. Many emergent applications face significant challenges when being transferred to industrial practice. A line of research has developed which focuses on investigating the factors that affect successful adoption of such systems including issues such as technology acceptance and usability (Davis, 1989; Brooke, 1996). Usability tests have been performed to evaluate AR applications in practice. For example, (Albertazzi, Okimoto, & Ferreira, 2012). Albertazzi, Okimono, & Ferreira (2012) evaluate whether AR helps in learning how to use a new project approach. These tests were conducted to evaluate if AR helps the user interact with the product or if it becomes a distraction and an additional item to process as part of the task. Challenges exist in the interoperability of systems, especially since there are so many options of AR software and hardware available (Baresi et al., 2015; Oyekoya et al., 2013). Overcoming common challenges can bring the potential benefits of AR assistive systems to a wider range of organizational settings and applications.

1.2 Operational Performance Management

Operational performance management leverages performance information for decision-making and continuous improvement. Operational performance measurement (OPM) is a subset of performance management and uses processes and systems to monitor defined measures over time (Mathur et al., 2011). OPM is essential in improving productivity in an organization (Mathur et al., 2011). OPM can be used to better understand business processes along with their capabilities

(Kaydos, 1998). It is also used to ensure that the goals of an organization align with their respective strategy and that it gets communicated to the key stakeholders (Kaydos, 1998). This helps improve operations and is used to control and manage the effectiveness of day-to-day activities in an organization. The use of OPM is not just an operational task, but also an indicator of important process improvement activities and operational effectiveness (Dal, Tugwell, & Greatbanks, 2000). Performance measurement both gauges where an organization is and plans to be in the future by measuring progress of the company's vision (Sharma & Bhagwat, 2007). Common challenges in this area include integrating or standardizing data from different systems (Maestrini et al., 2017). Hecklau et al. (2016) also describe challenges associated with interconnectivity and automation. Many organizations look for a customized solution, but this flexibility can create new challenges of not having systems integrated with each other or having a unique solution for individual issues (Gjeldum et al., 2016; Landscheidt & Kans, 2016).

Although there have been significant advancements in the area of OPM, the specific field of technology-assisted OPM is lacking. Recent advancements including real-time dashboards and advanced analytics to assist with OPM (Bremser & Wagner, 2013). However, empirical studies of these applications are limited (Machuca et al., 2011; Rikhardsson & Yigitbasioglu, 2018). AR is one technology that could contribute to the effectiveness of OPM; however, this topic has not been explored in the literature.

1.3 Operations Management & Decision-Making

Management styles can take many different forms in operational environments. One popular style is Management by Walking Around (MBWA) (Tucker & Singer, 2015). This leadership style intended for managers to better connect and communicate with their employees (Boardman, 2004). When leaders remained attentive and responsive to employee's concerns while walking around, organizations were able to see this as an effective leadership strategy (Boardman, 2004). Another popular management style is Authoritarian management style in which the manager provides a specific direction they want their team to follow. They use control to lead their teams and attempt to hold their power instead delegate power to their team, making it a more rigid leadership style (Thau et al., 2009). This management style is usually not seen as effective as others (Vasilev & Todorova, 2016). Transformational leadership style aims to encourage employees to be creative when solving problems and motivates the team by upholding interests of the team, and not just their own (Bass & Avolio, 1993). Studies have shown that when managers use transformational leadership, the more they were able influence their employees to achieve the goals of the organization (Nanjundeswaraswamy & Swamy, 2014).

Technologies to aid in decision-making have been become increasingly popular in recent years. Artificial Intelligence (AI) can be paired with human intuition to enhance the organizational decision-making processes (Jarrahi, 2018). Even though AI tools have shown some success to support decision-making, many have experienced challenges such as being cost-effective or providing a system users can trust (Phillips-Wren, 2012). Burke and Miller (1999) state that relying just on analytics without human intuition is insufficient. Decision-making tools have been developed which can be adopted in larger organizations, but many smaller businesses need a product that can be adopted without huge financial implications. Intelligent support tools have also shown to make systems more adaptable (Chan et al., 2000). Decision-making support tools have been more customized for the organization rather than a wide-spread solution being adopted across organizations (Ostropolets et al., 2020). Another example of operational decision-making is in inventory control systems which help the supervisor optimize storage and order quantities (Shirokova & Iliashenko, 2014).

This study proposes using Augmented Reality with OPM to better understand this technology's effect on the decision-making process. There is little guidance in the available literature regarding appropriate scales for decision-making in this context. A review of the literature failed to identify a reliable, externally-validated scale that could be adopted for this study. Therefore, a customized scale was developed to assess decision-making based on previously established scales from related research areas and the results of the proposed expert study.

1.4 Technology Acceptance

Technology adoption is a process that organizations execute when introducing innovative technological solutions to their operational environment (Molinillo & Japutra, 2017). Technology adoption includes characteristics such as risks, barriers, and outcomes (Molinillo & Japutra, 2017). A few popular frameworks to describe and measure technology acceptance exist including the technology acceptance model (TAM) and the United Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). The TAM provides variables that are quantifiable and helps understand the factors the affect adoption (Davis, 1989). The UTAUT is another technology acceptance model, but since UTAUT is a newer model than the TAM, it has been tested and validated less (Dwivedi et al., 2019). The UTAUT has thought to be more specific to certain types of technology, such as specific computer applications (Straub, 2009). The TAM was selected for this dissertation since it is thought to be a more generic technology acceptance model and is well established in the research literature.

The technology acceptance model (TAM) was theorized by Fred Davis and focuses on what factors drive acceptance of a new technology when introduced to the consumer (Davis, 1989). Using Augmented Reality for managerial tasks, such as OPM, is still in the early stages; however there has been research on how using the Technology Acceptance Model with Augmented Reality can aid in the adoption of the new technology. The model aims at understanding and explaining the user acceptance of a new technology. A summary of the model is shown in Figure 1. Revised versions of the TAM have been researched, such as including additional variables such as Perceived Risk and Cost in a study focused on mobile commerce (Wu & Wang, 2005). Wu and Wang (2005) found that cost was not a major factor in their research, but that perceived risk had a positive influence on Intention to Use. This study focused on using the original version of the TAM as the proposed experiment could not accurately project adoption cost or risk associated with adoption. All of the survey questions included in the original TAM were reviewed and considered appropriate for this study.

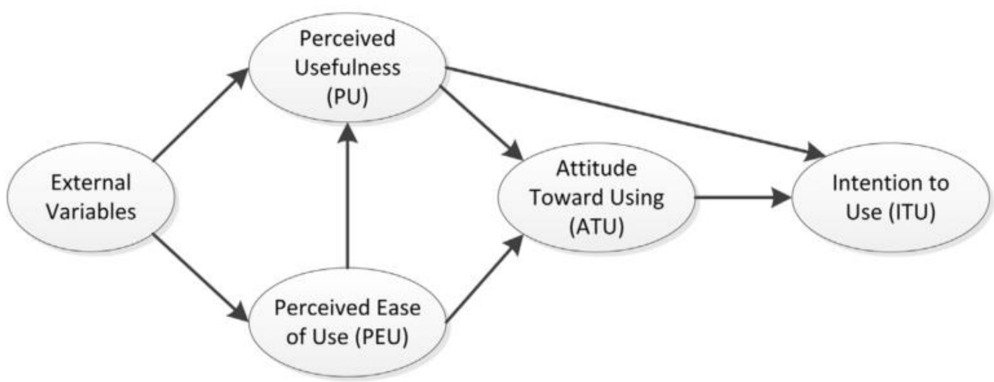

Figure 1: Basic Technology Acceptance Model

Reprinted from Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly, 13(3), 319–340.

The factors that could influence the acceptance and use of the system include the two well-known factors of perceived usefulness (PU) and perceived ease-of-use (PEOU). Perceived usefulness is defined as the degree to which a person believes that using a particular system would enhance his or her job performance (Davis, 1989). If the users can see the benefit to improve job performance, they will be more likely to approve and adopt the new technology. If the individual sees that Augmented Reality can boost their performance or can help in getting their job done more effectively, they will be more likely to use it. Perceived ease-of-use is referred to as the degree to which a person believes that using a particular system would be free of effort (Davis, 1989). If the application of Augmented Reality is easier to use than a previous application, the more likely an individual will adopt the new technology. Also, if the new technology is easy to use the more likely they are to use it. Davis's study included a step-by-step process used to develop new multi-item scales having high reliability and validity for each construct considered. The research also concluded that one of the most significant findings is the relative strength of the usefulness-usage relationship compared to the ease of use-usage relationship. In both of the studies, it was found that usefulness was significantly more strongly linked to usage than ease of use (Davis, 1989).

The technology acceptance model has been used with Augmented Reality in a tour sharing application (Lin & Chen, 2017). In this application, Augmented Reality is introduced to an intelligent tour service system to promote tourist attractions in Thailand. The study aimed to predict gratification, usage intention, and user attitudes toward marketed attractions in the Augmented Reality tour sharing app (Lin & Chen, 2017). 446 questionnaires were returned which resulted in finding that self-presentation and perceived usefulness directly influenced gratification (Lin & Chen, 2017). They also found that perceived entertainment indirectly influenced gratification through perceived ease of use and perceived usefulness (Lin & Chen, 2017). Based on these results, the study continued and is projected to be used in other marketing applications.

In another application, Augmented Reality is being used to enhance classical learning in a ubiquitous learning environment (Chang & Liu, 2013). The study uses situated learning and mobile learning and evaluates how Augmented Reality is accepted. A 25-item questionnaire is developed on a five-point Likert scale and given to 60 participants. The reliability of the questionnaire was tested and confirmed with a Cronbach alpha greater than .7 for each variable. Table 1 below shows the 6 different variables with the Cronbach alpha of each:

Table 1: Reliability Coefficients Statistic

Reprinted from Chang, Y. H., & Liu, J. C. iang. (2013). Applying an AR technique to enhance situated heritage learning in a ubiquitous learning environment. Turkish Online Journal of Educational Technology, 12(3), 21–32. https://doi.org/10.4018/978-1-4666-9837-6.ch011

Variable	**Number of items**	**Alpha (α)**
AR function	5	.986
Content quality	6	.873
Environment interaction	3	.751
Perceived usefulness	3	.768
Perceived ease of use	5	.889
User intention to use	3	.781

The study found that the three items with the highest scores were the "animation of learning material content is very interesting," "It is very interesting to see the combination of virtual and real environments in the smart phone and this makes me want to use the system," and "Using the ubiquitous learning system of Augmented Reality and Situated Learning improves my learning efficiency" (Chang & Liu, 2013). Some of the suggestions for improvement included ensuring that the 3D animation was more complete and that there is a more convenient way to create the 3D objects that are needed. If the 3D animation starts to become more of a distraction rather than a learning aid, it may become less effective. In another study, factors that affect relationship behavior toward Augmented Reality interactive technology (ARIT) is researched (Huang & Liao, 2015). The study revealed that consumers' level of cognitive innovativeness affects their sustainable relationship behaviors towards (ARIT).

The study incorporated relationship marketing research which incorporates how firms can build productive, interactive, and sustainable relationships with consumers. The paper included relational behavior, relationship investment, and re-patronage intentions as three elements of sustainable relationship behavior (Huang & Liao, 2015). The study continues to extend the technology acceptance model to predict what factors may affect consumers' relationship behavior toward using ARIT. Both perceived ease of use and perceived usefulness are important factors from the technology acceptance model (TAM) that are needed in interactive technology like Augmented Reality. Perceived usefulness is proposed to have a more significant impact towards using new information technology in compared to perceived ease of use (Huang & Liao, 2015).

Aesthetics of the application is another important factor of the adoption of new technology. Aesthetics includes visual appeal which can be controlled through design, color, and vividness (Huang & Liao, 2015). If the application is aesthetically pleasing, the more likely individuals will be to use the new technology. If the aesthetics also provides entertainment, it also adds to the likelihood of the adoption of the new technology. Huang and Liao describe that aesthetics is not the only factor that affects how one can use the ARIT to successfully accomplish a shopping task, but also the most important factor to maintain the relationship between the retailer and the consumer (Huang & Liao, 2015). Other factors that contribute to Augmented Reality adoption include playfulness and service excellence. Playfulness in the online retail environment allows consumers to feel enjoyment while using the technology. It helps in evaluating the product as well as completion of a task. Playfulness if different from aesthetics as it creates a fun atmosphere and not just visualization appeal (Huang & Liao, 2015). Huang and Liao conclude their study with indicating that usefulness, ease of use, service excellence, aesthetics, and playfulness are five key factors in the relationship behavior between the consumer and Augmented Reality in the retail application (Huang & Liao, 2015).

Maintenance training has also applied the technology acceptance model to better understand aviation students' perceptions toward Augmented Reality maintenance training instruction (Wang, Anne, & Ropp, 2016). The technology acceptance model is used to explain and predict relationships among ease of use, usefulness, attitude, and intention regarding the adoption of

Augmented Reality based maintenance training instructions. Maintenance workers who use the common and traditional forms of information delivery may not have access to include the work instructions in the area they are working and may need to divert their attention between the document and the work. Augmented Reality can help increase the worker's productivity as well as reduce injuries and potential for error (Wang et al., 2016). The technology acceptance model (TAM) proposes that external variables, perceived usefulness, perceived ease of use, attitudes, and intentions to use indirectly and directly affect a user's actual use of a technology system (Wang et al., 2016). The study included 41 participants who were undergraduate aviation students. They were given a paper survey of 16 7-point Likert scale items intended to examine the technology acceptance model with the adoption of Augmented Reality in aviation training operations (Wang et al., 2016). The survey had an accepted value of reliability for each of the four factors shown in Table 2 below. All Cronbach's alpha scores were greater than .7 which demonstrates a high internal consistency and reliability (Wang et al., 2016).

Table 2: Reliability of Test Items

Reprinted from Wang, Y., Anne, A., & Ropp, T. (2016). Applying the Technology Acceptance Model to Understand Aviation Students' Perceptions toward Augmented Reality Maintenance Training Instruction. International Journal of Aviation, Aeronautics, and Aerospace, 3(4), 1–13. https://doi.org/doi.org/10.15394/ijaaa.2016.1144

Item	**Alpha (α)**
Perceived Ease of Use	.738
Attitude towards using	.857
Perceived usefulness	.907
Intention to use	.885

Across all the students in the survey, the study did not indicate any negative attitudes towards the use of Augmented Reality maintenance training materials. The survey results supported the advantages of using AR work instructions in both ease of use and usefulness (Wang et al., 2016).

In another application, Augmented Reality is being used in teaching environments (Wojciechowski & Cellary, 2013). As part of the study, Wojciechowski and Cellary evaluate learning by doing through physcial movements using an Augmented Reality environment. Some of the advantages of AR applications in the education field include activity of learners, cost, and safety (Wojciechowski & Cellary, 2013). This application can also support a cost reduction as the virtual environment can replace expensive supplies and material that would normally need to be bought as part of the curriculum. Some of the additional facets of teaching include simulation of dangerous envrionments, actitivity that would normally not be visible by the naked eye, and visualization of complex topics (Wojciechowski & Cellary, 2013). Eleven hypotheses were formulated to test in the study. Regression anaylsis supported that perceived usefulness has a positively affect attitude toward using and that perceived enjoyment will positively affect attitude toward using. Also based on the stepwise multiple regression analysis, intention to use depended on attitude toward using and perceived enjoyment as shown in Table 3 below:

Table 3: Stepwise Regression Analysis.

Reprinted from Wojciechowski, R., & Cellary, W. (2013). Evaluation of learners' attitude toward learning in ARIES augmented reality environments. Computers and Education, 68, 570–585. https://doi.org/10.1016/j.compedu.2013.02.014

The stepwise regression analysis.

Dependent variable	Predictors	R^2	p
Attitude toward using (ATU)	Perceived usefulness (PU)	0.827	<0.001
	Perceived enjoyment (PE)		<0.001
Intention to use (ITU)	Attitude toward using (ATU)	0.737	<0.001
	Perceived enjoyment (PE)		0.020

Their emprical study concluded that both perceived usefulness and perceived enjoyment had a similar effect on attitude toward using image based Augmented Reality. For intention to use of Augmented Reality environments, perceived enjoyment was a much more significant factor than perceived usefulness (Wojciechowski & Cellary, 2013). The study also included interface styles as an external variable to be measured which may affect the attitudes of the students toward the system. Using Augmented Reality during lessons could add extra motivation for students to learn. It could viewed as a fun, new technology that the students uses to both learn and to have enjoyment. Since Augmented Reality is a new application in the education domain, the novelty of the technology could add to the positive attitudes of the students.

1.5 Research Gap

A brief review of the literature shows that the amount of research that specifically pertains to using AR as a performance measurement tool is limited. There is evidence of using AR to monitor assembly lines and to analyze Quality Process Control, but these areas are also not well developed. Potential contributions that could be made in this area include leveraging this technology to improve OPM best practices. Improving OPM will lead to improvements in organizational performance and sustainability. Further, using AR technology with OPM is an innovative solution that can add to the current literature in the field. The purpose of this research is to investigate the potential application of AR technology to OPM to improve real-time decision-making and management practice. This research consisted of two phases (i.e., research synthesis and empirical investigation). Phase one was completed as the preliminary work and the second phase consisted of both an expert study and laboratory experiment to empirically test the effect of adopting the tool on managerial decision-making.

1.6 Research Questions & Objectives

The initial review of the literature showed that AR applications for complex and managerial tasks are lacking. This research aims to investigate the potential application of AR technology to OPM to improve real-time decision-making effectiveness and management practice. In order to achieve this purpose, the following research questions have been developed to guide this study:

- How and to what extent has AR been applied for management tasks including operational performance management?
- Can a procedurally generated AR dashboard be developed to accurately report operational performance in real-time?
- How can managerial decision-making be assessed and measured?
- Does an AR dashboard improve real-time decision-making effectiveness?
- What are the ‘factors’ that affect the successful adoption of AR technologies in organizations?

Three distinct sub-studies were conducted as part of this dissertation to address the research questions. The research design and methodologies used in each sub-study are discussed in depth in the Methodology chapter (Chapter 2) as well as in greater detail in their respective chapters (Chapters 3- 5). A systematic literature review was used to determine what extent AR has been used for management tasks. An expert study was then conducted to address the factors that affect successful adoption as well as evaluate how managerial decision-making can be assessed and measured. Both the expert study and the lab experiment were used to determine if an AR dashboard can be developed to accurately report operational performance in real-time. The lab experiment then empirically assessed whether the AR dashboard improves real-time decision making.

1.7 Potential Contributions

The results of the literature review determined a large gap in the application area of operations management, specifically operational performance measurement (OPM). This research provides a new perspective on accessing information to assist real-time decision-making by creating an immersive performance environment for managers. Since research in this application area is in the early stages, there is potential for new knowledge contribution as well as practical applications that can be used immediately in industry. Further, insights regarding applications to complex tasks in operations management may also contribute to development of applications for other types of complex tasks in other areas.

The results contribute to the academic literature on technology-enabled OPM, which is a quickly growing field focused on leveraging technology to support the future of work, by providing empirical evidence demonstrating the potential benefits of such a system as well as expert insights into potential challenges for adoption. This research also provides a tool to make performance measurement systems more effective. Supervisors and managers in industry will find this research useful as there are currently methods to obtain metrics real time, but they may not be as available or convenient to view where the actual work in occurring. The results provide key insights to industry professionals interested in adopting AR to support management functions. These results also suggest that these systems have the potential to improve operations and performance management; however, there are many challenges that must be addressed to support the transition of these technologies to practice.

1.8 Overview of Dissertation

This dissertation uses a blended manuscript-style format with three core manuscripts supported by traditional introduction, methodology, and conclusions chapters to provide greater context and depth of discussion. Each of the major chapters has been written as a manuscript suitable for publication in an academic, peer-reviewed journal and, as such, each chapter contains a separate discussion of relevant background, methodological approaches, and results as relevant for that sub-study. As mentioned previously in the discussion of objectives, this doctoral research consisted of three primary sub-studies. Chapter 3 summarizes the results of a Systematic Literature Review (SLR) and bibliometric analysis which evaluated the current state of this research area and identified gaps in the research. An expert study was then conducted, as documented in Chapter 4, to further explore adoption of AR in industry including interviewing both AR and OPM experts and then performing a thematic analysis on the qualitative results to explore the factors that could potentially affect the successful adoption of an AR assisted OPM tool. The results from the expert study were then leveraged to design a laboratory experiment to investigate the effect of implementing an AR tool for OPM on the effectiveness of real-time decision-making, which is discussed in Chapter 5. This work is multi-phased with each phase holding a distinct purpose and is grounded in a thorough literature review, expert experience, and empirical investigation as described in each of the respective chapters. Conclusions and future work of this dissertation study are discussed and summarized in Chapter 6.

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CHAPTER TWO: METHODOLOGY

The purpose of this work is to investigate the application of AR technology to OPM to improve real-time decision-making and operations management practice. This work is multi-phased with each phase holding a specific purpose. Three distinct objectives have been defined for this doctoral study: a systematic literature review (SLR), an expert study, and a laboratory experiment. First, a rigorous SLR and bibliometric analysis was performed to evaluate the current state of the research. Next an expert study was conducted to explore potential factors that may affect the successful adoption and use of an AR assistive system for OPM. This study consisted of a series of individual interviews and a thematic analysis to investigate the characteristics of effective managerial decision-making. Finally, a laboratory experiment was conducted to test the potential impact of adopting such an AR assistive system for OPM. This experiment utilized pre- and post-survey questionnaires to assess constructs related to technology acceptance and perceived decision-making effectiveness. By using a multi-phased approach, this methodology addresses the five research questions for this study (Chapter 1). This chapter describes the overall research design as well as an overview of the methodologies used in each phase in this study.

2.1 Research Design Overview

This research was organized into three phases (i.e., Literature Review, Expert Study, and Laboratory Experiment) as summarized in Figure 2. As discussed in the previous chapter, the primary purpose of this research was to investigate the application of AR technology to Operations Performance Management (OPM) to create immersive performance environments featuring procedurally generated dashboards portraying real-time data. To achieve this goal, the research design leverages advancements from the literature, experiences and opinions from subject-area experts, and empirical evidence for the effect of such a device on managerial decision-making from a Design of Experiments-based laboratory study featuring a proof-of-concept device.

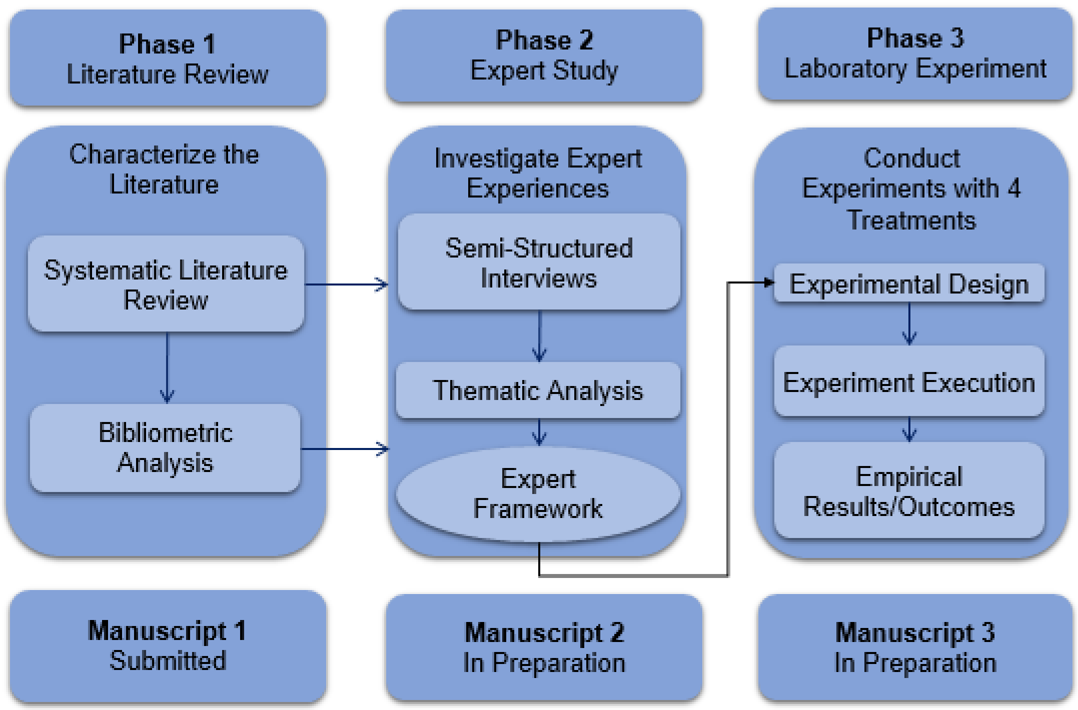

Figure 2: Research Design Overview

The three phases are summarized below. Each phase of the research resulted in a manuscript fit for publication in a peer-reviewed journal.

- Phase 1 (Literature Review): A systematic literature review (SLR) and bibliometric analysis was performed to evaluate the current state of the research (Chapter 3).
- Phase 2 (Expert Study): Expert Study which identified and interviewed experts in the fields of AR and OPM. Results were synthesized and used for construct development (Chapter 4).
- Phase 3 (Laboratory Study): A formal laboratory study conducted on the UCF main campus to measure differences between 4 different treatments. Pre/post surveys were conducted to refine constructs developed in Phase 2 (Chapter 5).

Each of these phases address the research questions stated in Chapter 1 and are linked by sequentially providing outputs that act as inputs for the next phase. Phase 1 evaluated the current state of the literature, which identified a gap in applying AR to OPM and identified key challenges, prompting the expert study. Phase 2 synthesized expert experiences providing rich data to create a decision-making effectiveness construct to be evaluated in a laboratory experiment. Finally, the lab experiment empirically tests differences in using AR assisted devices with and without real-time data utilizing the constructs developed and insights gained during Phase 2.

This dissertation utilizes a mixed-methods approach consisting of three sequential studies (Bergman, 2008; Creswall & Clark, 2017; Johnson et al., 2007). Results from Phase 1 suggest that the state of the literature is exploratory and generation of fundamental evidence is required to support the development of this field. Phase 2 used this information to leverage expert experiences in both AR and OPM in an inductive a qualitative study. This was then followed by Phase 3, which consisted of a quantitative study to empirically evaluate key hypothesized relationships among the constructs. This dissertation follows a manuscript style so that each of the three sub-studies is documented as a distinct manuscript prepared for submission to a peer-reviewed academic journal. Therefore, this chapter summarizes the overall research design and individual methodological approaches for each phase while a more detailed discussion of the approaches used in each phase are available in their respective chapters (Chapters 3-5).

2.2 Phase 1 – Literature Review

Systematic literature reviews (SLR) provide a thorough approach and process to identifying existing research that has been conducted regarding a specific subject or topic (Okali & Schabram, 2010). This SLR includes a scoping study which is a traditional exploratory review that searches for available literature on a topic to help identify gaps within a field of research and gain preliminary insights into the area (O'Brien et al., 2017). The results of the scoping study are then used to develop an explicit search strategy and defined exclusion criteria to reduce bias and increase transparency in the review. Each of these steps are discussed in more detail in the following sub-sections.

2.2.1 Search Strategy

A traditional scoping study was first conducted to initially assess the area of research which resulted in identifying seven papers. These results suggested that there was relatively less research in the area of using Augmented Reality (AR) for management functions with many examples focusing on enhanced vision for surgical applications and procedural tasking (Gao et al., 2019; Kim et al., 2013; Palmarini et al., 2018; Petruse, 2014; Sielhorst, Feuerstein, & Navab, 2008) The scoping set focused more on using AR as an aid in monitoring metrics in production environments, construction sites/projects, and in the medical field. This scoping set was used as a preliminary data set from which the search strategy was developed that helped extract key terminology and selection of academic search platforms. This initial set of papers help shape the direction of this study.

The seven papers for the scoping set were used to create a literature search strategy. ProQuest, Web of Science, and EBSCOhost were the research platforms selected for this research due to these databases covering both academic and industry publications across many different disciplines. Main concepts were then defined which included industrial terms for operations management applications and related AR terminology. Search terms within these concepts were developed from reviewing keywords from publications and were then tested to determine if they would be included in the final search strategy. Testing of search terms included conducting targeted searches using each term within a concept paired with the string of terms in the second concept and determining if applicable publications were found and evaluate the impact and relevancy of the search term. This process resulted in a final set of search terms that was used in the formal SLR. The full description of the methodology applied is provided in Chapter 3.

2.2.2 Bibliometric Analysis

The SLR was initially conducted in 2018 and then updated and maintained throughout the entire dissertation with the final update in May of 2020. Within each search platform, searches were saved along with notifications setup to generate search alerts of any new publications that fit the search criteria. Once all of the relevant publications were included in the final paper set, a bibliometric analysis was conducted to quantitatively investigate the development of this field based on the publications that were selected from the search results (Zhang et al., 2017). The bibliometric analysis includes publication categorization, publication trends, authorship characteristics, content characteristics, and methodological characteristics. Chapter 3 describes further detail on the results of the bibliometric analysis including conducting a maturity assessment and evaluating the impact of the current state of the literature.

2.3 Phase 2 - Expert Study

An Expert Study was conducted to further explore the factors that could potentially affect the successful implementation of an AR assisted OPM tool. The expert study was needed as the SLR did not provide many examples of an AR assisted OPM tool. Additionally, the expert study helped identify AR application challenges as well as challenges faced in effective OPM implementation. Further, the results of this study can be used to develop a construct for decision-making that can be used during the laboratory experiment. The primary challenge of this study is the definition of expert as this is a relatively new area of study with few, if any, established experts. Therefore, this expert study consisted of two samples to provide complementary perspectives for a grounded study: OPM experts who use technology to conduct PM in practice and AR experts who specialize in developing or implementing AR experiences. Interview and survey responses from the expert study were reviewed and synthesized for decision-making construct development. The intended sample size for this study was15 experts from each group. After many rounds of invitations, this study resulted in a sample size of 12 AR experts and 11 OPM experts. Miles and Huberman (1994) found that a reasonable minimum number of experts required for this type of study is ten (Tri Putri, Mohd. Yusof et al. 2014). Van de Ven and Gustafson (1975) suggest that ten to fifteen subjects could be sufficient if the background of the expert subjects is homogeneous.

The Expert Study consisted of semi-structured interviews to gather qualitative information about expert experiences, opinions, and perspectives (Maestas, 2016). Specifically, participants were asked to provide feedback on an AR assisted OPM concept and to discuss potential challenges for implementation based on prior experience with related systems. Further, the participants from the OPM group were asked to define decision-making effectiveness to provide initial data for construct development. Once all interview and survey responses were collected, responses were imported into NVivo analysis software to extract and process themes from the data. The expert study protocol documents are available in Appendices A and B.

2.3.1 Expert Selection

Experts were selected based on selection criteria, meaning that certain characteristics have to be met to qualify as an expert (Hsu and Sandford 2007). In this study, two sets of selection criteria were identified for both AR and OPM groups. The selection criteria included industry professionals with relevant expertise as well as academic experts. This resulted in a mix of industry and academic experience to provide a robust perspective for the study. Academic experts were identified based on related published research and industry experts were identified based on current professional position. The selection criteria also included a minimum of three years of experience in the expert's respective field.

Both AR and OPM groups were accessed through membership in relevant professional societies and social networks. Experts from these groups were also recruited from publications identified during the SLR or by using contact information located on academic web pages. Experts had to have worked directly either with OPM or an AR application in a similar area within the last three years. Experts were contacted via cold emails or LinkedIn messaging with a provided information sheet located in Appendix F. LinkedIn groups were also used for recruitment with the information sheet posted in listed AR or OPM groups.

2.3.2 Semi-Structured Interviews

A series of individual semi-structured interviews and surveys were conducted with the participants (Kelley et al., 2013). Both the interviews and surveys contained identical content including the introductory material and instructions as well as the same structure and flow to ensure that the data collected was consistent across modalities. The interviews allowed for moderation of participant responses including prompting for concise answers and redirection if participants spend too long answering a single question (Longhurst, 2003). This provided richness and depth of data that could be used for result synthesis. Surveys provided convenience to the expert to participate without concern for scheduling an interview while still allowing for richness of response by providing open-ended questions with no word limit and structuring the survey so that experts could return to continue refining their responses. Survey responses were automatically grouped by question using the template from Qualtrics, the survey platform used for the expert study. Interviews were 20-30 minutes long and conducted virtually (i.e., phone, skype, etc.). With permission, the interviews were audio recorded and a transcribing tool (i.e., Trint Transcripts) was used to create exact text transcripts of each interview. Protocol for the interview/surveys are available in the Appendices. This protocol was pilot tested with three experts from both groups (for a total of 6 pilot observations) before beginning the full-scale data collection. Six pilot observations were used since this would represent about 10-20% of the total results collected in the formal study (Connelly, 2008). Feedback from pilot testing was directly incorporated back into the protocol. This feedback included restructuring the interview/survey questions for better flow and sending the interview questions in advance so the participant could review ahead of the formal interview.

2.3.3 Thematic Analysis

The qualitative data obtained from the semi-structured interviews were synthesized using a thematic analysis to inductively extract and organize the insights and findings to support the development of constructs (Strauss and Corbin, 1994; Charmaz and Belgrave, 2007). This approach consists of three primary phases: open coding, axial coding, and selective coding. This process began with a line-by-line analysis to identify and extract any relevant statements as well as initially defining codes. Then, axial coding focused on categorizing and refining the code definitions and structure. Finally, selective coding was conducted by revisiting the original documents and comparing the codes to the raw data to ensure that all relevant data had been extracted and coded. This process was then repeated in iterations until the results become saturated, which is when future iterations do not provide any further revisions to the code definitions or structure (Ando et al., 2014). The qualitative data from the interviews was analyzed using the NVivo qualitative analysis tool, which assisted in investigating key relationships and themes as well as drawing conclusions. This analysis resulted in a list of codes and sub-codes that represent key themes that emerge from the collective expert responses and experiences.

Data from two of the questions were used to develop Likert-items to be included in the data collection instrument including defining sub-codes representing dimensions of perceived decision-making effectiveness. These items were then used in the pre/post survey questionnaires conducted during the laboratory experiment. Responses to other questions included in the Expert Study were used to identify current challenges in AR applications and effective OPM implementation, which were used to help guide the development of the treatments in the laboratory experimentation (Chapter 5).

2.4 Phase 3 - Laboratory Experiment

This study was based on a Design of Experiments (DOE) approach (Montgomery, 2013). DOE is a statistical process of planning an experiment so that applicable data can be collected and analyzed (Montgomery, 2013). Experimentation was used to gather empirical data that could be statistically analyzed to determine what combination of variables had the largest impact on effective decision-making. The defined conceptual model contains two, two-level categorical variables of interest and, therefore, a standard 2^2 factorial model was used. The two variables of interest are AR assistance and access to real-time data. These each have two levels that were evaluated (i.e., AR assisted vs, AR unassisted, and real-time data vs. historical data). As mentioned previously, data for the constructs of interest (technology acceptance and decision-making effectiveness) were gathered through Likert-based pre/post-experiment survey questionnaires.

2.4.1 Conceptual Framework

The key variables of interest to study are technology acceptance, perceived decision-making effectiveness, and operational performance. Technology acceptance was assessed using commonly accepted Likert scales from the Technology Acceptance Model (TAM) that were adopted for this study (Davis, 1989). Operational performance was specific to the task defined for the experiment (e.g., profit from a simulation). A review of the literature showed that there is no commonly accepted scale for managerial decision-making effectiveness. Therefore, a customized scale was developed as part of the expert study. This work posits that having a real-time assistive technology improves decision making and operational performance and that increased levels of tech acceptance are also associated with improvement in perceived decision-making effectiveness and operational performance. Figure 2.2 summarizes the preliminary conceptual framework for this study.

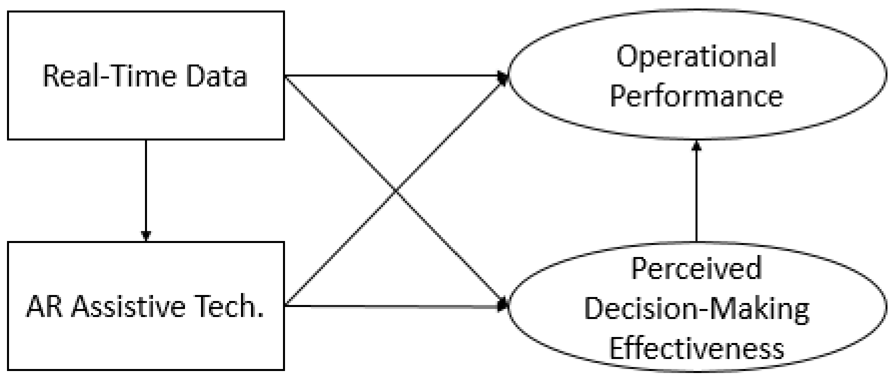

Figure 3: Guiding Conceptual Framework

This relationship shows that real-time OPM has a direct effect on operational performance and perceived decision-making effectiveness, but also shows that pairing real-time OPM with an AR-assisted device also has a positive effect on both outcomes. Perceived decision-making effectiveness is also hypothesized to have a positive relationship with operational performance. To optimize operational performance, real-time data, AR assistive technology, and managerial decision-making effectiveness are needed.

2.4.2 Experimental Design

This experiment contained four unique treatment combinations as summarized in Table 4. This experimental design allowed for a statistical analysis to test hypotheses regarding the effect of each of the predictors on the four defined response variables using an analysis of variance. The experiment was conducted in an operational environment with participants needing to optimize work allocation and inventory management in a grocery store setting. Further, this design was replicated eight times resulting in 32 observations. A sample size of 32 was the minimum sample size initially estimated to obtain a statistical power of .75 using a standard deviation and effect size of 500 (Djimeu & Houndolo, 2016). Since the starting profit for the participant is $10,000, an effect size of 500 was thought be a value that would be a minimum detectable difference between treatments (Fritz et al., 2012). Results of the pilot testing also supported these values. This experiment is a between-subjects design where participants only experienced one treatment and did not participate in any other treatments.

Table 4: Factorial Design

	Assisted	Real-Time	Description
(1)	-	-	Neither assisted nor real-time
a	-	+	Real-time data provided without AR technology
b	+	-	AR technology provided without Real-Time data
ab	+	+	Both Real-time data and AR technology are provided

The first treatment used a tablet device, but was not assisted by AR and did not have access to real-time data. The second treatment did have access to real-time data, but did not use AR technology. The third treatment used AR on the tablet simulation, but used historical data while the fourth treatment had access to both real-time data and was assisted by AR. All four treatments had equal observations in the experiment.

Two separate DOE models were used with two outcome variables, operational performance (i.e., profit) and perceived decision-making effectiveness. The first model was a basic set-up focused on a simple operational process with different performance indicators. There were performance issues that must be diagnosed by the participants using the provided resources. Participants were given operational performance data (e.g., last month of performance data) or provided simulated real-time data (i.e., the data was simulated but appeared to be real-time to the participants). Similarly, participants were either given a prototype of the AR assistive technology or a stationary performance dashboard. Participants were randomly assigned to treatment combinations by a Run Order created from Minitab to reduce the any potential for bias by running like treatments together. The second model focused on using the pre/post surveys to refine the decision-making effectiveness construct development. Every participant would complete the same set of surveys regardless of what treatment they were assigned.

2.4.3 Device Development

A four-semester UCF 4912 research course was conducted in which industrial engineering and computer science students were recruited to develop both AR and non-AR simulations for a tablet device. Two AR experiences were created which either used simulated real-time data or historical data (i.e., data from the previous month). Computer science students used Unity and Vuforia software to create the AR simulations and used Android Studio software to create the non-AR versions. The experiment simulates an operational environment on an electronic tablet and uses key metrics for operational performance management. The simulations went through many development iterations and revisions before they were finalized and ready for formal pilot testing.

Once the study completed many rounds of testing, the simulations were ready for formal pilot testing which consisted of eight UCF industrial engineering graduate students going through the actual procedure at the UCF lab location. The pilot testers also provided valuable feedback on the experiment setup and execution. A few changes were made as a result of pilot testing include updated wording on the pre/post questionnaires and adding more clarity to the experiment brief. Also, the pilot testers recommended one simulated day of practice prior to starting the formal run of seven days, which was implemented for the formal observations.

2.4.4 Experiment Execution

The experiment consisted of four treatment combinations that were replicated eight times resulting in a total sample size of 32. The sampling frame for this study was University of Central Florida undergraduate and graduate business students. Since the experiment simulated being a grocery store manager, business students were directly recruited as they were thought to be best positioned to understand this task given to them since they take management and supply chain classes. Students were recruited though announcements posted to listservs and physical locations (e.g., flyers dispersed in UCF business buildings) as well as announcements in key business courses. Once the study held the first few observations, a snowball recruitment method was used where participants also referred the study to other business students to help obtain the sample size needed (Biernacki & Waldorf, 1981). To encourage participation, an incentive worth $20 was offered to each participant in the form of an electronic Amazon gift card that was sent to directly to the participant via email once the post-survey was complete.

The experiment consisted of an initial briefing introducing the experiment to participant. Next the participant would complete a pre-survey followed by the experimental run and, finally, a debriefing session with a post-survey. All participants engaged in two practice days prior to starting the formal experiment run. During the experimental run, observations were used to collect objective data and pre/post-surveys were used to collect perceptual data (i.e., Likert items). Each participant spent approximately one hour to complete the full experiment. Figure 4 below shows the flow of the experiment study from the initial experiment brief to discharge.

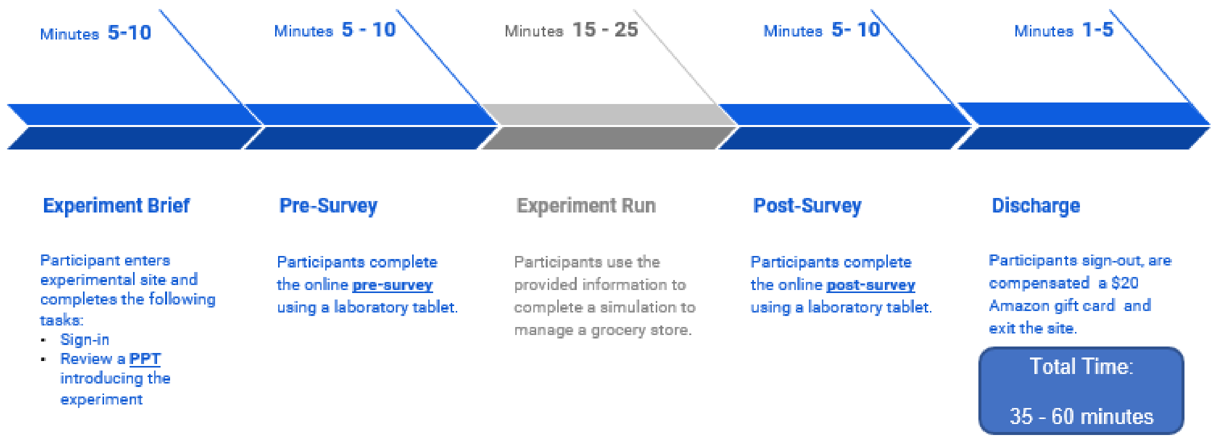

Figure 4: Experiment Flow

The participant starts with an experiment brief and then proceeds to take the pre-survey. Once the survey is complete, the actual experiment began. After the participant finishes the experiment, they then completed the post survey and was compensated with a $20 gift card.

2.4.5 Statistical Analysis

First, reliability analysis (i.e., Cronbach's Alpha) was conducted to evaluate and refine the existing Likert constructs adopted from the literature based on the empirical evidence. Next, an exploratory factor analysis was conducted on the perceived decision-making effectiveness survey items to see how many factors the survey items represent. Reliability analysis was then run for this construct to determine if the survey scale produces consistent results. Once the constructs had been finalized, a DOE analysis was conducted to evaluate the hypothesized relationships for both operational performance and decision-making effectiveness. Both operational performance and perceived decision-making effectiveness were outcome variables that were included in the DOE model. Operational performance was the outcome variable used in the first DOE model to investigate key relationships between treatments and perceived decision-making effectiveness was used in the second DOE model to investigate key relationships in survey responses. A pre-post comparative analysis was conducted on the survey results to evaluate if there were differences in responses from each treatment group after the experimental run was complete. The data consisted of categorical predictors and continuous response variables, which were integrated into the DOE analysis. Minitab was used to run the DOE analyses as well as conduct residual analysis to ensure model validity. Specifically, homoscedasticity and normality of the residuals were evaluated along with Cronbach's alpha to evaluate model validity and reliability (Montgomery, 2013; Tavakol & Dennick, 2011)). Along with this evaluation, a normality test was conducted for this set of data to ensure that a DOE analysis could be completed and validated. Demographic data were collected in the pre-surveys which included age, gender, college major, and school standing (e.g., Sophomore, Junior, Senior). A detailed discussion of the data analysis approach is provided in Chapter 5.

2.5 Outcomes & Contributions

The overall design consisted of a doctoral study with three sequential phases. This work is multi-phased with each phase holding a distinct purpose grounded in a thorough literature review (Chapter 3), expert experience (Chapter 4), and empirical investigation (Chapter 5). Each phase works together and builds from the previous phase; outputs from the earlier chapters are inputs for the later chapters, all linked together under an overarching research strategy. Each of the three chapters have a separate and detailed methodology section to support the specific research phase. These methodology sections include additional information on respective research approaches.

Outcomes of the dissertation study include distinct three manuscripts prepared for submission to peer-reviewed academic journals. Academically, this research contributes to the literature on technology assisted OPM as well as providing expert insight into adoption challenges. This research will also be of interest to practitioners who are interested in adopting AR systems to potentially improve operations management. Conclusions of this dissertation study are discussed and summarized in Chapter 6. The available appendices include all IRB documentation in Appendix C & D, Expert Study interview recruitment and protocol in Appendix F, and all of the data output files used during the analysis of the experimentation data in Appendix H.

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CHAPTER THREE: SYSTEMATIC LITERATURE REVIEW & BIBLIOMETRICS

Systematic Review of Augmented Reality Applications in Industry: Progress and Challenges

3.1 Abstract

Augmented Reality technology has advanced rapidly in recent years and a breadth of applications can be found in practice. While many of these tools have been demonstrated to be effective in improving operational or worker performance, applications related to engineering management practices, such as monitoring work practices and process control, are less common and reportedly experience additional challenges due to the complexity of these tasks. This paper reports the results of a systematic review of the literature conducted to evaluate developments in this research area and identify directions for future research. The results show that there are many potential applications for AR technologies in operations and engineering management. However, there are many challenges that need to be addressed to develop best practices for these applications.

Keywords: augmented reality, industrial applications, operations management, systematic literature review, bibliometric analysis, thematic analysis

3.2 Introduction

Augmented Reality (AR) technologies project a virtual overlay onto real space so that the user can see a superimposed image over the real-world background (Raghavan et al., 1999; Zollmann & Poglitsch, 2014). Though the concept of AR is well-established, the technologies used vary significantly across application areas and users with a distinct lack of best practices to guide adoption of AR tools (Ojer et al., 2020). As AR technology rapidly develops, a wide variety of practical applications have emerged across many industries, such as in the medical field, education, and manufacturing (Baran et al., 2019; Liebert et al., 2016; Novak et al., 2014). Although these technologies have been viewed as novelties in the past, they are quickly becoming a practical tool to improve work practices.

AR was first developed in the 1960s and mainstream applications appeared in the entertainment industry in the 1990s leading to an increased attention from both researchers and industry professionals (Arth et al., 2015). Since then, AR technologies have been used in the entertainment and education sectors to engage users in interactive and enriching experiences (Baran et al., 2019; Caggianese et al., 2015). Educational applications use AR to facilitate and motivate learning in classrooms to improve learning outcomes (Baran et al., 2019). These applications have been shown to increased student engagement and enjoyment (Chen, Liu, Cheng, & Huang, 2017) and are used to generate student learning scenarios and support new activities and learning strategies (Chu et al., 2019).

In addition to creating interactive experiences, AR has also been used to augment human skills and capabilities. For example, some applications in the medical field provide surgeons with additional information that is traditionally obscured, such as the location of veins beneath the skin, mapped onto the patient providing the surgeon with a form of ‘x-ray vision” (Gao et al., 2019). Sielhorst et al. developed an system that can augment data directly onto the patient providing an important visualization tool for medical professionals when conducting sensitive procedures (Sielhorst, Feuerstein, & Navab, 2008). Further, the system can be used by multiple users such that the augmented images can be seen by multiple users simultaneously. AR has also been used to measure human perceived distance both in the real world and in comparison using Virtual Reality to support the development of advanced map and navigation applications (Swan, Kuparinen, Rapson, & Sandor, 2017).

In addition to direct augmentation of human skillsets, AR technologies are also being used to guide procedural tasks such as assembly (Raghavan et al., 1999; Yuan, Ong, & Nee, 2008). In the medical field, surgeons are using AR tools to project instructions or critical data onto their workspace to avoid having to reference a monitor or other device (Liebert, 2016). Similarly, AR has been shown to be an effective tool to guide assembly workers completing tasks by projecting instructions into the workers view rather than having them reference an assembly manual reducing errors and improving efficiency (Petruse, 2014). These tools are also used to train workers providing an interactive and adaptive experience that helps them to gain proficiency more quickly (Horejsi 2014). In the construction industry, AR is used to indicate progress and priority of work tasks in the real space (Kim, Park, Lim, & Kim, 2013). A construction worker can load their geographical location and locations of work tasks are superimposed to the real world showing the construction worker what tasks need to be accomplished. When the user faces their mobile device in different directions, different tasks are superimposed onto the real construction site (Kim, Park, Lim, & Kim, 2013).

More recent applications of AR technologies have begun to focus on more complex tasks. For example, AR is also being used in the construction industry for more project-management related tasks such as overlaying metrics onto the construction site regarding whether particular tasks are on time (Kim, Park, Lim, & Kim, 2013). In addition, AR is also being used in the maintenance field to restore functionality to a product within its lifecycle (Matthews et al., 2015). These applications support workers in proactive maintenance by providing data that supports decision-making (Palmarini, Erkoyuncu, Roy, & Torabmostaedi, 2018). It can also add virtual instructions for the maintenance worker as well as identify and procedurally display tasks needed as part of the maintenance procedure. While there are many examples emerging across a wide variety of industries, there is a distinct lack of best practices for adopting these technologies and many applications in the literature report facing significant challenges (Ojer et al., 2020).

Although AR is becoming a practical tool in many areas of industry, there are relatively few studies that focus on applying AR to higher-level tasks such as management and knowledge-based work. In particular, a better understanding of how these tools can be used to support operations and engineering management is needed. This paper summarizes the results of a systematic literature review (SLR) and bibliometric analysis of research that focuses on applications AR for management or supervision tasks. The purpose of this work is to evaluate current application related to management practices, such as monitoring work practices, process control, and providing feedback. The review analyzes the current development in this research area and how it has matured providing an overview of key application areas identified. The results are then used to highlight current gaps in the literature for future research.

3.3 Methodology

In order to identify and analyze the available literature, two primary methodologies were utilized. First, a systematic literature review (SLR) was used to identify relevant publications from three platforms (Stone, 2012; Tranfield. 2004): ProQuest, Web of Science, and EBSCOhost. The review identified 44 papers, which were then evaluated using bibliometric analyses to investigate the development of this research area and assess the maturity of this research area (Keathley et al. 2016).

3.3.1 Systematic Literature Review

An initial traditional literature review was conducted as a scoping study to initially assess the area of research and seven papers were identified (Kim 2013, Kollatsch 2014, Liebert 2016, Novak 2014, Raghavan 1999, Segovia 2015, Zollmann 2014). The results of this initial review identified seven publications and the results suggested that there was relatively less research in this area supporting the need for a thorough review of AR applications for management functions to support the advancement of this field. These seven publications are known as the scoping set. The majority of the scoping set concentrated on using Augmented Reality (AR) to help monitor metrics for productions lines, construction projects, and hospital rooms. These papers helped shape the direction of the study and gave insight into this area of research. They were used as the foundation for the search strategy and were used to test the reliability of the search results.

The seven scoping study papers were used to develop the search strategy. ProQuest, Web of Science, and EBSCOhost were chosen as research platforms for this research due to their coverage of academic and industry-focused works across a range of disciplines. Next, the main concepts were defined (i.e., operations and engineering management applications and AR) and potential search terms were tested to determine if they should be included in the search strategy. The terms were iteratively tested using the capture rate (i.e., the number of scoping study papers that were captured by the search) as a measure for the rigor of the search. This process resulted in the final set of search terms, which are summarized in Table 6 below:

Table 5: Concept Decomposition & Final Search Terms

Industrial Applications	***Augmented Reality***
monitoring	augmented reality
monitored	AR monitoring

management	AR System(s)
managing	wearable computer
process	wearable computers
evaluate	mixed reality
evaluation	real world overlay
control	smart glasses
visualize	smart glasses
visualization	extended reality
dashboard	google glass
measure	HoloLens
measuring	augmented virtuality
audit	wearable technology
auditing	VR application
assessment	
assess	
report	
reporting	

Due to the relatively few publications identified in this area, broad search terms that represented a range of management functions and behaviors were selected to capture a comprehensive set of applications beyond those identified in the scoping study. The final search strategy was executed across the three different search platforms by searching titles and abstracts, which resulted in approximately 32,000 titles and abstracts to review for inclusion. The search results were limited to the English language but no other limiters were used to capture as many applicable publications as possible. The search results were reviewed in two phases. Initially the titles and abstracts were reviewed for inclusion and relevant publications were collected. Next, they were reviewed by evaluating the full paper and applying detailed exclusion criteria. When evaluating the search results, publications that only focused on the development of AR technology, used AR as a simple visualization tool, used AR for work task guidance, or focused on training or teaching were excluded. This exclusion criteria were consistent across all three databases.

3.3.2 Bibliometric Analysis

An existing framework developed by Keathley et al. (2016) was applied to evaluate the maturity of this research area. This evaluation consisted of conducting a series of bibliometric analyses on the 44 publications identified by the SLR and focused on evaluating the various application areas, author characteristics, publication characteristics, data collection methods, data analysis methods, and keywords. These bibliometrics help assess maturity of the research and give insights on the direction and trends of the research.

3.3.2.1 Bibliometric Results

Once the search strategy was finalized, the search was executed on the three platforms and the exclusion criteria were applied to identify the final paper set, which was then analyzed using bibliometric analyses to assess the development of this area. This section summarizes the results of the bibliometric analysis and discusses the maturity of this research area. The findings related to current applications are then summarized in the following section.

The search was executed on the three platforms and Table 7 summarizes the raw and limited results in addition to the search function and time period for the literature review.

Table 6: Papers Selected

Platform	Raw Results	Limited (English)	Search Function
ProQuest	9297	9156	Title or Abstract
Web of Science	12301	11849	Title or Topic
EBSCO Host	11202	10737	Title or Abstract

As described before, the search resulted in approximately 32,000 results that were first evaluated based on the title and abstract. Titles and abstracts of publications that included general themes of Augmented Reality use for monitoring or measuring were downloaded for further evaluation. This process resulted in 396 publications, which were reviewed in detail and screened using the defined exclusion criteria. Figure 5 shows the PRISMA flow of information (Moher 2009) through the different phases of this review.

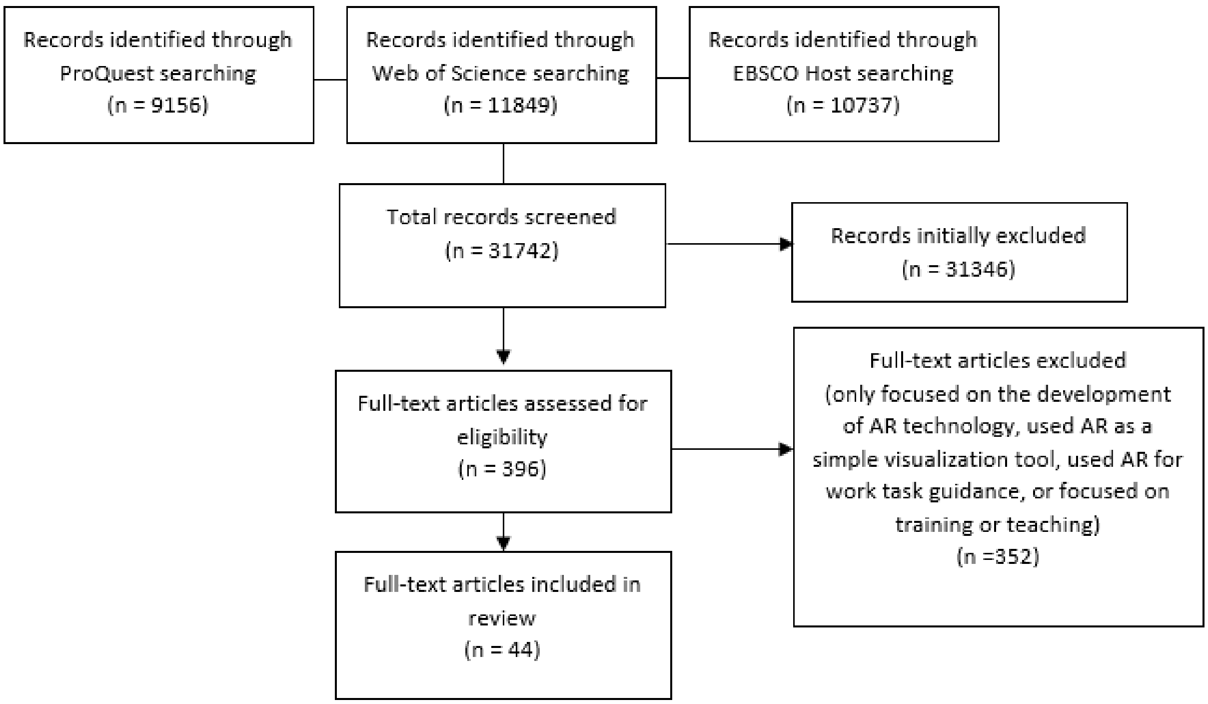

Figure 5: PRISMA Flow Diagram

During the full-text review the publications were organized into different categories as summarized in Table 8. As the focus of this review was on management functions and behaviors, only this category was retained and analyzed in this study; however, a list of the citations from the remaining categories is available upon request. While the search captured a range of applications, it is important to note that the search terms were focused on management functions and, therefore, the publications identified by this search represent only a portion of the current research in these areas.

Table 7: Publication Categorization

Category	Description	No. of Publications
Management Functions	Higher-complexity tasks such as managing work, monitoring performance, and decision-making.	44
Augmented Vision	Enhancing or augmenting human vision (e.g., veins beneath the skin or pipes within a wall).	142
Work Guidance	Guiding work tasks and enhancing work performance efficiency.	86
Development of Technology	Developing hardware or software to advance AR technology.	36
Non-specific uses	Investigative work that may not have conclusive results or specific use cases.	31
Teaching/Training	Applications used during teaching or training exercises to support and engage learners.	57

To further investigate the development of this area, the trends in publications from each category were tracked over time as summarized in Figure 6. It is important to note that this search was completed in May of 2020 and, therefore resulting in a relatively lower number of publications for that year. It is evident from this chart that management functions have been studied less than other categories and studies only emerged since approximately 2008. This is further discussed in the following section, which focuses specifically on publications within the Management Functions category.

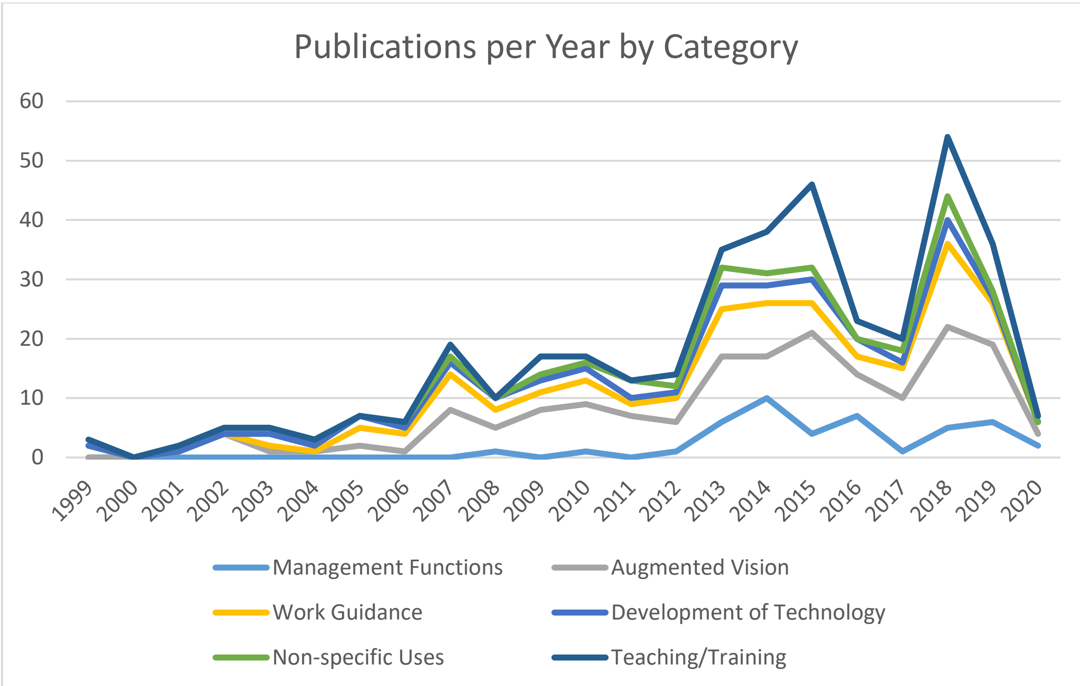

Figure 6: Publications per Year by Category

Organizing the publications into the different categories provided an initial taxonomy to understand how this field is developing. The results show that the majority of the work conducted in this area is focused on augmenting or enhancing human vision such as providing surgeons "x-ray vision" by seeing organs or veins beneath the skin (Gao et al., 2019). Another common application is in work task guidance, where workers are given procedural instructions while completing a task to improve performance efficiency (Petruse 2014; Raghavan et al., 1999; Yuan, Ong, & Nee, 2008).

The selected category focuses on management functions and behaviors and includes a variety of applications for higher-complexity tasks (Novak-Marcincin et al., 2014; Segovia et al., 2015). These publications describe how AR has evolved to help operations and engineering managers in completing routine tasks such as monitoring work progress and decision-making (Kim, Park, Lim, & Kim, 2013; Kollatsch et al., 2014). These publications were then further analyzed to evaluate the development of this research area and to identify opportunities for development. This category consisted of 44 publications focused on AR applications for management functions, which were analyzed using bibliometric information. This analysis focused on investigating publication, authorship, methodological, and content characteristics as well as impact. The key findings and contributions of these works are discussed in the next section.

3.3.2.2 Publication Trends

To begin the publication characteristics were evaluated including trends over time as well as key sources. Figure 7 summarizes the publications per year, which shows that management function related publications are sporadic with bursts from 2013-2016 and more recent publications in 2018 and 2019.This may suggest that the research area is still maturing with inconsistent interest in this area.

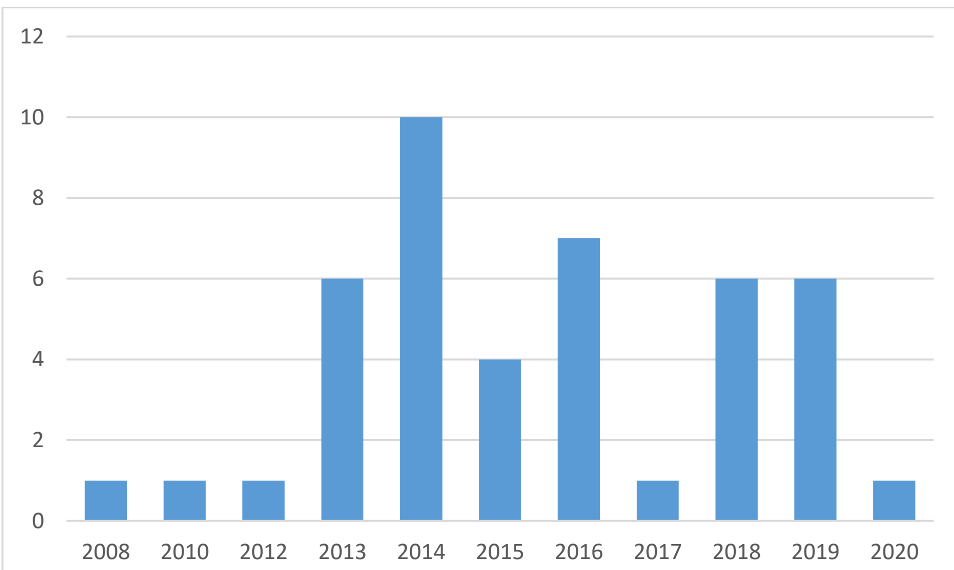

Figure 7: Publications per Year

Of the 44 publications evaluated, 32 journals were found to be unique among the publications. Figure 8 below lists the journals that were cited in the bibliometric analysis. *Automation in Construction* had the highest number of publications represented (7) in the review. Initially, it is surprising that the construction industry is adopting AR so widely since the industry may need more ruggedized equipment in a construction setting. Even though the construction industry does show evidence of AR adoption, it does not necessarily indicate that the use of AR headsets is being adopted as headsets may not be required for project management and task completion tracking. AR can be utilized with a hand-held phone or tablet and may be just as effective in monitoring project progress (Kim, Park, Lim, & Kim, 2013).

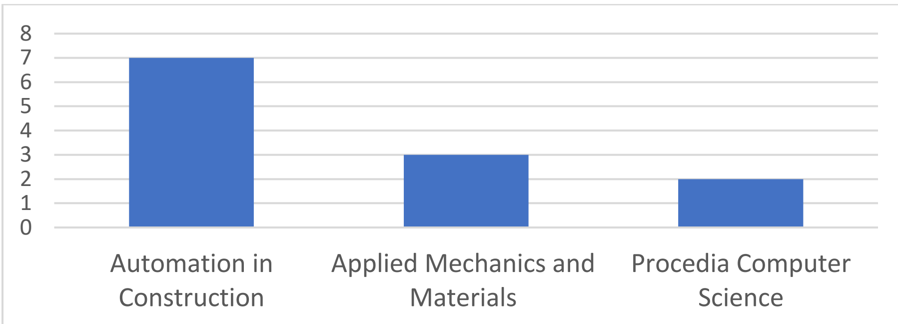

Figure 8: Most Prevalent Journals

These three journals represent 27% of the publications included in the study. The publications vary across many different journals suggesting that there is widespread interest and application in AR adoption.With only 3 journals prevalent in this area, this suggests that the research is being published in a variety of areas with no centralized source for AR applications for management functions. For example, some of the identified publications were published in various medical journals, construction journals, and computer vision journals.

3.3.2.3 Authorship Characteristics

Next, the authors of the publications were investigated to learn more about their contributions to this field. Figure 9 below summarizes authors who contributed to more than one publication in the final paper set as well as the number of times they published along with the year the paper was published (Baek et al. 2019; Gheisari et al. 2016; Irizarry et al. 2014; Kim et al. 2013; Kwon et al. 2013; Novak et al. 2013; Novak et al. 2013; Park et al. 2013; Segovia et al. 2015; Segovia et al.

2015; Wang et al. 2014; Wang et al. 2014). In the bibliometric analysis, no author appeared more than three times, which emphasizes the lack of emerging experts or research communities who are directly focused on this research area. The author with the most publications from this review is Xiangyu Wang from Kurtin University in Korea (Park et al., 2013; Wang et al., 2014; 2014). He has 3 publications in the analysis focusing on Augmented Reality applications in construction. All of his publications discuss integrating AR within BIM applications in construction. They include researching onsite contruction modelling and information systems. The remaining authors had between 1-2 publications identified by the review.

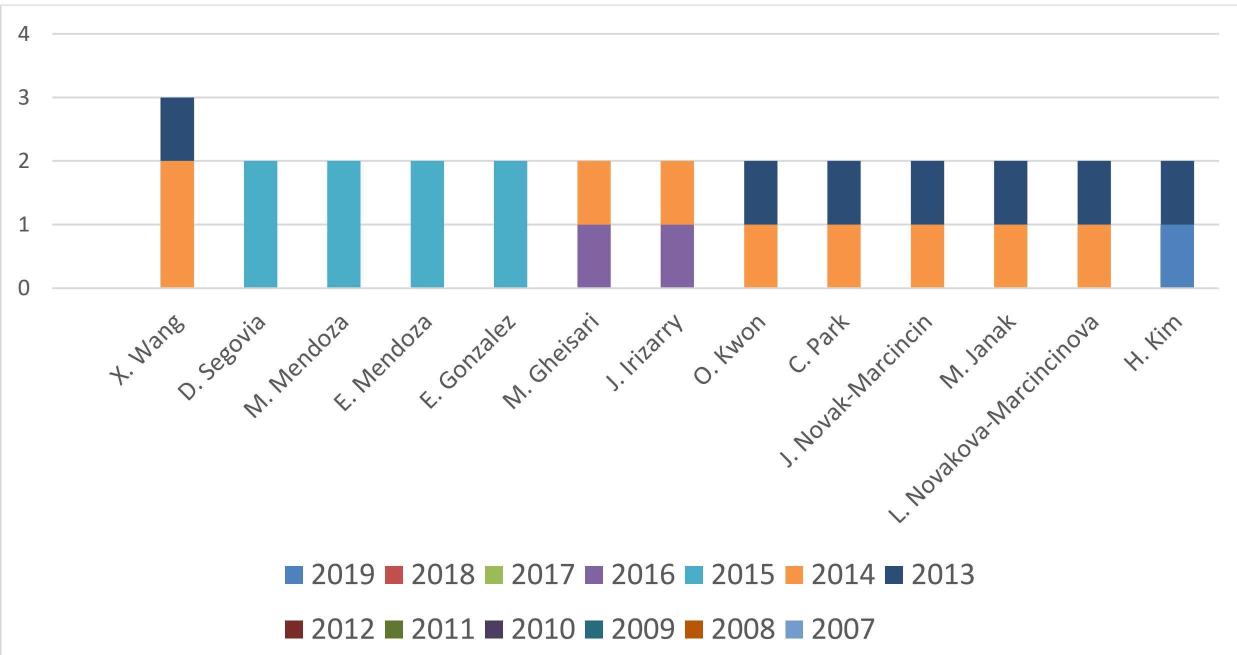

Figure 9: Prevalent Authors & Publication Year

In total, 145 unique authors were identified representing 20 different countries. Authors from the USA represented the most publications, with approximately 13% of the total publications. Korea, Italy, and Canada had next amount of leading publications representing 11%, 9%, and 9%, respectively. It is also important to note that all continents except for Africa were represented in the final paper set. A majority of the authors are academics publishing this work. These characteristics suggests that there are not many emergent experts in this area of research yet (i.e., authors who routinely publish in this research area); however there are several authors from many countries partipating in this research demonstrating the international interest in this area.

3.3.2.4 Content Characteristics

In the literature results, several publications provide information on how and where Augmented Reality is being used, but few describe how it is being used to aid and improve decision making. To investigate potential trends in these publications, the keywords used by authors were investigated. Out of the publications collected, “Augmented Reality” was the most common keyword among the publications surveyed with a count of 30 out of 44 (68%) publications. Even though all 44 publications included AR applications, some authors may not have thought their work focused enough on AR to include it as a keyword. The keywords were grouped into different categories to see which groups had the most keywords. After grouping like keywords together, Table 9 shows the affinity of the keywords. The keyword grouping supports that Augmented Reality is the central topic from these publications with additional focus on mobile and management applications. Monitoring/Metrics were a keyword for only seven of the publications, even though they were terms that were directly included in the search strategy. This may suggest that even though this concept was included in the search strategy, this topic was not a focus of the publication. The lack of these keywords among the results may also indicate that the author used the search terms in their title or abstract, but it was not a central theme across the article. The publications that used monitoring or metrics as keywords are directly discussed later in this chapter.

Table 8: Keyword Grouping

Keyword	Count
Augmented Reality	30
Mobile Device/Computing	14
Management	13
Building Information Modeling (BIM)	10
Monitoring/Metrics	7
Construction	6

Mobile Device/Computing and Management are the next most common keywords in the paper set. This is aligned with the search criteria that was used supporting the rigor and scope of the search strategy. With these keywords being so common among the articles, it suggests that Augmented Reality is considered a mobile computing device and that it has started to be used with management activities. Building Information Management (BIM), which is a construction visualization tool (Kwon et al., 2014) and Constuction were also common keywords found in the analysis, which further supports the finding that Augmented Reality is maturing quickly in constuction management. This is also consistent with *Automation in Construction* being the most common journal published in this field as well as BIM being a central theme across publications including a construction application.

The 44 publications were also evaluated to identify the respective AR application areas. Figure 10 represents the different application areas that were included in the selected publications. Approximately 49% of publications discussed construction as their application area, which is consistent with the keyword grouping. This suggests that the construction industry is evaluating or adopting AR applications more rapidly than other application areas. The next highest application area is manufacturing with approximately 21% of publications representing it as the application area in the respective publication. Construction and manufacturing are related application areas representing 70% of the AR application areas. Both fields involve building or assembly physical objects which may partially explain why these areas have become so popular in AR applications.

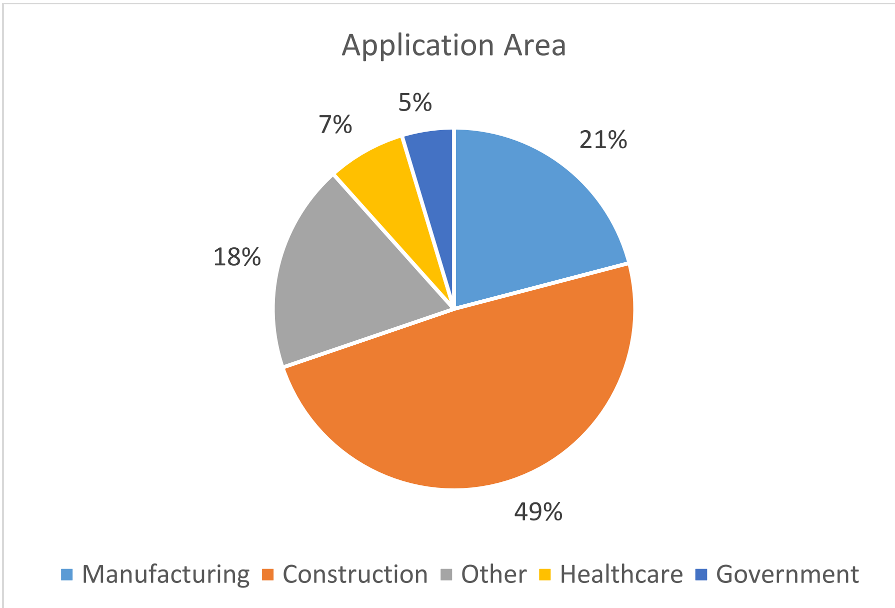

Figure 10: Publication Application Area

Many of the publications that used “Monitoring” or “Metrics” as a keyword had applications in manufacturing as discussed in subsequent sections. Any application areas that were not prominent were grouped as “Other” meaning that there were several other industries that have exposure to AR, but it was not common. Items in this category include applications that were more generic such as in education, automotive, and navigation. Even though there are examples of AR in these application areas, AR usage has just started to be explored.

3.3.2.5 Methodological Characteristics

Next, the data collection and analysis methods were extracted for each of the publications to investigate the types of studies being conducted. Each paper was reviewed for any methodological techniques described in the paper and documented as part of the bibliometric analysis. Figures 11 and 12 show the results for each data collection and data analysis methods identified in the final paper set. Organizational data was the most highly used data collection method, which was used in 23 of the 44 publications. Organizational data is data used by the authors that were previously collected by a company and applied Augmented Reality to better visualize the data. Data collected by observation was used in 13 of the 44 publications. This category includes the author collecting data by directly observing the participant. Surveys and case studies were the next highest data collection methods for these publications emphasizing the exploratory nature of the research.

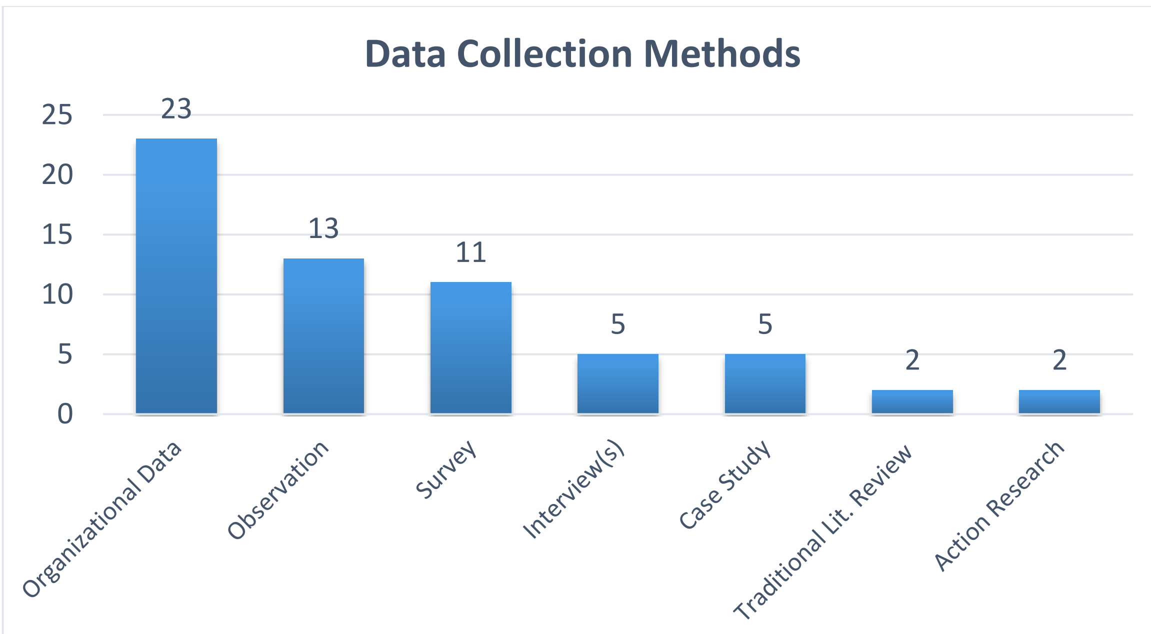

Figure 11: Data Collection Methods

Figure 12 summarizes the most common data analysis methods. Visualization was the most popular data analysis method with 32 of the 44 publications using visualization in the form of Augmented Reality to help in data analysis. Next were methodologies related to traditional analytics to help answer business questions. The studies also include methodologies focused on evaluating the impact or outcomes of leveraging AR devices such as statistical analyses and mathematical modeling.

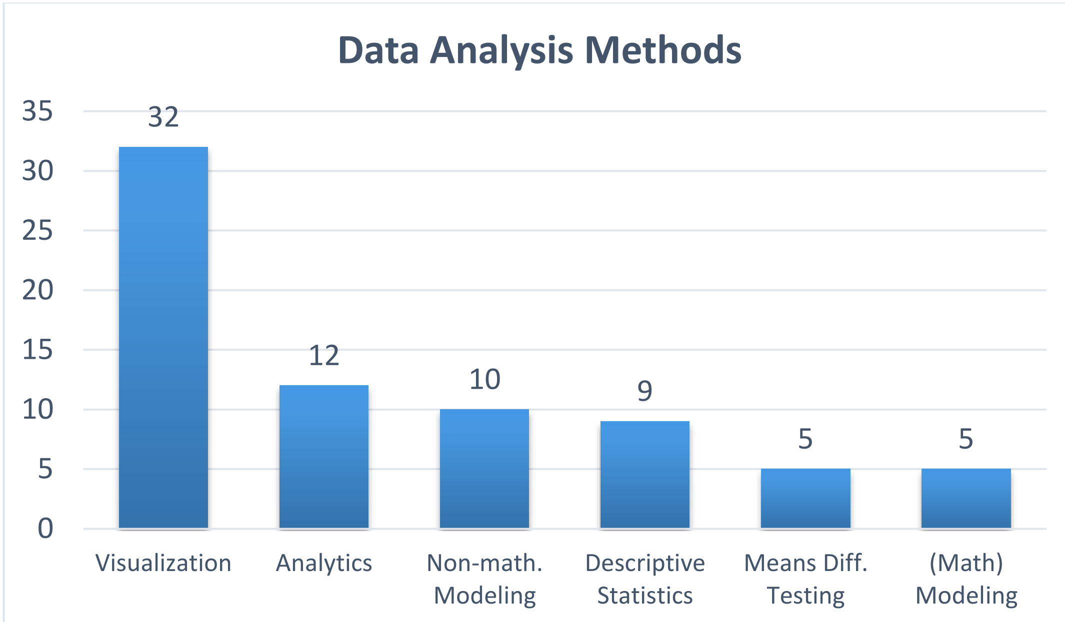

Figure 12: Data Analysis Methods

The results of this analysis showed that much of the work in this area is exploratory with many examples of device or application designs. While some of the studies focused on empirical evaluation of these tool, much of the work is still exploratory and further research is needed to investigate the effectiveness of these applications including potential outcomes and challenges.

3.3.2.6 Impact

Finally, the average citations per year were calculated for each of the publications to investigate the impact of these publications and identify the most impactful studies in the final paper set. *A framework for proactive construction defect management using BIM, augmented reality and ontology-based data collection template* from Automation in Construction was the highest cited paper with an average of 24 citations per year. This paper discussed how they applied Augmented Reality and BIM in construction management (Park, et al. 2013). It also shows that defects inevitably occur in the construction process, which contributes to delays in project schedules. The paper discussed some of the traditional defect management approaches as well as proposes a defect management system aided by AR and BIM. This system was evaluated and was shown to have the potential to greatly improve defect management across the construction industry (Park, et al. 2013). Table 10 summarizes the top ten most highly cited publications.

Table 9: Most Highly Cited Publications

Average citations per year	Article Title
24.0	A framework for proactive construction defect management using BIM, augmented reality and ontology-based data collection template
17.0	Integrating Augmented Reality with Building Information Modeling: Onsite construction process controlling for liquefied natural gas industry
13.5	On-site construction management using mobile computing technology
11.0	Augmented reality tools for industrial applications: What are potential key performance indicators and who benefits?
10.0	Evaluating the application of augmented reality devices in manufacturing from a process point of view: An AHP based model
9.8	A defect management system for reinforced concrete work utilizing BIM, image-matching and augmented reality
9.6	Augmented Reality for Construction Site Monitoring and Documentation
7.3	Google Glass-Directed Monitoring and Control of Microfluidic Biosensors and Actuators
6.0	Precision study on augmented reality-based visual guidance for facility management tasks

Although there were relatively few publications identified in this area, the results show that some of the publications are well-cited suggesting that there is significant interest in this area. In addition, many of the high-impact works (Park et al., 2013; Wang et. al., 2014; Zollmann et al., 2014) in this area are focused on BIM or construction; however, several of these are related to manufacturing, facility management, and industrial applications further supporting the finding that new application areas are developing.

3.4 Applications for Management Functions

The results from the literature review identified many unique application areas related to management functions. They are found in different application areas including Manufacturing, Quality Management, Facility Management, Healthcare, and Construction. This section discusses the results found in the publications by application area.

3.4.1 Construction

Augmented Reality (AR) is being used in the construction industry to visualize project information real time. This presents a new onsite management technique to monitor the construction site, manage construction tasks, and share project information real time (Kim et al., 2013). Figure 13 shows an example of construction tasks being overlaid in AR (Kim et al., 2013). The construction industry can also use AR to virtually plan a construction site. This aids the work site planner in positioning construction material, machines, equipment, and handling devices. The augmented image includes a 3D model superimposed to the construction site with the plans laid out virtually (Kodeboyina & Varghese, 2016).

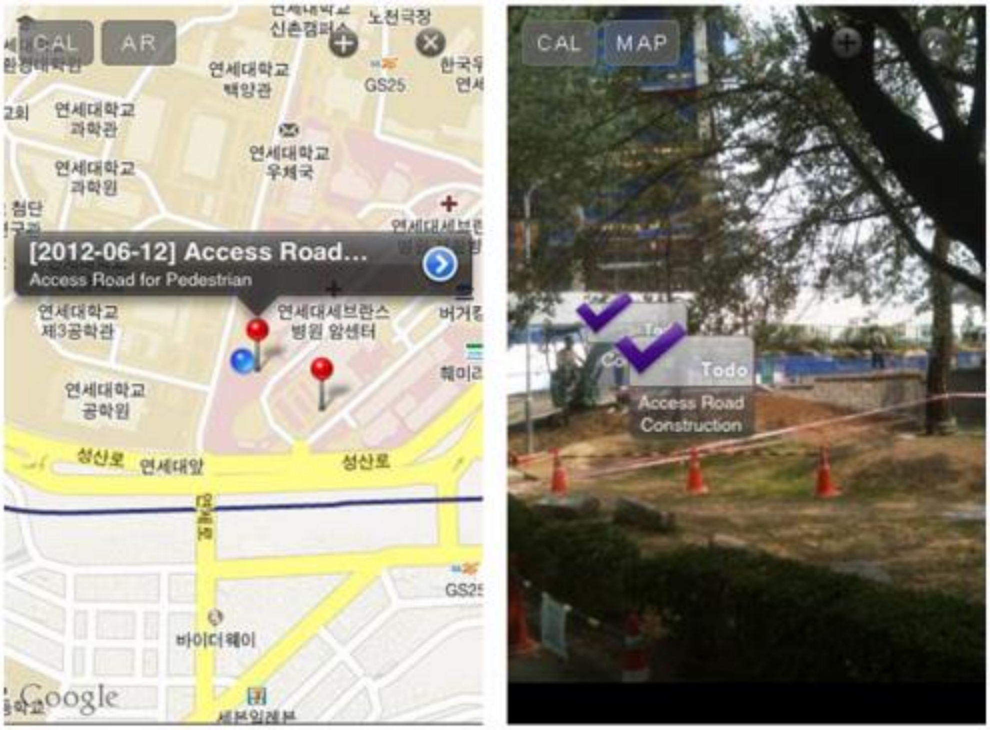

Figure 13: AR Work Task Visualization

Reprinted from Kim, C., Park, T., Lim, H., & Kim, H. (2013). On-site construction management using mobile computing technology. Automation in Construction, 35, 415–423. https://doi.org/10.1016/j.autcon.2013.05.027

AR is also being used to monitor progress of construction sites. AR can provide a visualization of progress as an overlay to the construction site (Zollmann et al., 2014). In order to get an accurate AR, overlay to the real world, the surrounding environment must be registered through a Global Positioning System (GPS). Another technique used was to take time-lapse photographs and perform 3-D reconstruction based on the camera's data. By overlaying the AR image onto the camera image, the progress can be visualized in relation to the surrounding environment as shown in Figure 14 (Zollmann et al., 2014) . There are different techniques to 3D overlaying using AR with respect to construction progress. One is to use a "naïve overlay", which renders 3D information over a video image (Zollmann et al., 2014). Another technique is to use alpha blending which combines 3D mesh data with the video image to create a new virtual image (Zollmann et al., 2014). This technique works well to visualize both the 3D image and the overlay, but can lead to too much information clutter. A third technique is to use a ghosted view which is an x-ray technique that holds the image structure, but blends the real world with the AR overlay with greater transparency (Zollmann et al., 2014).The AR application can also be used to save progress over time. The different points in time can be shown in different colors and mark completion by date. This works as an additional visual indicator representing what portions of the project have been completed or are in progress.

Figure 14: Construction Site Monitoring

Reprinted from Zollmann, S., Hoppe, C., Kluckner, S., Poglitsch, C., Bischof, H., & Reitmayr, G. (2014). Augmented reality for construction site monitoring and documentation. Proceedings of the IEEE, 102(2), 137–154. https://doi.org/10.1109/JPROC.2013.2294314

Building Information Modeling (BIM) is also using Augmented Reality technology. BIM is a digital representation of physical and functional characteristics of a building (Matthews et al., 2015). Using BIM can result in increased information accuracy, reduced operating costs, and support of operation and maintenance activities (Matthews et al., 2015). BIM can be used with AR to easily view the differences between the planned construction build and the actual construction build. The AR model helps the user make decisions with a virtual model rather than consuming time to make decisions on the construction site where it would be more costly and inconvenient. The AR based BIM model can also help monitor progress of phases of the construction project.

3.4.2 Manufacturing and Production

Augmented Reality is being used in many application areas and one of the largest areas for its application is in Manufacturing (Bottani & Vignali, 2019). In manufacturing, AR can be used to see how well machines are being utilized and what percent of the manufacturing process is complete (Novak-Marcincin, Torok, Janak, & Novakova-Marcincinova, 2014). In these applications, a virtual image is projected on the glass or screen of the technology being used, while keeping the real-world background. The projected view does not distort while at the same time the user can see through the projected view to the real manufacturing environment of the working area (Novak-Marcincin et al., 2014). The operational layout of the workplace includes several manufacturing machines where a 3D overlay appeared on top of each to describe the state of the manufacturing process. These tools project a sign above each machine showing the state of production such as if production has started and the percent of actual sequence time left. It could also show if the machine was down for repair or maintenance. The AR signs and objects can be adjusted or updated as needed. The user can also change the style or colors being used in the AR image to represent different metrics or conditions.

Figure 15 shows a production environment and the material flow across the assembly floor. In a production plant, AR can show conditions of the production line, as well as where the material needs to travel next in the manufacturing flow. Overlays with designated colors can show different conditions of the working state. For example, a colored box overlay can show that a box is almost full and will need to be replaced by an empty one (Novak-Marcincin et al., 2014).

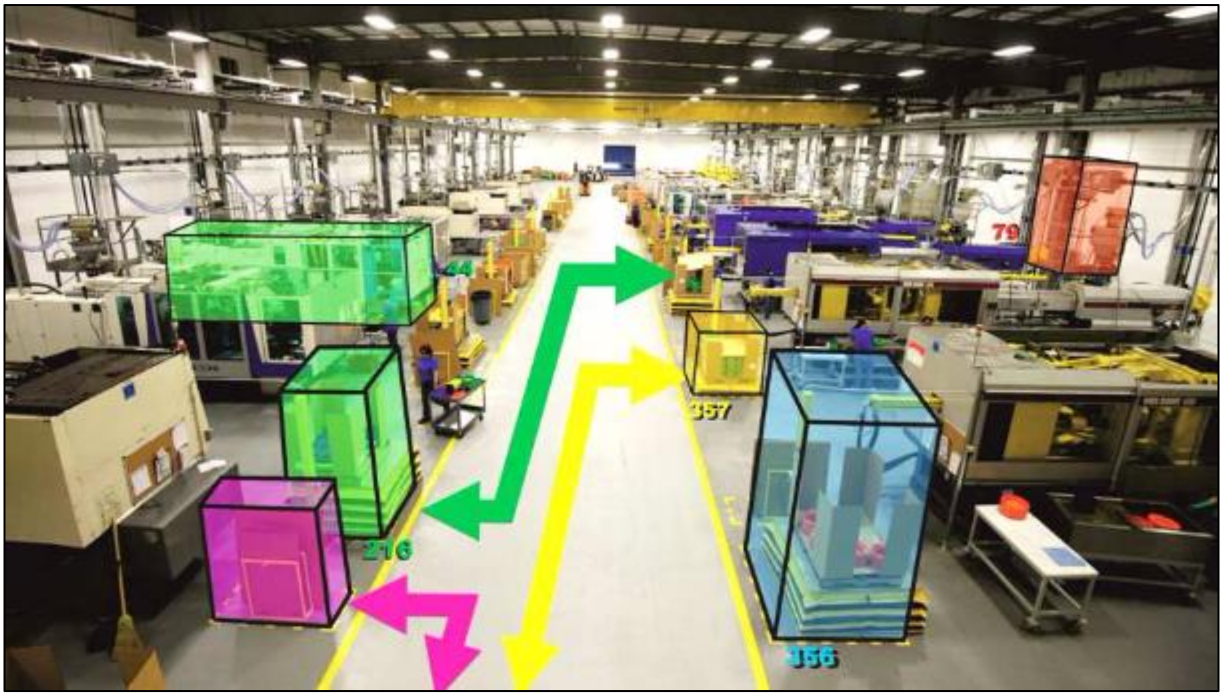

Figure 15: Augmented Reality as Depicted on a Production Floor

Reprinted from Novak-Marcincin, J., Torok, J., Janak, M., & Novakova-Marcincinova, L. (2014). Interactive Monitoring of Production Process with Use of Augmented Reality Technology. Applied Mechanics and Materials, 616, 19–26. *https://doi.org/10.4028/www.scientific.net/AMM.616.19*

When using AR in a manufacturing environment, operations managers and staff can see much more information about the production conditions in real time without having to go to a computer and obtain information they need to track. Augmented Reality is also being used to monitor production processes. The production process could consist of several process steps and, without a dashboard, the user would have to query all the required data to obtain the current process values (Kollatsch, Schumann, Klimant, Wittstock, & Putz, 2014). When using Augmented Reality, the user can get all the necessary information on site where the production is occurring. Using this AR application will not interrupt the production process, but will monitor it for issues or trends. In the same study, Kollastch describes that the interface can capture all the current and important process values and any malfunctions so if the user needs to correct anything in the process, they will be able to (Kollatsch et al., 2014). Using AR, the user can visualize the important process information of the entire assembly line. If the assembly line is large and complex, it can be useful to obtain the needed process information easily and in real time.

Typically, a database stores all of the assembly line data which is then presented graphically to the user based on what the user would like to view. To identify the correct data for each of the AR applications, a marker needs to be placed next to where the process occurs. Tracking is performed to identify the marker and orientates itself based the position and orientation of the virtual camera (Kollatsch et al., 2014). The process data needs to be transferred from the database to the graphical interface that the user experiences, which does not present an issue if using a network connection. Having the graphical data displayed for a certain assembly line can expedite the decision-making process for the managers that need to react to how a process is performing as shown in Figure 16. They are able to detect errors quickly, and change the process if necessary. This will assist in monitoring the production floor and finding errors earlier to control the process more effectively (Kollatsch et al., 2014).

Figure 16: Tablet using Augmented Reality on a Machine

Reprinted from Kollatsch, C., Schumann, M., Klimant, P., Wittstock, V., & Putz, M. (2014). ScienceDirect Mobile Augmented Reality based Monitoring of Assembly Lines. Procedia CIRP, 23, 246–251. https://doi.org/10.1016/j.procir.2014.10.100

Manufacturing Engineers can also use AR to evaluate different assembly operations. This could reduce operational cost and provide on-site assembly evaluation (Raghavan, Molineros, & Sharma, 1999). The user could use AR to simulate the manufacturing assembly process as it would actually occur and evaluate the sequences to find constraints and bottlenecks. Assembly sequence planning is a reoccurring issue in the manufacturing industry. There is huge potential for cost savings and process improvements on a production line when using AR (Raghavan, Molineros, & Sharma, 1999). Using AR can assist in visualizing the constraints and finding the best possible assembly sequence. This will also aid engineers in determining if a prototype part will have any assembly interferences. By visually identifying each sequence, the assembly planner can see virtually what the most efficient sequence of operations is and determine what operations are causing the assembler the most issues (Raghavan et al., 1999). When using Augmented Reality in production there is a real-time connection between the manufacturer and the designer which also creates an opportunity to make the operator part of the design process (Liverani, Amati, & Caligiana, 2006). Currently the assembly information used to instruct human operators are detached from the equipment and exist as hard copy instructions. Operators then have to alternate their focus between the actual assembly and paper instructions or instructions provided by a traditional computer (Yuan, Ong, & Nee, 2008). The same principal could be applied to production supervisors who rely on information that is only located at their desks or at inconvenient locations. AR helps enhance the production floor by giving employees an interface to receive information or instruction in a unique way (Wang et al., 2020).

One of the biggest issues in manufacturing is human error and defect management in performing the operations. Assembly errors can increase production time and cost as well as affect the quality of the product, which could damage the entire production system. Augmented Reality is also being used by supervisors to monitor the assembly sequence and alert the operator if they create an error while assembling the product (Mura, Dini, & Failli, 2016). A force sensor is placed under the workbench and it is used to monitor the assembly process by collecting data with respect to a reference system. A pattern recognition technique is used to detect when an error has occurred and will alert the operator when this has happened (Mura et al., 2016) This reduces defects that are added to the manufacturing system that would need to be monitored and corrected by the production supervisors. Using AR in production can also support workers in the field making it especially useful in training and education of manufacturing personnel. AR can help increase the human sensory capacity by including virtual components over the real world. AR is also used to check if an assembly process will work or not, can be used as a training tool and guidance for manual assembly, and display assembly instructions on a screen that is able to record the exact procedure in a 3D format (Mura et al., 2016). Not only can AR detect when an error has occurred in the assembly process, but it could also guide the operator to build the product right the first time. In this application, three types of visual aids have been created which include text instructions, virtual elements, and CAD models. The text instructions simply explain the operations of that sequence. The virtual aspect are arrows and symbols used to guide the operator, and the CAD aspect is the portion that is superimposed to the real space and shown in a way that tells the operator what they need to do next. The three biggest features of using AR in this application is AR performing error detection, ability to know how to fix the error, and the ease of adopting the technology, which allows the operator to visually see their instructions.

3D printing can also utilize AR to monitor and track the printing process. Using AR with 3D printing will create a virtual, superimposed model to the real one being printed. AR can be used to detect if there are errors while the product is being printed. This avoids wasting additional material and time on the machine. With 3D printing no molds are needed, the entire process is additive. Since AR is a real time technique, when the user moves the camera, the virtual overlay is also updated to maintain its alignment with the real scene (Ceruti, Liverani, & Bombardi, 2017). The 3D overlay can be superimposed at any stage of the printing, so that a new image is not needed at different stages of the printing. In cases of the 3D printed part failing, AR can be used to help detect the cause of the failure with the CAD model (Ceruti et al., 2017).

Another time saving opportunity for AR is in warehouse operations. The warehouse personnel would wear the smart glasses which displays the information for the task given to them. They then are guided through an optimal picking route by 2D and 3D objects displayed in the smart glasses. The smart glasses can read a barcode of the article in stock and change its location from "in stock" to "in delivery" in the stockroom database (Hořejší, 2015). This reduces search time for the stockroom personnel as well as looking back and forth at paper instructions to know what the next task is to be performed (Hořejší, 2015). This also helps the warehouse supervisor have better inventory accuracy by implementing automatic location changes through the smart glasses. Another application in the study is to help drivers of end customer delivery with tagging different delivery items together in the vehicle according to the delivery route (Hořejší, 2015).

Augmented Reality has also been used in training in crisis management. The training provided typically lacks the stress created by a real crisis. Behavior and decision making are significantly affected by stress, so it is important that training puts the trainees in as real environment as possible. Augmented Reality provides an original, realistic, and immersive experience for the training environment, where the stress can be managed individually by the trainer (Bacon et al., n.d.). Augmented Reality provided the trainees a more realistic training environment compared to Virtual Reality as the demographics and environment are important to be blended with the real world instead of being completely immersed with the virtual world. AR can also be used to create virtual cues, directions, or “X-ray vision,” which could show objects that are present in the real world, but may be hidden or obstructed from view (M. A. Livingston et al., 2004).

3.4.3 Quality Management

Augmented Reality has also been used to monitor and show process capability and control charts to help track issues in production lines. In Segovia’s 2015 paper, the author discusses Quality Data Analysis software that allows the user to verify quality goals such as process control, cost reduction, process optimization, and compliance documentation (Segovia, Mendoza, Mendoza, & González, 2015). Knowing these process indicators can help management make decisions faster and more efficiently. It also helps in reducing the number of defects, reducing the need of developing correction plans after they occur. Data collection in each of their workstations can be transmitted to the quality software wirelessly. This can contribute to real-time data access and better data accuracy. Having this wireless connection also allows supervisors to better monitor the production process by having more timely access to the quality reporting.

Figure 17 shows how AR projects Cpk analysis results above each of the workstations (Segovia et al., 2015). This allows the supervisor to see the metrics associated with each machine directly above it to better understand the performance where the work is actually occurring. It is important to note that the data displayed above the user’s field of view is not misplaced with other workstations as that would depict data that doesn’t represent its current state.

Figure 17: AR used in Quality Measurement

Reprinted from Segovia, D., Mendoza, M., Mendoza, E., & González, E. (2015). ScienceDirect 2015 International Conference on Virtual and Augmented Reality in Education Augmented Reality as a Tool for Production and Quality Monitoring. Procedia - Procedia Computer Science, 75, 291–300. https://doi.org/10.1016/j.procs.2015.12.250

Segovia's research found that using the Quality software application without also using Augmented Reality to display the reports was tedious and time consuming. The software is very robust, but lacks a user-friendly interface. By using Augmented Reality in conjunction with the Quality software, users are able to take advantage of the Quality software's calculations while utilizing AR's easy interaction to display instant reports and to perform real time analysis (Segovia et al., 2015).

3.4.4 Healthcare

There are also numerous applications for using Augmented Reality in the medical field. One area of application is using AR to monitor vital signs while performing a surgery. The surgeon would perform an operation and have the vital signs in front of them in real time. While traditional vital sign monitoring also displays the patient's information real time, the display isn't always visible or convenient for the physician performing the surgery (Liebert, Zayed, Aalami, Tran, & Lau, 2016). Critical vital signs changes can frequently be overlooked using the traditional method, especially when the patient needs a conscious sedation and an assistant is not present. (Liebert et al., 2016). Figure 18 shows vital signs projected through Google Glass in a training setting. The study also confirmed that real time wireless streaming of vital signs is possible without time delay (Liebert et al., 2016). This can help the surgeon make decisions regarding the patient and procedure more quickly.

Figure 18: Augmented Reality displayed as Vital Monitor

Reprinted from Liebert, C. A., Zayed, M. A., Aalami, O., Tran, J., & Lau, J. N. (2016). Novel Use of Google Glass for Procedural Wireless Vital Sign Monitoring. Surg Innov, 23(4), 366–373. https://doi.org/10.1177/1553350616630142

Augmented Reality is creating new education opportunities in the medical field by the allowance of a virtual layer being superimposed on top of reality. The simulation of situations creates an opportunity for the medical professionals to train without affecting the safety of the patient. With AR, the user gets to see a blended environment in which they experience an immersive and interactive environment. In certain areas of the medical field, AR simulator training is used for procedural tasks which provide information and statistics regarding a specific task (Barsom, Graafland, & Schijven, 2016). Similar advancements have been seen in construction and manufacturing training as well. AR also helps in increasing the medical student's learning retention and performance (Barsom et al., 2016). It allows the student to learn the spatial relationship between the tasks given to them. AR could also lead to training better physicians and increasing patient safety.

3.5 Discussion

This results of this SLR indicate a need for advancing operations and engineering management practice and leveraging emerging technologies could help. Operations and engineering management includes many different facets of organizational leadership. Some supervisors manage operations by walking the floor to see first-hand how well their department in performing. Other supervisors use transformative leadership and integrate leadership techniques from the top down (Shields, 2010). Many also have a set of metrics that they monitor and work to improve operations. Effective operations and engineering management has been challenging for many organizations (Akkerman & Grunow, 2010). With greater organization complexity, more tools and techniques are needed to help guide difficult scenarios (Melnyk et al., 2014). Effective decision making is closely related to operations management and continues to be an area needing improvement. One small improvement of better presentation of data and results to the decision maker may significantly improve the effectiveness of decisions made (Turpin & Marais, 2004). The presentation of results can be even more important in organizations where timely decisions are essential. Decision-making for management is commonly approached as a multi-step process where different options or alternatives are assessed to meet an organizational goal (Intezari & Pauleen, 2018). Intezari and Pauleen also described that, in order to make wise decisions, the decision maker needs to be able to easily acquire the information they need (Intezari & Pauleen, 2018). Effective decision making for leaders is vital in face-paced operations environments.

One area that could benefit from advancing AR technology is operational performance measurement (OPM); however, a brief review of the literature reveals that this potential application area has not yet been explored. Operational Performance Measurement (OPM) is used to control and manage the effectiveness of day-to-day activities in an organization (De Leeuw & Van Den Berg, 2011). The use of OPM is not just an operational task, but also an indicator of important process improvement activities and operational effectiveness (Dal, Tugwell, & Greatbanks, 2000). Common challenges in this area include not choosing relevant measures and failure to provide accountability for production processes (Mariotti, 1999). Another challenge includes managing a large number of metrics and the difficulty of building effective dashboards. Although there have been significant advancements in the area of OPM, the specific field of technology-assisted OPM, such as business analytics, is still developing. Many gaps and opportunities for advancements exist for transferring emerging technology to practice. Recent advancements including real-time dashboards and advanced analytics to assist with OPM activities (Bremser & Wagner, 2013). However, empirical studies of these applications are limited. Further, the link between use of these technologies and managerial decision-making is relevant but not clearly supported in the literature. AR is one technology that can contribute to the effectiveness of OPM; however, this topic has not been explored fully in the literature. This review did not identify any studies related to the application of AR to support OPM, but did identify many applications relevant to management activities that empirically demonstrate the benefit of adopting such a technology such as reducing errors and improving the efficiency of the decision-making process for an organization or individual.

3.5.1 Maturity Assessment

The bibliometric analysis was conducted across five dimensions of research area maturity to investigate the development in this area. Each of the five dimensions were then rated as emerging, developing, or mature based on the results of the bibliometric analyses as summarized in Figure 19.

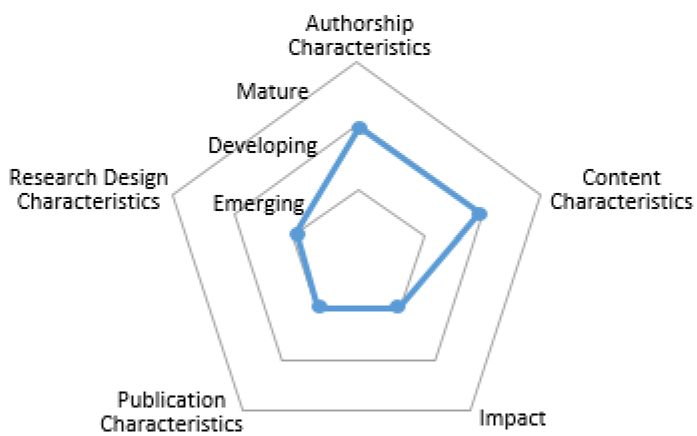

Figure 19: Maturity Assessment

The overall maturity for this area of research is still emerging with some evidence of growing maturity based on the internationalization and breadth of content areas but many opportunities for additional research and development. A few authors have published more than once in this area, but there is no clear emergence of experts. Publications appear to be sporadic with no central journal or source which may suggest there is potential for both practical and academic impact in this area of research as publications are found across many different types of journals, but not well established in one area. Since this research area is in low maturity, there are not many publications on similar topics yet which provide an opportunity to researchers to contribute to this field. The search criteria had to become broader to attempt to catch as many related publications as possible for this review.

The results of the literature review determined that, although there has been some interest in this area, the research is in a relatively early stage of maturity with several gaps and limitations that should be noted. This research will eventually develop to support operations, engineering, project, and performance management by providing tools to make information more readily available to managers. These tools need to be able to perform in a real-time environment, as non-real time operations will not benefit as much from such a tool. This access is proposed to improve real-time decision-making though further evidence is needed to validate this claim. As this technology develops, it will be used as new approach to support performance measurement and management systems by creating immersive performance environments where data is both captured and analyzed in real-time.

3.5.2 Challenges

Supervisors and managers will find this research useful as there are currently methods to obtain metrics in real-time; however, these solutions still need to be custom-built and may not be as available or convenient to use at this time. Custom-built solutions may take too many design iterations to out-weigh the benefits of implementation. These types of solutions may not be able to integrate easily with other commercial systems or scale if needed. Further, many challenges and barriers to the adoption of such a technology are have emerged, which will need to be further investigated by the community. Some challenges identified in this review include interoperability, limited hardware options, and adoption cost. Hardware options have advanced in recent years resulting in increased AR usage and adoption, however can still remain a challenge in successful adoption (Jetter et al., 2018). End users of AR implement the technology when benefits are shown, but need to be proven to be superior to the existing technology and show performance improvement (Re, 2013). Even when significant process improvement is validated, adoption can be challenging when considering potential ergonomic issues. Head worn devices have improved, but can still remain an ergonomic issue if worn for an extended period of time. Head or eye discomfort can also hinder adoption in industry. Even though AR has proven to be successful as a proof of concept, continuous wear still needs be investigated further as human factor issues may hinder widespread industry adoption (Nee et al., 2012).

3.5.3 Implications for Engineering Managers

Engineering managers will find this research useful as there are currently methods to obtain metrics real time, but they may not be as available or convenient to view where the actual work is occurring. They may especially find the results useful if they need to continuously walk the production floor as part of their leadership technique in order to gain essential information on how well their team is performing. Augmented Reality will add a visual aid for management to use when reviewing the performance of what is being measured.

Practitioners can also use this research to benchmark the current state of the industry and apply any of the findings of this study directly to their field of work. Many of the applications for AR and especially those associated with higher-level tasks are still emerging and this research provides detail into the current state of the literature. This research can also be used when determining what progresses or challenges to consider to evaluate the effectiveness of implementing a new tool to be used in practice. Adoption of such a tool is risky and the outcomes have not been fully validated. However, there is opportunity to further explore adoption factors to mitigate this risk as there are examples of successful implementation, but is not wide-spread. The results also provide key insights for engineering managers interested in adopting AR to support management functions.

3.5.4 Potential Areas for Future Research

From the bibliometric analysis, there is evidence that there has been little progress in using Augmented Reality for performance measurement and management applications when considering higher-order metrics with many publications focused on tasks such as training, procedural tasks, and production applications. This is a relatively new field that leverages a rapidly developing technology and, as such, the work currently available in the literature is exploratory research that is occurring across many different applications. Augmented Reality will add a visual aid for operations and engineering managers to use when monitoring or measuring operational performance and progress in day-to-day operations. As this is a relatively new field, there is new research that is occurring with many different uses and exploring AR applications for operations and engineering management will contribute to the continued transfer of this technology to industry. Studies are needed that specifically look at the challenges of interoperability and how best to address this issue. Future work includes validation of the outcomes of these results are also needed and may benefit from additional empirical studies. Additional technology evaluations should also be conducted to both continue technology advancement as well as explore commercially available options.

3.6 Conclusions

Although many practical AR applications have emerged, a review of the literature shows that managerial-focused applications of AR are only beginning to emerge and more research is needed in this area. There is research that supports AR being used successfully for simple tasks such as visualization, X-ray vision, and showing steps in a process. However, applications for more complex work tasks are limited. There appears to be a gap in the research on using AR for more complex tasks that could assist in managerial work such as in operations and engineering management including decision-making support. The results show that Augmented Reality has been used in many application areas ranging from the medical field to manufacturing to education Augmented Reality has been demonstrated to aid in assembling production parts and being used as a training device for students which improves work efficiency and student/learner engagement. The amount of research that specifically pertains to using Augmented Reality as a management tool, specifically in the area of performance measurement and management is limited and not yet well-developed. The bibliometric analysis shows that there is evidence of using Augmented Reality to monitor assembly lines and hospital rooms, but this is still a low maturity area.

Limitations to this study include the traditional limitations of conducting a SLR; however, the search strategy was developed to mitigate these limitations to the extent possible. Three different databases were used representing a wide range of disciplines and focus areas and the list of search terms and concepts were created to capture a range of management functions and behaviors. While this search was comprehensive, they represent only a subset of the publications currently available in the literature and expanding the search terms or platforms searched may identify additional relevant publications.

Future work will consist of an expert study along with a laboratory experiment to investigate applications for performance measurement and management that leverage higher-order metrics including whether these tools support real-time decision-making. The expert study will be conducted to further explore the factors that could potentially affect the successful adoption of an AR assisted OPM tool. Further, this study will be used to develop a construct for operational decision-making that can be used during the laboratory experiment. The primary challenge of this study is the definition of expert as this is a relatively new area of study with few, if any, established experts. Therefore, this expert study will consist of two samples to provide complementary perspectives for a grounded study: OPM experts who use technology to conduct OPM in practice and AR experts who specialize in related application areas. A laboratory experiment will also be conducted, which will consist of a Design of Experiments approach to test the impact of AR dashboards and real-time data on managerial decision-making. This empirical study will help validate some of the benefits identified in the study as well as contribute to addressing this gap in the research area.

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CHAPTER FOUR: EXPERT STUDY

An Expert Study on Leveraging Augmented Reality for Operational Performance Measurement

4.1 Abstract

Augmented Reality technology has rapidly advanced resulting in many different applications across industries in recent years. Even though this technology shows evidence of wide-spread adoption, using AR for managerial tasks is lacking. This paper reports the results of an expert study conducted to evaluate the potential use of augmented reality technologies to improve operational performance management (OPM). Experts were recruited for participation across professional networks, LinkedIn groups, and academic contacts listed on university webpages. Two sets of experts were interviewed including 12 Augmented Reality experts and 11 OPM experts. Responses were then analyzed using a thematic analysis to identify key themes and insights from the data. The results of this inductive synthesis were used to develop a 6-point Likert scale for perceived decision-making effectiveness, which can be used in future studies for additional evaluation and validation. Further, the results provide key insights related to potential challenges and best practices for adoption.

Keywords: Augmented Reality, Operations Management, Operational Performance Measurement, Expert Study, construct development

4.2 Introduction

Augmented Reality (AR) technology has been rapidly developing across many industries with various applications ranging from construction to manufacturing to entertainment (Caggianese et al., 2015; Liebert et al., 2016; Novak et al., 2014). AR can utilize different hardware devices to project a virtual image onto a real-world background (Raghavan et al., 1999; Zollmann &

Poglitsch, 2014). Head-wearables, tablets, and phones can all be used with Augmented Reality technology and the benefits of each varies depending on the application. If a hand-free solution is needed, the user may want to utilize a head-wearable device. However, if convenience and storage is more important the user can easily use their phone for an AR experience.

AR has been implemented in many manufacturing applications that use the technology as a procedural guide in assembling processes or to aid in inspecting production parts (Raghavan et al., 1999; Yuan, Ong, & Nee, 2008). It has also been used in manufacturing to monitor machine performance superimposed in the shop floor environment providing critical information quickly to floor supervisors (Segovia et al., 2015). AR has also been used in the construction industry as a way to monitor project progress on job sites or guide the construction worker through tasks (Kim et al., 2013). A worker could turn on their location and instantly have a series of tasks pop-up for each location at the construction site. AR has also been widely used in the medical field as a tool for “X-ray” vision to augment human capability to see anatomy under the skin. Another benefit for using AR in the medical field is to display critical information about the patient in a more accessible, flexible location. The system could display a dynamic dashboard that could follow the physician’s eyes so that they do not need to look outside the line of sight to view critical metrics regarding a procedure. Further, an AR system could be set up for every employee in an operating room so that they each have an optimal display of the image’s information.

In addition to applications that augment human performance or provide procedural guidance, AR technology has begun to be applied to more sophisticated and complex applications (Chapter 3). One example is using AR for project management by overlaying metrics in the construction field and displaying if tasks are on time or delayed (Kim, Park, Lim, & Kim, 2013). Another example is using AR to assist in real-time decision making by conveniently displaying data for maintenance related issues (Palmarini et al., 2018). This application could also be used to display step by step instructions needed for standard repairs or maintenance. There is also potential to incorporate Artificial Intelligence (AI) or exploring decision nudging technology in these applications as well (Weinmann & Schneider, 2016).

Although there are many examples of AR being used in industry for various applications, there is still a need for better understanding challenges and novel opportunities associated with adopting AR for management functions. This research conducts an expert study where experts in the fields of Augmented Reality and Operational Performance Measurement (OPM) were recruited to participate in either a semi-structured phone interview or an open-ended online survey to share progresses and challenges of their respective experiences. Once all of the expert data was collected, this qualitative data was transcribed and imported into NVivo software for inductive synthesis. Many themes were identified across the data and these results are used to develop a multi-item Likert construct for perceived decision-making effectiveness that can be used in future research as well as a framework of potential challenges and benefits of OPM and AR adoption.

4.3 Background

AR has many practical applications in industry; however, a review of the literature suggests that AR applications associated with managerial decision-making is not well explored (Chapter 3). Most commonly, industrial AR applications have been developed for simple tasks to aid in visualization and guiding workers through steps in a process. AR applications for more complex tasks have limited examples in this field of research (Chapter 3). AR being used for operations management to aid decision-making had not been well explored and some existing examples encounter challenges when implemented in industry (Mariotti, 1999).

Operational Performance Management (OPM) is used to increase total productivity and to control and manage the effectiveness of day-to-day activities in an organization (De Leeuw & Van Den Berg, 2011; Kaydos, 2020). Using OPM can also be a trigger for potential process improvements and an indicator or how effective the organization is operating (Dal, Tugwell, & Greatbanks, 2000). A few examples of issues in this field are not choosing appropriate metrics or failing to provide accountability in industry settings (Mariotti, 1999). Dashboards have made it possible for managers to receive information available in real-time (Vasarhelyi and Alles, 2008). Recently, more examples are available to utilize real-time dashboards and analytics to assist with OPM (Bremser & Wagner, 2013; Reinking & Sutton, 2020). Reinking & Sutton (2020) found that aligning with an organization's strategy improves interactive management control that directly links to increased dashboard use by managers. OPM applications have shown significant progress, but the area of pairing OPM with novel technology applications is lacking. Linking AR technologies with OPM activities such as effective decision-making is not well explored in the literature but has huge potential for OPM effectiveness (Chapter 3).

Along with examples of OPM challenges, research has been conducted to investigate what contributes to successfully implement various types of novel technology. Technology acceptance and usability tests have been performed to evaluate the effectiveness of implementing new technology in industry (Davis, 1989; Dey et al., 2018). In other research, Albertazzi et al. (2012) explored the use of AR interaction with a new product and tries to determine if the technology is helpful or becomes a nuisance (Albertazzi, Okimoto, & Ferreira, 2012). Being able to solve such issues can bring benefits and success in AR implementation at the organizational level. Several usability studies have also been conducted on AR applications that have focused more on handheld displays (Dey et al., 2018). This may be related to ergonomics challenges from wearing an AR headset. These studies have also found that the most popular data collection method is questionnaires and that more field studies need to be conducted to gain empirical evidence on the current ergonomic challenges (Dey et al., 2018). Although several usability studies have been completed, there is still a lack of best practices in this area of research.

A brief review of the literature shows that the amount of research that specifically pertains to using AR as a performance measurement tool is limited. Evidence exists of using AR to monitor assembly lines and to analyze Quality Process Control (Segovia et al., 2015), but these areas are also not well developed with few examples found in the literature. Potential contributions in this area include leveraging this technology to improve OPM best practices such as optimizing dashboard effectiveness and streamlining decision-making processes. Improving OPM and operations management can lead to improvements in organizational performance and sustainability (Speziale & Klovienė, 2014). This study seeks to contribute to this area of research by conducting an expert study to identify the opportunities and challenges of levering AR technologies for OPM applications.

4.4 Methodology

An expert study was conducted to evaluate the potential use of AR technologies to support OPM. Both OPM and AR experts were recruited by invitation to this study. A set of open-ended questions were developed to offer the study in two different modalities, which consisted of either semi-structured interview or survey questions. The different modalities offered the potential participant an interview if they would not want to type their responses in an online survey or a second option of completing a survey if that was a more convenient option. Once the data were collected, an inductive synthesis on several key topics was completed using thematic analysis. This qualitative study was conducted to provide rich data that captures insights from expert experiences.

4.4.1 Data Collection

A dual-modality approach was used for this expert study, which consisted of a structured interview and an online survey questionnaire (Kelley et al., 2013). Each modality was consistent with the same instructions and context as well as having the same order of identically worded questions. One challenge this study experienced was defining the characteristics of an expert in this area of research as this is a low maturity area with few professionals having direct experience in this area. With a lack of established experts in the field, this study focused on two different samples to provide perspectives from both OPM and AR subject-area experts. The targeted sample size from each group was 15 as Miles and Huberman (1994) found that a minimum number of experts required for an expert study is ten (Tri Putri, Mohd. Yusof et al. 2014) and Van de Ven, and Gustafson (1975) suggest that ten to fifteen subjects could be sufficient if using experts with similar background. The expert study resulted in a total sample size of 23 subjects (11 OPM experts and 12 AR experts), which meets the minimum of ten per group as previously discussed. Experts were identified from professional industry networks, LinkedIn Groups, LinkedIn direct messaging from reviews of individual profiles, Research Gate, and academic contacts from university webpages. Many rounds of invitations were sent in iterations along with additional reminders to increase the sample size. The study documents, including the IRB protocol, recruitment letters, and data collection instruments, are provided in Appendix E, F, & G.

This expert study consisted of two samples to provide complementary perspectives for a grounded study: OPM experts who use technology to conduct PM in practice and AR experts who specialize in related application areas. Potential participants needed to have at least three years of relevant experience in either field to be eligible to participate in the study. Experts were selected based on a set of inclusion criteria, defining the particular characteristics that have to be met for the person to be considered as a subject-area expert (Hsu and Sandford 2007). In this study distinct inclusion criteria have been identified for both AR and OPM groups which consisted of both industry as well as academic experts which provided a mix of experience to be included in the study. Academic experts were identified based on related published research and industry experts were identified based on current professional position or experience.

The interview/survey questions were used as the data collection instrument for this study. Questions differed between the two sets of experts, but also shared a couple of the same type of questions. The set of questions for AR experts included 8 questions and the set for the OPM experts included 12 questions. The first question for both sets of experts asked the expert to describe their current and previous experience in their respective field. Both sets of questions would ask about challenges and progresses the expert knew of in their area. Each of the participants would also comment about a proof-of-concept AR device and what benefits or challenges may be expected in implementation. They were also asked if the proposed system should have any other capability that was not discussed. The full set of interview questions are located in Appendix E.

Once the invitations were sent out, participants were able to choose between an audio interview and an online survey. If the audio version was chosen, an interview would be scheduled and conducted over the phone. A protocol was followed for the audio interview including asking for permission to be recorded so the data could be evaluated once all the results were finalized. If the online survey option was selected, the expert would use a UCF link to Qualtrics to complete the same open-ended questions. Once all the experts completed the survey, survey responses were collected for inductive synthesis.

4.4.2 Data Analysis

Thematic Analysis is an iterative method of identifying and organizing patterns and themes across a set of data (Clarke et al., 2015). After all the interviews and surveys were finalized, the qualitative data were processed to prepare for inductive synthesis. The interviews were transcribed using Trint software and the surveys were exported from Qualtrics, an online survey platform. All of the interview and survey data were then imported to NVivo to support the qualitative analysis and ensure rigorous and accurate management of the data.

First, the data set was evaluated and an initial round of open coding was conducted to extract key insights and themes from the text (Clarke et al., 2015, Scott & Medaugh, 2017; Vollstedt & Rezat, 2019). Once the initial set of open coding was complete, axial coding began which inductively categorizes some of the qualitative data results (Clarke et al., 2015, Scott & Medaugh, 2017; Vollstedt & Rezat, 2019). Each code label was specifically defined which would begin a third iteration of coding to match these definitions. NVivo's auto-coding feature was also utilized to evaluate what labels were automatically extracted from the data and provide initial insight into potential codes or code structure. Data from the final set of coding would be compared to original data text and any new data points would be captured to eliminate any remaining gaps. This iterative process that included both custom coding and auto-coding helped reduce bias and increase study rigor. Once saturation, which is when additional cycles are not providing any additional changes to the code definitions or structure, was met by using this process, a final set of codes would be included in the study (Ando et al., 2014).

4.5 Discussion of Results

A thematic analysis was conducted to synthesize the qualitative data collected from both groups of experts across each of the categories of questions included in the study. Both modalities of interview questions and the online survey questionnaire were consistent with the same instructions with the same questions and listing order. Some of the responses shared common themes among each group of experts, others shared unique perspectives that led to valuable insights which are discussed in the following sections.

4.5.1 Demographics

A total of 23 experts were included in this study including 11 OPM experts and 12 AR experts. As mentioned previously these interviews either took place over the phone or were completed using a Qualtrics online survey questionnaire consisting of open-ended questions. As discussed previously, AR experts must have had a minimum of three years' experience using, developing, or implementing Augmented Reality as part of their current occupational or academic role. All participants were industry experts that held positions in major corporations or were academic scholars with expertise in this area. The individuals interviewed from OPM had a minimum of three years' experience as academic professionals, production supervisors, production directors, general managers, engineering managers, and program managers across various industries. Participants were from large corporations including those in the manufacturing, healthcare, and entertainment. This provided an adequate sample consisting of many different perspectives from a variety of industry areas and experiences. Since the AR and OPM experts had diverse experiences and backgrounds, this resulted in a collection of different backgrounds and perspectives included in the results of this study. Even with a diverse background among the experts, many commonalities exist across responses which will be further discussed in the following sections.

4.5.2 Augmented Reality

Experts from the Augmented Reality group were very passionate about their past experiences using and implementing such a novel tool. Their experiences varied in application areas such as manufacturing, education, and communications, however, many common themes existed which are discussed in detail in the below sections. Throughout this section, unique perspectives are also discussed and shared as valuable insights to this study.

4.5.2.1 Challenges in AR Applications

Many (8 of 12) of the AR experts interviewed commented that a common challenge in AR is the hardware. The AR wearable hardware has improved over time, but is still not sleek enough to use that it is not bothersome to users. Most of the high-fidelity headsets that project robust 3D images can also feel heavy when worn over an extended period of time. Another hardware limitation is the field of view can be narrow depending on what type of device is being worn. Field of view can be very important depending on the application. A user may not want to scan an entire area multiple times to view the 3D image. If the supervisor was using this across the entire shop floor, some information may be out of the user's field of view. Both head-wearable and handheld devices can experience field of view issues, even though the issue is more pronounced while wearing the headsets. The results of the Thematic Analysis showed that 25% of experts listed human-factors related issues such as comfort, fatigue, and even hygiene. This is aligned with findings reported in the literature such as the study by Nee et al. (2012) and Masood & Egger (2019). Nee et al. (2012) also found that human factor issues affect wide-spread AR adoption. Human-computer interaction needs to include a balance of efficiency and features, which in AR technology has even greater importance since AR can be mobile and uses a blend of real-world and virtual content (Dey et al., 2018). Interoperability between the AR system and other systems is required or the user lacks the ability to easily transfer applications from one context to another (Baresi et al., 2015; Oyekoya et al., 2013).

Getting the AR image to align perfectly over the real-world content is also another challenge identified from the experts. As one expert commented, “One barrier that I always encounter would be model placement precision.” This precision issue may be more pronounced when working with crucial geometry that is close together compared to aligning an AR image over a large object. There has been progress on AR alignment issues, but still remains a challenge in AR adoption. These issues can create frustration for the user which directly affects how well the technology can be fully implemented. Even though there are commercial solutions available for AR development, many applications still require customized coding or an in-house expert to maintain systems (Mota et al., 2018).

Another challenge discussed by the experts is AR adoption and implementation. If AR is to be adopted in an organization, there are investment costs in getting an AR application deployed such as AR software development and device costs. One expert shared that a detailed business case is traditionally drafted to show a return on investment, but it may be difficult to capture every aspect of cost reduction. Many existing manuals and documentation may need to be converted to AR for implementation and this can be costly if the current method is still a viable option for the company. If AR is used for any new documentation or applications there may be a mix of traditional and AR documentation until the traditional work instructions are phased out. If AR is being used for a new application, it may be more cost effective than converting existing applications. Experts expect that the AR wearable market will mature over the next few years, which will help with industry adoption and human factors. BIS Research (2018) projects that the AR market will grow 74% between 2018 and 2025. Many experts saw Virtual Reality (VR) headsets mature in the past and they expect AR devices to go through a similar cycle.

One technical development issue that was expressed is ensuring AR sensor information does not interfere with each other. If multiple sensors or markers are being used in the AR system, there is potential that AR data may collide with each other or that the AR sensor may pick up on a marker that you were not expecting it to pick up on. There may be similar issues if multiple devices are used and connected to the same data. If the AR images are static in one location and multiple people needed to view the data, there may be location issues associated with using the technology in this way.

The AR experts recommended making the training as seamless as possible as the little annoyances can cause frustrations that make the technology adoption less likely to be successful. If the device is not intuitive or easily learned from the start, it can make implementation much more difficult. As one expert shared, "People have a tendency to shut down when facing something they have never seen or interacted with before." The device needs to easily be navigated to display the needed information.

4.5.2.2 Successful AR Application Areas

This section includes a synthesis of responses regarding the success of implementing AR across different applications. Many different applications were included from the expert responses. Using AR for training is the most common application area found among the expert interview data. One expert commented "Students can train wherever they need to, instead of traveling to training grounds to book time in a simulator." One expert shared that by adopting AR applications for training, employees can reduce the learning curve impact to employers. When an employee becomes proficient at their task more quickly, training costs will be reduced. AR adoption can result in a more productive workforce if implemented properly, which will result in lower labor costs for the organization.

AR Experts also asserted that AR has been successful in process improvement, especially in assembly. When the assembler can use an AR wearable device, they have both of their hands free and can view the instructions and content overlayed right where the work occurs. Not having to refer to a separate set of instructions that need to be held and placed somewhere while the assembly occurs is advantageous and helps in error reduction and producing a more consistent product. Using a headset is also helpful when the user can use voice commands to navigate through the procedural steps. This application could directly benefit leaders who need to manage by walking the floor in operational environments. Management by Walking Around (MBWA) is a leadership style intended for managers to better connect and communicate with their employees (Boardman, 2004). Introducing an AR technology to support this role could increase their job effectiveness.

Experts shared that education and retail industries have also seen some success by adopting AR technologies. One example of using AR for education is schools can use AR devices to teach concepts and give experience before going out into the real-world. Some of the experts discussed consumer applications and the importance of the service sector. For example, retail offers consumers AR images that can be used in homes to see how well their product fits in the space they have or try out their product virtually before committing to a purchase. As one expert shared, "The ability to display anything in front has a huge upside. Simple face filters can help retail stores sell hats online."

4.5.2.3 AR Applications for Management

Management related applications for AR were limited as 3 of 12 experts were not able to provide an example or have seen an application yet of AR being used for management tasks. Other AR experts described logistic applications where companies use AR for vision picking and inventory. Remote Subject Matter Expert (SME) applications are also becoming more common where a technician can call an expert and annotate the real word of front of them in AR (Gurevich et al.). This helps reduce travel costs that may be associated with having multiple people on location to troubleshoot issues. As one expert commented, “AR can provide the ability to have Remote SME capabilities to reduce troubleshooting time, provide real-time work collaboration across physical locations, and save on labor/travel costs.” Additionally, access to a Remote SME helps in times such as COVID-19 where physical contact restrictions are in place. Having a remote SME available may provide a much quicker resolution to an issue and reduce the need for many people to view the same issue in a crowded location.

Another logistics application described was an ability to have mobile logistics data for warehouse operations and metric analysis. Having this information displayed in a novel way can help reduce the time it takes to process the information displayed. One expert commented, “Mobile logistics data and inputting for warehouse operations and work station metrics is a capability AR could provide." If a warehouse picking route was optimized for reduced travel time, this could be displayed in AR to guide the employee through the most efficient path in selected the parts needed from the warehouse.

AR is also being used as an inspection application where the inspectors can use an AR checklist to guide them through the detailed inspection being conducted. As one expert shared his experience, “One current application I’ve worked on is one that would describe to a user how to run through an inspection checklist on a vehicle and take notes on the conditions of different items.” This can help by having the information right in front of them instead of referring to a separate device or inspection manual. In addition to checklists, AR is sometimes used with other technologies for automated inspection and optical character recognition (OCR). All of these applications can reduce inspection time associated with a production process.

4.5.2.4. Benefits of Implementing an AR System

All 12 experts stated how beneficial it would be to a shop floor to implement an AR system where key metrics are displayed above working machines on a shop floor. A supervisor could walk onto the shop floor, scan a marker or use image detection to have AR images appear. The AR images could appear where needed and provide metrics such as throughput, capacity, or other key metrics collected by the organization. One expert included how this could directly make the supervisor's job more efficient by being able to status the machines on the shop floor at a glance rather than a set of manual procedures. Another expert shared "The benefits of the overlay above would allow a single person to tend to multiple machines, showing important information that would be crucial to move forward."

By implementing such an AR system, the shop floor supervisor could have the ability to make production adjustments in real-time while speaking to floor personnel. Another expert commented on how the user would have a much greater retention of information by the way the data is displayed compared to traditional methods to analyze the data given to them. AR can display visuals in a more appealing way that makes data interpretation much easier and quicker. As one expert stated, "[this application] requires less movement and would allow the user to ignore the fine running machines and get to the ones that need more hands-on help."

Additional features to the AR system were also proposed by the AR experts. One feature described was that the AR system not only provides the information, but will also suggest what decision needs to be made. This system could potentially be combined with Artificial Intelligence (AI) or machine learning to further enhance the effectiveness of using this tool. When AR information is displayed to the user it could prompt possible decisions based on historical or predictive data. Data connectivity would be largely beneficial to a successful deployment of such a system.

Some user interface suggestions were also made such as including a help icon, search features, and authentication. When asked about additional features this system could provide, one expert commented, “Possibly a help menu that can describe what symbols mean and what their intent is.” If this system could potentially be used by many supervisors or managers, it will need to be secure on a trusted network. Feedback from the user could be collected on what additional features would be most helpful. The interface needs the most useful information upfront and ensure supplementary information does not crowd the field of view.

4.5.3 Operations Performance Measurement

A total of 11 OPM experts also choose to participate in either the interview or the online survey questionnaire. The participants held shared experiences with OPM approaches, implementation, and even discussed recent challenges seen in practice today. Further discussion of their insights is provided below. All experts met the inclusion criteria of the study and had a minimum of three years of OPM experience either in industry or academia.

4.5.3.1 OPM Approaches & Technologies

OPM frameworks currently being used by the Experts in this study include utilizing The Balanced Scorecard and data fed dashboards which continuously connects data to the dashboard application. Both are vital for organizations to better visualize the data and support decision making. Some of the scorecards mentioned by the Experts include scorecards that have the traditional Red, Yellow, Green coding to help indicate the performance within the organization. Developing the measures included on the scorecard can be challenging task. Many organizations iterate what measures are included on the dashboard or cycle through advocates that use the dashboard to keep the analysis current to the needs of the organization. Data presentation and visualization are important to OPM Experts as many have indicated how essential it is to their organizations. Experts have commented that the dashboards being used are displayed on monitors throughout their companies to help have the information easily accessible when needed. These dashboards could also be accessible from a mobile device.

Common technologies being used among the experts include using Microsoft Excel and Tableau. Most organizations are familiar with Excel and many of the experts indicated the additional implementation and use of Tableau. Excel was mentioned in 73% of the responses and is helpful as it is a tool that many people already have access to and the data manipulation can be customized by creating Excel Macros. Tableau was included in 45% of the results and is an interactive dashboard that is used to transfer data into meaningful displays. The Experts prefer easier ways to visualize their data instead of consuming several hours of data manipulation or customization to make it meaningful. Tableau helps streamline this data visualization. Other experts (27%) mentioned that they use Systems, Applications, & Products (SAP) as the main technology used to support their performance measurement activities. SAP is a popular data processing software that also provides meaningful metrics to its customers. The metrics may not be presented in a meaningful way, but is able to process and hold large amounts of data.

All 11 experts expressed that technology helps lead to more effective OPM. Several organizations have a culture of innovation that want to adopt the best technology to help increase team performance (Singh et al., 2019). Technology in OPM has also led to a lot of automation. Automation in reporting the metrics along with systemically sending it to the managers that need to make data-based decisions. This process helps reduce the number of hours in data collection as well as reduces delayed decision making. Managers that are also able to communicate the purpose to the key individuals also supports the use of technology, and particularly new technology that is being implemented. People want to know how something new will affect them and their role in driving the metric.

Technology is not the only factor that leads to more effective OPM, but it is a key factor as stated by 27% of the experts. Other important factors used along with technology include leadership still being able to make educated decisions based on their experience to help in making the right decisions for their teams or organizations. Technology will help individuals see their performance more easily and help connect it to the overall goals of the organization. When asked if technology leads to more effective OPM, one participant responded “Yes absolutely, technology is the key to real-time data which is often easier for individuals to understand as opposed to having to think back to a previous time.”

All 11of the OPM experts agreed that implementing an AR system on a shop production floor would make the supervisor’s job more efficient. They also asserted that adopting an AR system that gives a supervisor information quicker, and the ability to tend multiple machines more easily would be valuable for the production floor. In one expert’s experience “The supervisor can easily identify which processes are in control and which processes are likely to fail.” Having this information easily accessible will be more meaningful to both the employees doing the work and the leaders responsible for making decisions based off of the data. This application would also be mobile, allowing information to be fed into the AR device to get up-to-date information. This information could also be used to discuss machine performance with the operator in real time which would provide the ability to make adjustments quickly while on the floor speaking with the floor personnel.

Implementing an AR system on the shop floor also helps the user navigate areas of concern in a novel way leading to decisions being made more easily and quickly. This system could be deployed on either an AR wearable device or on a phone/tablet. If it is important to the user to have their hands free, the supervisor could use a wearable device to scan the shop floor, and immediately be notified about any issues or how well the shop floor is performing. If a hands-free approach is not necessary, they could also scan the shop floor with a phone or tablet and easily be mobile with it. One participant shared, “I think AR will be a game changer if implemented correctly. Real time feedback will increase efficiency.” In an instant, the supervisor would get information needed to make decisions to better manage the shop floor.

4.5.3.2 Most Significant Challenges for Effective OPM

All participants reported challenges in the field of OPM. One of the most significant challenges in OPM as reported by 36% of the experts is initially establishing the system. OPM experts have expressed how difficult it can be selecting the right metrics to track and display. Once the initial set of measures are created, the organization needs to fully understand why these data are being tracked. Another theme from 36% of the expert responses is the lack of focus and priority can become significant challenges. In fast-paced environments, lack of focus becomes a real challenge. Focus and priority in real-time operations also includes engagement in ensuring the metrics or scorecards that are being used bring value to the organization. If the leaders of the organization want to succeed in OPM, they must be engaged and prioritize that the right measures are tracked, enforced, and implemented. Figure 20 shows the final codes and frequency of mention for challenges for effective OPM. Establishing the OPM system and lack of focus are the two biggest challenges found which represent 36% of expert responses.

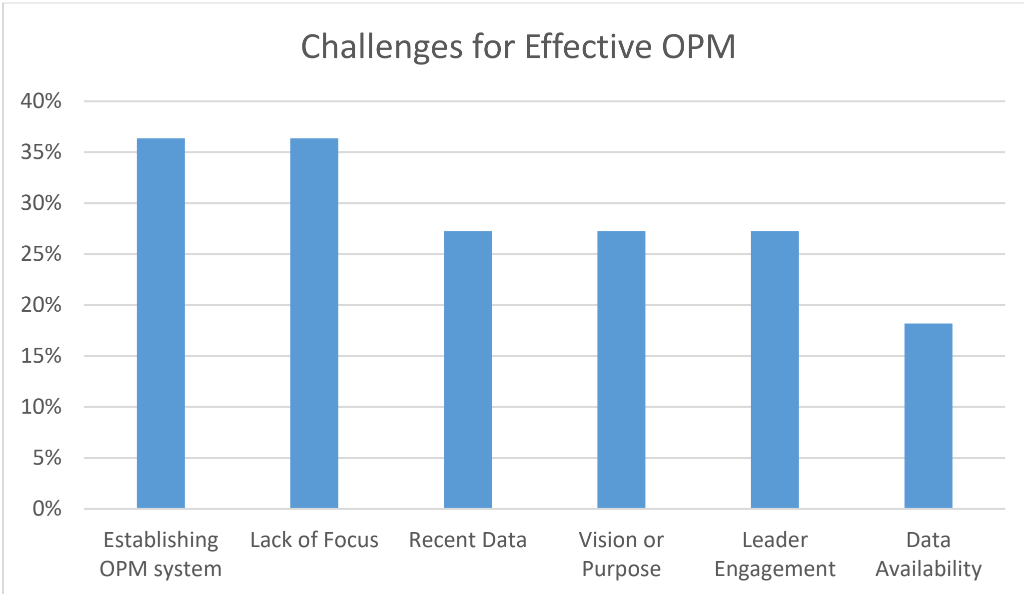

Figure 20: Challenges in OPM

One theme across OPM experts is that not having recent enough data to base their decisions on is a major challenge. Some dashboards are dynamic and can update relatively quickly, others do not get data quickly enough to make an effective decision. One expert shared, "In my opinion, the most significant challenges in OPM are system availability, system capability, and human understanding or engagement." Getting the team to understand the vision behind OPM can be a significant challenge that needs to be addressed so that the team can works towards the goals of the organization to make it successful.

OPM Experts also reported experiencing challenges while using their existing technologies. A common challenge found among 27% of expert responses is system integration. When organizations lack system integration, adopting new technologies becomes an even larger challenge. The experts commented that the availability and lack of standardization of the data makes data interpretation and actionable insight very difficult. With the lack of standardization, identifying root causes also becomes a challenge. When referring to challenges associated with using existing technologies, one expert shared, "Not available or customized for front line staff to understand their performance.” OPM may be used by many project or functional managers, but having their constituents understand how it relates back to their performance can be a challenging issue.

Another challenge Experts face is the ability to communicate purpose with the existing technologies that are being used. Many of the participants struggle to find meaning behind the metrics or measures that are being used. One expert shared, “I think spending time defining and understanding the purpose of the technology is the most important part.” Connecting the purpose of the metric or the data to operations is a huge discriminator and opportunity to improve the effectiveness of the current technologies deployed to companies.

Challenges of implementing an AR system were also discussed with the experts. Experts reported that AR hardware will continue to be a challenge if choosing to use a wearable device. The wearable devices will be clunky for a supervisor to wear and walk the production floor with. Using a phone or tablet will make using the AR system more convenient and comfortable for the user to interact with if needing to be mobile while using the AR application. Smart phones may be preferred by supervisors as they can easily be carried around the production floor and can be less difficult to process any new software changes.

Another challenge discussed in the interviews is data connectivity. If an AR application were developed to support OPM, it would really only be useful in real-time environments. The information will have to be quickly accessible, and if a marker is used, the marker would need to be placed in convenient locations. Successful system implementation would be another potential challenge. Along with implementing an AR system, the OPM focus would need to include that the right metrics are displayed by the AR images.

Since developing an AR application for OPM will most likely be a new technology introduction, training the user and getting them up to speed may be another potential challenge. The user may need some time to get use to the chosen AR device and learn how best it will help guide their decision-making. A related issue would be ensuring the correct people are able to see and interpret the images. One expert shared the following potential challenge, “Only the supervisor can see the metrics; it would be valuable to have the shop floor employees see and understand the metrics to provide their hands-on explanations of the causes of variation and failure.”

4.5.3.3 Effective Decision Making

Experts in this study describe effective decision making as timely (27%) and data-driven (36%). Many have described that effective decision-making is accountability and the ability to see clear objectives quickly and easily. Decision making also needs to be aligned with their company’s operational and strategic goals. When asked how to describe effective decision making, one expert responded “Ensuring not to get lost in the weeds and instead being able to show your team the big picture quickly and easily. Perfect data is not always effective data.” Leaders should be able to make a decision quickly with the information displayed to them. The OPM dashboard’s information should be complete and an individual should be able to take action immediately by viewing it. Figure 21 shows the final results of the coding process.

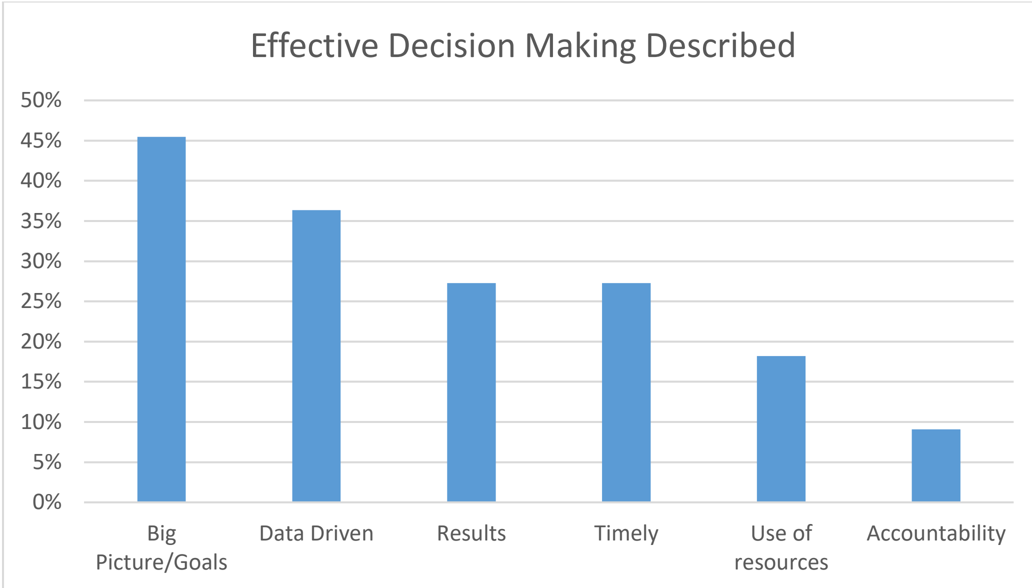

Figure 21: Effective Decision Making Described

Big picture/goals, data driven decisions, results, and timely decision making all have the highest frequency of mention by the experts. Big picture/Goals was mentioned by 45% of the experts, making it the most frequently mentioned code for effective decision-making. As one expert shared "There's a lot of tiny decisions they can make on a daily basis and have to see how those might contribute to the bigger picture." Being able to see the corporation's big picture is a driver to making effective decisions along with being able to tie goals to those decisions (Adinolfi, 2020; Stimpert & Duhaime, 1997). Another expert shared "All decision-making should be aligned to the organization's operational and strategic goals." Obtaining the expected result is another key indicator that the decision being made was effective or not. Using data can drive many types of decisions in operational environments and can be referenced in the future to determine the decision's impact.

Evaluating effective decision making can take many forms. The experts that participated in this study stated decision-making is effective if financials are trending positively. If the financials are trending as projected, then the decisions being made were effective. OPM leaders are able to look back one year and compare their past decisions with the different outcomes that occurred throughout that year.

A few experts (18%) shared that measuring decision-making effectiveness is a challenge. When one expert was asked how they measure decision-making effectiveness, he responded. “You know, I think that's probably a gap, that's a good question.” Another participant responded “I really don't think I have any good examples of a measurement of effectiveness. I really don't feel like that's a piece of leadership that I've accomplished and actually know.” Other experts (18%) included that when they need to make a major decision, they put together several documents describing the solution proposed including any applicable implications. Then after the project has been implemented, they like to go back and see which decisions could have been altered to make the project even more effective.

After the iterative process and inductive synthesis was complete, Table 10 below shows the dimensions of effective decision making which can be leveraged for future studies. It includes six main themes that were extracted from the thematic analysis process.

Table 10: Dimensions of Decision-making Effectiveness

Frequency	**Dimension**
45%	Big Picture/Goal Alignment
36%	Data-driven decisions
27%	Improvement in Results
27%	Timely
18%	Efficient use of resources
18%	Intuition/ “gut” feeling

Achievement of the manager’s goals as well as alignment of the organizations goals and big picture was a top topic within the interview and survey results. This is included in the dimensions of decision-making effectiveness as big picture and financials were common themes throughout the inductive synthesis with 45% of experts including this topic in their response. Many experts (27%) shared that improvement in results helped guide them to knowing how effective their decision-making was. Data-driven decisions is included as a final code after rounds of auto-coding and custom coding. Experts who were able to use data to drive their decisions found their decisions were more successful. Timely decisions or the ability to make decisions quickly is an important factor for most managers. Jarrett & Schaar (2020) describe timely decision making as having an ongoing, active strategy as well as the ability to execute decisions under pressure. The ability to use resources effectively is the next most frequently mentioned dimension with 18% of experts including it in their response. If the experts knew they were optimizing resources, they were confident in their decisions. The last dimension identified is intuition. Intuition or a "gut feel" was included as a way managers make their decisions. Research has also supported the use of intuition as an aid in making critical decisions and successfully completing tasks (Hayashi, 2001; Isenberg, 1984; Shirley & Langan-Fox; 1996). Hayashi (2001) found that executives rely on their intuition to help solve complex issues and that many companies require the use of business instinct to make decisions quickly.

4.6 Conclusion

The objective of this study was to evaluate the potential use of AR technologies to improve OPM. Research suggests there is a lack of focus on Augmented Reality applications for managerial functions specifically pertaining to aiding decision making (Chapter 3). This study investigated insights from both AR and OPM experts to better understand the progress and challenges associated with adopting an AR-assisted device to aid in decision-making. As part of this study,23 experts were interviewed or surveyed across OPM and AR disciplines. This study helped answer if managerial decision-making can be assessed and measured. Many experts shared that their organization does not have an effective way to measure successful decision-making. Their insights from this study revealed six dimensions of decision-making effectiveness. Some experts shared common themes of aligning to the organizational goals or objectives that can aid in effective OPM. Others identified challenges such as adopting head-wearable AR devices and integrating systems together for successful dashboard implementation. Data connectivity remains a current challenge in industry today. These themes across the interviews were used to help develop a construct in decision-making. A construct for decision-making effectiveness was refined and recommended for future evaluation.

Many of the insights found in this study will be directly applied to the development of a laboratory study. A proof-of-concept AR-assisted device will be developed and tested in the study to understand its effect on decision-making. One insight that can be directly applied to this development is the need for real-time data. Practitioners say that this is critical for effective decision-making (Curry et al., 2019). Access to real-time data has proven to be a limitation, but AR devices have the ability to incorporate real-time data for AR applications (Garon et al., 2016). Combining access to real-time data and Augmented Reality use has the potential for added efficiencies and better data display. Since there were few examples of AR being used with operations management this is an area that could benefit from further evaluation.

Limitations of the study include recruitment and participation from the area experts. Many experts have busy schedules that do not always accommodate or incentivize participation in this type of research. To mitigate this, professional networks were leveraged to help increase the sample size. Other experts work in industries where best practices are not encouraged to be shared with general public. A larger sample of experts would improve the rigor and depth of insights. Since no AR

OPM experts were identified, the study split the experts into two groups that specialize in the related application areas.

Findings from this expert study can be directly utilized for practice and research. Many challenges were identified from both the AR and OPM groups that could benefit from additional research. Applying AR to OPM may create additional unique challenges that may need to be mitigated or addressed as this is still a low maturity research area. Many benefits were also discussed that can be applied directly to current work. Experts shared positive experiences of successful AR implementation and dimensions of effective decision making that can be leveraged across different industries of application areas. Practitioners can apply these findings in industry if attempting to implement an AR-assisted managerial application.

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CHAPTER FIVE: LABORATORY EXPERIMENT

Augmented Reality in Operational Performance Management: Creating Immersive Performance Environments to Support Real-Time Decision Making

5.1 Abstract

AR is rapidly expanding into new applications; however, a review of the literature suggests that using Augmented Reality (AR) for managerial-related tasks is limited and practical use-cases for operational performance management (OPM) is lacking. A laboratory study conducted using the Design of Experiments (DOE) methodology to determine if using Augmented Reality with real-time data could aid in making managerial decisions in the simulated context of a grocery store. Pre- and post-survey questionnaires were used to validate a construct for perceived decision-making effectiveness, which was used in combination with existing, externally validated technology acceptance constructs to investigate potential impacts of an AR-assisted device. Eight observations were made for each of the four different simulation treatments resulting in a total of 32 observations for the study. The results of the experiment showed that using real-time data had the largest effect on the operational performance, as measured by end-of-week profit, and pairing real-time data with Augmented Reality technology was associated with optimal operational performance.

Keywords: Operational Performance Measurement, Operations Management, Augmented Reality, Laboratory Experiment, Real-time data, Technology Acceptance

5.2 Introduction

Augmented Reality (AR) has recently started to expand with novel applications across many different industries. What was once used primarily to guide procedural tasks in the medical and manufacturing sectors is now emerging to other industry areas and being applied to other categories of work tasks (Albertazzi et al., 2012; Baran et al., 2019; Chang & Liu, 2013; Liebert et al., 2016; Kim, Park, Lim, & Kim, 2013; Novak et al., 2014). Augmented Reality superimposes a virtual object into real-space to provide additional visualization of key information, which can be implemented with traditional mobile devices, such as a tablet or phone, or can be used with an AR headset (Raghavan et al., 1999; Zollmann & Poglitsch, 2014). AR has started to become widely adopted in industry, but its application to managerial-related tasks is limited with most current applications focused on augmenting human vision or guiding procedural tasks (Mura et al., 2016; Palmarini, Erkoyuncu, Roy, & Torabmostaedi, 2018; Sielhorst, Feuerstein, & Navab, 2008).

Operational Performance Management is used across many industries to guide management of operational performance and improvement efforts and to make data more meaningful and insightful (Dal, Tugwell, & Greatbanks, 2000). Operational performance measurement (OPM) is a subset of performance management and uses processes and systems to monitor defined measures over time (Mathur et al., 2011). Using OPM supports the proactive management of organizational effectiveness as well as to identify and monitor progress toward vital operational improvements (Dal, Tugwell, & Greatbanks, 2000). Not being able to choose meaningful metrics and provide accountability are common issues in the area, which are currently active areas of research (Maestrini et al., 2017). Other challenges in this area include access to real-time data and difficulties sustaining OPM practices once they have been implemented (Chapter 4). Although there has been significant advancement in OPM tools and practice, technology-assisted OPM is lacking in industry as adoption and utilization of these tools is often faced with significant challenges (Kleindorfer et al., 2005; Olsen & Tomlin; 2020). These technologies are advancing, but applications are not advancing or being adopted at the same pace.

The purpose of this study is to develop and test an AR application to support managerial decision -making in a fast-paced operational environment. The study consisted of developing a series of simulations in the context of a grocery store, representing both an inventory management and work allocation problem space. A Design of Experiments-based laboratory study was conducted to investigate whether leveraging AR for such tasks can aid in decision-making effectiveness for operations managers. A construct for perceived decision-making effectiveness was developed and analyzed as part of the research study and used along with existing, externally validated constructs for perceived usefulness and perceived ease of use to evaluate potential challenges for practical adoption. Since there is a lack of applications pertaining to applying AR technology to OPM, this work with further contribute to this area of research by providing a tool to help facilitate better decision-making.

5.3 Background

Operational Performance Measurement (OPM) have been shown to improve productivity in an organization (Mathur et al., 2011). OPM can also be helpful in better understanding business processes and capabilities (Kaydos, 1998). Ensuring that organizational goals align with their respective strategy and is effectively communicated to key stakeholders is another area where OPM is utilized (Kaydos, 1998). This can help control and manage effectiveness of day-to-day activities. Using OPM is also a tool to support performance management improvement activities and drive operational effectiveness (Dal, Tugwell, & Greatbanks, 2000). Performance measurement helps to benchmark an organization and measures progress of the company’s vision

(Sharma & Bhagwat, 2007). Common challenges in this field include not choosing applicable measures and failing to provide accountability for developed processes (Mariotti, 1999). Although there has been progress in the area of OPM, the specific field of technology-assisted OPM is still in the early stages of development (Rikhardsson & Yigitbasioglu, 2018). Recent improvements include using real-time dashboards and advanced analytics to assist with OPM (Bremser & Wagner, 2013). However, empirical studies of these specific applications are limited (Machuca et al., 2011). Additionally, the connection between using these technologies and improvements in managerial decision-making appears to be beneficial, but not sufficiently demonstrated in the literature. AR is a technology that can contribute to OPM effectiveness; however, could benefit from an empirical study. This study explores the use of an AR tool in operations management, specifically work allocation and inventory management.

There have been many practical examples of implementing AR for process improvement. For example, AR has been shown to aid in assembling production parts and being effective as a training device for students (Moher, 2009). AR is also being used in the maintenance field to preserve product lifecycle where AR is being used to guide decision-enabled tasks (Matthews et al., 2015). Further, AR can help enhance human performance in carrying out maintenance tasks and support maintenance managerial decision-making (Palmarini, Erkoyuncu, Roy, & Torabmostaedi, 2018). These tools add virtual instructions for the maintenance worker as well as identify and display tasks needed as part of the maintenance procedure. The medical field has also been using Augmented Reality in various applications where one significant benefit from using AR is related to having "X-ray Vision" (Gao et al., 2019). The system can augment data directly onto the patient providing an important visualization tool for medical professionals when conducting sensitive procedures (Sielhorst, Feuerstein, & Navab, 2008). The advantage of this is that the image can be seen by multiple users simultaneously and they also have the ability to see things that are typically not visible, such as veins beneath the skin (Yang et al., 2016). Surgeons also using AR tools to support procedures in the operating room to avoid needing to look at a monitor, which may not be conveniently located (Liebert, 2016). Augmented Reality is also currently being used in the construction industry to overlay work tasks virtually over the real-world environment. The construction worker loads their geographical location and information about work tasks is superimposed onto the real world showing the construction worker what tasks need to be accomplished. When the user positions their mobile device in different directions, different tasks are superimposed onto the real construction site to show details of the work that needs to be accomplished. (Kim, Park, Lim, & Kim, 2013). Education is using Augmented Reality to promote learning motivation and increase better learning performance which leads to increased student engagement and enjoyment (Chen, Liu, Cheng, & Huang, 2017). It is used to generate more student learning scenarios and to train students on new activities and learning strategies.

Although many practical AR applications have emerged, a review of the literature shows that managerial-focused applications of AR are currently lacking (Chapter 3). There is research that supports AR being used for simple tasks such as visualization, X-ray vision, and showing steps in a process. However, applications for more complex works tasks are limited. There appears to be a gap in the research on using AR for more complex tasks that could assist in managerial work such as in operations management and decision-making. Further, many emergent applications face significant challenges when being transferred to industrial practice. A line of research has developed which focuses on investigating the factors that affect successful implementation of such systems including issues such as technology acceptance and usability. Usability tests have been performed to evaluate AR applications in practice. For example, Albertazzi, Okimono, & Ferreira

(2012) evaluate whether AR helps in learning how to use a new project approach. These tests were conducted to evaluate if AR helps the user interact with the product or if it becomes a distraction and an additional item to process as part of the task. The results of this study indicated that this interaction helped in reducing the number of errors made by the user. Overcoming common challenges can bring the potential benefits of AR assistive systems to a wider range of organizational settings.

Managers that are able to make better and more timely decisions can lead to more efficient organizations (Shirokova & Iliashenko, 2014). Ostropolets et al. (2020) researched two different types of decision-making tools in a clinical application: data-driven tools and expert-driven tools. Data driven tools use patient data to drive decisions in real-time and expert-driven tools use algorithms created by experts to incorporate practice-based evidence (Ostropolets et al., 2020). They found that the tool needs to be able to provide the needed information at the point of care, which was not always supported. Ostropolets et al. (2020) concluded in their review of 25 decision support systems that evidence of effectiveness was lacking.

5.3.1 Decision Making Effect on Operational Performance

Traditional decision-making support systems have been created for inventory control systems which consists of determining optimal storage and order quantities (Shirokova & Iliashenko, 2014). These types of models can have a large impact in real-time operational environments. Many other decision-making support tools have been investigated such as Artificial Intelligence (AI) support tools. These tools can also show positive results, but can experience challenges such as being cost effective or producing quantifiable results (Phillips-Wren, 2012). Manufacturing systems can also become more adaptable when adopting intelligent decision-making tools (Chan et al., 2000). Adopting types of decision-making support tools like these can help improve performance outcomes in real-time operational environments.

The real-time operational environment for this laboratory experiment is a grocery store. A grocery store setting was chosen as it would be a familiar environment for the study participants to interact with. The participant's goal is to maximize profit for this grocery store as the simulation allows for profit to occur when the cost of goods and labor are less than the revenue from selling grocery items in the store. The participant in the experiment acted as the manager of the grocery store and leads the five departments (i.e., produce, dairy, frozen, dry goods, and cash registers). In the AR treatments, each department was represented by a marker that was identifiable for the experiments when the augmented reality treatment is used. Penalties for ineffective decision making include having food expire while in the store, over-ordering food, or not properly managing the number of rush orders needed, which are orders that include an expedite fee for a faster delivery. Therefore, the participant needs to make decisions on the numbers of items to purchase for inventory, when to purchase inventory, what inventory is expired or going to expire, and how many cash registers to open. The option to adjust the amount of cash registers open helps the flow of customers checking out; each register is operated by one cashier. The participant had the ability to over-order inventory since there is a limit to how many items can be held in back-of-house. However, there is an inventory penalty associated with over-ordering, making it undesirable.

If the simulation runs with no assistance the store inventory will run out and there will only be one cash register open. By not restocking needed items, less items will be sold leading to less profit for the store. Not having enough registers open can lead to lines backing up. Both the historical and the real-time data require the participant to make decisions on work allocation and inventory control to continue effective business operations for the grocery store.

5.3.2 Technology Acceptance

As reported in Chapter 4, experts reported that technology acceptance would be a key barrier to overcome and will be explored in this study (Chapter 4). Adoption of technology can be challenging in many industries due to several different factor's organizations face (Khan et al., 2014; Prause, 2019). The technology acceptance model (TAM) is one widely-used model theorized by Fred Davis and focuses on what factors drive acceptance of a new technology when introduced to the consumer (Davis, 1989). Using Augmented Reality in the Operations Management field is still in the early stages, however there has been research on how using the Technology Acceptance Model with Augmented Reality can aid in the adoption of new technology. The model aims at understanding and explaining the user acceptance of a new technology.

The factors that could influence the acceptance and use of the system in the TAM include the two well-known factors of perceived usefulness (PU) and perceived ease-of-use (PEOU). Perceived usefulness is defined as the degree to which a person believes that using a particular system would enhance his or her job performance (Davis, 1989). If the users can see the benefit to improve job performance, they will be more likely to approve and adopt the new technology. Different extensions of the TAM have been explored in the literature. Venkatesh and Davis (2000) developed TAM2 which incorporates social influences such as voluntariness and image. In another TAM extension, Venkatesh and Bala (2008) continue to add anchors such as perceptions of external control and computer self-efficacy. The original TAM was selected for this study since it is thought to be a more generic technology acceptance model and is well established in the research literature.

Perceived ease-of-use is a measure of the degree to which a person believes that using a particular system would be free of effort (Davis, 1989). If the application of Augmented Reality is easier to use than a previous application, the user will be more likely will adopt the new technology. Davis's study included a step-by-step process used to develop new multi-item scales having high reliability and validity for each construct considered. The research also concluded that one of the most significant findings is the relative strength of the usefulness-usage relationship compared to the ease of use-usage relationship. In both of the studies, it was found that usefulness was significantly more strongly linked to usage than ease of use (Davis, 1989). This model is still being used 30 years after it was developed with multiple studies validating its constructs (Cakmak et al., 2013; Wong, 2013). One study used TAM for a mobile augmented reality application focused on providing history education overlaid on top of present-day scenes (Haugstvedt & Krogstie, 2012). Another study was able to leverage TAM to technology acceptance of AR smart glasses which proposed an exploratory model of smart glasses adoption (Rauschnabel & Ro, 2016).

5.3.3 Research Gap

Augmented Reality applications for industry is a relatively new field and has recently started to become more practically useful in a wide range of applications. Many industries are finding applications for AR in ways not imagined until recently. A detailed review of the literature was conducted that focused on evaluating current applications of AR technology for managerial tasks (Chapter 3). However, this review revealed that there are very few studies in this research area and applying AR technology to OPM has not been explored in any depth in the literature. Evaluating applications of AR technology specifically to operations management has the potential to contribute new methods of decision-making assistance in this field of research as this area is still in the early stages.

5.4 Methodology

This study used a mixed-methods approach that included human-subject research in a lab-based experiment. It addressed key elements of TAM while investigating impact of AR in the context of real-time decision making. The experiment utilized pre- and post-experimental survey questionnaires to assess constructs related to technology acceptance and perceived decision-making effectiveness. The purpose of this study is to develop and test an AR application to support managerial decision -making in an operational environment. The following research questions have been defined to guide this research:

- Does an AR dashboard improve operational performance and perceived decision-making effectiveness?
- How can perceived decision-making effectiveness be assessed and measured?

These research questions were used to guide the design of a laboratory experiment as discussed in the following sub-sections. This laboratory study developed an AR dashboard to measure operational performance and perceived decision-making effectiveness in the context of a simulated grocery store to answer the research questions.

5.4.1 Experiment Design

The experiment design was structured for the participant to be able to make decisions in a simulated operational environment based on the information that is given to them to manage operational performance. A Design of Experiments (DOE) approach was selected as the base experimental design to allow for multiple factors to be included in an analysis to determine their effect on a response (Montgomery, 2013). A DOE approach provides an experimental framework that can statistically evaluate the effects between categorical factors. A key benefit of this is being a multi-factor experiment that can test two factors and their interaction simultaneously. A standard 2^2 factorial model was used for this study. The two variables of interest are AR assistance and access to real-time data. These each have two levels that were evaluated (i.e., AR assisted vs. AR unassisted, and real-time data vs. historical data) resulting in four different treatments. Depending on the experiment treatment, the information that that the participant had access to was either historical or real-time data. The participant used these data in making informed decisions to help maximize profit.

5.4.1.1 Variables

The observed variables of interest to study are technology acceptance, decision-making, and operational performance. This work argues that having a real-time assistive technology will improve perceived decision-making effectiveness and operational performance, and that increased levels of tech acceptance are also associated with improved decision-making and operational performance. Therefore, two factors are defined to track the use of real-time OPM and the use of the AR assistive technology. Table 11 summarizes the customized construct for perceived decision-making effectiveness that was developed for this study, as discussed previously. Since an existing construct for decision-making effectiveness was not found, this construct was created based on the results of an expert study, which identified six dimensions of managerial decision-making effectiveness (Chapter 4).

Table 11: Initial Decision-Making Effectiveness Construct

Item	Description
1	This [tablet/tool] helped me maximize profit.
2	This [tablet/tool] helped me understand if I was making good decisions.
3	This [tablet/tool] helped me make decisions faster.
4	This [tablet/tool] helped me to achieve my goal(s).
5	This [tablet/tool] helped me use resources more effectively.
6	I trusted my intuition more than data when making decisions.

The six items of this construct were adapted from the results of an expert study where OPM experts were asked to define managerial decision-making effectiveness (Chapter 4). The six dimensions of perceived decision-making effectiveness were adapted to be phrased appropriately for this study regarding the tablet/tool being used during the experiment. This construct was refined and validated as part of the survey results described in later sections.

5.4.1.2 Design of Experiments (DOE)

This study is based on a DOE approach (Montgomery, 2013). The defined conceptual model contains two, two-level categorical variables of interest (i.e., assisted vs, unassisted, and real-time vs. standard) and, therefore, a standard 2^2 full-factorial model was used. Data for technology acceptance and perceived decision-making effectiveness were gathered through pre/post-experiment survey questionnaires given to each participant. This experiment consisted of four unique treatment combinations as summarized in Table 12.

Table 12: Factorial Design

	Assisted	**Real-Time**	**Description**
(1)	-	-	Neither assisted nor real-time
a	-	+	Real-time data provided without AR technology
b	+	-	AR technology provided without Real-Time data
ab	+	+	Both Real-time data and AR technology are provided

This experimental design allowed for a statistical analysis to test hypotheses regarding the effect of each of the predictors on the four defined response variables. Further, this design was replicated eight times resulting in 32 observations for the statistical analysis. A sample size of 32 was the minimum sample size initially estimated to obtain a statistical power of .75 using a standard deviation and effect size of 500 (Djimeu & Houndolo, 2016). Since the starting profit for the participant is $10,000, an effect size of 500 was thought be a value that would be a minimum detectable difference between treatments (Fritz et al., 2012). Business students were directly recruited for this sample frame since they have the most management and supply chain related classes in their curriculum. Since this tool is designed to support managerial activities, it was important to have students that have experience or background in management related topics.

5.4.1.3 Hypotheses

Hypotheses testing were conducted within the DOE as part of this experiment and followed general Design of Experiments (DOE) guidelines. The null hypothesis, H0, stated that the effect of the treatment (τ, β, or tβ) were the same and the alternative hypothesis, H1, stated that at least one effect was different between the treatment groups. The core hypotheses in both the operational performance and the perceived decision–making effectiveness models consist of:

1. Use of ***Real-time Data*** (Factor A) affects operational performance and perceived decision-making effectiveness:

   H0: $\tau 1= \tau 2=0$

   H1: At least one $\tau i \neq 0$; i=1, 2
2. Use of ***Augmented Reality*** (Factor B) affects operational performance and perceived decision-making effectiveness:

   H0: $\beta 1= \beta 2=0$

   H1: At least one $\beta i \neq 0$; i=1, 2
3. Use of ***Real-time Data*** (Factor A) and ***Augmented Reality*** (Factor B) affects operational performance and perceived decision-making effectiveness:

   H0: $(\tau\beta)ij= 0$; i,j=1, 2

   H1: At least one $(\tau\beta)ij \neq 0$; i,j=1, 2

These hypotheses were tested in both the DOE model for operational performance (i.e., profit) and the DOE model for the perceived decision-making construct. In addition to these central hypotheses, several other supporting tests were conducted as part of the analysis.

5.4.2 Experimental Context

OPM is being used in real-time operational environments such as hospitals, manufacturing, and the service industry (Kritchanchai et al., 2018; Maware & Adetunji, 2019). Being fast-paced work environments, work allocation and inventory control can be areas of concern. Work allocation is applicable in most industries and is an area with opportunity for improvement to increase efficiency in the organization. The implementation of AR in this area can allow the manager to easily access more information thus facilitating faster and more effective decisions. Work allocation was implemented throughout the grocery store simulation based on opening and closing registers, calling in and releasing employees, and assigning employees to different departments.

There are many different factors that can affect work allocation, which can range from the type of industry to the workers, processes, and products (Roels, 2014). Currently in the workforce there is an even larger scale of factors that can affect decisions on work allocation which can derive from different managerial perspectives, competitors, technical points, and workers' point of view (Marotti de Mello et al., 2011). For the study, workers are already trained and can perform any task in the store. All four treatments contain ten workers which can be assigned to any of the 5 departments and while they are not working, they are in a breakroom. The study simulated an accelerated 7-day period with each day having 3 shifts that are 4 hours long each. The participant would manage inventory of eight different items from four product departments of a grocery store: Dairy (Cheese and Milk), Dry Good (Cereal and Cookies), Frozen Goods (Pizza and Dessert), and Produce (Apples and Bananas).

5.4.2.1 Operational Performance

Four different dashboards were developed for the four experiment treatments. Criteria were developed to be included on the dashboards of the four different treatments. This was then integrated into the formal dashboards that would be used as part of this experiment. After many iterations and testing of the four different simulations, the dashboards were finalized for the formal experiment.

5.4.2.1.1 Historic Data

In order to provide the participants with necessary information for decision-making, OPM dashboards containing historical data were designed for both AR and non-AR devices. These dashboards were developed to show the participant average historical data related to the store's inventory, employees and sales trends through a collection of charts for every day over a seven-day period of time.

A non-AR dashboard included four different sections displayed at the same time on the tablet screen: Storage Information, Employee Information, Financial Information and Register Information. The Storage quadrant contained information about the status of eight different items from four product departments of a grocery store: Dairy (Cheese and Milk), Dry Good (Cereal and Cookies), Frozen Goods (Pizza and Dessert), and Produce (Apples and Bananas). Each department was allocated a color and dark and light shades of each color were used to illustrate two products from a particular department. The data was displayed on the following charts: "Average Product Quantities", demonstrating the average quantities of each product in the Front of House (FOH), Back of House (BOH) and Transit, "Average Storage Quantities", showing how many items in total on average are stored in the FOH, BOH as well as a quantity of empty spots and "Average Expired Items", displaying an average number of expired products. This set of data was chosen to best represent work allocation and inventory control for the operational environment. Figure 22 below shows an example of the Non-AR interface using historical data.

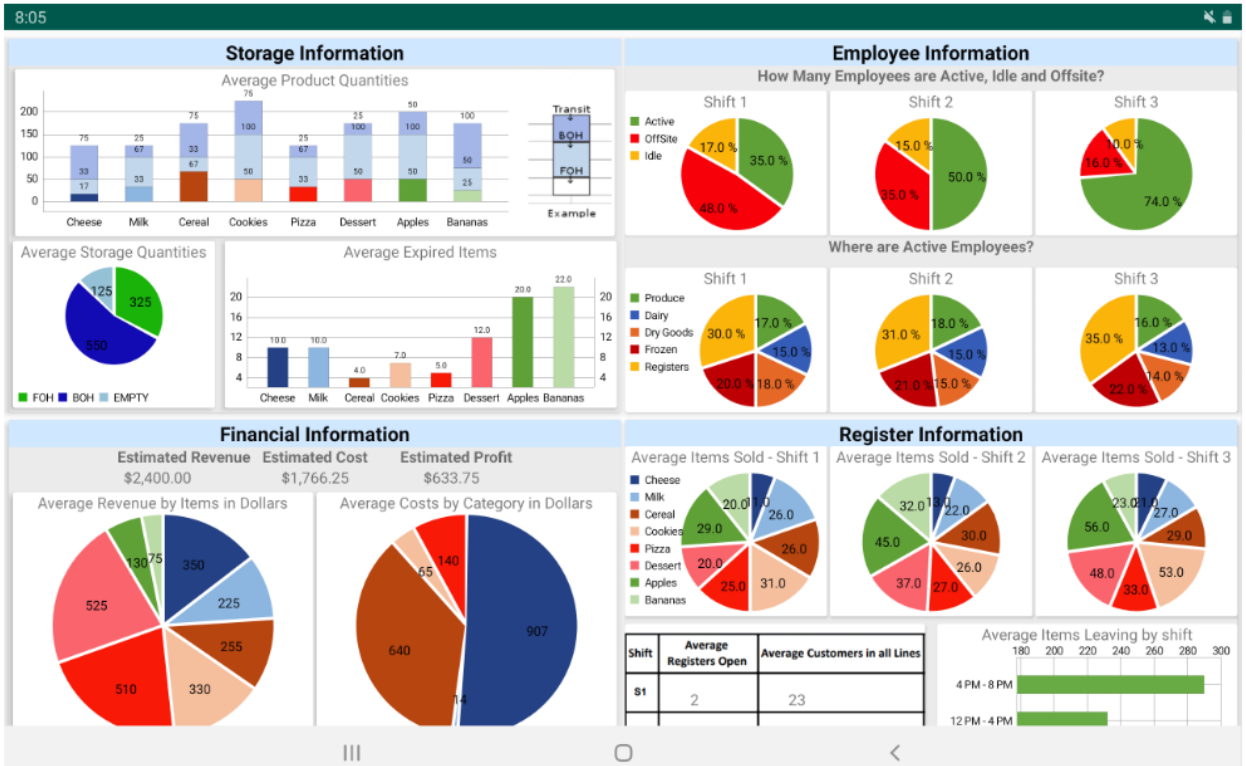

Figure 22: Non-AR Interface using Historical Data

Each day of the simulation includes three shifts that are four hours long each. The Employee Information quadrant included pie charts that were used to show, for each of the three shifts, the percentages of Active, Idle and Offsite employees as well as the percentages of Active Employees working in each department. These metrics were included to know how efficient the store's employees were which help the participant make decisions related to work allocation.

The Financial quadrant contained information about the total Estimated Revenue, Cost and Profit displayed in a form of equation with the values corresponding to each component of the equation located below it. In order to provide the participant with more detailed information about the Revenue, a pie chart was designed containing the data about the revenue received from selling each of the products. Similarly, a pie chart was designed to show Average Costs by the following categories: Delivery, Expiration Penalty, Employee Wages, Product Cost and Inventory Penalty.

The Register Information quadrant included a table displaying an average number of registers open and customers in line for each of the three shifts, a bar chart showing the average number of items leaving the store during each shift and pie charts demonstrating an average number of items sold during each shift. Figure 23 is an example of an AR interface using historical register data.

Figure 23: AR Interface using Historical Register Data

Similarly, in order to see the information about the performance information from a particular department, the participant directed the AR device at the marker corresponding to that department. As a result, two column charts "Average Item Quantities" and "Average Number of Expired Items" for the items from the viewed department appeared.

5.4.2.1.2 Real-time Data

To report operational performance in real-time, interactive dashboards of simulated real-time data related to the store's inventory, employees and sales trends were designed for both AR and non-

AR devices. Unlike dashboards containing historical data, real-time dashboards represented current information about the storage, employees, financials and registers displayed simultaneously on a tablet screen that was constantly changing as the participant was making decisions. Even though the real-time data was constantly updating to reflect the decisions being made, the metrics and content was consistent across all four treatments.

The storage section of this dashboard contained information about the real-time status of the eight different items from the four product departments of a grocery store. A clustered bar chart “Percentage of Shelf Space Restocked” was used to show how much of the available shelf space for each product in the Front of House of the store is already restocked and how much empty space is still available. A pie chart “Total FOH, BOH and Empty Quantities in Store” represented how many items in total are currently stored in the FOH, BOH as well as a quantity of empty spots and a clustered column chart demonstrated the quantities of each product in the FOH, BOH and Transit. A line graph “Cumulative Items Expired” was designed to show the number of expired items for each product on the day(s) prior to the current one.

The employee information quadrant included a pie chart that was used to show the real-time number of Active, Idle and Offsite employees, a clustered column chart demonstrating the number of employees in each department and a rectangular box displaying a number of employees currently traveling from offsite location to the store.

The financial quadrant was designed similarly to the one in the Historical non-AR dashboard but here it displayed a real-time information about the total Estimated Revenue, Cost and Profit in a form of an equation. It also contained values corresponding to each component of the equation located below it and pie charts representing the data about the current Revenue received from selling each of the products and current Costs by categories. The Current Register Information quadrant included a table displaying a number of customers in each of the three register queues, a clustered column chart showing a utilization rate for each register and a pie chart demonstrating a number of each item currently being sold. Figure 24 below shows an example of the Non-AR interface using real-time data.

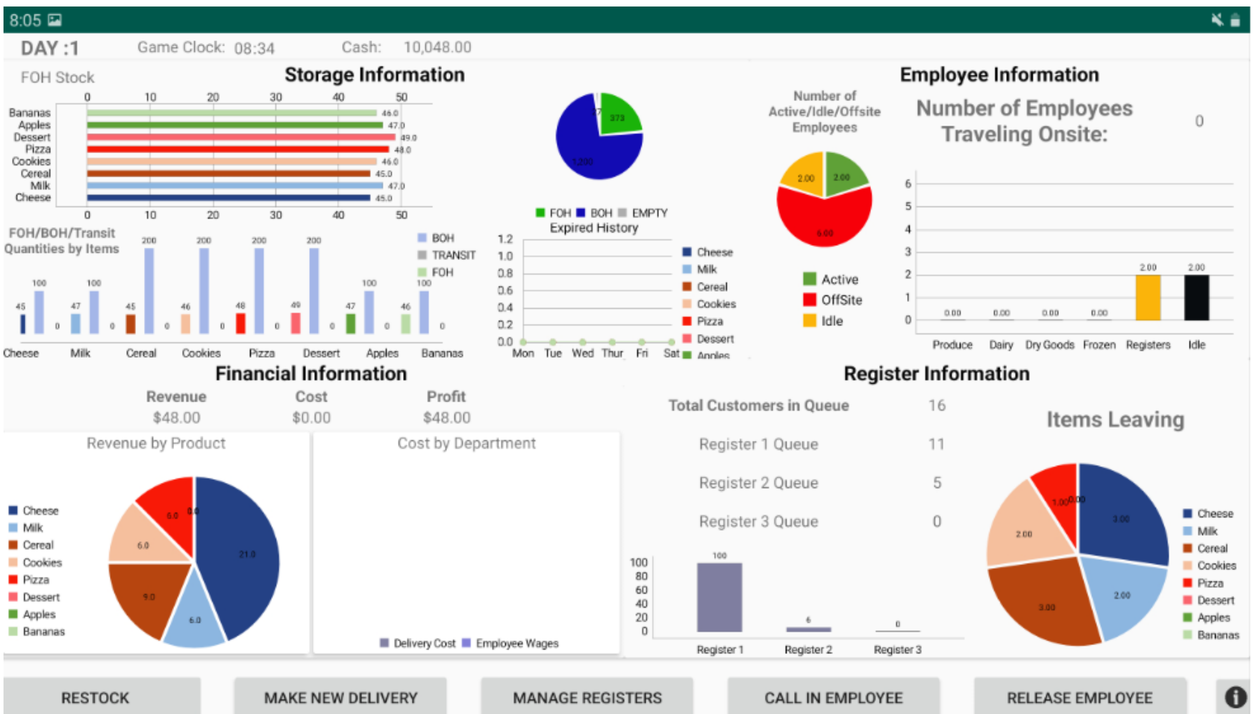

Figure 24: Non-AR Interface using Real-time Data

An AR dashboard with real-time data contained the same charts as the one for a non-AR device, however, the way users were able to utilize the data changed. Using an AR device, the participant was always able to see the Critical Display. It included a pie chart "Total FOH, BOH and Empty Quantities in Store", a pie chart showing a current number of Active, Idle and Offsite employees, a clustered column chart demonstrating the number of onsite employees in each department and a box displaying how many employees are now traveling from offsite to the store. Figure 25 below shows an example of Augmented Reality using real-time data to monitor the dairy department.

The data the participant is viewing changes in the moment. The participant's score can be seen in the top-right corner.

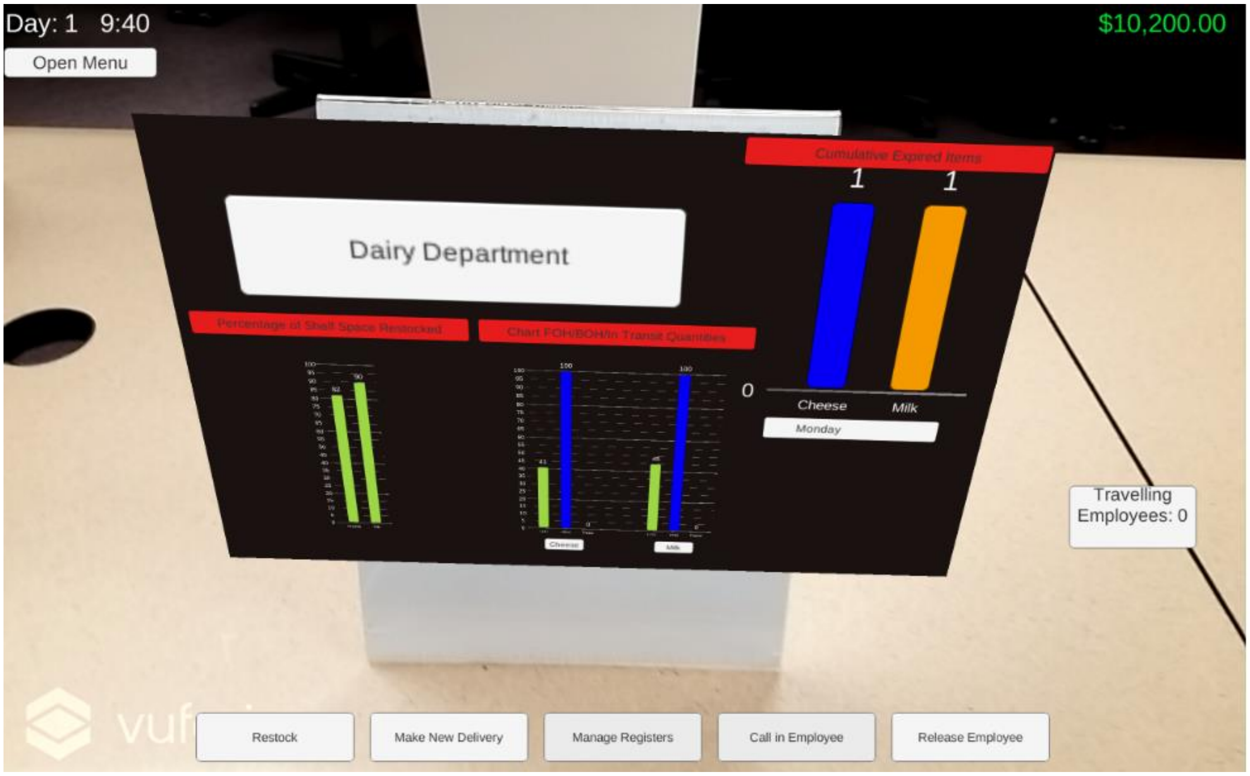

Figure 25: AR Interface using Real-time Data

In order to access real-time information about particular products, the participant held and directed the device at the marker corresponding to the respective department. As a result, the user saw the following information about the products from that department: a clustered column chart "BOH/FOH/In Transit Quantities", a bar chart "Percentage of Shelf Space Restocked" and a line graph "Cumulative Expired Items." To access real-time information about the financials and registers, the user had to hold and direct the device at the corresponding markers.

Figure 26 below shows an example of the Non-AR interface using real-time data. This interface shows similar information to the AR version using real-time information, but all of the information is located on the same screen for the user. The score and time are always viewable to participant as well as dynamic graphs showing their respective information.

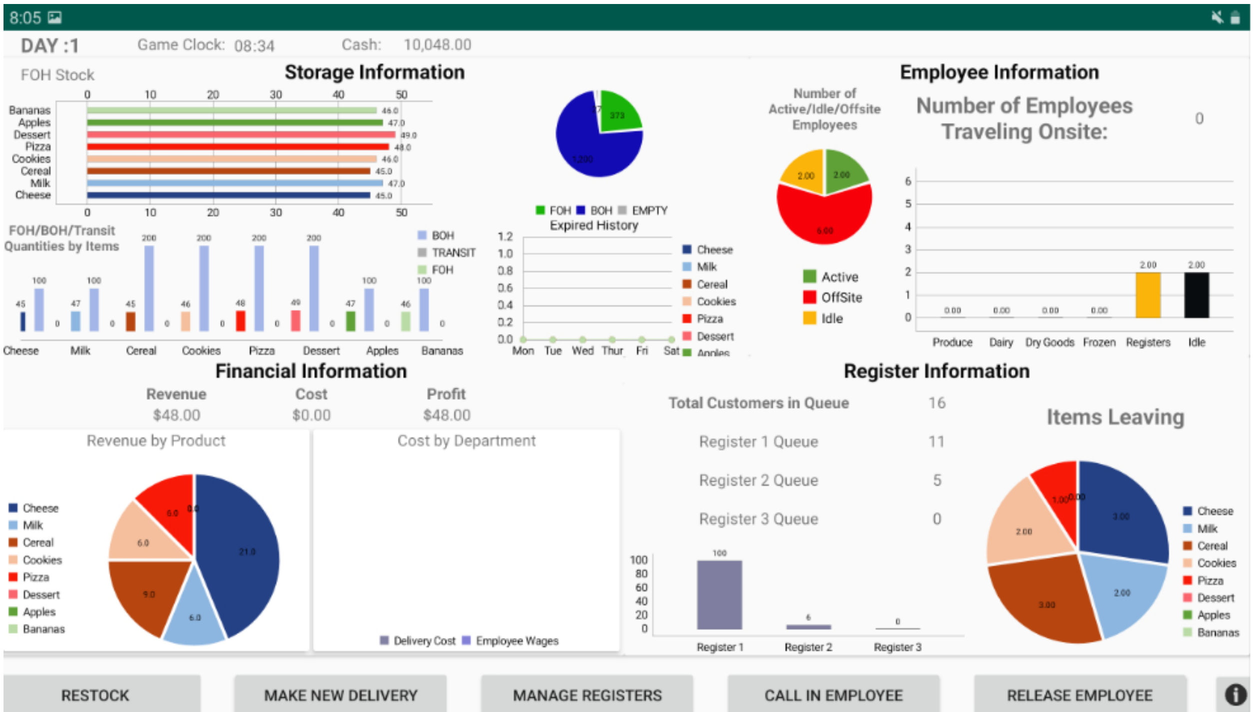

Figure 26: Non-AR Interface using Real-time Data

These dashboards were used to represent operational performance data across the four simulated treatments. The following subsections describe the simulation environment in more detail.

5.4.2.2 Simulated Environment

The simulated environment was developed for the four different treatments of the experiment all using a single tablet device. Each treatment was developed as a separate application with embedded buttons and interactions for the tablet using either Vuforia or Android Studio. Vuforia was used to develop the AR applications and Android Studio was used to develop the non-AR applications. All data and performance information were consistent across all four treatments. Each of the four different treatments are explained in the following sub-sections

5.4.2.2.1 Non-AR with Historic Data

This experimental treatment aimed at achieving a more traditional approach of managing a grocery store with no AR technology as well as only using historical data from the previous period. The user was provided with an android app that displayed a dashboard of historical data related to the store's inventory and workers. On the app, there was a table set for inputting decisions for each day. This included allocating tasks among the workers as well as ordering and restocking items. In the app there was also a reference table that allowed the participant to see information regarding the cost for deliveries, revenue to sell per item, shelf life, and FOH and BOH storage limits. The user was able to utilize the data on the historic dashboard and the reference table to guide their decisions on the app. Once the participant was done making all the decisions for a day, he or she was able to see an end-of-day report before starting the following day. The end-of-day report included a summary of how much money was spent on employees and deliveries as well as any penalties incurred. It would also list FOH and BOH inventory levels. This allowed participants to see how their decision impacted the performance measures including net profit and a summary of expenses and food expired. All four interfaces had an end-of-day report that was common between the different versions. Once the participant reviewed the end-of-day report, they would be routed back to the main screen of the simulation to start the next day.

5.4.2.2.2 Non-AR Tablet with Real-time Data

In this experimental treatment, the participant acted as a manager of the same operational environment including the five departments (i.e., produce, dairy, frozen, dry goods, and cash registers). In this case, the participant was still not using AR technology; however, the dashboard consisted of simulated real-time performance data that was provided on the tablet. Real-time operational environments are generally recognized as beneficial, however are technically challenging in practice. The participant was able to use a tablet that consisted of a dashboard that displayed real-time data related to the store's inventory, workers, and sales trends. All data and performance information were consistent across all four treatments. Although the participant was not able to see the information overlaid onto objects in real life, he or she was able to see all the real-time information needed from the tablet. The real-time component allowed the participant to see what was happening to the stock levels at all times throughout the accelerated 7-day period. During the experiment, charts and graphs displayed the metrics for inventory and worker allocation. Using the tools that were provided and their own judgement, the participant was able to select a decision from the given options and see the results at the end of each day.

5.4.2.2.3 AR Tablet with Historic Data

The participant in this experimental treatment also focused on traditional OPM, where only historic data was provided. This treatment introduced AR technology while allowing the study to comparatively evaluate the effects of using AR and seeing the information superimposed onto the real world. The participant was able to see historical data on a tablet equipped with AR by walking around the room and using the department markers. Figure 27 shows the AR Markers setup in the lab.

Figure 27: AR Marker Set-up

These markers represented each of the five departments. Similar to the other treatments, the AR Historical application displayed a dashboard that consisted of charts and graphs with information about inventory, worker allocation, and financial performance.

5.4.2.2.4 AR Tablet with Real-time Data

This treatment focused on two main components of the study: AR and real-time. In this experiment, the participant used an AR equipped tablet to see information in real-time. Similar to the previous treatment, the tablet detected visual markers, which represented the five different departments. The participant walked around the laboratory space (representing a grocery store layout), with the ability to approach each of the department markers to see real-time performance information. The real-time data aspect of this treatment allowed the participant to see how each of his or her decisions would affect the operational performance. Like the previous treatments, this treatment allowed the participant to see the information in the store regarding the levels of stock, the employees in each department, and the financials. The participant also had the reference sheet, which gave information regarding the cost of the items and deliveries. The decisions for this experiment were made on the tablet and chosen from suggestions and at the end of each of the 7 days, the participant was able to see the results.

5.4.3 Simulation Design & Development

An interdisciplinary team of computer science and industrial engineering students were recruited as part of a four-semester long research course. Individual applications for each of the treatments were developed as part of the study. The Industrial Engineering students focused on the content and logic needed for the treatment simulation, and the Computer Science students developed the simulation applications to be used on the tablet device.

5.4.3.1 Software

In order to best gather the experimental data and execute the simulated environment, it was necessary to create a multiplatform application using various programs and software. The central software which enabled the Augmented Reality component is the Vuforia Engine developed by PTC, which is the world's most widely deployed AR software. Furthermore, it became evident that the Unity Game Engine and Android Studio would be required. The multiplatform capabilities and native components of both would serve well for what would essentially become a mobile app featuring moving graphs and utilizing a device's onboard camera. Specifically, both engines are industry standard for developing augmented reality headset applications. The simulation development mimicked many design philosophies from video game design.

5.4.3.1.1 Unity

The Unity engine was released by Unity Technologies in Denmark in 2005, and it integrates a custom rendering engine with the NVidia PhysX engine and MonoDevelop, which is the open-source implementation of Microsoft's .NET frameworks (Richter, 2002). Several reasons lead to the decision to use the Unity engine for AR development over other counterparts. A few reasons being that the engine can reach the widest possible audience with multi-platform distribution, provide close collaboration with leading device manufacturers, and provide built-in AR support.

The Unity engine comes with a complete documentation with examples for its entire API. The documentation is possibly one of the biggest advantages that Unity has over its counterparts such as Unreal, which provide partial documentation to non-paying users. The Unity forums are highly diversified with conversational topics that are grouped into specific categories. A general discussion group could also be utilized if topics were not found within these specific forums. Importing files and packages into Unity is straight forward as the editor accepts not only the traditional way of receiving files from an external source, but also receives them by the user dragging and dropping, which makes the editor much more convenient to work with.

5.4.3.1.2 Android Studio

Android study was used to develop the non-AR tablet applications. Android is an open source and Linux-based Operating System for mobile devices such as smartphones and tablet computers (Fernandez et al., 2017). It was developed by the *Open Handset Alliance*, led by Google, and other companies. Android offers a unified approach to application development for mobile devices which means developers need only develop for Android, and their applications should be able to run on different devices powered by Android. Android Studio is the most common IDE that developers use to build android apps, and the typical languages used in building such projects are either Java or Kotlin. Java was used as the primary language and XML as the markup language.

5.4.3.1.3 Vuforia

Vuforia Engine is a software platform for creating Augmented Reality apps. Developers can easily add advanced computer vision functionality to any application, allowing it to recognize images and objects, and interact with spaces in the real world (Liu et al., 2018). Because Unity is one of the platforms that Vuforia supports, the study can utilize such a tool to conduct research and build an AR focused project that takes advantage of Unity's power. There have been studies that use Unity 3D modeling to create a three-dimensional model of the scene and to detect and track the totem functions of the Vuforia engine which can set animation and play video (Liu et al., 2018). Interactions between virtual buttons and virtual reality can also be created as virtual buttons.

5.4.3.1.4 Scripting

Scripting was initially done using .NET principles in Unity. The namespace in C# and Java known as System. Collections contains data structures such as queues, dictionaries, and array lists which can be utilized for simulating a grocery store. After the object-oriented centric creation of a food class with parameters pertaining to a food's farmer price, selling price, max quantities in-house and on the shelf, and identifying labels, a simulation script started the process of creating new food objects and allocating them to a dictionary with the corresponding quantities. Once this was complete, a queue is processed as the main driver of profit for the simulation. A MakeAction script was created which is built on switch statements that would represent user choices. A TimeController script would set the simulation in motion where a relative time was set to 0.16 seconds per in-game minute, leading to an ideal run time of 13.44 minutes if a user does not wait during the simulating. For graphical displays, the graphs need to be manually set up in Unity or Android Studio's interface. Data would then be captured to update the bars in the bar charts or segments in the pie charts. Along with other scripts not mentioned, the code would rely on this structure for the rest of the simulation. In the case of treatments developed in Android Studio, these coding principles were then translated into Java syntax.

5.4.3.2 Augmented Reality Devices/Scripting in Unity

The Unity Engine was used to power the AR applications as a versatile platform with capabilities of handling various applications such as video games, web, mobile, and AR applications. Unity can take in as many scenes, which are views that the player can make edits in, as the developer desires to build the project application. The engine also allows for 2D and 3D applications, by which the study uses the 2D aspect to build the User Interface (UI) and the 3D aspect to make the AR objects come to life. Developers can add custom functionality to different game objects in scenes by creating scripts that use C#, which is a simple, modern, object-oriented, and type-safe programming language that combines the high productivity of rapid application development languages with the raw power of C and C++. The language is also safer than C and C++ as it provides a built-in garbage collector that helps programmers better avoid memory leaks and provides more convenience for memory management in other aspects as well. One of the most popular and well-known features that Unity offers over its competing counterparts such as the Unreal Engine, is that all of its projects can be ported on several different third-party operating systems such as Android, iOS, tvOS, Xbox one, PlayStation 4, WebGL, and Facebook. Such a variety of options gives the study more flexibility and ability to reach out to more grocery store companies that may use at least one of the operating systems mentioned above.

5.4.3.3 Human Interface

Augmented reality allows the user to see the real-world background, but with additional markers attached to objects. The study recreated a grocery store, where participants were given real-time data with live information displayed to monitor performance. A tablet was given to participants to interact and monitor the store's inventory, purchasing and employees. Pie and bar charts are displayed on the dashboard to visually monitor data. The displays included information on inventory in back-of-house (BOH), front-of-house (FOH), revenue, cost, items in storage and number of employees traveling. A bar chart displays where each employee is in real time, allowing the user to better assess how many employees are needed.

The participant had the option to restock, make new deliveries, manage registers, call employees and release employees from the bottom of the screen. The interface included a system of buttons and hierarchy of possible decisions. To restock a product, it required one employee to shelve with inventory in BOH. In order to have inventory in BOH, deliveries must be made. The participant could choose to order any inventory item in a bulk of 25, 50, or 75 and select a delivery time. Goods can either arrive the next day for a standard fee, or in five hours for an expedited fee.

5.4.3.4 Dashboard/UI Programming

Dashboard designs were initially developed and reviewed for feasibility based on factors like screen size and engine capabilities. The dashboard programming was less complex in Android studio, as Android studio commonly supports app development involving metrics much like the graphical displays designed by the industrial engineering students. In Unity, there is no native graphing support, making it necessary to utilize the asset store to purchase a third-party asset with common-use licensing. Once this was done, the process became similar in both engines: a programmer would set up the graphs according to their requirements and then hook up the displays to the data structures passing food, money, or customers around in memory. Not only does this benefit the user, it also creates visual feedback for the programmer to study and debug backend code in action.

5.4.3.4.1 User Menu

The user menu was a simple flowchart button design, where one button might create user action in the simulation, such as “make a delivery.” This would be specified in the MakeAction script, and then proceed the following hierarchy containing details to further specify the quantity or type. This is much like the structure of a linked list (Rajeev & Sharma, 2019. There is a main node of the flowchart known as layer 1 from which all other nodes can be accessed. This menu was designed so that it can be easily accessed based on screen size. There are more options for such devices like voice commands but the best option is a scrollable menu or one that takes up large portions of a screen, to keep things consistent between treatments and not affect decision-making results based on input.

5.4.3.4.2 Image Targets

Image Targets in Augmented Reality are well-supported by the Vuforia Game Engine (Liu et al., 2018). Images that were used in the experiment were selected based on characteristics such as having enough detectable features that could be recognized by the Vuforia software consistently. An image would have to contrast against the other images that would also be used and would require complicated detail beyond just blocks of colors or abstract shapes. It was sufficient to use public domain images representing each department of the simulation: a collection of images comprising cereal boxes, dry beans, and nuts for the dry foods department, for example as shown in Figure 28 below.

Figure 28: Dry Goods Marker

These were then uploaded to the Vuforia database and exported to the Simulation project. Canvases containing parts of our graphical displays (separate pie charts, bar charts, and other simulation feedback) would then be set up so that they render upon image target detection. This method and image targets are effective for overlaying data in space, in reference to the intents and purposes of this project.

5.4.3.5 Generating Experiment Data for Analysis

To create experimental data that could be analyzed, backend development of the simulation would need to be coded to format the data to be compatible with the data analysis software. The study used a comma-separated values (CSV) plain text format, as it displays information in a table format and is a common file extension. The data was ordered in a text file using delimiters to shape into a csv format. This file could then be imported to a program capable of converting delimiters and txt files to csv like Microsoft Excel. Creating pivot charts, comparing columns and rows, or re-sorting data could then be completed by Microsoft Excel or similar software.

5.4.4 Experimental Procedure

The in-person experiment was conducted in a laboratory that held five markers corresponding to one of the store's departments – Dairy, Dry Goods, Frozen Goods, Produce and Registers. Each department was represented for both the experiments with and without AR. The experiment began with a student participant entering the lab, signing in and receiving their participant number. The student read an introductory PowerPoint presentation that introduced the experiment and explained the concepts and objectives. Next, the participant completed the pre-survey online with questions regarding perceived decision-making effectiveness and technology acceptance as listed in Appendix J. After the participant completed the survey, they would review and acknowledge a consent form. Once this process was complete, the experiment would then start. For 15 to 20 minutes the participant was engaged in the simulation and made decisions for the grocery store. Once the experiment was complete, the participant would complete the post-survey to answer similar questions from the pre-survey and receive compensation for participation.

The research experiment was conducted on the UCF campus during the COVID-19 pandemic. Researchers and participants both adhered to the appropriate standards as dictated by UCF and the UCF Standard Safety plan. When the research participant arrived to the lab, surfaces that were used as part of the experiment were sanitized witnessed by the participant. Personal Protective Equipment (PPE), such as mandatory face coverings, and physical distancing were in effect for all laboratory experiments conducted. The participant would be in the lab for approximately one hour.

5.5 Results

The results of the laboratory experiment are described in the following sections for both operational performance and perceived decision-making effectiveness. Statistical analysis was conducted in both Minitab and SPSS software depending on which analysis was needed. DOE analysis occurred in Minitab while survey analysis would be completed in SPSS. The survey analysis included exploratory factor analysis, construct validation, and pre/post testing of the survey responses.

5.5.1 Pilot Testing

Pilot testing was conducted on the UCF campus. A total of eight pilot testers were used to run through the experiment prior to formal experimentation. All of the pilot students were active UCF Industrial Engineering graduate students. Two students were assigned to each treatment. These pilot students gave valuable feedback on both the user interface of the simulation and the method on how the data is retrieved after the simulation was complete. They also helped refine the process through the different steps in the experimentation process. Some of the feedback that was implemented from the pilot testing included having the participant run through a practice day before they begin the formal experimentation. Other feedback included revising the wording of the survey questions so that they would make more sense to someone not as familiar with the experiment and spelling out any acronyms that were not already introduced to the participant.

5.5.2 Demographics

A total of 42 experiments were conducted, however 10 were un-useable due to the participant not being a business major or for running an experiment that had an error. The error was fixed immediately by the computer science students and the experiment runs were repeated to reconcile the run order. A total of 32 observations were used in this between-subjects study. All students that participated were active UCF Business School undergraduates. Further, the results showed that 16 participants were female (50%), 13 participants were male (41%), and 3 students did not provide their gender (9%) providing a relatively balanced sample. Figure 29 below shows a graph of the different business majors that participated in the study.

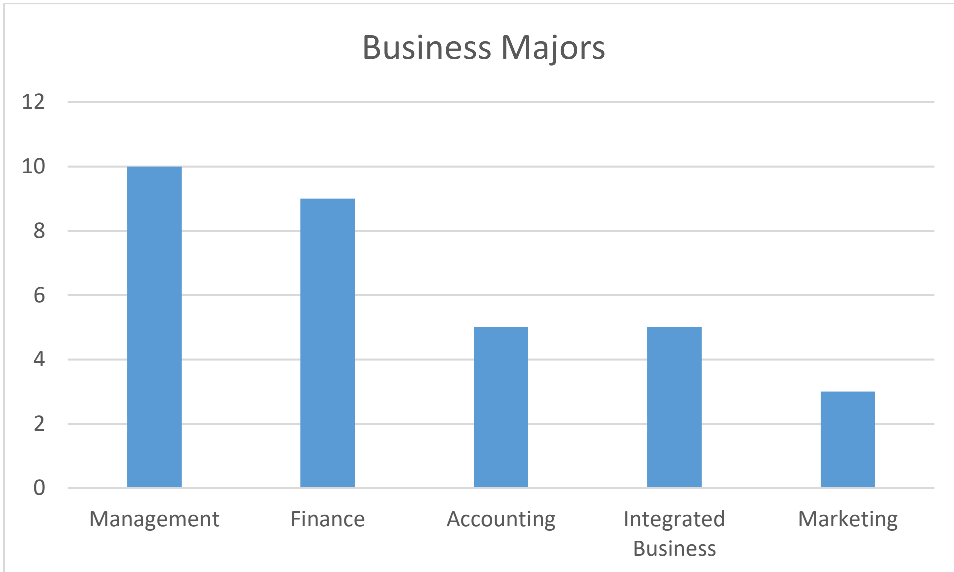

Figure 29: Business Majors

Business students were directly recruited since they have the most management related classes in their curriculum. Management was the most popular major with 10 students followed by finance major with 9 students. Sophomores (10%), Juniors (34%), and Seniors (47%) were all represented in the study; 2 participants did not indicate their major. Student ages ranged from 19 to 24, which is a common range of ages for undergraduate students. This sample frame provided the data needed to conduct the experiment as the intended college major for this study was business students, which was the major for all of the participants that were included in this analysis. ANOVAs were used to test if there were key differences among participants on survey responses or profit scores. The results indicated that the 32 observations came from a single sample.

5.5.3 Validation of Existing Constructs

Survey analysis is being conducted to validate adopted constructs. The results from the post survey were analyzed using SPSS statistical software. First, Cronbach's alpha was identified for the Perceived Usefulness construct. This construct already existed and the results were tested to see if it also fit the model in this experiment. This determines if the construct is valid for this study as well as indicating that the study produced reliable results. Table 13 displays Cronbach's alpha, which displays all values >.9 which indicates reliability in the survey data.

Table 13: Perceived Usefulness Cronbach's Alpha

Reliability Statistics

Cronbach's Alpha	N of Items
.953	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PUQ2	28.9688	45.902	.908	.938
PUQ5	28.8438	48.136	.869	.943
PUQ3	29.0000	44.968	.903	.939
PUQ4	29.0938	44.862	.893	.940
PUQ6	28.5938	49.733	.777	.953
PUQ1	28.4688	51.805	.795	.952

Table 14 shows a similar table, but with the results for the Perceived Ease of Use construct. This also validates a pre-existing construct with all Cronbach's Alpha values greater than .86 indicating consistency and reliability in the survey data collected. This indicates that both constructs adopted from the TAM were also validated for this study.

Table 14: Perceived Ease of Use Cronbach's Alpha

Reliability Statistics

Cronbach's Alpha	N of Items
.900	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PEQ10	31.2188	18.757	.787	.882
PEQ7	30.8125	24.996	.647	.895
PEQ8	31.1250	20.694	.836	.865
PEQ9	30.6875	24.544	.652	.894
PEQ11	30.9375	21.351	.797	.872
PEQ12	30.6875	24.931	.786	.883

5.5.4 Construct Refinement

Exploratory Factor Analysis (EFA) was conducted using the survey results. Specific model specifications for the EFA included using principal axis factoring with direct oblimin rotation. Table 15 shows initial EFA results. The determinant is .043, non-zero, which indicates a factor analysis can be completed. The Kaiser-Meyer-Olkin (KMO) test result is at .775 which is above the .6 threshold. Bartlett's test is also significant at .000 (Williams et al., 2010).

Table 15: Perceived Decision-Making Effectiveness EFA Model Fit

Correlation Matrix[a]

a. Determinant = .043

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.775
Bartlett's Test of Sphericity	Approx. Chi-Square	88.880
	df	15
	Sig.	.000

Next, the communalities were evaluated to determine the proportion of each variable's variance that can be explained by the factors in the model. Often communality values of less than .20 are eliminated from the analysis (Yong & Pearce, 2013) Communalities are shown in Table 16 below. DMQ17 is very low at .047 which is less than .20 which supports removing this question from the survey set.

Table 16: Communalities

Communalities

	Initial
DMQ34	.763
DMQ15	.612
DMQ17	.047
DMQ13	.512
DMQ14	.754
DMQ33	.418

Extraction Method: Principal Axis Factoring.

Total Variance Explained is shown in Table 17 below. This helps determine the number of significant factors to be included in the construct development. Hair et al. (1995) suggest extracted factors to should explain at least 50-60% of the variance. Factor 1 accounts for approximately 57% of the variance in the model which meets this criterion.

Table 17: Total Variance Explained

Total Variance Explained

	Initial Eigenvalues		
Factor	Total	% of Variance	Cumulative %
1	3.420	56.993	56.993
2	1.011	16.844	73.837
3	.665	11.091	84.928
4	.503	8.381	93.309
5	.259	4.324	97.633
6	.142	2.367	100.000

Extraction Method: Principal Axis Factoring.

Visually, the scree plot in Figure 30 below also suggests that all survey questions load to one factor as Factor 1 is the factor with an eigenvalue clearly above one. Since factor 2 has an eigenvalue of 1.011, a two-factor model was also tested, but was not able to converge to two factors even with adjusting the parameters to force the data to fit to more than one factor.

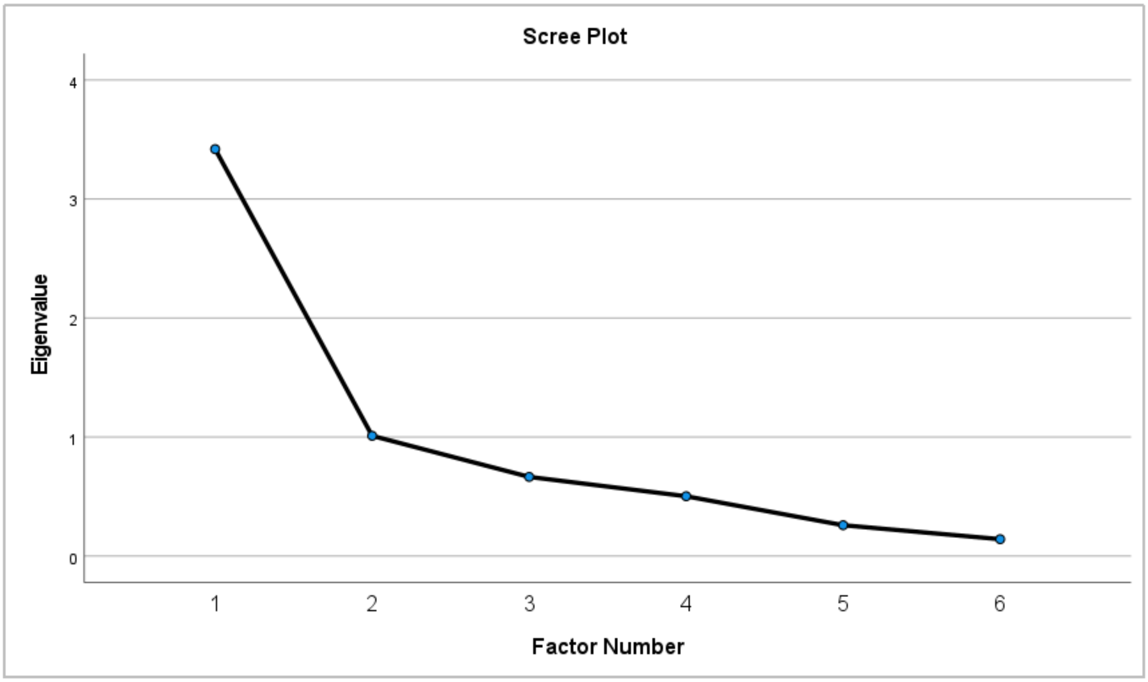

Figure 30: Scree Plot

Using these survey results confirms that DMQ17 should be removed from this survey set. DMQ17 stated "I trusted my intuition more than data when making decisions." Table 18 lists the final perceived decision-making effective items included in the survey set. Minitab and SPSS output files are located in Appendix H.

Table 18: Final Perceived Decision-Making Effectiveness Construct

Item	Description
1	This [tablet/tool] helped me maximize profit.
2	This [tablet/tool] helped me understand if I was making good decisions.
3	This [tablet/tool] helped me make decisions faster.
4	This [tablet/tool] helped me to achieve my goal(s).
5	This [tablet/tool] helped me use resources more effectively.

Dimensions of perceived decision-making effectiveness was developed as part of an Expert Study (Chapter 4). These dimensions were used to create a perceived decision-making effectiveness construct and evaluated using the survey data from this lab experiment. The initial reliability results for the decision-making construct are shown in Table 19 below.

Table 19: Decision-Making Initial Cronbach's Alpha

Reliability Statistics

Cronbach's Alpha	N of Items
.766	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
DMQ34	26.9375	28.512	.747	.661
DMQ15	26.4375	31.996	.693	.687
DMQ17	28.1875	44.286	-.064	.883
DMQ13	26.3438	33.136	.590	.712
DMQ14	26.5000	29.548	.805	.653
DMQ33	26.2188	34.757	.535	.727

Initially Cronbach's alpha was .766 using the 6 items on the scale. The table shows that Cronbach's alpha can be increased to .833 if question "DMQ17" is removed. Once removed, and the analysis re-ran, Table 20 confirms that Cronbach's Alpha is .833 with a 5-item survey.

Table 20: Decision-Making Cronbach's Alpha with Item Removed

Reliability Statistics

Cronbach's Alpha	N of Items
.883	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
DMQ34	23.0000	25.871	.815	.834
DMQ15	22.5000	29.935	.715	.858
DMQ13	22.4063	30.443	.650	.873
DMQ14	22.5625	27.415	.839	.828
DMQ33	22.2813	32.209	.584	.886

5.5.5 Operational Performance Design of Experiments (DOE)

Experimentation was used to gather empirical data that could be statistically analyzed once all of the results had been collected to determine what combination of variables had the largest impact on perceived decision-making effectiveness. After all of the results were collected and processed, 32 observations were determined to be useable for the study.

Table 21 below displays the descriptive statistics for this set of data. This data had an average end score of $10943 with a standard deviation of $2262. The sample size is low with 32 observations

Table 21: Descriptive Statistics

Variable	N	N*	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3	Maximum
End Score	32	0	10943	400	2262	4825	9700	11111	12898	14695

This study tested at a standard 95% statistical significance level. The first DOE model of the operational performance outcome variable shown in Table 22. This model used the participant's end score as the response variable. The model fit index indicates that the model fits well and is valid with a p-value of less than .05 suggesting a statistically significant difference between treatment means. The model terms Real-Time, Augmented Reality, and the interaction between the two also have p-values less than .05 meaning that there is statistically significant difference in treatment means.

Table 22: Operational Performance ANOVA

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Model	3	71761445	45.26%	71761445	23920482	7.72	0.001
Linear	2	49576152	31.27%	49576152	24788076	8.00	0.002
Real-Time	1	32615936	20.57%	32615936	32615936	10.52	0.003
Aug Reality	1	16960216	10.70%	16960216	16960216	5.47	0.027
2-Way Interactions	1	22185293	13.99%	22185293	22185293	7.16	0.012
Real-Time*Aug Reality	1	22185293	13.99%	22185293	22185293	7.16	0.012
Error	28	86802205	54.74%	86802205	3100079		
Total	31	158563650	100.00%				

Figure 23 below shows the Model Summary. R^2 for the model is at 45.26%. This R^2 value is relatively low with the model only explaining 45.26% of the variance. Adjusted $R^{2\text{ has}}$ even lower percentage at 39.39% which would consider the impact from any additional independent variables. Predicted R^2 is at 28.5% which gives an indication of how well the model would predict new observations. Increasing the sample size of the study will help increase the R^2 values.

Table 23: Model Summary

Model Summary

S	R-sq	R-sq(adj)	PRESS	R-sq(pred)	AICc	BIC
1760.70	45.26%	39.39%	113374309	28.50%	577.15	582.17

Table 24 below shows the coded coefficients for the study which shows size and direction of the relationship between the model term and the response variable. This table indicates that having real-time data had the largest positive effect on the end score.

Table 24: Coded Coefficients

Coded Coefficients

Term	Effect	Coef	SE Coef	95% CI	T-Value	P-Value	VIF
Constant		10943	311	(10306, 11581)	35.16	0.000	
Real-Time	2019	1010	311	(372, 1647)	3.24	0.003	1.00
Aug Reality	-1456	-728	311	(-1366, -90)	-2.34	0.027	1.00
Real-Time*Aug Reality	1665	833	311	(195, 1470)	2.68	0.012	1.00

On average, the end score increases by $2019 if the participant was using Real-time data. If the participant were to use just use Augmented Reality, the participant's end score is expected to decrease by $1456 on average. The interaction between the two terms is expected to increase the end score by $1665. By using this model, there is 95% confidence that the end score is between $10306 and $11581. These main effects are also shown graphically in Figure 31. A "1" on the bottom axis indicates that the measured condition is present and a "-1" indicates the condition is not present.

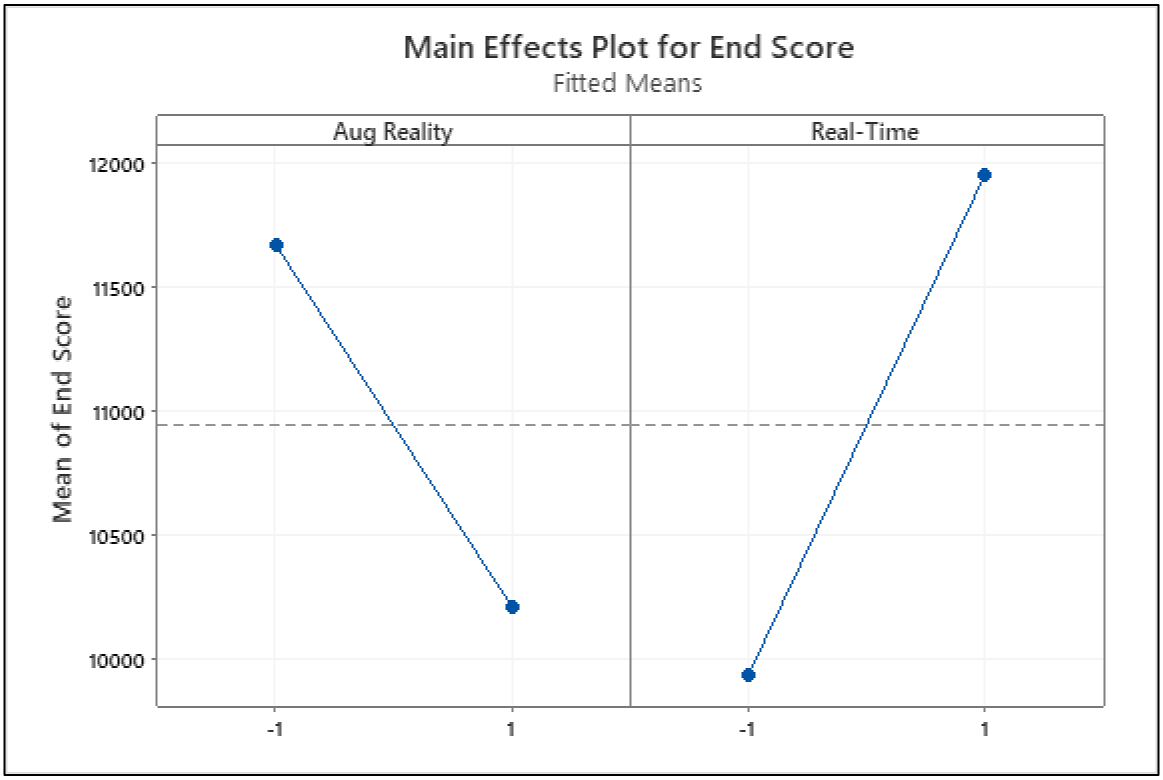

Figure 31: Coded Coefficients

The associated regression model is summarized below:

$$End\ Score\ = 10{,}943\ + 1{,}010(RealTime) - 728(Aug\ Reality)\ + 833(RealTime * Aug\ Reality)$$

This regression model is created based off of the coded coefficients described earlier and combines them into one equation. The end score can be predicted using this equation based on the treatment combination.

Figure 32 below shows the interaction plot for the End Score. This chart shows that even though even though real-time data had the largest effect on end score, the combination of real-time data and Augmented Reality results in the highest average end score. Implementing real-time data positively affects operational performance, but adding AR to assist in decision making has an even larger impact.

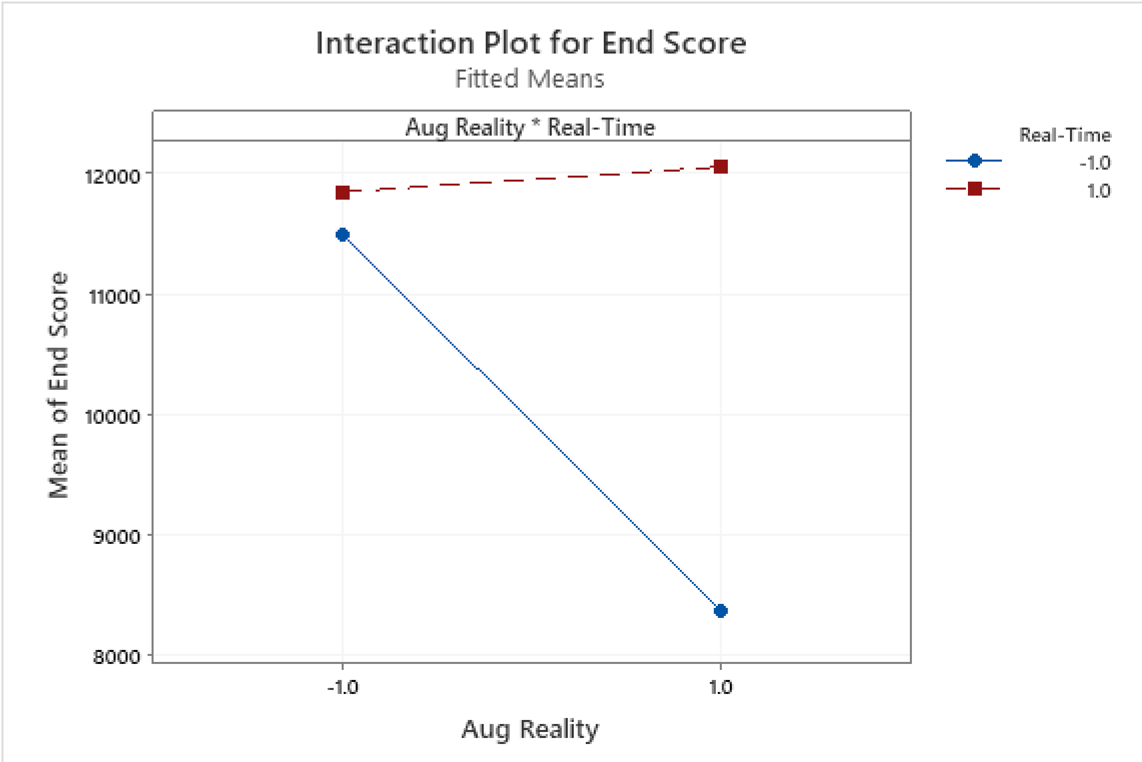

Figure 32: Interaction Plot for End Score

Figure 33 below shows the data's histogram under a normal curve. The data is slightly skewed to the left, but follows a roughly normal curve. Further tests were completed to test for normality.

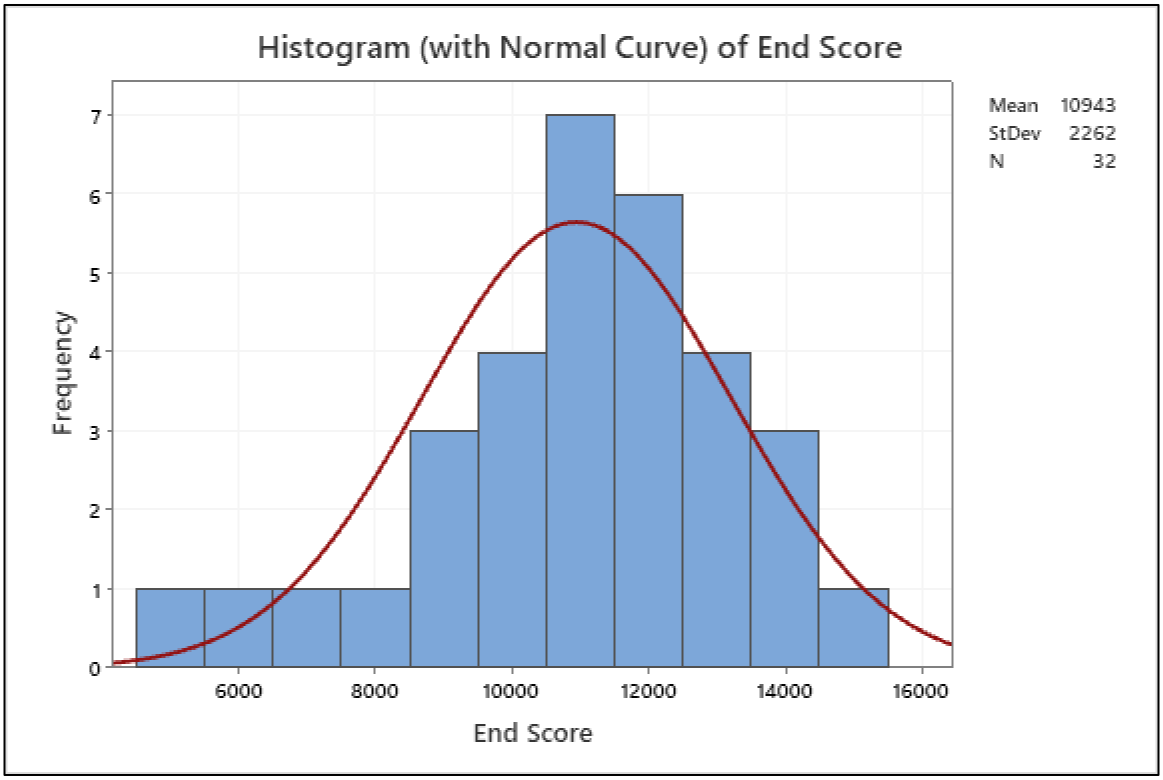

Figure 33: Normality Curve

Figure 34 below shows the residual plots for the end score. The graphs are not clear if the normality assumption is satisfied, however no pattern exists among the residuals plotted in the graph.

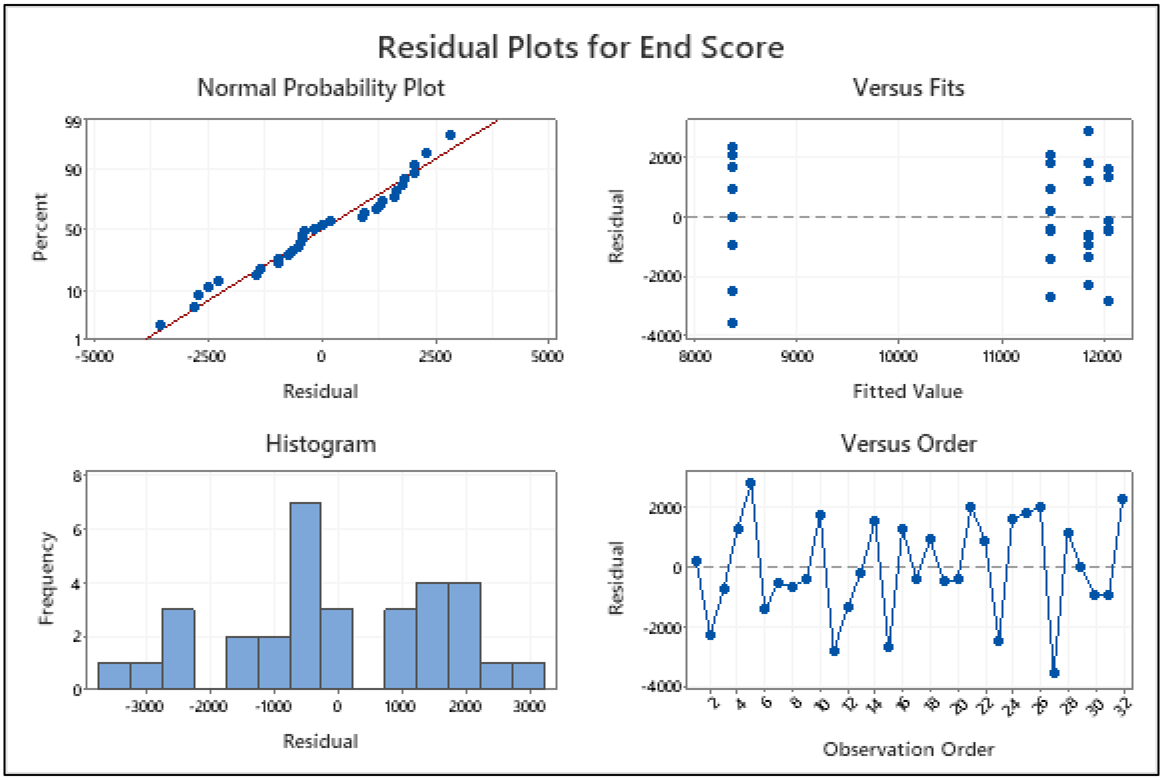

Figure 34: Residual Plots

A formal Ryan-Joiner (RJ) test for normality was conducted and the results are shown in Figure 35. The RJ score is .973 which is close to 1 indicating the data is likely to be normal. The p-value is > .100 which fails to reject the null hypothesis which stated that the data do follow a normal distribution. It can be concluded that the study's data sufficiently follows a normal distribution.

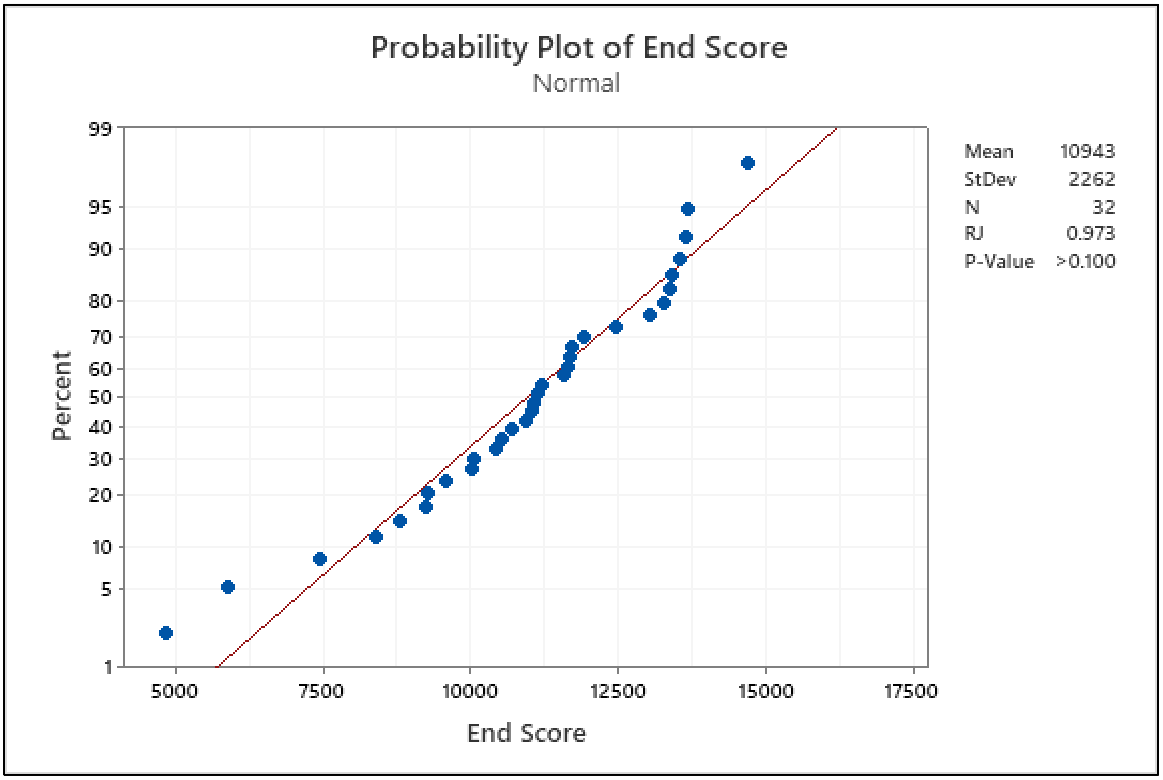

Figure 35: RJ Normality Test

Originally, a study with 32 samples and an effect size and standard deviation of 500 would result in a power of .779. Even though all p-values were recorded to be <.05 and suggests statistical significance between the different treatments, statistical power was calculated post-hoc. Since a standard deviation of 2262 is higher than the estimated standard deviation of 500, a post-hoc power calculation results in a statistical power of .092. Lenth (2007) states that once a study has completed, power calculations do not give any added value to interpretation of the study. Levine and Epsom (2001) and Thomas (1997) recommend using confidence intervals to determine if the effects are statistically consistent with the data. The effect value is calculated as twice the size of the coefficient value, and the confidence interval for the coefficient does not contain zero, it can be stated there is 95% confidence that the difference between treatments is not due to chance, but due to the design of the experiment. Table 2 shows the values of the confidence intervals, which no confidence interval contains the value zero. All p-values for the model, separate factors, and the interaction between the factors are <.05 which suggest statistical significance of the model.

5.5.5 Perceived Decision-Making Effectiveness Design of Experiments (DOE)

The second DOE model focused on using the survey data for analysis by leveraging the perceived decision-making effectiveness construct as the response variable. Every participant completed the same set of surveys regardless of what treatment they were assigned. Table 25 below displays the descriptive statistics for this set of data. This data had an average value of 5.638 with a standard deviation of 1.331. The sample size is low with 32 observations.

Table 25: Descriptive Statistics

Variable	N	N*	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3	Maximum
DM Avg	32	0	5.638	0.235	1.331	3.000	4.550	6.100	6.800	7.000

The survey data was then analyzed in Minitab to check for statistical significance between the treatment groups. Table 26 below shows the ANOVA summary of the data. Since all of the reported p-values are very high, the null hypothesis is failed to reject indicating that means between the treatment groups are not statistically significant from each other. There is no evidence to suggest a difference exists in survey responses based on what treatment was conducted.

Table 26: Perceived Decision-Making Effectiveness Construct ANOVA

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Model	3	0.4050	0.74%	0.4050	0.13500	0.07	0.976
Linear	2	0.2250	0.41%	0.2250	0.11250	0.06	0.944
Aug Reality	1	0.0450	0.08%	0.0450	0.04500	0.02	0.880
Real-Time	1	0.1800	0.33%	0.1800	0.18000	0.09	0.763
2-Way Interactions	1	0.1800	0.33%	0.1800	0.18000	0.09	0.763
Aug Reality*Real-Time	1	0.1800	0.33%	0.1800	0.18000	0.09	0.763
Error	28	54.5100	99.26%	54.5100	1.94679		
Total	31	54.9150	100.00%				

A Box-Cox transformation was needed adjust model to ensure that the residuals were normally distributed. Figure 36 below shows the transformed data's histogram under a normal curve. There are possible deviations from normality as it is not clear from the graph if the data are normal. Further tests were completed to test for normality.

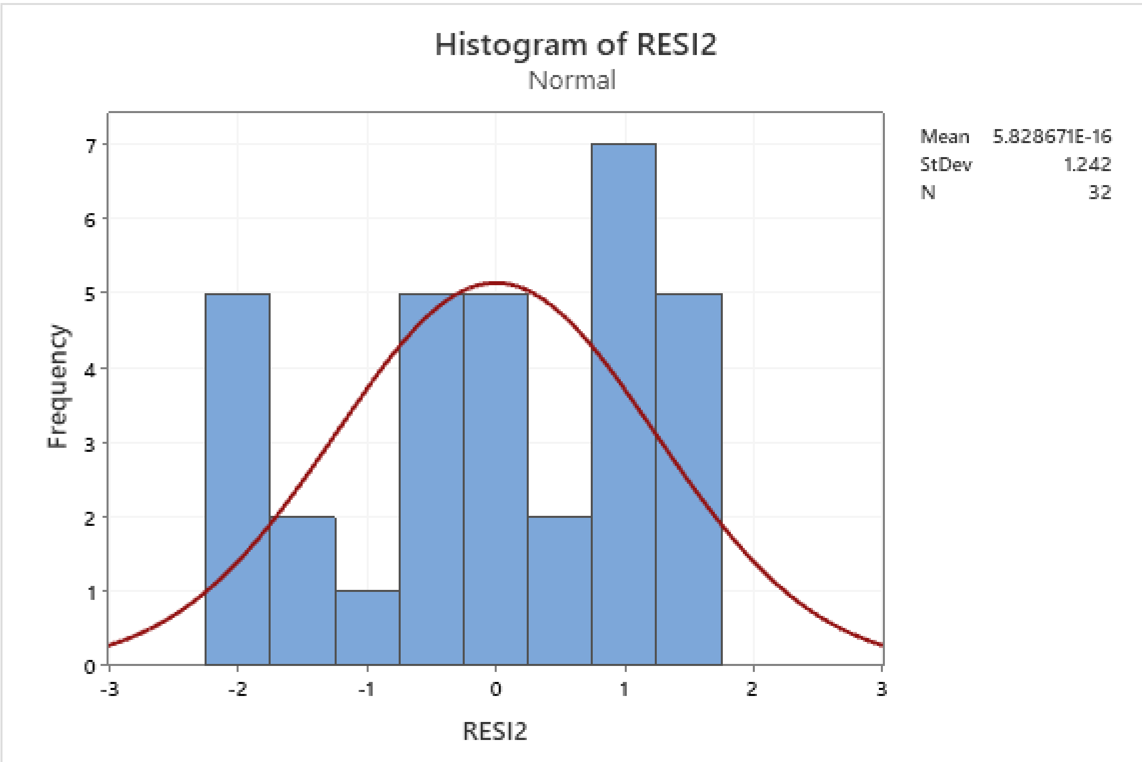

Figure 36: Normality Curve

Figure 37 below shows the residual plots for the transformed survey scores. The graphs are not clear if the normality assumption is satisfied, however no pattern appears to exist among the residuals plotted in the graph. The residuals for the normality plot appear to have a small deviation. A more formal normality test was conducted.

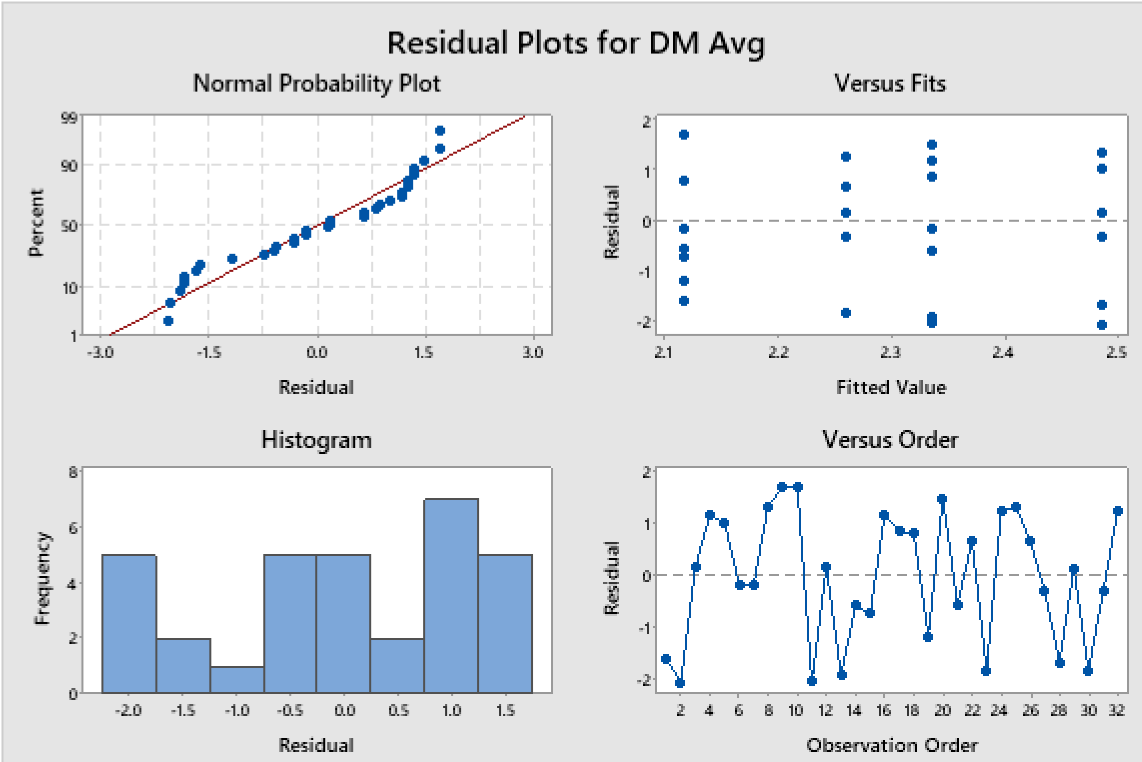

Figure 37: Residual Plots

A formal Ryan-Joiner (RJ) test for normality was conducted and the results are shown in Figure 38. The RJ score is .968 which is close to 1 indicating the data is likely to be normal. The p-value is > .05 which fails to reject the null hypothesis which stated that the data do follow a normal distribution. It can be concluded that the study's data sufficiently follows a normal distribution.

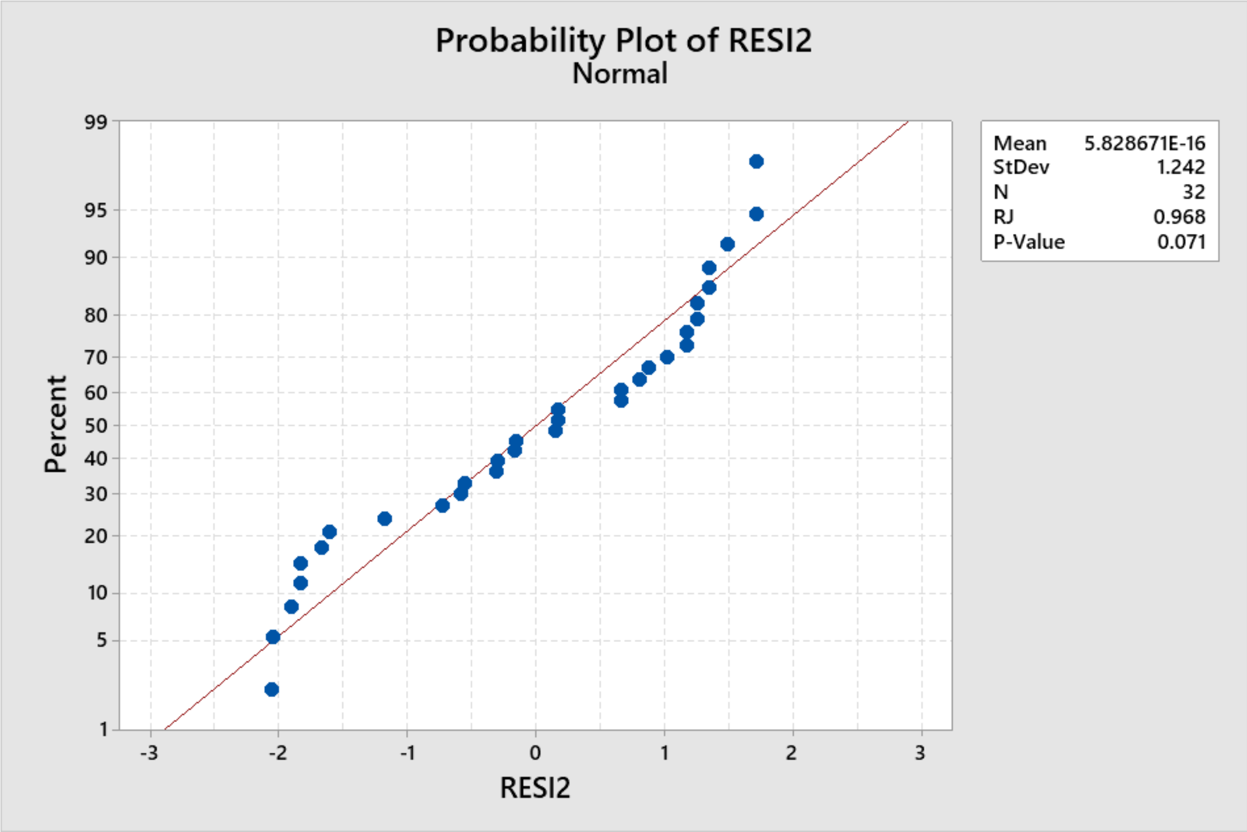

Figure 38: RJ Normality Test

5.5.6 Pre/Post Survey Analysis

A paired t-test was conducted to check the differences between participant's responses in the pre/post surveys for the perceived decision-making effectiveness construct. The pre-survey mean for the decision-making construct was 5.125 and the post-survey mean was 5.638 indicating the tool may have helped increase perceived decision-making effectiveness. The p-value for this test is .049 which gives statistical significance to this test. These results provide evidence that suggests that participants scored the survey higher once they completed their experimental run. Participants may have scored the survey higher because they had a positive experience using the device as part of this experiment.

5.6 Discussion and Conclusions

A laboratory experiment was executed that resulted in 32 observations across 4 different simulation treatments. The study consisted of pre/post surveys along with conducting an experiment to compare results between different treatments of a simulation. This study helped investigated the research question of if managerial decision-making can be assessed and measured. This study has further evaluated the dimensions of perceived decision-making effectiveness (Chapter 4) and results of the data analysis suggests that this construct should be revised from a six-item construct to a five-item construct.

This experiment also helped answer if an AR dashboard could be developed to accurately report operational performance in real-time. This AR dashboard tool was developed and empirically tested against other dashboards with DOE analysis. The lab study results also suggest this could be a useful tool in real-time environments. This study also researched if an AR dashboard improves real-time decision making and found that objective performance was improved but effects on perceived decision-making effectiveness were not significant.

This experiment suggests that using Real-time data leads to better decision making. The combination of the using Real-time data with an Augmented Reality assisted tool can also further improve decision-making effectiveness. The results of this study have implications for research and practice as these results suggest that technology assisted managers perform better.

5.6.1 Limitations

Limitations of this study include using UCF undergraduate business students as experiment participants. Business students were chosen purposely as it was thought they were best positioned to understand the simulation from a management and supply chain perspective. Since this study was conducted during the COVID-19 pandemic and most classes were held virtually, recruiting students for in-person participation was challenging, even after increasing the participation incentive to $20.

Limitations of this study also include that this experiment had a relatively small sample size. Rigorous DOE analysis was completed to maximize potential value of the sample. Using business school students also helped to mitigate a small sample size by helping to ensure all observations came from the same sample population. A controlled and familiar environment was used in this study to simulate a real environment. Future work should focus on a field study to validate the results of this experiment. Since students were directly recruited for this study the participant age range is 19-24, which may not be reflective of the working professional age range. This is a common limitation when using students for this type of research. Individuals of this age range may also have a technology bias compared to an older population. Technology bias was not included as part of this study.

5.6.2 Future Work

Future work includes extending the study to also include hands-free AR wearables. This study focused on first piloting AR use on a tablet, but would benefit from replicating the study with a sleek, non-obtrusive headset. As the AR hardware continues to improve, the easier it will be for research participants to use an AR wearable as part of this study. Future work may also include using different AR software applications to replicate or extend the experiment. The AR technology for this experiment was developed using Unity and Vuforia, but there are several other software packages that support AR development (Sanii, 2019; Schreiber et al., 2019). A replication of the study may also compare end scores between different types of AR software that's developed. Extensions of this study could also open the sample to include other majors and see what effect major has on the simulation's end scores.

Additionally, future work includes expanding the sample size of this study for stronger statistical power. The study would also benefit from replicating the experiment with actual managers or in a field experiment that would include a real environment instead of a simulated environment. Since this study focused on a between-subject design, a within-subject design could further test key relationships in a lab experiment to further explore perceived decision-making effectiveness.

Further exploring or replicating the perceived decision-making effectiveness construct among different treatments in a lab experiment also needs to be conducted. Technology bias was not included in this study, but may help understand why students scored perceived decision-making effectiveness with similar values across treatments. Students may have also scored the survey similarly as they only experienced one type of treatment, and did not understand what the other treatment capabilities were. Additional future work may include significantly higher samples sizes to see if there are differences between the groups at a higher sample size.

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CHAPTER SIX: DISCUSSION & CONCLUSIONS

The purpose of this work was to investigate the application of Augmented Reality (AR) technology to operational performance measurement (OPM) to improve real-time decision-making and management practice. This work is multi-phased with each phase holding a distinct purpose and is grounded in a thorough literature review, expert experience, and empirical investigation. Although there are many practical applications of AR, the results of the bibliometric analysis of the publications identified by the systematic literature review (SLR) suggests that using OPM with a novel technology such as Augmented Reality is an emerging area of research with many opportunities for future developments (Chapter 3). Existing studies have shown that using AR for procedural tasks, "X-ray" vision, and as a general visual aid have been beneficial in practice (Gao et al., 2019; Liebert 2016; Petruse, 2014; Raghavan et al., 1999; Yuan et al., 2008). However, using AR for more complex tasks, such as managerial or supervisorial tasks, is lacking.

The SLR identified gaps in the research pertaining to using advanced technology with operations management applications (Chapter 3). Using the results of the SLR triggered a need to research more about the current challenges in both Augmented Reality implementation and the challenges experienced in OPM. There is some evidence of using AR for managerial level tasks such as construction site management and production floor monitoring (Matthews et al., 2015; Segovia et al., 2015; Wang et al., 2020; Zollman et al., 2014), but this is an emerging research area providing many opportunities for research contributions.

The gap identified in the SLR triggered additional research to investigate applications for performance measurement and management that utilize higher-order metrics and whether they support linking real-time data directly to the device that displays the metrics. If a device connected to real-time data could be used to help make managerial decision-making more effective, it could help improve overall operational effectiveness and sustainability. Few studies incorporated the use of AR as an assistive tool in such an application. An expert study was conducted to help identify industrial applications and identify challenges or factors associated with adopting such advanced technologies. An initial challenge was identifying experts that had backgrounds in both operations management and Augmented Reality. Since few experts were known in this relatively new research area, the study included samples from both OPM and AR.

The Expert Study consisted of a series of interviews and surveys to collect qualitative data based on expert experiences, which was inductively synthesized to investigate common themes and unique perspectives. Many challenges were identified in both research areas as well as benefits associated with implementation of technology. Some challenges of AR adoption include connectivity of data to the device as well as getting the constituents to see the value of implementation. This interoperability challenge has also been found to be common in the literature (Baresi et al., 2015; Oyekoya et al., 2013). Another common challenge identified was use of a head-wearable device which is consistent with recent research (Dey et al., 2018; Nee et al., 2012). The results of the expert study also identified 6 factors associated with effective managerial decision-making. Many of the OPM experts described successful decision making as timely and data driven and that decisions need to be aligned with the company's operational and strategic goals. The ability to make decisions quickly is a necessary factor for many managers. Jarrett & Schaar (2020) describe timely decision making as having an ongoing, active strategy as well as the ability to make decisions under pressure. The resulting dimensions of decision-making effectiveness include big picture/goal alignment, data-driven decisions, improvement in results, timely decisions, achievement of goals, efficient use of resources, and sometimes the need to follow intuition over data.

The results of the expert study promoted research involving a laboratory experiment to determine if technology-assisted OPM could result in more effective decision making. A decision-making construct was developed using the results of the expert study that was then be validated as part of the experiment. The lab study was based on a Design of Experiments (DOE) methodology (Montgomery, 2013) in which two, two-level factors were evaluated in two 2^2 full factorial experiments. This model consisted of four different treatments with separate simulations for each condition set (summarized below), which were all implemented on a commercially available tablet device.

- Real-time data supported by AR technology
- Historical data supported by AR technology
- Real-time data not supported by AR technology
- Historical data not supported by AR technology

The study resulted in 32 samples (8 replicates for each treatment) which were analyzed using Minitab statistical software. This study tested at a standard 95% statistical significance level in which Real-Time, Augmented Reality, and the interaction between the two variables resulted in p-values less than .05 resulting in statistically significant difference in means between the different groups in the operational performance DOE model (as measured by the end-of-week profit in the simulation). Results from the perceived decision-making effectiveness DOE model suggest that perceptions of decision-making effectiveness were not significantly different between treatments in this study. The interaction of Real-time data with Augmented Reality had the largest effect on operational performance, which resulted in the largest average end score of the simulation. Other studies have found benefits of using AR with real-time data as well. One study paired and AR-assisted tool that was linked to real-time data to help employees tend to machines more effectively (Liu et al., 2017). Another study uses this technology pairing to create digital twins for smart manufacturing which is used to help perform more efficient decision-making (Zhu et al., 2019).

Survey results were also analyzed to understand the impact of the experiment results. For the adopted constructs perceived usefulness and perceived ease of use, reliability analysis was used to evaluate the suitability of the constructs to this study using Cronbach's alpha. These constructs were validated and were found to be reliable. An exploratory factor analysis (EFA) was then conducted on the perceived decision-making effectiveness construct developed from the expert study results. All six survey items of the EFA loaded to one factor which suggested that all survey items load to one construct. The results suggested that there was a weaker relationship with the item related to use if intuition suggesting that it may need to be removed from the construct. Reliability analysis supported revising the construct from a 6-item scale to a 5-item scale where all survey items had a Cronbach's alpha greater than 0.80. The results of the laboratory experiment support that utilizing an AR assisted device with real-time data improves operational performance. Results from the perceived decision-making effectiveness DOE model suggest that decision making effectiveness was not directly affected between treatments in this study. A paired t-test was conducted to check the differences between participant's responses in the pre/post surveys for the decision-making construct and found that the differences in scoring was statistically significant. The experiment also validated a 5-item survey construct for perceived decision-making effectiveness that can be used that can be used to measure the effectiveness of decisions made by mangers in real-time operational environments.

One finding that was unexpected is that there was not a statistically significant difference found between average survey responses regarding perceived decision-making effectiveness across treatments. This may suggest that when the survey was completed, the participant answered in way that would preference the technology regardless of what simulation treatment they had completed in the experiment. The participant was also not exposed to the other treatment options; a within-treatments approach that allows participants to interact with all four treatments may provide further insights. Average responses in all four treatments suggested a positive association of using the device and the ability to make effective decisions.

6.1 Discussion of Results across Sub-Studies

The SLR results supported an expert study which identified many challenges in the application of Augmented Reality and managerial functions as well as themes regarding decision-making effectiveness. These themes from the expert study were consistent with the SLR findings that this research area is still not well developed and there is opportunity to make an impact in this specific area. Decision-making effectiveness dimensions from the OPM experts were used to develop a construct for decision-making effectiveness that was tested and validated in the lab experiment. The lab experiment supported that access to real-time data had a significant effect on performance. Real-time data as its own variable had the largest effect on the end score across all treatment options. Combining AR as an assisted device with access to real-time data resulted in the highest simulation scores. A review of the literature did not identify a measure for managerial decision-making effectiveness. The experts also did not currently use or were aware of a related measure.

All three sub-studies supported AR as being a useful tool when implemented properly. The SLR showed evidence of this in the publications that were captured using the search strategy. When experts were informed of AR and its potential applications, they responded positively to its implementation affirming that this type of application could support the organization's goals and be integrated with other systems. In the lab experiment, the treatment that paired AR use with real-time data saw the largest average score across the operational performance DOE model. This result is consistent with the recent literature finding that using AR with real-time data results in process improvements (Liu et al., 2017; Zhu et al., 2019). Based on the results from the SLR and expert study, it was expected that an AR-assisted device would aid in the decision-making process. This was validated as part of the operational performance DOE model studied in the lab experiment in which performance improvements were found when the AR tool was used. Having access to real-time data without an AR-assisted device was also validated in the experiment which was a common challenge mentioned by both the experts and identified in the SLR (Chapter 3, Chapter 4). Additional research is needed to continue supporting AR assistance with operational performance measurement. This research area is still in the early stages and could benefit from additional studies or experiment replication and extension.

6.2 Contributions to Research and Practice

This research provides a new perspective on accessing information to assist real-time decision-making by creating immersive performance environments. Since research in this application area is still in the early stages, there is potential for new knowledge contribution as well as practical applications that can be used immediately in industry. The SLR identified gaps in the research that the Expert Study and lab experiment were able to contribute new knowledge to. A construct for decision-making was developed from the Expert Study and evaluated and refined by the lab experiment. The lab experiment validated that an AR-assisted tool that provides real-time data and metrics is more effective than traditional methods.

6.2.1 Implications for Research

This research supports operational performance measurement by providing a tool to make decision-making support systems more effective. It will be used as a new approach to explore such systems and operations management. The results of this research can also be used when determining what factors to include in a new study when evaluating the effectiveness of implementing a new tool. This research has set the stage for follow-on work to continue refining tools that can make OPM-related work more effective.

As the SLR indicated, there are examples of AR being used for managerial related activities in quality assurance, construction, and manufacturing but it is limited and less common (Kim et al., 2013; Novak-Marcincin et al., 2014; Segovia et al., 2015). The SLR identified areas of future research to guide development in this area. The Expert Study helped to identify progress and challenges to close this development gap. Many of the experts shared valuable insight into common themes of challenges and progresses is this area. The expert study also identified key features that need to be considered in research such as incorporating Artificial Intelligence (AI). The lab experiment provides a proof-of-concept tool to support future lab and field experiments. The existing constructs of TAM were validated as well as the newly developed construct of perceived decision-making effectiveness, which can be evaluated in future studies to quantify management effectiveness.

6.2.2 Implications for Practice

Supervisors and managers will find this research useful as there are currently methods to obtain metrics real time, but they may not be as available or convenient to view where the actual work is occurring. Supervisors in real-time environments may especially find the results useful if they need to continuously walk the production floor as part of their leadership technique in order to gain essential information on how well their team is performing. Augmented Reality will add a visual aid for management to use when reviewing the performance of what is being measured. The decision-making construct can be used in industry for pre/post surveys when evaluating the implementation of a new technology tool.

Practitioners can also use this research to benchmark the current state of the industry and apply any of the findings of this study directly to their field of work. Many of the applications for AR and especially those associated with higher-level tasks are still emerging and this research provides detail into the current state of the literature. The SLR showed an early stage of research so practitioners should be cautious of rushing into adoption. There is a strong potential for benefits, but key challenges may make adoption risky. The expert study surveyed many people across different industries and backgrounds and many of the results were insightful on what common challenges are in industry as well as where others have made progress.

6.3 Study Limitations

Limitations of this study include limitations associated with conducting SLRs; however, a robust search strategy was used to minimize its effect on the study. The search strategy included using three different search databases that included a wide range of applications and disciplines. Search concepts and associated search terms were developed, revised, and expanded to capture as many publications in this research area as possible. While the search was comprehensive, they may only represent a portion of all the available publications in the literature. Expanding the databases used or including additional search terms may help identify additional publications to include in the study.

Known limitations of this expert study include those related to the development of survey questionnaires and use of thematic analysis. To mitigate this, surveys were reviewed by experts in a pilot study for content and structure prior to releasing the formal study. Many iterations of both manual and automatic coding were conducted to help remove any bias in the inductive synthesis. Another limitation in this study is recruitment of participants for the Expert study. The sample size of the expert study met the required minimum; however, a larger group of experts may have produced broader results.

A limitation associated with the laboratory experiment of this study includes using UCF undergraduate business students as laboratory experiment participants. Another limitation of lab studies is that they are isolated and do not represent the actual environment. To address this, a real-time operational environment of a grocery store was simulated with an adequate sample size. Business students were chosen for the sample frame as they have a background in management in supply chain. Since the experiment study was conducted during the COVID-19 pandemic and most UCF classes were held virtually, recruiting students for participation was challenging even with increasing the participation incentive to $20. Many strategies were used to help encourage participation such as building a rapport with students and requesting they share the students with their business friends and business groups. It is estimated that more than half of the students signed up through a referral from a friend. Several UCF business professors were contacted to post the announcement in their classes. Recruitment flyers were printed and spread out in the business college buildings frequently during the sign-up period, but not many students occupied the buildings. If the study were offered as extra credit towards the end of a semester, that may also encourage additional participation. Even with increasing the monetary incentive, referrals from participants, and all of the recruiting efforts, the sample size for this study was still low. Statistical significance was still shown with the smaller sample size, but the study could benefit from a larger sample size.

6.4 Conclusions & Future Research

There is evidence that there has been progress in using Augmented Reality for performance measurement applications (Chapter 3). As shown throughout this review, Augmented Reality has numerous uses in various fields. As this is an emerging field exploring the latest technology, there is new research that is occurring with many different uses. There is research that supports AR being used successfully for simple tasks such as visualization, X-ray vision, and showing steps in a process (Gao et al., 2019; Mura et al., 2016; Raghavan et al., 1999; Sielhorst, Feuerstein, & Navab, 2008; Yuan, Ong, & Nee, 2008;). However, applications for more complex work tasks are limited. The amount of research that specifically pertains to using Augmented Reality as a management tool, specifically in the area of performance measurement and management is limited and not yet well-developed.

Results from the expert study provided factors that affect the successful implementation of AR technologies in organization (Chapter 4). This study recruited experts in both OPM and AR to better understand the progress and challenges associated with adopting this technology. As part of this study, 23 experts across OPM and AR disciplines were interviewed. Each of the interviews were transcribed and included in the thematic analysis. Thematic analysis resulted in identifying different themes across both disciplines. Many experts shared that their organization does not have an effective way to measure successful decision-making. Some experts shared common themes of aligning to the organizational goals or objectives that can aid in effective OPM. Others identified challenges such as adopting head-wearable AR devices and integrating systems together for successful dashboard implementation. Data connectivity remains a current challenge in industry today. These themes across the interviews were used to help develop a construct in decision-making. A construct for decision-making effectiveness was refined and recommended for future evaluation.

The expert study provided many insights that were directly applied to the laboratory study design. One popular insight that can was used for this development is the need for real-time data. Practitioners do not want to base their decisions on past data (Curry et al., 2019). Access to real-time data is a common challenge, but many AR devices have the capability to incorporate real-time data for AR applications (Garon et al., 2016). Merging the ability to access data in real-time with Augmented Reality use has the potential for added process improvements and gaining efficiencies.

A laboratory experiment was executed that resulted in 32 observations across 4 different simulation treatments. The study consisted of pre/post surveys along with conducting an experiment to compare results between different treatments of a simulation. This study has further evaluated a Decision-Making construct (Chapter 4) and the data analysis from this study suggests that the construct should be revised from a six-item construct to a five-item construct.

Using Real-time data leads to better decision making (Chapter 5). The combination of the using Real-time data with Augmented Reality can also further improve decision-making effectiveness as seen in the results of the lab experiment. This has implications for research and practice as these results suggest that technology assisted managers perform better. It is concluded that a procedurally generated AR dashboard that was evaluated as part of the lab experiment accurately reports operational performance in real-time and improves real-time decision making.

All five research questions were answered in the study. This study investigated the extent AR has been applied for management tasks related to operational performance and found that applications in operations management are emerging and developing with very few examples of operational performance measurement. Next, the study identified many factors from both the literature and experts which affect the successful adoption of AR technologies in organizations. These factors will continue to guide future work.

This studied researched if managerial decision-making can be assessed and measured and found OPM expert insights revealed six dimensions of perceived decision-making effectiveness. A construct was developed and refined during the expert study and laboratory experiment. The expert study and experiment also helped answer if an AR dashboard could be developed to accurately report operational performance in real-time. Expert feedback and empirical lab study results suggest this could be a useful tool in real-time environments. Lastly, this study wanted to research if an AR dashboard improves real-time decision making and found that objective performance was improved but effects on perceived decision-making effectiveness were not significant.

To further this study, ongoing research in performance measurement systems using Augmented Reality needs to be conducted. Future work includes extending the study to also include hands-free AR wearables. This study focused on using AR on a tablet, but would benefit from replicating the study with a sleek, non-obtrusive headset. As the AR hardware continues to improve, the easier it will be for research participants to use an AR wearable as part of this study. AR wearables can be especially valuable when having a hands-free approach is needed. This study could also benefit from replicating the study using a smart phone instead of a tablet. A smart phone could be even more convenient to carry around and would not require the purchase of another device to be able to utilize the AR application. Being able to fit the needed information of the dashboard to a smaller screen may become more challenging when applying this technology to a smart phone. However, the benefits of ease and convenience that a smart phone exhibits justifies the need to further explore this application.

Future work should also include continued efforts to validate the construct for perceived decision-making effectiveness across additional settings along with its role in technology acceptance. This could be explored through additional studies with students or investigated in industrial settings that have access to real-time operational data. An industrial setting where managers or supervisors are constantly struggling with many challenges encountered during their day could benefit from this type of empirical study.

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APPENDIX A: IMPORTANT INFORMATION ABOUT COVID-19 AND RESEARCH PARTICIPATION

UCF	**Important Information about COVID-19 and Research Participation**

At the University of Central Florida our primary responsibility related to research is to protect the safety of our research participants.

COVID-19 refers to the Coronavirus that is being spread across people in our communities. We need to provide you with important information about COVID-19, and to tell you about ways your study participation might change because of COVID-19 related risk.

If you are considering joining a study at this time or are currently enrolled in a study, <u>it is important that you consider the following information to determine if study participation is right for you at this time</u>.

How is COVID-19 spread? COVID-19 is a respiratory virus spread by respiratory droplets, mainly from person-to-person. This can happen between people who are in close contact with one another (less than 6 feet). It is also possible that a person can get COVID-19 by touching a surface or object (such as a doorknob or counter surface) that has the virus on it, then touching their mouth, nose or eyes.

Can COVID-19 be prevented? Current ways to minimize the risk of exposure to COVID-19 include "social distancing" which is a practice to decrease the potential for direct exposure to others who may have been exposed to COVID-19, for example by avoiding large gatherings or refraining from shaking hands with others. <u>It is important to understand that since study participation may include increased travel outside of your home and increased exposure to others within a research site it may increase your exposure to COVID-19.</u> Currently, there is no vaccination to prevent COVID-19 infection.

What are the risks of COVID-19? For most people, the new coronavirus causes only mild or moderate symptoms, such as fever and cough. For some, especially older adults and people with existing health problems, it can cause more severe illness, including pneumonia. While we are still learning about this virus, the information we have right now suggests that about 3 out of every 100 people who are infected might die from the virus.

Who is most at risk?

- Persons over 65 years of age
- Persons with chronic lung disease or moderate to severe asthma
- Persons with diabetes
- Persons with serious heart conditions
- Persons with severe obesity (body mass index of 40 or higher)
- Persons with liver disease
- Persons with chronic kidney disease undergoing dialysis
- Immunocompromised individuals (cancer treatment, bone marrow/organ recipients, those with chronic immunodeficiencies, poorly controlled HIV or AIDS, prolonged use of corticosteroids and other immune weakening medications)

How could your participation in this research change as a result of COVID-19? There are several ways we try to minimize your risk. If possible, we limit the number of times you have to come to a research site. We will ask every research participant if they have the symptoms of COVID-19 or have been in close contact with anyone who has or had COVID-19 using the following questions:

Health Screening Questions:

1. **IN THE PAST 24 HOURS**, have you had any of the following symptoms? **YES NO**
   - Fever
   - Cough
   - Sore throat
   - Shortness of Breath
   - Loss of smell or taste
   - Chills or repeated shaking with chills
   - Muscle fatigue
   - Headache
   - Nausea, vomiting, or diarrhea
   - Congestion or runny nose

   If "**YES**", **DO NOT participate in this study.**

2. Have you **TRAVELED INTERNATIONALLY** in the past 14 days? **YES NO**

   If "**YES**", **DO NOT participate in this study.**

3. Have you **TRAVELED DOMESTICALLY (U.S)** to areas of high COVID-19 prevalence (e.g., New York City, south Florida, etc.) in the past 14 days? **YES NO**

   If "**YES**", **DO NOT participate in this study.**

4. Have you had **CLOSE PERSONAL CONTACT** with anyone who has been diagnosed with COVID-19 in the past 14 days (per criteria below)? **YES NO**

   a. Within 6 feet for prolonged period of time
   b. In direct contact with infectious secretions (been coughed/sneezed upon, etc.)

   If "**YES**", **DO NOT participate in this study.**

During your research visits, we try to reduce the time you are exposed to other people as much as possible. You will be asked to wear a cloth face covering upon arrival to the research location and during most, if not all, of the research procedures. Please let the study team know if you need a face covering provided to you or if you can bring your own. Your study team will review the Informed Consent Form with you and discuss if there are any study procedures during which you will be asked to briefly remove the covering or use a different type of face covering.

If you are suspected to be positive for COVID-19, there may be last minute changes to how research procedures are performed [such as a change from an in-person visit to a telephone call] or cancellations of research tests or procedures to ensure your safety. It is even possible that your research procedures will be put on hold or stopped because of COVID-19.

The information related to risks of COVID-19 changes every day. The leaders at UCF are monitoring these risks and deciding how these risks should change our research. If you have questions about COVID-19 and your participation in research, please talk to your study team.

You will find a hotline to use to report any concerns you have with this study related to COVID-19 here.

Please contact the principal investigator of this study if you develop symptoms of COVID-19 or test positive within two weeks of your study participation.

Adapted with permission from the Johns Hopkins University.

APPENDIX B: COVID-19 HUMAN SUBJECT RESEARCH (HSR) STANDARD SAFETY PLAN

UCF	**COVID-19 Human Subject Research (HSR) Standard Safety Plan**

Instructions

This plan can be used to conduct in-person HSR if you can follow all elements of this plan:

- **New studies:** reference this plan in your study protocol and wait for IRB approval.
- **Existing studies wishing to resume in-person research**: add a comment to your study dashboard to indicate that you are restarting research following this plan.

If you are NOT able to follow all elements of this plan, develop a COVID-19 Human Subject Research (HSR) Study-Specific Safety Plan that includes the safety steps you will take and also how you will address the elements below that you are not able to follow.

Plan Contents

- **Before Subject Arrival**
  - When scheduling appointments for human subjects, instruct subjects to call ahead and discuss with them the need to reschedule their appointment if they develop fever or symptoms of COVID-19 on the day they are scheduled to be seen.
  - Advise human subjects, as well as anyone accompanying the human subject, of all procedures concerning their visit and that they all must wear cloth face coverings before entering the facility. Ask the participant if he or she will need a face covering provided or if they will bring their own.
  - Advise subject of the location of parking lot to be used and the entry point to the building that they will use. For research locations other than UCF facilities, provide adequate directions for the subjects to arrive at the location.
  - Provide a copy of "Important Information about COVID-19 and Research Participation" to the research subjects. This information contains a list of medical conditions that increase the risk for developing serious COVID-19 illness so that they can decide whether to participate.
  - Advise the subjects of the check-in and screening procedures to be used:
    - The day before the visit, contact the subject to conduct a verbal health screening over the phone. You do not need to document the specific answers, only that the screening took place.

Health Screening Questions for Participants:

1. **IN THE PAST 24 HOURS**, have you had any of the following symptoms? **YES NO**
   - Fever
   - Cough
   - Sore throat

- Shortness of Breath
- Loss of smell or taste
- Chills or repeated shaking with chills
- Muscle fatigue
- Headache
- Nausea, vomiting, or diarrhea
- Congestion or runny nose

If "**YES**", **DO NOT participate in this study.**

2. Have you **TRAVELED INTERNATIONALLY** in the past 14 days? **YES NO**

If "**YES**", **DO NOT participate in this study.**

3. Have you **TRAVELED DOMESTICALLY (U.S)** to areas of high COVID-19 prevalence (e.g., New York City, South Florida, etc.) in the past 14 days? **YES NO**

If "**YES**", **DO NOT participate in this study.**

4. Have you had **CLOSE PERSONAL CONTACT** with anyone who has been diagnosed with COVID-19 in the past 14 days (per criteria below)? **YES NO**

a. Within 6 feet for prolonged period of time
b. In direct contact with infectious secretions (been coughed/sneezed upon, etc.)

Upon Subject Arrival and During the Visit

- Limit and monitor points of entry to the facility.
- Advise subjects and visitors entering the facility to put on a cloth face covering or facemask before entering the building and await screening for fever and symptoms of COVID-19.
- Maintain 6 ft separation between all individuals associated with the HSR activities at all times.
  - Maintain 10 ft separation between all individuals associated with HSR activities that involve physical exertion.
- Sanitize all touch points and research-related equipment before and after use following CDC guidelines.
- Do not ask subjects to ingest food, liquids, medications, supplements, etc.
- Take steps to ensure everyone adheres to respiratory hygiene and cough etiquette, hand hygiene, and all human subjects and visitors follow the procedures throughout the duration of the visit.
  - Post visual alerts (e.g., signs, posters) at the entrance and in strategic places (e.g., waiting areas, elevators, cafeterias) to provide instructions (in appropriate languages) about hand hygiene, respiratory hygiene, and cough etiquette.

Instructions should include wearing a cloth face covering or facemask for source control, and how and when to perform hand hygiene.

    - Provide supplies for respiratory hygiene and cough etiquette, including alcohol-based hand rub (ABHR) containing 60-95% alcohol, tissues, and no-touch receptacles for disposal, at facility entrances, waiting rooms, and human subject check-ins.
    - Consider establishing screening stations outside the facility to screen individuals before they enter.
        - Ensure that, at the time of subject check-in, all visitors and subjects are asked about the presence of fever, symptoms of COVID-19, or contact with patients with possible COVID-19.
        - Refuse access to individuals with symptoms of COVID-19 and advise they contact their health care provider for advice and follow-up care.
  - Review local, state, and national public health agencies advisories and incorporate questions about new onset of COVID-19 symptoms into daily screening as they become identified by the public health officials.

- **Additional Strategies to Minimize Chances for Exposure:**
  - Implement alternatives to face-to-face visits.
  - Consider suspending group activities (e.g., group therapy or other group activities) until circumstances permit.
  - Justify the need for in-person focus groups (why not remote?)
  - Postpone all non-essential activities until circumstances permit

APPENDIX C: INSTITUTIONAL REVIEW BOARD (IRB) APPROVAL DOCUMENTS

UNIVERSITY OF CENTRAL FLORIDA

Institutional Review Board
FWA00000351
IRB00001138, IRB00012110
Office of Research
12201 Research Parkway
Orlando, FL 32826-3246

APPROVAL

April 3, 2020

Dear Joshua Nelson:

On 4/3/2020, the IRB reviewed the following submission:

Type of Review:	Initial Study
Title:	Leveraging Augmented Reality for Real-Time Operational Performance Management
Investigator:	Joshua Nelson
IRB ID:	STUDY00001615
Funding:	None
Grant ID:	None
IND, IDE, or HDE:	None
Documents Reviewed:	• Experiment Brief.pdf, Category: Debriefing Form; • Flyer_ Recruitment_jmn.docx, Category: Recruitment Materials; • irb_HRP-502-CONSENT_DOCUMENT_Adult_Joshua Nelson.pdf, Category: Consent Form; • irb_HRP-503-Protocol_ Joshua Nelson.docx, Category: IRB Protocol; • Post Survey.pdf, Category: Survey / Questionnaire; • Pre-Survey.pdf, Category: Survey / Questionnaire; • Video Brief PPT.pdf, Category: Debriefing Form;

The IRB approved the protocol from 4/3/2020. Due to current COVID-19 restrictions, in-person research is not permitted to begin until you receive further correspondence from the Office of Research stating that the restrictions have been lifted.

In conducting this protocol, you are required to follow the requirements listed in the Investigator Manual (HRP-103), which can be found by navigating to the IRB Library within the IRB system. Guidance on submitting Modifications and a Continuing Review or Administrative Check-in are detailed in the manual. When you have completed your research, please submit a Study Closure request so that IRB records will be accurate.

If you have any questions, please contact the UCF IRB at 407-823-2901 or irb@ucf.edu.
Please include your project title and IRB number in all correspondence with this office.

Sincerely,

Adrienne Showman
Designated Reviewer

UCF

UNIVERSITY OF CENTRAL FLORIDA

Institutional Review Board
FWA00000351
IRB00001138
Office of Research
12201 Research Parkway
Orlando, FL 32826-3246

EXEMPTION DETERMINATION

October 11, 2019

Dear Joshua Nelson:

On 10/11/2019, the IRB determined the following submission to be human subjects research that is exempt from regulation:

Type of Review:	Initial Study, Exempt Category
Title:	Leveraging Augmented Reality for Real-Time Operational Performance Management
Investigator:	Joshua Nelson
IRB ID:	STUDY00000750
Funding:	None
Grant ID:	None

This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made, and there are questions about whether these changes affect the exempt status of the human research, please contact the IRB. When you have completed your research, please submit a Study Closure request so that IRB records will be accurate.

If you have any questions, please contact the UCF IRB at 407-823-2901 or irb@ucf.edu. Please include your project title and IRB number in all correspondence with this office.

Sincerely,

Adrienne Showman
Designated Reviewer

APPENDIX D: INSTITUTIONAL REVIEW BOARD (IRB) CLOSURE DOCUMENTS

Institutional Review Board
FWA00000351
IRB00001138
Office of Research
12201 Research Parkway
Orlando, FL 32826-3246

UNIVERSITY OF CENTRAL FLORIDA

CLOSURE

October 23, 2020

Dear Joshua Nelson:

On 10/23/2020, the IRB reviewed the following protocol:

Type of Review:	Continuing Review
Title:	Leveraging Augmented Reality for Real-Time Operational Performance Management
Investigator:	Joshua Nelson
IRB ID:	CR00000804
Funding:	None
Grant ID:	None
IND, IDE, or HDE:	None

The IRB acknowledges your request for closure of the protocol effective as of 10/23/2020. As part of this action:

- The protocol is permanently closed to enrollment.
- All subjects have completed all protocol-related interventions.
- Collection of private identifiable information is completed.
- Analysis of private identifiable information is completed.

If you have any questions, please contact the UCF IRB at 407-823-2901 or irb@ucf.edu. Please include your project title and IRB number in all correspondence with this office.

Sincerely,

Renea Carver
Designated Reviewer

Institutional Review Board
FWA00000351
IRB00001138
Office of Research
12201 Research Parkway
Orlando, FL 32826-3246

UNIVERSITY OF CENTRAL FLORIDA

CLOSURE

October 23, 2020

Dear Joshua Nelson:

On 10/23/2020, the IRB reviewed the following protocol:

Type of Review:	Continuing Review
Title:	Leveraging Augmented Reality for Real-Time Operational Performance Management
Investigator:	Joshua Nelson
IRB ID:	CR00000805
Funding:	None
Grant ID:	None
IND, IDE, or HDE:	None

The IRB acknowledges your request for closure of the protocol effective as of 10/23/2020. As part of this action:

- The protocol is permanently closed to enrollment.
- All subjects have completed all protocol-related interventions.
- Collection of private identifiable information is completed.
- Analysis of private identifiable information is completed.

If you have any questions, please contact the UCF IRB at 407-823-2901 or irb@ucf.edu. Please include your project title and IRB number in all correspondence with this office.

Sincerely,

Renea Carver

Renea Carver
Designated Reviewer

UNIVERSITY OF CENTRAL FLORIDA

Institutional Review Board
FWA00000351
IRB00001138
Office of Research
12201 Research Parkway
Orlando, FL 32826-3246

CLOSURE

October 23, 2020

Dear Joshua Nelson:

On 10/23/2020, the IRB reviewed the following protocol:

Type of Review:	Continuing Review
Title:	Leveraging Augmented Reality for Real-Time Operational Performance Management
Investigator:	Joshua Nelson
IRB ID:	CR00000806
Funding:	None
Grant ID:	None
IND, IDE, or HDE:	None

The IRB acknowledges your request for closure of the protocol effective as of 10/23/2020. As part of this action:

- The protocol is permanently closed to enrollment.
- All subjects have completed all protocol-related interventions.
- Collection of private identifiable information is completed.
- Analysis of private identifiable information is completed.

If you have any questions, please contact the UCF IRB at 407-823-2901 or irb@ucf.edu. Please include your project title and IRB number in all correspondence with this office.

Sincerely,

Renea Carver

Renea Carver
Designated Reviewer

APPENDIX E: EXPERT STUDY SURVEY QUESTIONS AND INTERVIEW PROTOCOL

[INTERVIEW PROTOCOL 1]

Participant ID: [ID NUMBER]

Greeting:

Thank you for agreeing to participate in this study; I really appreciate your time and contribution to my doctoral research.

As you know, you have been invited to participate in an interview that will take about twenty to thirty minutes to complete. Does that still work for you?

Okay, I am planning to use an audio recorder to record our conversation today to make sure that I get everything. We are planning to transcribe these recordings in the next few weeks and then delete the audio files and work with the anonymized data. Are you okay with me using the audio recorder during this interview?

That's great, thank you. As you know, the purpose of this study is to investigate expert experiences with technology-assisted operational performance management (OPM) as well as to evaluate a potential tool to support real-time OPM. This interview consists of a few questions to gain more information about your experiences and perspectives regarding these issues. It is important to note that we are interested in your professional experience and there are no right or wrong answers to any of the following questions.

Do you have any questions before we get started?

Interview Questions:

1. Please briefly describe your current and previous experience in the area of operational performance management.
2. What OPM frameworks or approaches have you used in the last five years (e.g., customized scorecard, etc.)?
3. What technologies have you used to support your OPM activities?
4. What barriers or challenges have you experienced when using these technologies?
5. On the other hand, what supported the use of these technologies?
6. In your experience, does use of technology lead to more effective OPM?
7. How would you describe effective decision-making in OPM?
8. What measures or assessment procedures have you used to evaluate decision-making effectiveness?
9. In your experience, what are the most significant challenges for effective OPM?

[Demonstration of AR Assisted OPM TBD]

10. What is your initial impression of this concept?
11. What do you think would be the benefits of implementing this system?
12. What potential challenges do you think would be faced during implementation?

Closing Remarks:

That is all of the questions that I have for you today. Do you have any other comments or feedback?

Okay, thank you again for contributing to this study. Please be sure to contact me if you have any other questions or concerns.

[INTERVIEW PROTOCOL 2]

Participant ID: [ID NUMBER]

Greeting:

Thank you for agreeing to participate in this study; I really appreciate your time and contribution to my doctoral research.

As you know, you have been invited to participate in an interview that will take about twenty to thirty minutes to complete. Does that still work for you?

Okay, I am planning to use an audio recorder to record our conversation today to make sure that I get everything. We are planning to transcribe these recordings in the next few weeks and then delete the audio files and work with the anonymized data. Are you okay with me using the audio recorder during this interview?

That's great, thank you. As you know, the purpose of this study is to investigate expert experiences with augmented and virtual reality application in operational and strategic management as well as to evaluate a potential tool to support real-time OPM. This interview consists of a few questions to gain more information about your experiences and perspectives regarding these issues. It is important to note that we are interested in your professional experience and there are no right or wrong answers to any of the following questions.

Do you have any questions before we get started?

Interview Questions:

1. Please briefly describe your current and previous experience in the area of augmented and virtual reality.
2. In your experience, what are the barriers or challenges to AR/VR application in these areas?
3. On the other hand, what supports the use of these technologies?

[Demonstration of AR Assisted OPM TBD]

4. Please briefly describe any AR/VR applications for operational or strategic management that you are aware of. For example, AR applications in project management are being used to show physical representations of project steps to improve accuracy and reduce human errors.
5. What do you think would be the benefits of implementing this system?
6. What potential challenges do you think would be faced during implementation?
7. Do you have anything else to add?
8. Is there something you think the system should have, but you haven't seen?

Closing Remarks:

That is all of the questions that I have for you today. Do you have any other comments or feedback?

Okay, thank you again for contributing to this study. Please be sure to contact me if you have any other questions or concerns.

APPENDIX F: EXPERT STUDY RECRUITMENT MATERIALS

Expert Study Protocol 1 (Performance Experts)

[STUDY INFORMATION SHEET]

Leveraging Augmented Reality for Real-Time Operational Performance Management

Technologies such as artificial intelligence, machine learning, and augmented reality were once considered novelties. However, recent advances have led to the emergence of a variety of practical applications across all industries. This trend is also reflected in management science, which has seen the development of tools that support operational and strategic activities such as project management as well as complex work tasks such as enhanced visualization and motor skills. **The purpose of this study is** to investigate the potential use of augmented reality technologies to improve operational performance management (OPM) as part of a doctoral study being conducted at the University of Central Florida. OPM is critical to organizational health and sustainability and improving best practices will support professionals in more effectively managing and improving operations.

This study is seeking academic and industry experts who have experience with OPM to participate in an online survey that takes approximately 20-30 minutes to complete. This survey will focus on experiences with technology-assisted OPM and perceptions of a potential tool. Approximately 30-40 surveys or interviews will be conducted and the results will provide valuable insights for the next phases of this doctoral study. All study results will be strictly confidential and only anonymized, aggregate results will be used for the analysis and dissemination ensuring that no individual participants are identifiable.

Study Participation
You have been identified as a potential participant in this expert study and whether you take part is up to you. Your email was obtained through your membership in [PROFESSIONAL SOCIETY]. If you would like to participate or if you have questions, concerns, or complaints please contact the principal investigator, Joshua Nelson, or his faculty advisor, Dr. Heather Keathley, at the contact information below.

Joshua Nelson	Heather Keathley, Ph.D.
Ph.D. Student	Assistant Professor, Academic Advisor
Industrial Engineering & Management Systems	Industrial Engineering & Management Systems
University of Central Florida	University of Central Florida
Phone: 407-409-6636	Phone: 407-823-4745
Email: JoshuaNelson@knights.ucf.edu	Email: Heather.Keathley@ucf.edu

IRB contact about your rights in the study or to report a complaint: Research at the University of Central Florida involving human participants is carried out under the oversight of the Institutional Review Board (UCF IRB). This research has been determined to be exempted from IRB review unless changes are made. For information about the rights of people who take part in research, please contact: Institutional Review Board, University of Central Florida, Office of Research & Commercialization, 12201 Research Parkway, Suite 501, Orlando, FL 32826-3246 or by telephone at (407) 823-2901.

Expert Study Protocol 2 (Augmented Reality Experts)

[STUDY INFORMATION SHEET]

Leveraging Augmented Reality for Real-Time Operational Performance Management

Technologies such as artificial intelligence, machine learning, and augmented reality were once considered novelties. However, recent advances have led to the emergence of a variety of practical applications across all industries. This trend is also reflected in management science, which has seen the development of tools that support operational and strategic activities such as project management as well as complex work tasks such as enhanced visualization and motor skills. **The purpose of this study is** to investigate the potential use of augmented reality technologies to improve operational performance management (OPM) as part of a doctoral study being conducted at the University of Central Florida. OPM is critical to organizational health and sustainability and improving best practices will support professionals in more effectively managing and improving operations.

This study is seeking academic and industry experts who have experience with augmented and virtual reality technologies to participate in an online survey that takes approximately 20-30 minutes to complete. This survey will focus on experiences with augmented and virtual reality application in operational and strategic management and perceptions of a potential tool. Approximately 30-40 interviews or surveys will be conducted and the results will provide valuable insights for the next phases of this doctoral study. All study results will be strictly confidential and only anonymized, aggregate results will be used for the analysis and dissemination ensuring that no individual participants are identifiable.

Study Participation

You have been identified as a potential participant in this expert study and whether you take part is up to you. Your email was obtained through your membership in [PROFESSIONAL SOCIETY]. If you would like to participate or if you have questions, concerns, or complaints please contact the principal investigator, Joshua Nelson, or his faculty advisor, Dr. Heather Keathley, at the contact information below.

Joshua Nelson	Heather Keathley, Ph.D.
Ph.D. Student	Assistant Professor, Academic Advisor
Industrial Engineering & Management Systems	Industrial Engineering & Management Systems
University of Central Florida	University of Central Florida
Phone: 407-409-6636	Phone: 407-823-4745
Email: JoshuaNelson@knights.ucf.edu	Email: Heather.Keathley@ucf.edu

IRB contact about your rights in the study or to report a complaint: Research at the University of Central Florida involving human participants is carried out under the oversight of the Institutional Review Board (UCF IRB). This research has been determined to be exempted from IRB review unless changes are made. For information about the rights of people who take part in research, please contact:

Institutional Review Board, University of Central Florida, Office of Research & Commercialization, 12201 Research Parkway, Suite 501, Orlando, FL 32826-3246 or by telephone at (407) 823-2901.

[INVITATION EMAIL (OPM)]

Subject:

Invitation: Expert Study on Leveraging Augmented Reality for Real-Time Operational Performance Management

Body:

Dear [NAME],

You are invited to participate in an expert study focused on Leveraging Augmented Reality for Real-Time Operational Performance Management as part of a doctoral study being conducted at the University of Central Florida. You were identified as a potential expert due to your previously published work in this area. Your email was obtained through your membership in [PROFESSIONAL SOCIETY].

The purpose of this study is to investigate the potential use of augmented reality technologies to improve operational performance management (OPM) as part of a doctoral study being conducted at the University of Central Florida. The study consists of a 20-30-minute online survey and the results will be used to support the development of constructs for future research. Study results will be strictly confidential and only anonymized, aggregate results will be used for the analysis and dissemination ensuring that no individual participants are identifiable.

The inclusion criteria include having at least 3 years of experience in Performance Measurement. If you are interested in participating or would like to learn more, please see the study information sheet attached. You may also contact either of the researchers via the contact information listed below.

Below is the link to the survey:
http://ucf.qualtrics.com/jfe/form/SV_2iyiyzgEGl6zXQF

Thank you for your time and consideration.

Joshua Nelson

Ph.D. Student

Industrial Engineering & Management Systems

University of Central Florida

Phone: 407-409-6636

Email: JoshuaNelson@knights.ucf.edu

Heather Keathley, Ph.D.

Assistant Professor, Academic Advisor

Industrial Engineering & Management Systems

University of Central Florida

Phone: 407-823-4745

Email: Heather.Keathley@ucf.edu

[INVITATION EMAIL (AR)]

Subject:

Invitation: Expert Study on Leveraging Augmented Reality for Real-Time Operational Performance Management

Body:

Dear [NAME],

You are invited to participate in an expert study focused on Leveraging Augmented Reality for Real-Time Operational Performance Management as part of a doctoral study being conducted at the University of Central Florida. You were identified as a potential expert due to your current or previous professional experience in the field of Augmented Reality. You were identified as a potential expert due to your previously published work in this area. Your email was obtained through your membership in [PROFESSIONAL SOCIETY].

The purpose of this study is to investigate the potential use of augmented reality technologies to improve operational performance management (OPM) as part of a doctoral study being conducted at the University of Central Florida. The study consists of a 20-30-minute online survey and the results will be used to support the development of constructs for future research. Study results will be strictly confidential and only anonymized, aggregate results will be used for the analysis and dissemination ensuring that no individual participants are identifiable.

The inclusion criteria include the participant having at least 3 years of experience in Augmented Reality. If you are interested in participating or would like to learn more, please see the study information sheet attached. You may also contact either of the researchers via the contact information listed below.

Below is the link to the survey:
http://ucf.qualtrics.com/jfe/form/SV_eaF0QwXVVmA132B

Thank you for your time and consideration.

Joshua Nelson

Ph.D. Student

Industrial Engineering & Management Systems

University of Central Florida

Phone: 407-409-6636

Email: JoshuaNelson@knights.ucf.edu

Heather Keathley, Ph.D.

Assistant Professor, Academic Advisor

Industrial Engineering & Management Systems

University of Central Florida

Phone: 407-823-4745

Email: Heather.Keathley@ucf.edu

[REMINDER EMAIL (All Participants)]

Subject:

Reminder: Expert Study on Leveraging Augmented Reality for Real-Time Operational Performance Management

Body:

Dear [NAME],

We recently sent you an invitation to participate in an expert study focused Leveraging Augmented Reality for Real-Time Operational Performance Management as part of a doctoral study being conducted at the University of Central Florida. **The purpose of this study is to investigate the potential use of augmented reality technologies to improve operational performance management (OPM) as part of a doctoral study being conducted at the University of Central Florida.** The study consists of a 20-30-minute online survey and the results will be used to support the development of constructs for future research.

If you are interested in participating or would like to learn more, please see the study information sheet attached. You may also contact either of the researchers via the contact information listed below.

Thank you for your time and consideration.

Joshua Nelson

Ph.D. Student

Industrial Engineering & Management Systems

University of Central Florida

Phone: 407-409-6636

Email: JoshuaNelson@knights.ucf.edu

Heather Keathley, Ph.D.

Assistant Professor, Academic Advisor

Industrial Engineering & Management Systems

University of Central Florida

Phone: 407-823-4745

Email: Heather.Keathley@ucf.edu

APPENDIX G: EXPERT STUDY IRB FORMS

UNIVERSITY OF CENTRAL FLORIDA

EXPLANATION OF RESEARCH

Title of Project: Leveraging Augmented Reality for Real-Time Operational Performance Management

Principal Investigator: Joshua Nelson

Faculty Supervisor: Dr. Heather Keathley

You are being invited to take part in a research study. Whether you take part is up to you.

Technologies such as artificial intelligence, machine learning, and augmented reality were once considered novelties. However, recent advances have led to the emergence of a variety of practical applications across all industries. This trend is also reflected in management science, which has seen the development of tools that support operational and strategic activities such as project management as well as complex work tasks such as enhanced visualization and motor skills. **The purpose of this study** is to investigate the potential use of augmented reality technologies to improve operational performance management (OPM) as part of a doctoral study being conducted at the University of Central Florida. OPM is critical to organizational health and sustainability and improving best practices will support professionals in more effectively managing and improving operations.

This study is seeking academic and industry experts who have experience with augmented and virtual reality technologies to participate in a phone interview that takes approximately 20-30 minutes to complete. This interview will focus on experiences with augmented and virtual reality application in operational and strategic management and perceptions of a potential tool. Approximately 30-40 interviews will be conducted and the results will provide valuable insights for the next phases of this doctoral study. It is important to note that the interview will be audio recorded to ensure accurate data collection. However, study results will be strictly confidential and only anonymized, aggregate results will be used for the analysis and dissemination ensuring that no individual participants are identifiable. Further, all audio files will be permanently deleted at the conclusion of this study. If the participant does not want to be audio recorded, they can still participate in the study.

Your participation in this study is voluntary. You are free to withdraw your consent and discontinue participation in this study at any time without prejudice or penalty. Your decision to participate or not participate in this study will in no way affect your relationship with UCF, including continued enrollment, grades, employment or your relationship with the individuals who may have an interest in this study.

You must be 18 years of age or older to take part in this research study and have at least 3 years of experience in Augmented Reality.

Study contact for questions about the study or to report a problem: If you have questions, concerns, or complaints please contact Joshua Nelson, Graduate Student, Industrial Engineering, College of Engineering and Computer Science, (407)409-6636 or by email at joshua.nelson@knights.ucf.edu or Dr. Heather Keathley, Faculty Supervisor, Department of Industrial Engineering and Management Systems at (407)823-4745 or by email at heather.keathley@ucf.edu.

IRB contact about your rights in this study or to report a complaint: If you have questions about your rights as a research participant, or have concerns about the conduct of this study, please contact Institutional Review Board (IRB), University of Central Florida, Office of Research, 12201 Research Parkway, Suite 501, Orlando, FL 32826-3246 or by telephone at (407) 823-2901, or email irb@ucf.edu.

UNIVERSITY OF CENTRAL FLORIDA

EXPLANATION OF RESEARCH

Title of Project: Leveraging Augmented Reality for Real-Time Operational Performance Management

Principal Investigator: Joshua Nelson

Faculty Supervisor: Dr. Heather Keathley

You are being invited to take part in a research study. Whether you take part is up to you.

Technologies such as artificial intelligence, machine learning, and augmented reality were once considered novelties. However, recent advances have led to the emergence of a variety of practical applications across all industries. This trend is also reflected in management science, which has seen the development of tools that support operational and strategic activities such as project management as well as complex work tasks such as enhanced visualization and motor skills. **The purpose of this study** is to investigate the potential use of augmented reality technologies to improve operational performance management (OPM) as part of a doctoral study being conducted at the University of Central Florida. OPM is critical to organizational health and sustainability and improving best practices will support professionals in more effectively managing and improving operations.

This study is seeking academic and industry experts who have experience with OPM to participate in a phone interview that takes approximately 20-30 minutes to complete. This interview will focus on experiences with technology-assisted OPM and perceptions of a potential tool. Approximately 30-40 interviews will be conducted and the results will provide valuable insights for the next phases of this doctoral study. It is important to note that the interview will be audio recorded to ensure accurate data collection. However, study results will be strictly confidential and only anonymized, aggregate results will be used for the analysis and dissemination ensuring that no individual participants are identifiable. Further, all audio files will be permanently deleted at the conclusion of this study. If the participant does not want to be audio recorded, they can still participate in the study.

Your participation in this study is voluntary. You are free to withdraw your consent and discontinue participation in this study at any time without prejudice or penalty. Your decision to participate or not participate in this study will in no way affect your relationship with UCF, including continued enrollment, grades, employment or your relationship with the individuals who may have an interest in this study.

You must be 18 years of age or older to take part in this research study and have at least 3 years of experience in Performance Measurement.

Study contact for questions about the study or to report a problem: If you have questions, concerns, or complaints please contact Joshua Nelson, Graduate Student, Industrial Engineering, College of Engineering and Computer Science, (407)409-6636 or by email at joshua.nelson@knights.ucf.edu or Dr. Heather Keathley, Faculty Supervisor, Department of Industrial Engineering and Management Systems at (407)823-4745 or by email at heather.keathley@ucf.edu.

IRB contact about your rights in this study or to report a complaint: If you have questions about your rights as a research participant, or have concerns about the conduct of this study, please contact Institutional

Review Board (IRB), University of Central Florida, Office of Research, 12201 Research Parkway, Suite 501, Orlando, FL 32826-3246 or by telephone at (407) 823-2901, or email irb@ucf.edu.

instructions: This form is used to establish whether your research can be determined to be "Human Research" that is exempt from IRB Review according to the federal regulations. To request a determination of exemption, please complete the protocol application and attach this form in Section 1.8 of the Basic Information Page of the online study submission. Also attach recruitment materials, study instruments, and, if a consent process is required, the HRP-254 Summary Explanation for Exempt Research. *The IRB Office will then make the final determination on whether the activity meets an exempt category under Health and Human Services regulations (HHS)45 CFR 46.101 (b).*

Investigator:	Joshua Nelson
Study Title:	Leveraging Augmented Reality for Real-Time Operational Performance Management
Co-Investigators(s) (if Applicable):	N/A
Faculty Advisor (if Applicable):	Dr. Heather Keathley

Section 1 – Justification of IRB Exemption **In order to be considered exempt, the research study MUST meet the following conditions:**	
A. The research protocol involves NO more than minimal risk. Minimal risk is the probability and magnitude of physical or psychological harm that is normally encountered in the daily lives, or in the routine medical, dental, or psychological examination of healthy persons. 45CFR46.303 (d).	
☒	Yes, this research involves NO more than minimal risk.
☐	No, this research involves GREATER than minimal risk. **STOP, your submission does not qualify for an exemption determination. Discard this form and complete a Protocol using Form HRP-503 for submission to the IRB.**
B. This study fits into at least one of the following 6 Exemption categories. Please indicate which of the following categories you think most clearly represents your research.	
☐	1. Research conducted in established or commonly accepted educational settings that specifically involves normal educational practices that are not likely to adversely impact students' opportunity to learn required educational content or the assessment of educators who provide instruction. This includes most research on regular and special education instructional strategies, and research on the effectiveness of or the comparison among instructional techniques, curricula, or classroom management methods.
☒	2. Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures or observation of public behavior (including visual or auditory recording) if at least one of the following criteria is met: ☐ (i) The information obtained is recorded by the investigator in such a manner that the identity of the Human Subjects cannot be readily ascertained, directly or indirectly through identifiers linked to the subjects; OR ☒ (ii) Any disclosure of Human Subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational advancement, or reputation; OR

	☐ (iii) The information obtained is recorded by the investigator in such a manner that the identity of the Human Subjects can be readily ascertained, directly or indirectly through identifiers linked to the subjects, AND there are adequate provisions to protect the privacy of subjects and to maintain the confidentiality of data. **Note: If your research includes surveys or interviews with minors, this study will not qualify for an exemption.** ☐ If the research involves children and is conducted, funded, or subject to regulation by DHHS, Dept. of Defense (DOD), Dept. of Education (ED), Environmental Protection Agency (EPA), or Veterans Administration (VA), the procedures are limited to (1) the observation of public behavior when the investigator(s) do not participate in the activities being observed or (2) the use of educational tests and at least one of the following criteria is met: ☐ (i) The information obtained is recorded by the investigator in such a manner that the identity of the Human Subjects cannot readily be ascertained, directly or indirectly through identifiers linked to the subjects; OR ☐ (ii) Any disclosure of Human Subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational achievement, or reputation.
☐	3. Research involving benign behavioral interventions in conjunction with the collection of information from an adult subject through verbal or written responses (including data entry) or audiovisual recording if the subject prospectively agrees to the intervention and information collection and at least one of the following criteria is met: ☐ (A) The information obtained is recorded by the investigator in such a manner that the identity of the Human Subjects cannot readily be ascertained, directly or indirectly, through identifiers linked to the subjects; OR ☒ (B) Any disclosure of the Human Subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational advancement, or reputation; OR ☐ (C) The information obtained is recorded by the investigator in such a manner that the identity of the Human Subjects can be readily ascertained, directly or indirectly through identifiers linked to the subjects, AND there are adequate provisions to protect the privacy of subjects and to maintain the confidentiality of data.
☐	4. Secondary research for which consent is not required: Secondary research uses of identifiable private information or identifiable biospecimens, if <u>at least one</u> of the following criteria is met: ☒ (i) The identifiable private information or identifiable biospecimens are publicly available; OR ☐ (ii) Information, which may include information about biospecimens, is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained directly or through identifiers linked to the subjects, the investigator does not contact the subjects, and the investigator will not re-identify subjects; OR

	☐ The research involves only information collection and analysis involving the investigator's use of identifiable health information when that use is regulated under 45 CFR parts 160 and 164 (HIPAA), subparts A and E, for the purposes of "health care operations" or "research" as those terms are defined at 45 CFR 164.501 or for "public health activities and purposes" as described under 45 CFR 164.512(b); OR ☐ The research is conducted by, or on behalf of, a Federal department or agency using government-generated or government-collected information obtained for nonresearch activities, if the research generates identifiable private information that is or will be maintained on information technology that is subject to and in compliance with section 208(b) of the E-Government Act of 2002, 44 U.S.C. 3501
☐	5. Research and demonstration projects which are conducted or supported by a Federal department or agency, or otherwise subject to the approval of department or agency heads (or the approval of heads of bureaus or other subordinate agencies that have been delegated authority to conduct the research and demonstration projects), and that are designed to study, evaluate, improve, or otherwise examine: public benefit or service programs, including procedures for obtaining benefits or services under those programs, possible changes in or alternatives to those programs or procedures, or possible changes in methods or levels of payment for benefits or services under those programs ☐ (i) Each Federal department or agency conducting or supporting the research and demonstration projects must establish, on a publicly accessible Federal website or in such other manner as the department or agency head may determine, a list of the research and demonstration projects that the Federal department or agency conducts or supports under this provision. The research or demonstration project must be published on this list prior to commencing the research involving human subjects.
☐	6. Taste and food quality evaluation and consumer acceptance studies, (i) if wholesome foods without additives are consumed or (ii) if a food is consumed that contains a food ingredient at or below the level and for a use found to be safe, or agricultural chemical or environmental contaminant at or below the level found to be safe, by the Food and Drug Administration or approved by the Environmental Protection Agency or the Food Safety and Inspection Service of the Dept. of Agriculture.

Section 2 – Study Details Complete each section	
Protocol Synopsis/Summary:	This study is seeking academic and industry experts who have experience with augmented and virtual reality technologies to participate in a phone interview or online survey that takes approximately 20-30 minutes to complete. This interview or online survey will focus on experiences with augmented and virtual reality application in operational and strategic management and perceptions of a potential tool. Approximately 30-40 interviews or surveys will be conducted and the results will provide valuable insights for the next phases of this doctoral study. There will be two sets of interviews. One set is for Augmented Reality Experts and the other set is for Performance Management Experts. They will be different sets with questions catered for each group as shown in the Interview Questions document. It is important to note that the interview will be audio recorded to ensure accurate data collection. However, study results will be strictly confidential and only anonymized, aggregate results will be used for the analysis and dissemination ensuring that no individual participants are identifiable. Further, all audio files will be permanently deleted at the conclusion of this study.

Objective/Background:	The purpose of this study is to investigate the potential use of augmented reality technologies to improve operational performance management (OPM) as part of a doctoral study being conducted at the University of Central Florida. OPM is critical to organizational health and sustainability and improving best practices will support professionals in more effectively managing and improving operations.
Study Design:	The study design will be an expert study. The structured interviews or surveys will be used to satisfy both approaches by including questions which will yield both quantitative and qualitative results. If participants are Pregnant Women or Adults over 65, it is incidental. Potential participants will be contacted via email. Email addresses will be obtained through membership in professional societies and LinkedIn groups. Interviews will be scheduled via email communication and will be carried out in person, over the phone, or via Skype. Surveys will be distributed via email or LinkedIn Groups.
Study Instruments: (List **all** materials the participant will view or hear. This list must match the document names attached in the Local Site Documents in the Huron IRB system)**:**	interview questions, recruitment materials, and Explanation of Research
Maximum number of participants:	40
Study Population: (check ☑ all that apply)	☒ UCF Students, Faculty or Staff ☐ Children or Young Adults Under the age of 18 ☒ Adults over 65 ☒ Pregnant Women ☐ Prisoners ☐ Adults to Unable to Consent ☐ Other (specify):
Recruitment Methods: (Unless the content is exactly the same for all versions, upload a copy of each type selected)	☐ Flyer ☒ Email ☒ Social Media Post ☐ Other (specify): ☒ The content is the same for all methods

Languages Included:	☒ English ☐ Other (specify): Note, the IRB will request translated versions of the study materials after the English versions are approved.
Research Locations: (check ☑ all that apply)	☒ UCF Owned or Operated Locations(s) (specify all applicable locations): ☐ Online ☐ Amazon M-Turk ☐ Sona ☐ Qualtrics ☒ Other (specify): Phone ☐ International (specify all applicable locations): ☐ Multi-site (specify all No-UCF locations): ☐ Other (specify):
Involves Deception: Note: If the research involves deceiving the subjects regarding the nature or purposes of the research, this exemption is not applicable unless the subject authorizes the deception through a prospective agreement to participate in research in circumstances in which the subject is informed that he or she will be unaware of or misled regarding the nature or purposes of the research.	☒ No ☐ Yes (Completion of HRP-509 – Debriefing Statement is required) If Yes, describe the nature of the deception:
Illegal activity/sensitive information (Drug use, underage alcohol use, rape, suicidal thoughts, etc.):	☒ No ☐ Yes If Yes, describe the nature of the sensitive information:
Compensation:	☒ No ☐ Yes

	If Yes, specify the form of compensation (check all that apply): ☐ Course Credit (students) **(if offering course credit, "Alternate Assignment" below must also be selected)** ☐ Alternate Assignment (students) ☐ Monetary (cash/check/gift card) ☐ Other (specify): ☐ Lottery (Note: In general, due to Florida's strict state laws regarding lotteries and the appearance of coercion in research studies, the IRB does not allow lotteries unless the study is investigating the lottery process or psychological effects of lotteries as the purpose of the study.
Type of Interaction(s)to Take Place for Research Purposes: (check ☑ all that apply)	☒ Online survey ☒ In-person/Face-to-Face ☒ Voice Call ☒ Voice/Video Call (i.e., Skype) ☒ Voice Recordings ☐ Video Recordings ☐ Observation (describe the nature of the observation): ☐ Other (specify):
Identifiable Data Collection: (check ☑ all that apply and upload the study data collection sheet)	☐ None ☒ Name ☒ Contact Information (email, phone number, address, etc.) ☐ NID ☐ Video Recording-- Face or another identifying personal attribute ☐ Protected Health Information (PHI) (includes any of the 18 HIPAA identifiers associated with medical records, biological specimens, biometrics, data sets) ☐ Biospecimens (describe):

	☐ Other (specify):
Data Retention: (check ☑ all that apply for both the identifiable and de-identified sections, as applicable)	**If You are Collecting Identifiable Data:** ☒ Identifiers deleted after transcription ☐ Identifiers deleted after data analysis ☐ Identifiers deleted at a specific timepoint (specify): **De-Identified Data:** ☒ De-identified data stored for a minimum of 5 years (per UCF policy) ☐ De-identified data stored for a certain amount of time or specific timepoint (specify):
Section 3 – Ethical Considerations **Complete each section**	
1. Describe how subject selection is equitable (describe inclusion/exclusion criteria):	The inclusion criteria include the following: Augmented Reality Experts: 3 years academic research or industry related experience in Augmented Reality Performance Measurement Experts: 3 years academic research or industry related experience in Augmented Reality
2. This study involves the collection of identifiable data:	☐ No ☒ Yes If Yes, describe the provisions in place to protect the confidentiality of the data: Names are used to send reports via email, but will be protected by only the primary investigator having access to this data. Identifiable data that will be collected includes names and contact information. All data will be stored securely as digital files and will be password protected.
3. There are interactions with participants (including surveys):	☐ No ☒ Yes **If Yes, question number 4 is required.**
4. Informed Consent Process (required for all studies involving subject interaction)	**Note: The Consent Process Must:** Disclose that the activities involve research;

	Disclose the procedures to be performed; Disclose that participation is voluntary; Disclose the name and contact information for the investigator. Disclose what identifiable data will be collected and the confidentiality provisions in place to protect that data. **Describe the informed consent process. This description should include information about how you are using the HRP-254 – Summary of Research Explanation and any other documents used to facilitate the consent process.** The researcher, a PhD candidate, will contact respondent via email after he/she agrees to participate in the study and ask them about their opinion based on their experience. Both interview and survey participants will receive the Explanation of Research via email. Email addresses will be obtained through membership in professional societies and LinkedIn Groups.
5. Subject Privacy	**Describe the provisions to maintain privacy interests:** All audio recordings of the interview will be discarded after being transcribed. All identifiable information will be known to the investigator. Interviews will be private and conducted over the phone or Skype in a closed off area. All surveys will be taken anonymously. The survey data will be anonymous to the investigator.

Section 4 – Certification and Investigator Sign-Off

Please be aware that the different activities listed under the categories for exemption do not automatically deem these activities as exempt from IRB review. Exempt determination does not designate that research is automatically excused from IRB submission or review, but rather are exempt only from certain federal regulations. The activities presented here only indicate that a significant portion of these types of research activities could be *eligible* for exemption procedures. In addition, this *eligibility* also depends on whether or not the specific circumstances surrounding the proposed research activities involves no more than minimal risk to the participants. ***Decisions regarding eligibility for exemption will be made on a case-by-case basis by the IRB Office***. **The IRB Office may request additional documentation, including the full protocol (HRP-503 – Protocol Template), in order to make the appropriate determination.**

<u>By entering your initials below, you certify that the information you have provided is complete and accurate. In addition, you acknowledge that any intended/proposed modifications to this research must first be submitted to the IRB as certain modifications may increase risk to participants or change the review category.</u>

APPENDIX H: MINITAB AND SPSS OUTPUT FILES

Validation of Existing Constructs

This section contains SPSS data outputs for validation of existing TAM constructs.

Pre-Survey Data:

Perceived Usefulness

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.940	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PUQ2	26.4063	27.797	.852	.925
PUQ5	26.5000	28.645	.790	.933
PUQ3	26.5000	28.000	.895	.920
PUQ4	26.6875	28.996	.781	.934
PUQ6	26.1875	29.254	.829	.928
PUQ1	26.4688	28.967	.777	.934

Perceived Ease of Use:

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.934	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PEQ10	28.8125	25.706	.605	.953
PEQ7	28.4063	25.733	.849	.917
PEQ8	28.6875	24.673	.866	.914
PEQ9	28.5938	25.539	.816	.920
PEQ11	28.4688	24.644	.886	.911
PEQ12	28.5938	25.539	.874	.914

Decision Making:

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.825	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
DMQ18	20.5000	16.516	.681	.773
DMQ15	20.6563	14.491	.687	.771
DMQ13	20.2813	17.370	.529	.815
DMQ14	20.6250	15.726	.752	.752
DMQ17	20.4375	18.383	.471	.829

Post Survey Data

Perceived Usefulness

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.953	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PUQ2	28.9688	45.902	.908	.938
PUQ5	28.8438	48.136	.869	.943
PUQ3	29.0000	44.968	.903	.939
PUQ4	29.0938	44.862	.893	.940
PUQ6	28.5938	49.733	.777	.953
PUQ1	28.4688	51.805	.795	.952

Perceived Ease of Use:

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.900	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PEQ10	31.2188	18.757	.787	.882
PEQ7	30.8125	24.996	.647	.895
PEQ8	31.1250	20.694	.836	.865
PEQ9	30.6875	24.544	.652	.894
PEQ11	30.9375	21.351	.797	.872
PEQ12	30.6875	24.931	.786	.883

Behavioral Intention to Use:

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.770	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
BIQ39	12.4063	3.733	.485	.910
BIQ40	12.2500	4.194	.769	.524
BIQ41	11.9688	5.064	.663	.667

With BIQ39 removed:

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.910	2

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
BIQ40	6.3438	.878	.842	.
BIQ41	6.0625	1.157	.842	.

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.910	2

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
BIQ40	6.3438	.878	.842	.
BIQ41	6.0625	1.157	.842	.

Perceived Decision-Making Effectiveness Construct Development

This section contains SPSS output files for perceived decision-making effectiveness construct development.

Decision Making:

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.766	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
DMQ34	26.9375	28.512	.747	.661
DMQ15	26.4375	31.996	.693	.687
DMQ17	28.1875	44.286	-.064	.883
DMQ13	26.3438	33.136	.590	.712
DMQ14	26.5000	29.548	.805	.653
DMQ33	26.2188	34.757	.535	.727

With DMQ17 removed:

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.883	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
DMQ34	23.0000	25.871	.815	.834
DMQ15	22.5000	29.935	.715	.858
DMQ13	22.4063	30.443	.650	.873
DMQ14	22.5625	27.415	.839	.828
DMQ33	22.2813	32.209	.584	.886

EFA:

Factor Analysis

Correlation Matrix[a]

a. Determinant = .043

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.775
Bartlett's Test of Sphericity	Approx. Chi-Square	88.880
	df	15
	Sig.	.000

Communalities

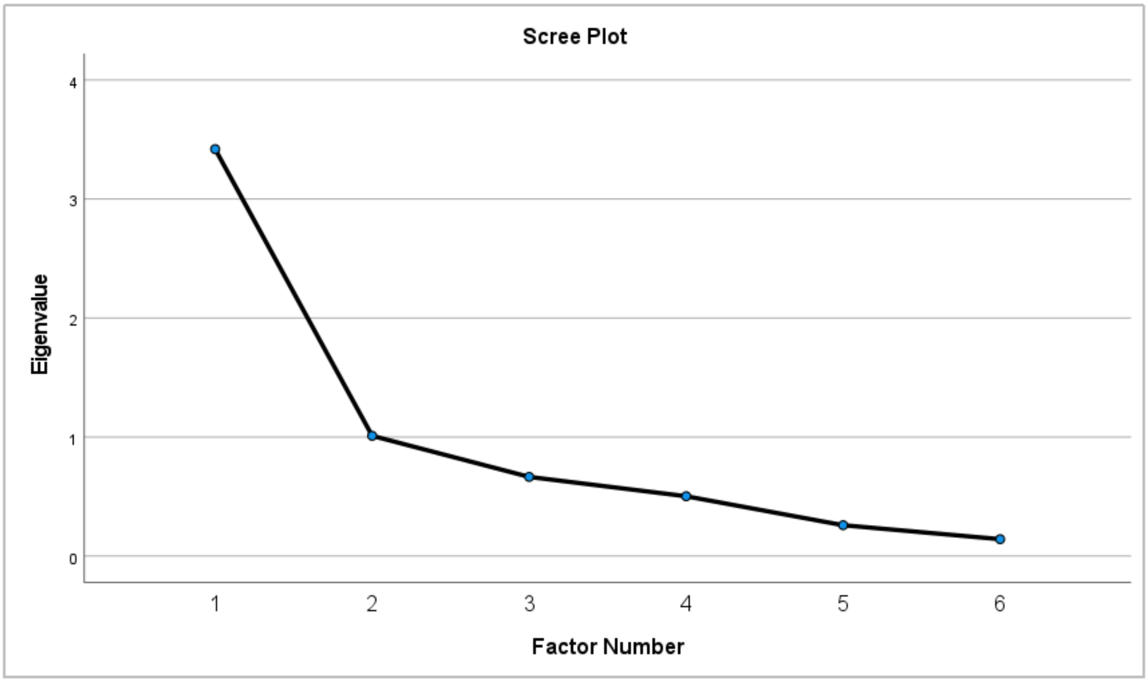
	Initial
DMQ34	.763
DMQ15	.612
DMQ17	.047
DMQ13	.512
DMQ14	.754
DMQ33	.418

Extraction Method: Principal Axis Factoring.

Total Variance Explained

	Initial Eigenvalues		
Factor	Total	% of Variance	Cumulative %
1	3.420	56.993	56.993
2	1.011	16.844	73.837
3	.665	11.091	84.928
4	.503	8.381	93.309
5	.259	4.324	97.633
6	.142	2.367	100.000

Extraction Method: Principal Axis Factoring.



Factor Matrix[a]

a. Attempted to extract 2 factors. In iteration 25, the communality of a variable exceeded 1.0. Extraction was terminated.

Removing DMQ17:

Factor Analysis

Correlation Matrix[a]

a. Determinant = .045

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.792
Bartlett's Test of Sphericity	Approx. Chi-Square	88.564
	df	10
	Sig.	.000

Communalities

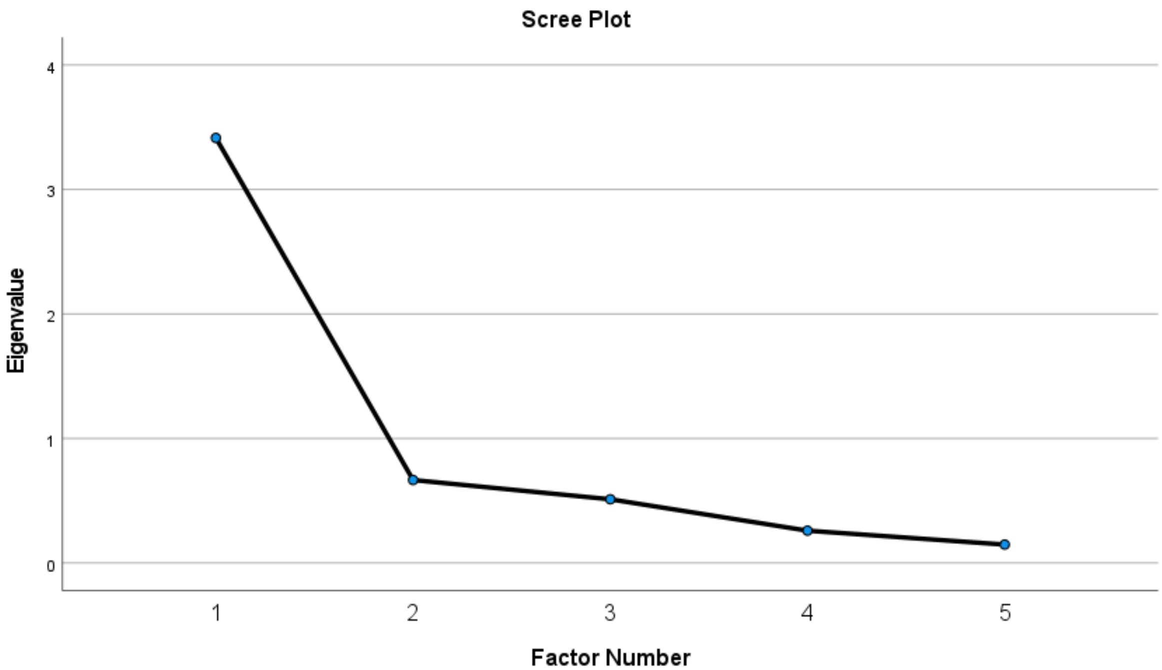
	Initial	Extraction
DMQ34	.757	.799
DMQ15	.607	.577
DMQ13	.508	.482
DMQ14	.748	.831
DMQ33	.410	.380

Extraction Method: Principal Axis Factoring.

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.414	68.286	68.286	3.069	61.373	61.373
2	.666	13.329	81.614			
3	.512	10.235	91.849			
4	.260	5.193	97.042			
5	.148	2.958	100.000			

Extraction Method: Principal Axis Factoring.


Scree Plot
Eigenvalue
4
3
2
1
0
1
2
3
4
5
Factor Number

Factor Matrix[a]

	Factor
	1
DMQ34	.894
DMQ15	.760
DMQ13	.694
DMQ14	.912
DMQ33	.616

Extraction Method: Principal Axis Factoring.

a. 1 factors extracted. 7 iterations required.

Rotated Factor Matrix[a]

a. Only one factor was extracted. The solution cannot be rotated.

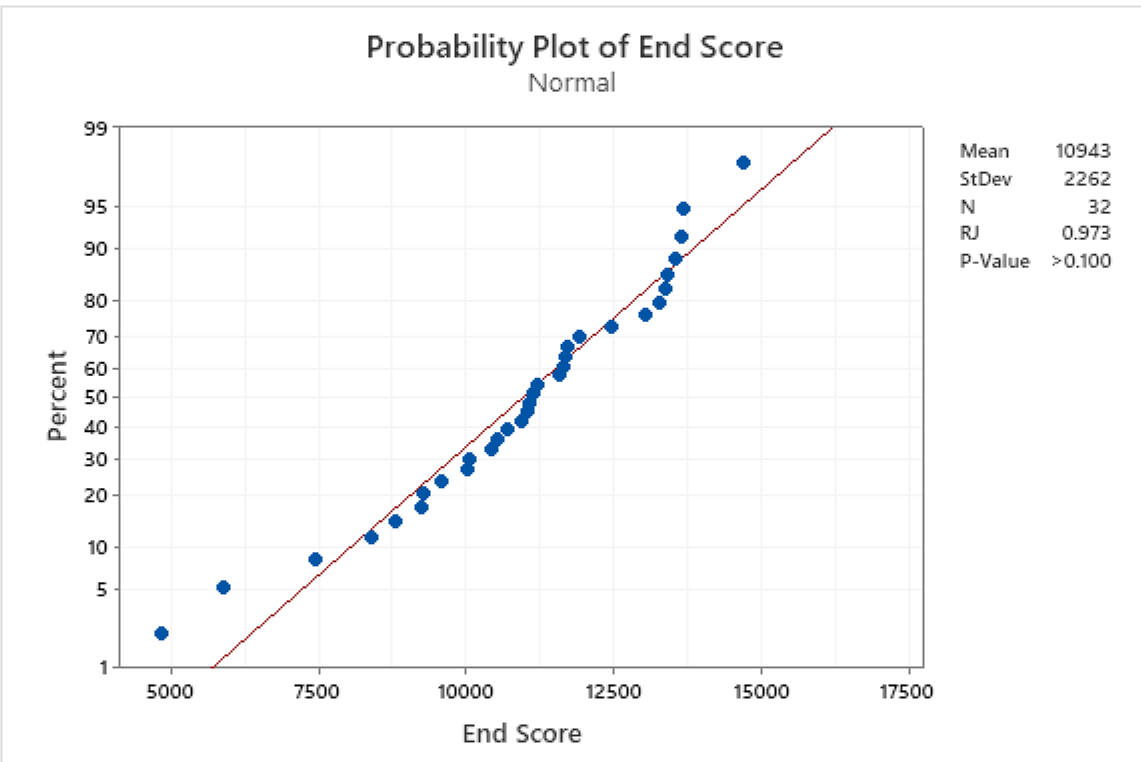
DOE Model 1: Operational Performance

This section contains Minitab output file for DOE Model 1 used to measure operational performance.

Normality Test:

WORKSHEET 1

Probability Plot of End Score



WORKSHEET 1

Factorial Regression: End Score versus Aug Reality, Real-Time

Coded Coefficients

Term	Effect	Coef	SE Coef	95% CI	T-Value	P-Value	VIF
Constant		10943	311	(10306, 11581)	35.16	0.000	
Aug Reality	-1456	-728	311	(-1366, -90)	-2.34	0.027	1.00
Real-Time	2019	1010	311	(372, 1647)	3.24	0.003	1.00

Aug Reality*Real-Time	1665	833	311	(195, 1470)	2.68	0.012	1.00

Model Summary

S	R-sq	R-sq(adj)	PRESS	R-sq(pred)	AICc	BIC
1760.70	45.26%	39.39%	113374309	28.50%	577.15	582.17

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Model	3	71761445	45.26%	71761445	23920482	7.72	0.001
Linear	2	49576152	31.27%	49576152	24788076	8.00	0.002
Aug Reality	1	16960216	10.70%	16960216	16960216	5.47	0.027
Real-Time	1	32615936	20.57%	32615936	32615936	10.52	0.003
2-Way Interactions	1	22185293	13.99%	22185293	22185293	7.16	0.012
Aug Reality*Real-Time	1	22185293	13.99%	22185293	22185293	7.16	0.012
Error	28	86802205	54.74%	86802205	3100079		
Total	31	158563650	100.00%				

Regression Equation in Uncoded Units

End Score = 10943 - 728 Aug Reality + 1010 Real-Time + 833 Aug Reality*Real-Time

Fits and Diagnostics for Unusual Observations

Obs	End Score	Fit	SE Fit	95% CI	Resid	Std Resid	Del Resid	HI	Cook's D
27	4825	8373	623	(7098, 9648)	-3548	-2.15	-2.32	0.125	0.17

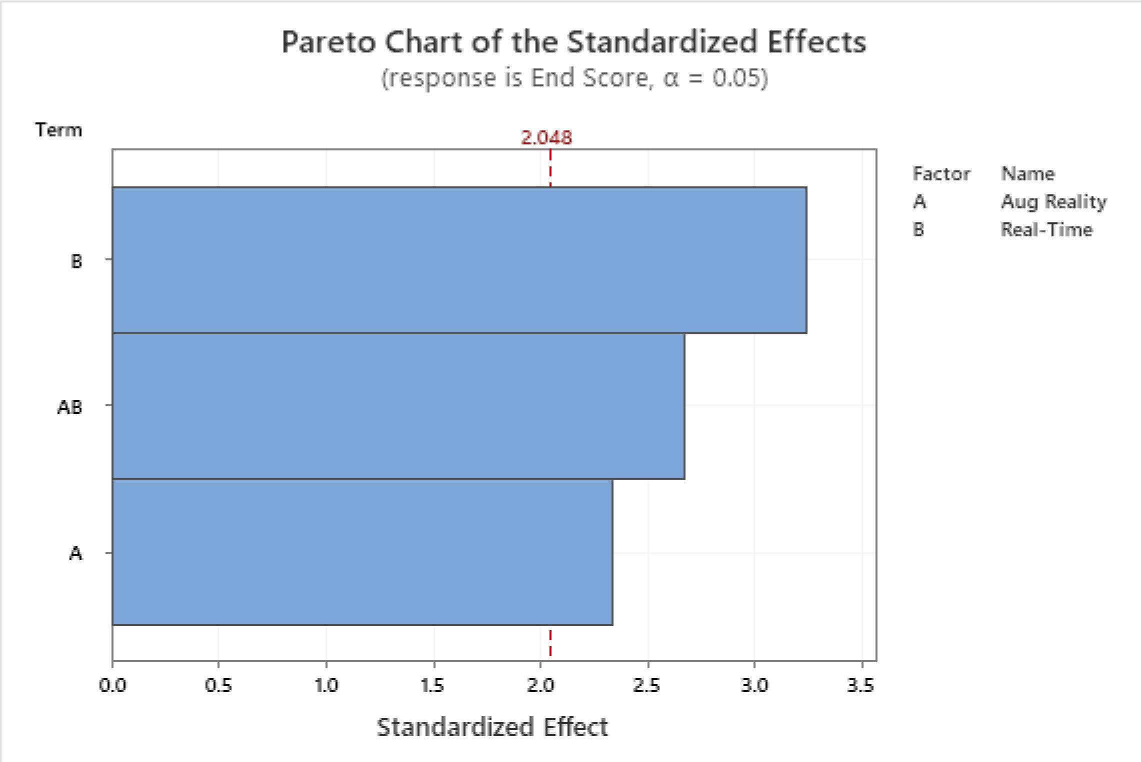
Obs	DFITS
27	-0.875472 R

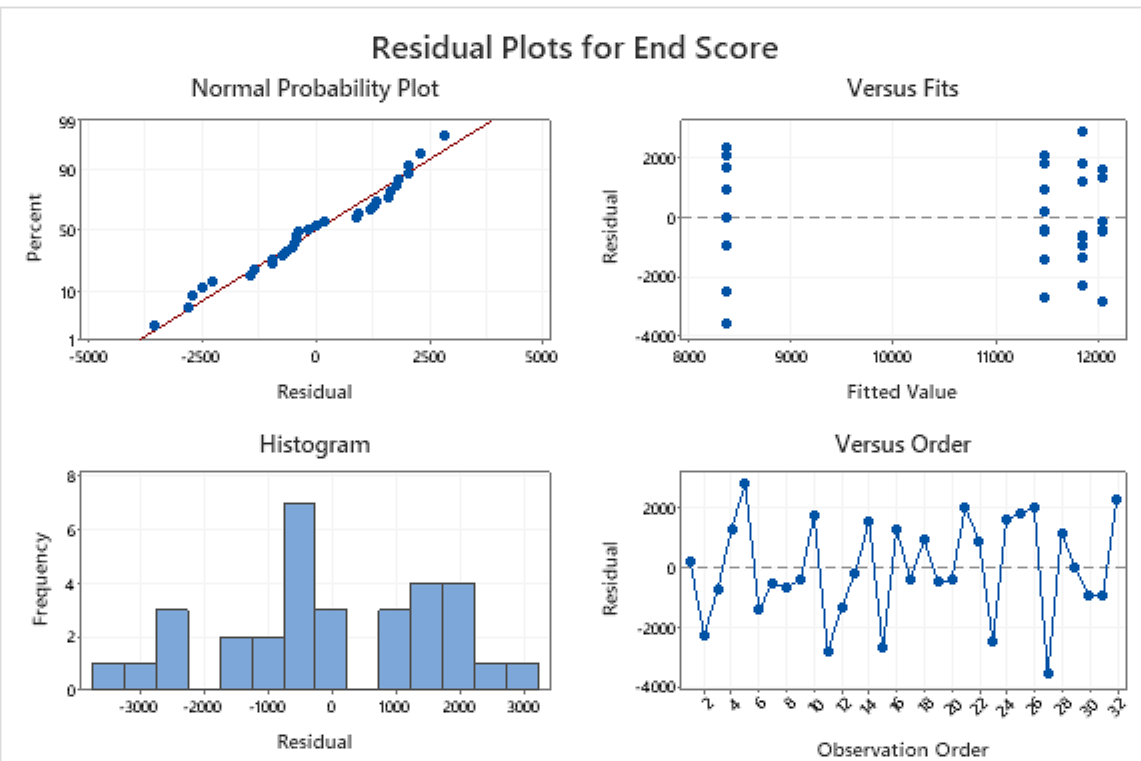
R Large residual

Alias Structure

Factor	Name
A	Aug Reality
B	Real-Time

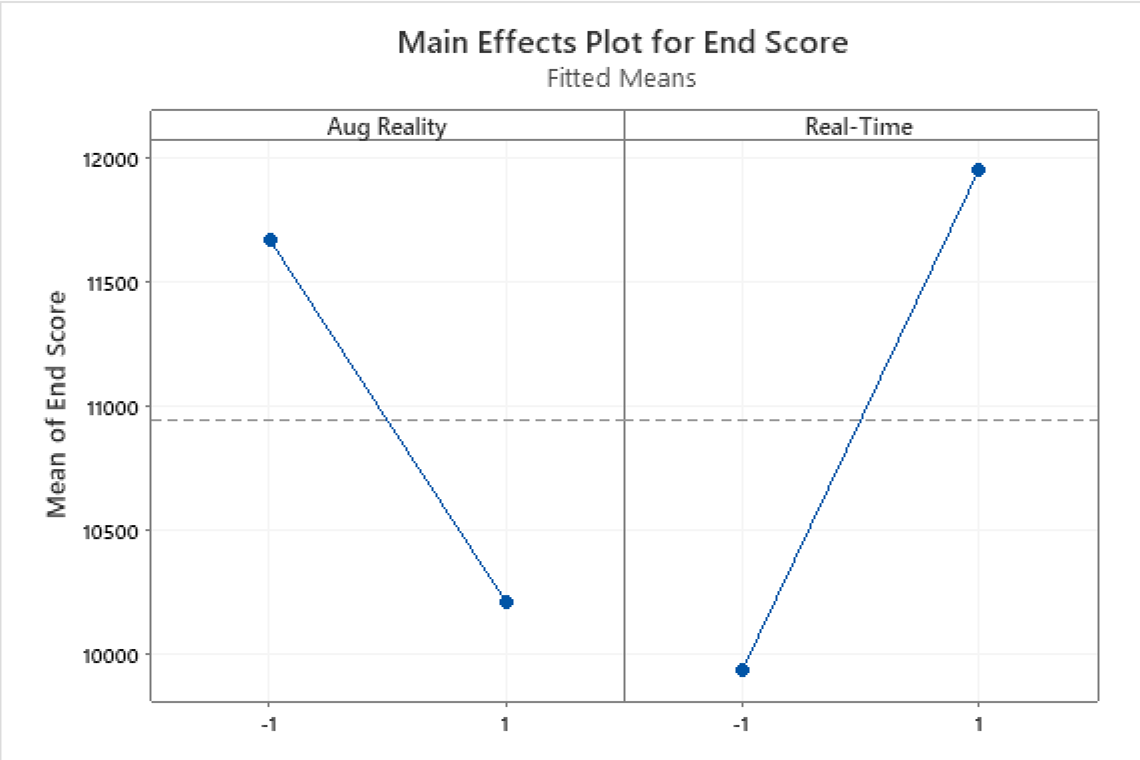
Aliases
I
A
B
AB

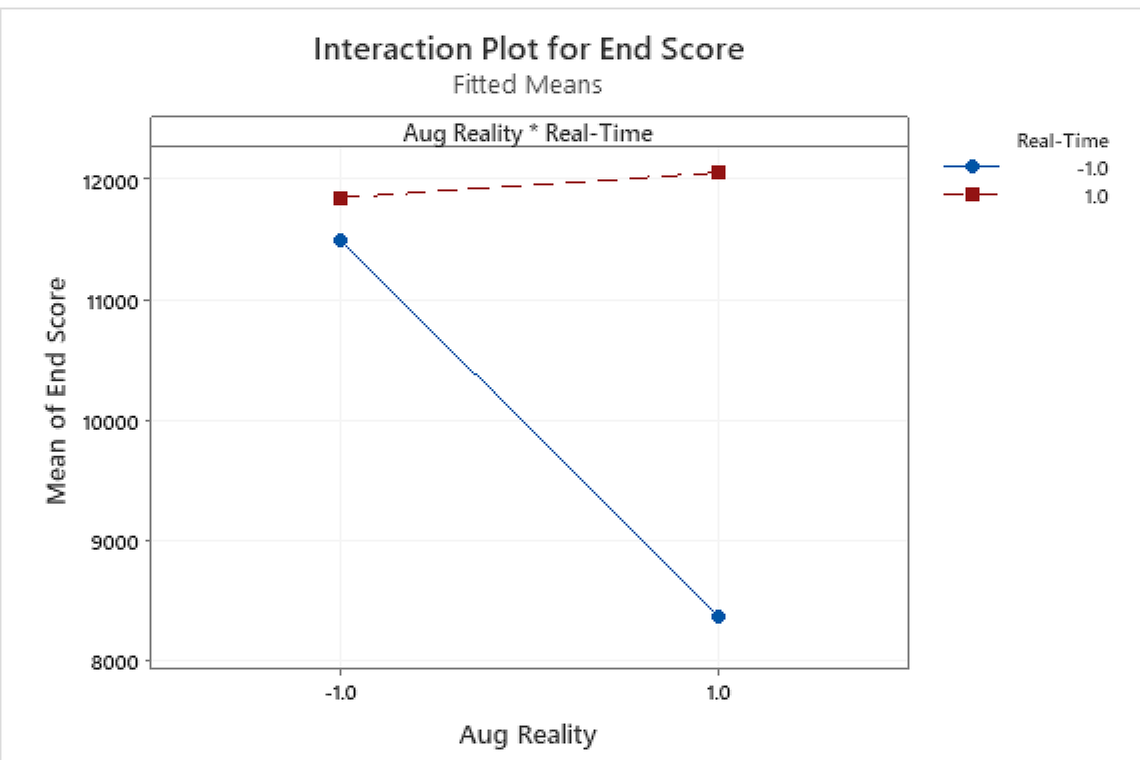

Pareto Chart of the Standardized Effects
(response is End Score, α = 0.05)
Term
2.048
B
AB
A
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
Standardized Effect
Factor Name
A Aug Reality
B Real-Time


Residual Plots for End Score
Normal Probability Plot
Percent
Residual
Versus Fits
Residual
Fitted Value
Histogram
Frequency
Residual
Versus Order
Residual
Observation Order

WORKSHEET 1

Factorial Plots for End Score





WORKSHEET 1

Test for Equal Variances: End Score versus Real-Time, Aug Reality

Method

Null hypothesis	All variances are equal
Alternative hypothesis	At least one variance is different
Significance level	α = 0.05

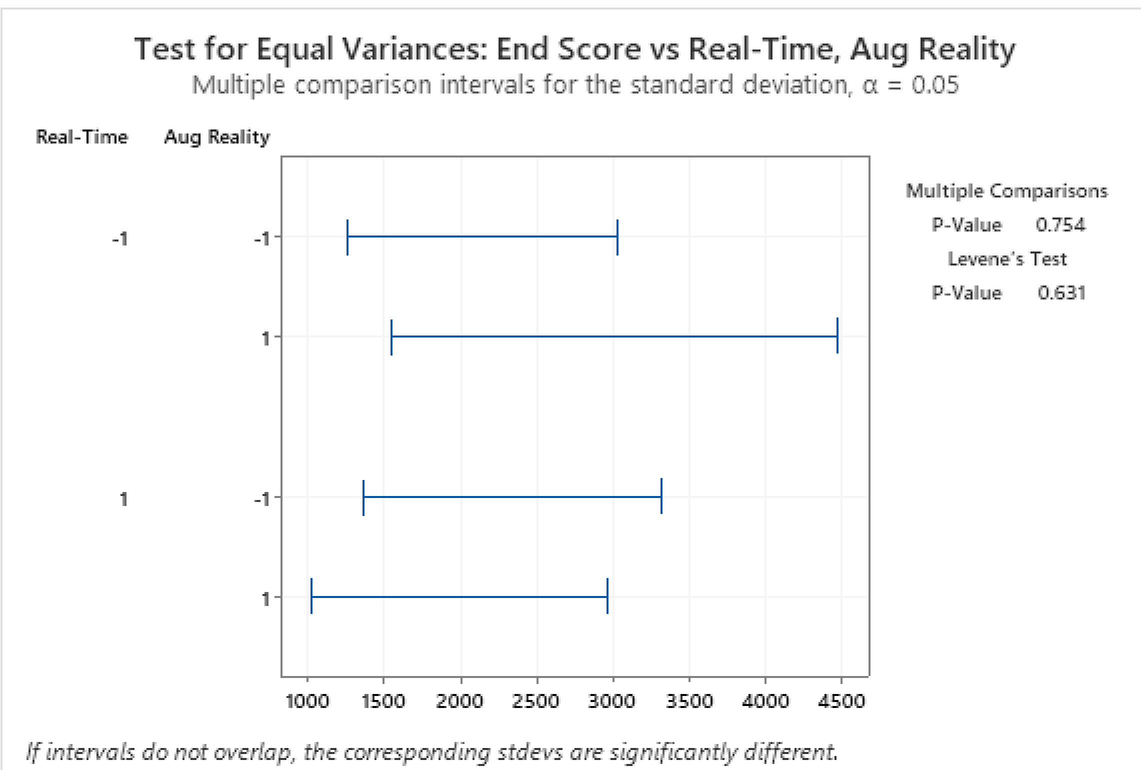
95% Bonferroni Confidence Intervals for Standard Deviations

Real-Time	Aug Reality	N	StDev	CI
-1	-1	8	1606.81	(823.32, 4559.35)
-1	1	8	2164.33	(1009.46, 6746.92)
1	-1	8	1751.37	(858.53, 5194.49)
1	1	8	1437.66	(592.39, 5072.84)

Individual confidence level = 98.75%

Tests

Method	Test Statistic	P-Value
Multiple comparisons	—	0.754
Levene	0.58	0.631

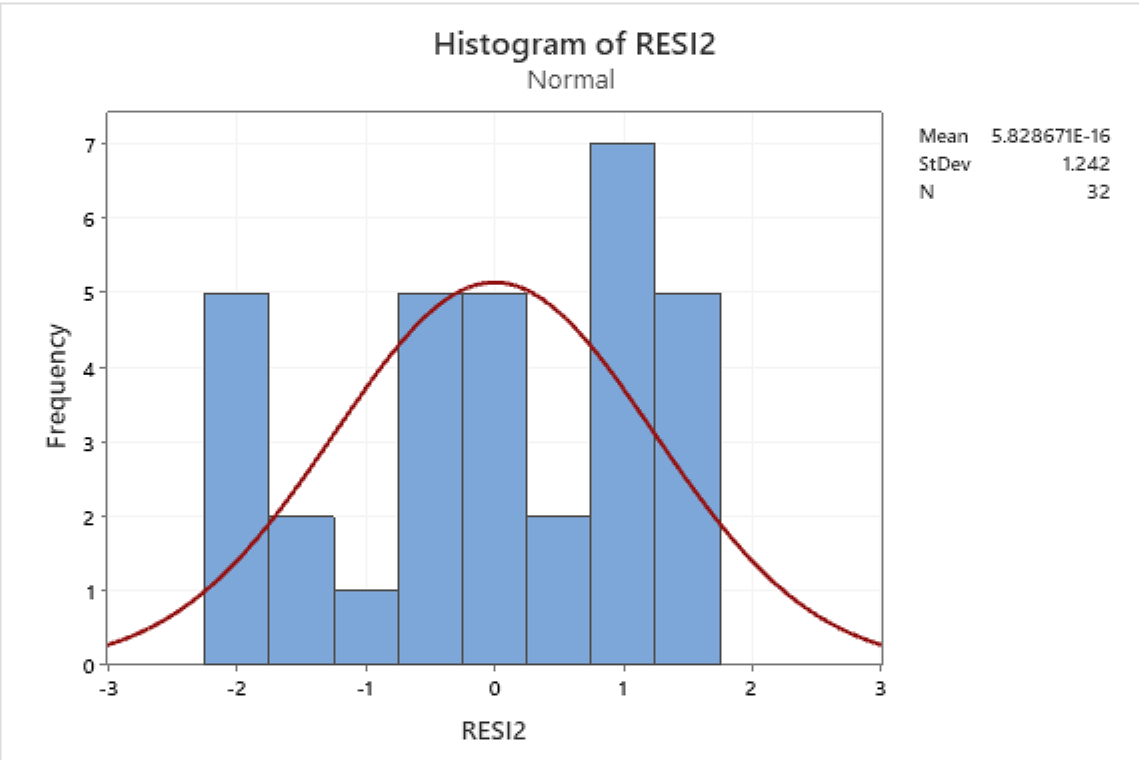


DOE Model 2: Perceived Decision-Making Effectiveness

This section contains Minitab output file for DOE Model 2 used to measure perceived decision-making effectiveness

WORKSHEET 1

Histogram of RESI2



Without Transformation:

Minitab Results with DMQ17 removed:

WORKSHEET 1

Factorial Regression: DM Avg versus Aug Reality, Real-Time

Coded Coefficients

Term	Effect	Coef	SE Coef	95% CI	T-Value	P-Value	VIF
Constant		5.638	0.247	(5.132, 6.143)	22.86	0.000	
Aug Reality	-0.075	-0.038	0.247	(-0.543, 0.468)	-0.15	0.880	1.00
Real-Time	0.150	0.075	0.247	(-0.430, 0.580)	0.30	0.763	1.00

Aug Reality*Real-Time	-0.150	-0.075	0.247	(-0.580, 0.430)	-0.30	0.763	1.00

Model Summary

S	R-sq	R-sq(adj)	PRESS	R-sq(pred)	AICc	BIC
1.39527	0.74%	0.00%	71.1967	0.00%	120.16	125.19

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Model	3	0.4050	0.74%	0.4050	0.13500	0.07	0.976
Linear	2	0.2250	0.41%	0.2250	0.11250	0.06	0.944
Aug Reality	1	0.0450	0.08%	0.0450	0.04500	0.02	0.880
Real-Time	1	0.1800	0.33%	0.1800	0.18000	0.09	0.763
2-Way Interactions	1	0.1800	0.33%	0.1800	0.18000	0.09	0.763
Aug Reality*Real-Time	1	0.1800	0.33%	0.1800	0.18000	0.09	0.763
Error	28	54.5100	99.26%	54.5100	1.94679		
Total	31	54.9150	100.00%				

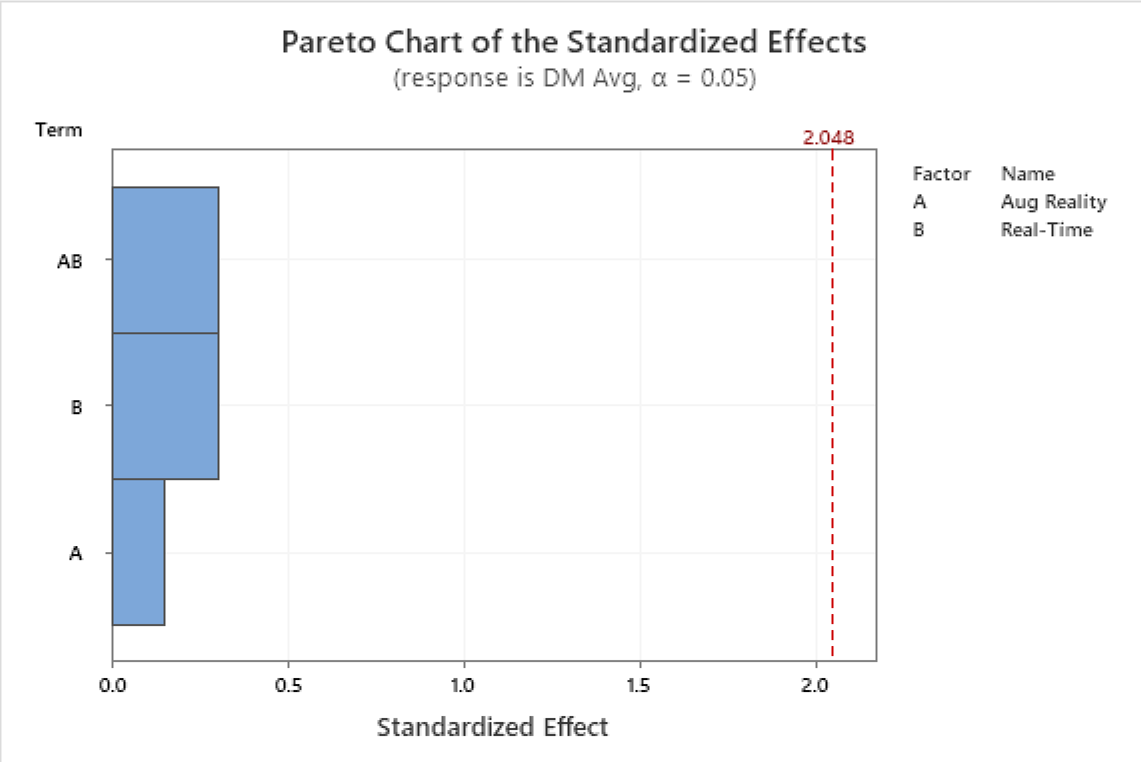
Regression Equation in Uncoded Units

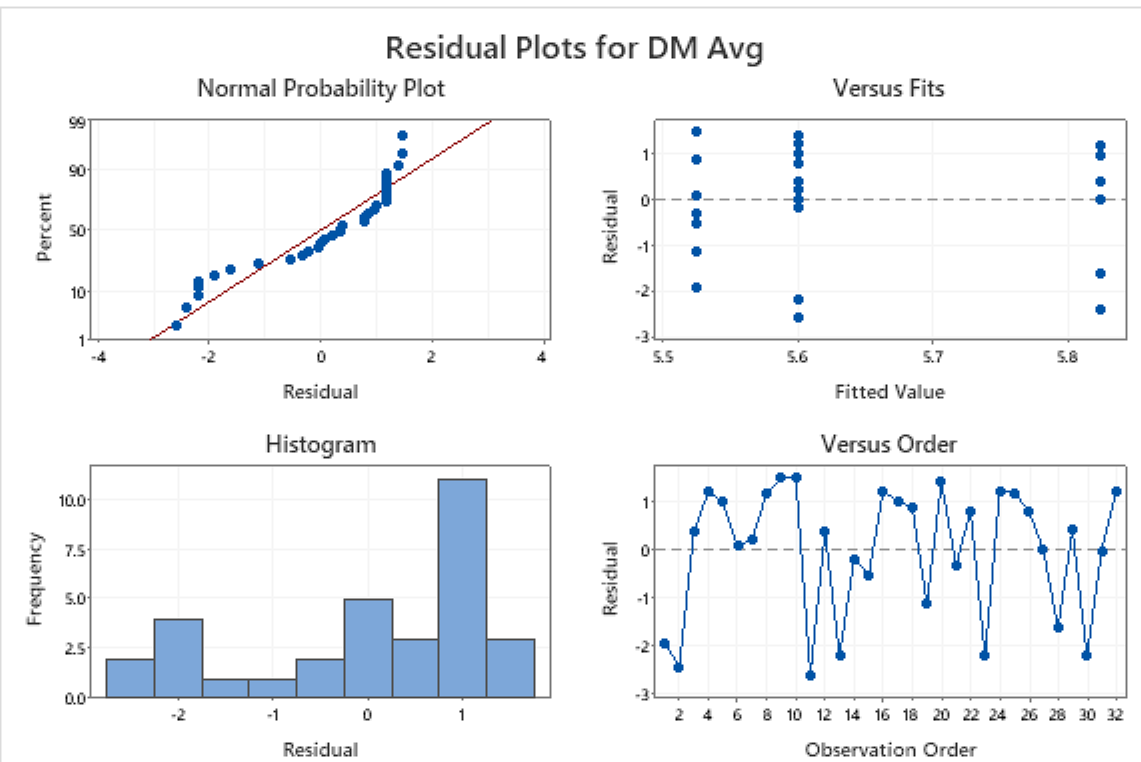
DM Avg = 5.638 - 0.038 Aug Reality + 0.075 Real-Time - 0.075 Aug Reality*Real-Time

Alias Structure

Factor	Name
A	Aug Reality
B	Real-Time

Aliases
I
A
B
AB


Pareto Chart of the Standardized Effects
(response is DM Avg, α = 0.05)
Term
2.048
AB
B
A
0.0
0.5
1.0
1.5
2.0
Standardized Effect
Factor Name
A Aug Reality
B Real-Time


Residual Plots for DM Avg
Normal Probability Plot
Percent
Residual
Versus Fits
Residual
Fitted Value
Histogram
Frequency
Residual
Versus Order
Residual
Observation Order

With BOX-COX Transformation

WORKSHEET 1

Factorial Regression: DM Avg versus Real-Time, Aug Reality

Method

Box-Cox transformation	
Rounded λ	3
Estimated λ	2.74937
95% CI for λ	(1.08387, 4.57887)

Coded Coefficients for Transformed Response

Term	Effect	Coef	SE Coef	95% CI	T-Value	P-Value	VIF
Constant		2.299	0.231	(1.826, 2.773)	9.95	0.000	
Real-Time	0.223	0.112	0.231	(-0.362, 0.585)	0.48	0.633	1.00
Aug Reality	-0.004	-0.002	0.231	(-0.475, 0.472)	-0.01	0.994	1.00
Real-Time*Aug Reality	-0.147	-0.073	0.231	(-0.547, 0.400)	-0.32	0.754	1.00

Model Summary for Transformed Response

S	R-sq	R-sq(adj)	PRESS	R-sq(pred)	AICc	BIC
1.30721	1.18%	0.00%	62.4930	0.00%	115.99	121.01

Analysis of Variance for Transformed Response

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Model	3	0.5705	1.18%	0.5705	0.19018	0.11	0.953
Linear	2	0.3988	0.82%	0.3988	0.19941	0.12	0.890
Real-Time	1	0.3987	0.82%	0.3987	0.39871	0.23	0.633
Aug Reality	1	0.0001	0.00%	0.0001	0.00011	0.00	0.994
2-Way Interactions	1	0.1717	0.35%	0.1717	0.17173	0.10	0.754
Real-Time*Aug Reality	1	0.1717	0.35%	0.1717	0.17173	0.10	0.754
Error	28	47.8462	98.82%	47.8462	1.70879		
Total	31	48.4168	100.00%				

Regression Equation in Uncoded Units

(DM Avg^λ-1)/(λ×g^(λ-1)) = 2.299 + 0.112 Real-Time
- 0.002 Aug Reality
- 0.073 Real-Time*Aug Reality

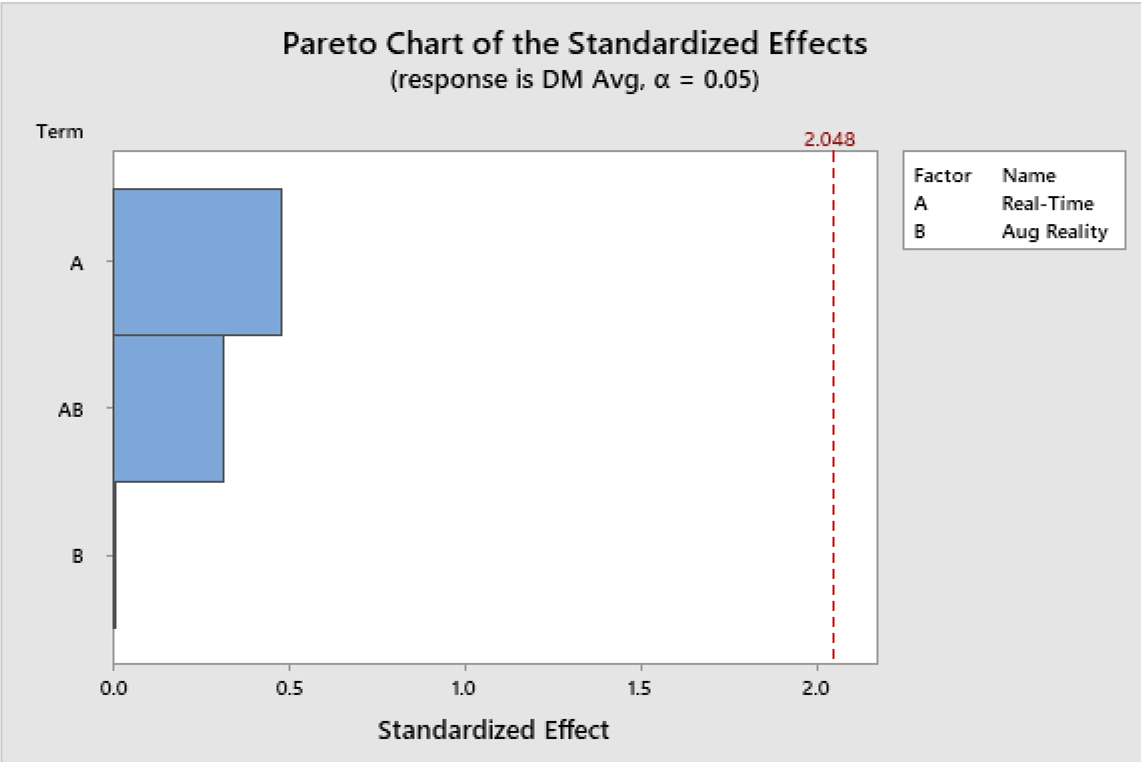
(λ = 3, g = 5.45824 is the geometric mean of DM Avg)

Alias Structure

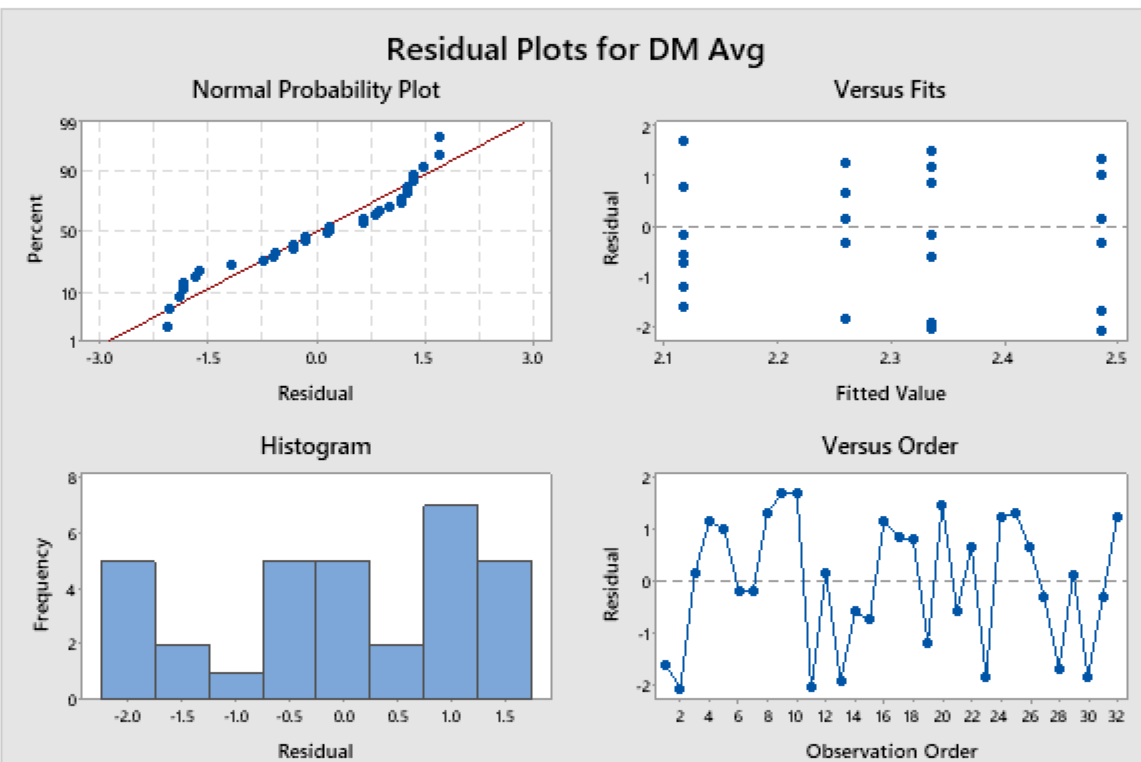
Factor	Name
A	Real-Time
B	Aug Reality

Aliases
I
A
B

AB



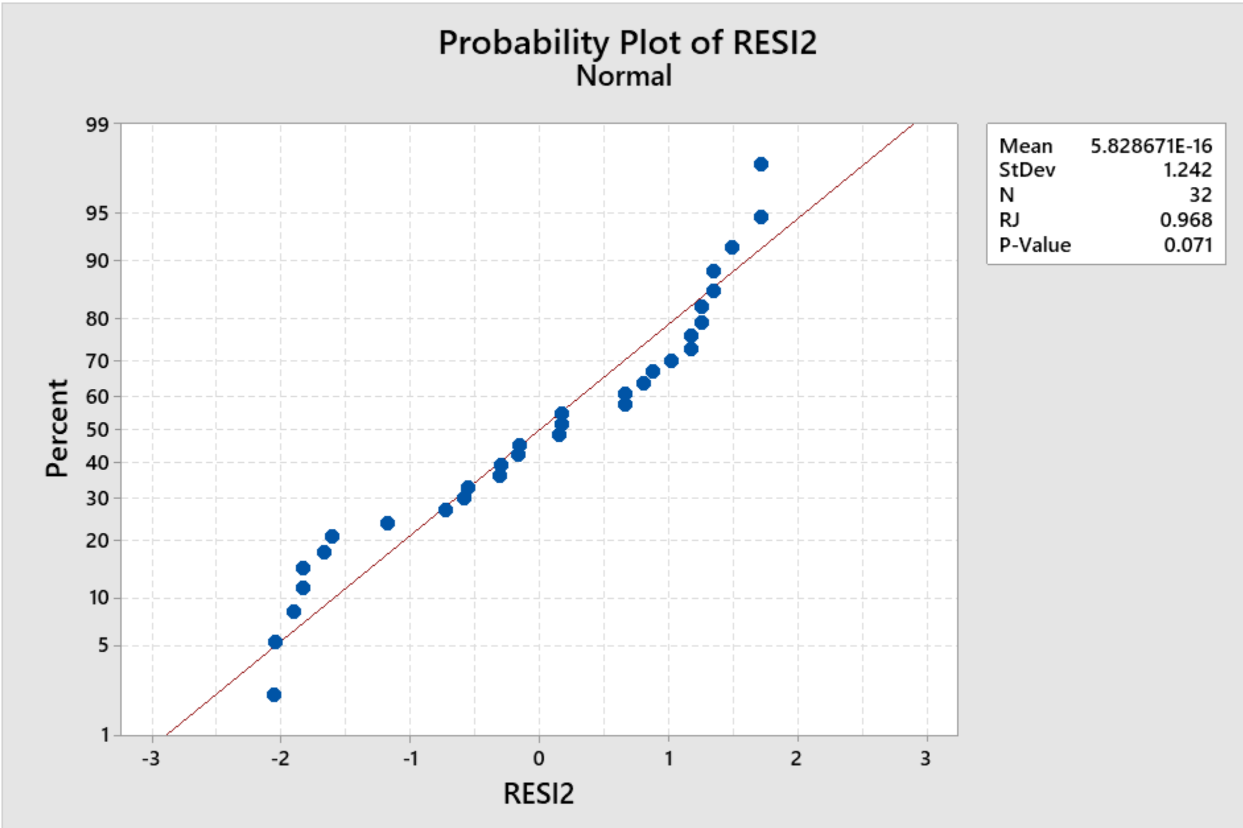
Pareto Chart of the Standardized Effects
(response is DM Avg, α = 0.05)
Term
2.048
Factor Name
A Real-Time
B Aug Reality
A
AB
B
0.0
0.5
1.0
1.5
2.0
Standardized Effect



Residual Plots for DM Avg
Normal Probability Plot
Percent
Residual
Versus Fits
Residual
Fitted Value
Histogram
Frequency
Residual
Versus Order
Residual
Observation Order

WORKSHEET 1

Probability Plot of RESI2



WORKSHEET 1

Test for Equal Variances: DM Avg versus Real-Time, Aug Reality

Method

Null hypothesis	All variances are equal
Alternative hypothesis	At least one variance is different
Significance level	α = 0.05

95% Bonferroni Confidence Intervals for Standard Deviations

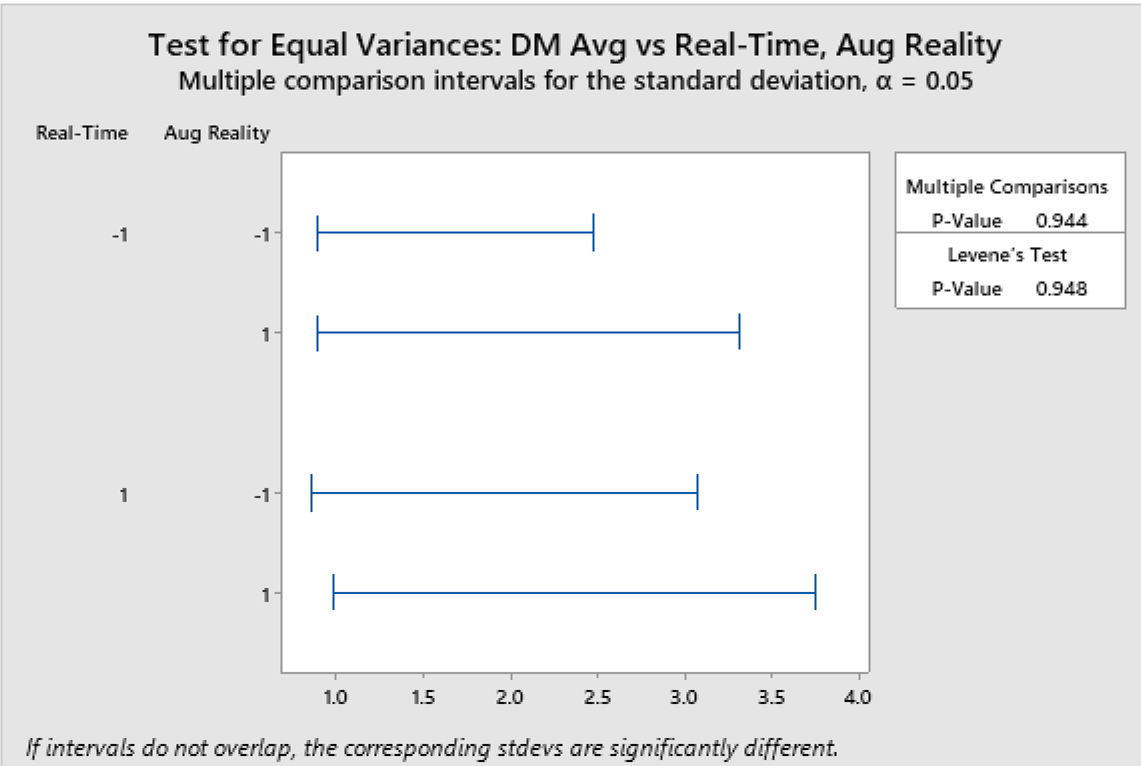
Real-Time	Aug Reality	N	StDev	CI
-1	-1	8	1.22329	(0.685411, 3.17432)
-1	1	8	1.41421	(0.452566, 6.42531)
1	-1	8	1.33711	(0.431728, 6.02100)

1	1	8	1.58204	(0.531793, 6.84289)

Individual confidence level = 98.75%

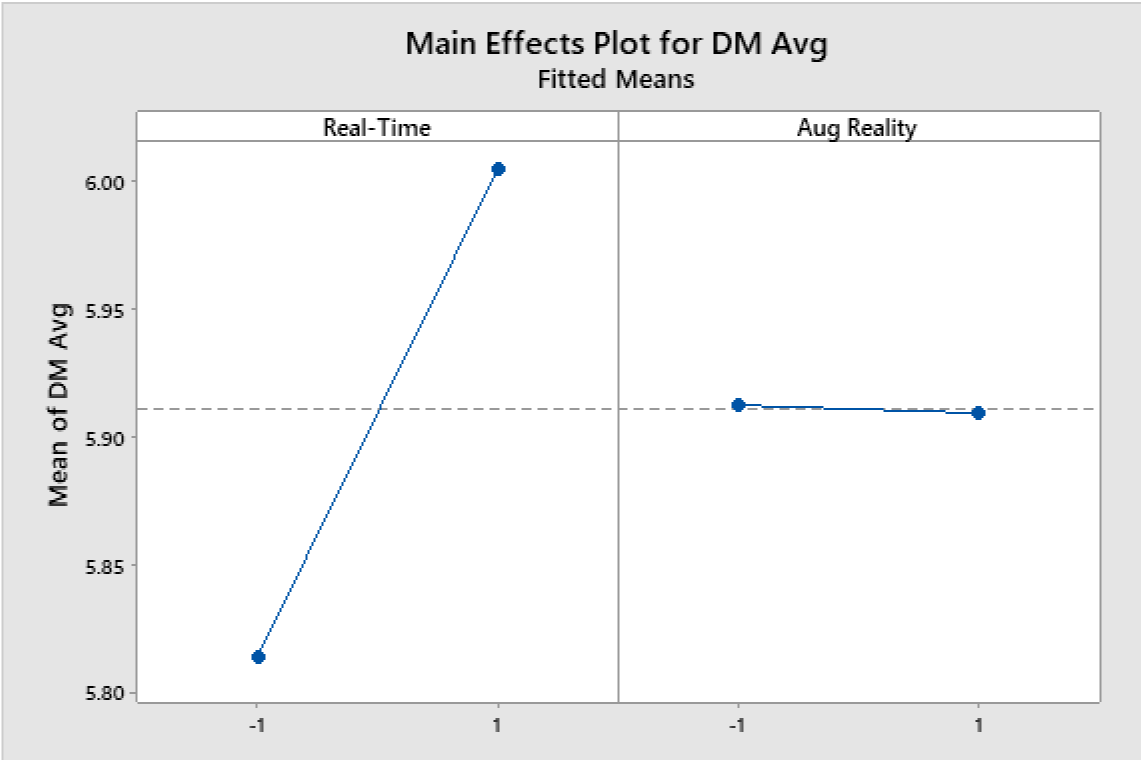
Tests

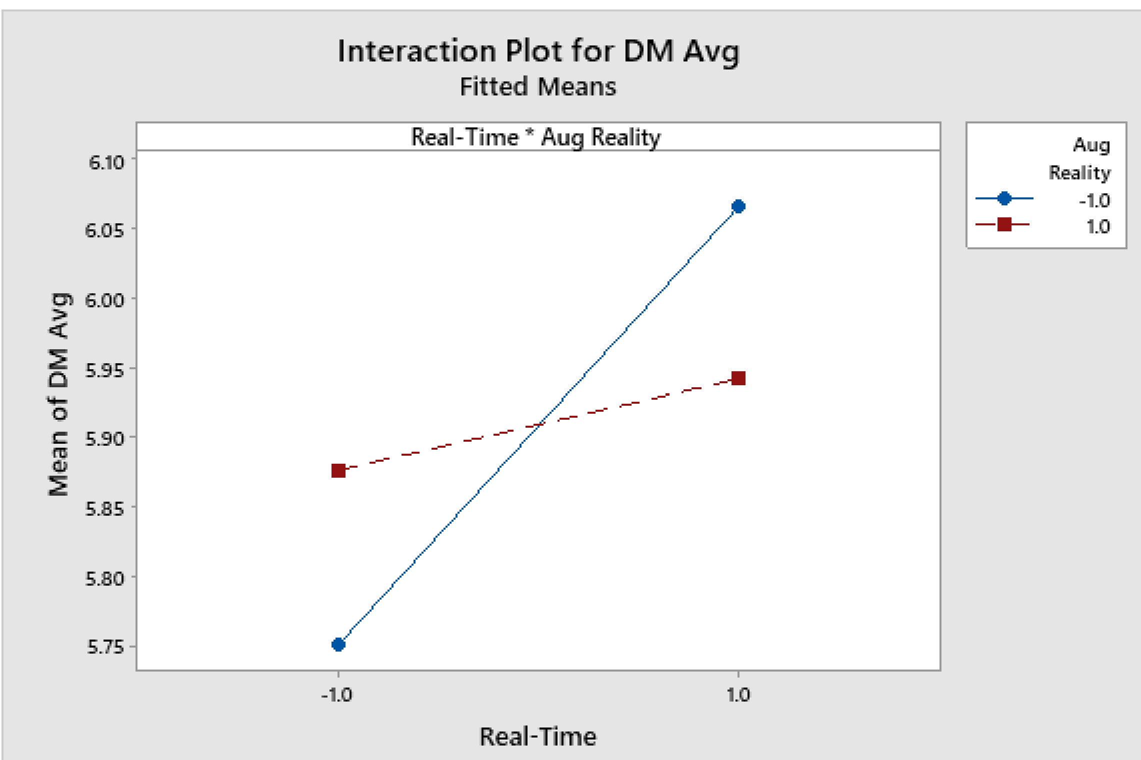
Method	Test Statistic	P-Value
Multiple comparisons	—	0.944
Levene	0.12	0.948



WORKSHEET 1

Factorial Plots for DM Avg





Marginal Means:

WORKSHEET 1

Descriptive Statistics: DM Avg

Results for Aug Reality = -1

Statistics

Variable	Real-Time	N	N*	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3	Maximum
DM Avg	-1	8	0	5.525	0.432	1.223	3.600	4.550	5.400	6.850	7.000
	1	8	0	5.825	0.473	1.337	3.400	4.600	6.200	6.950	7.000

Results for Aug Reality = 1

Statistics

Variable	Real-Time	N	N*	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3	Maximum
DM Avg	-1	8	0	5.600	0.500	1.414	3.400	3.950	6.200	6.700	6.800
	1	8	0	5.600	0.559	1.582	3.000	3.900	6.200	6.800	7.000

Pre/Post Survey Analysis

This section includes Minitab output files used for pre/post survey analysis.

Paired T-test: Decision Making:

WORKSHEET 1

Paired T-Test and CI: DM B, DM A

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
DM B	32	5.125	0.994	0.176
DM A	32	5.638	1.331	0.235

Estimation for Paired Difference

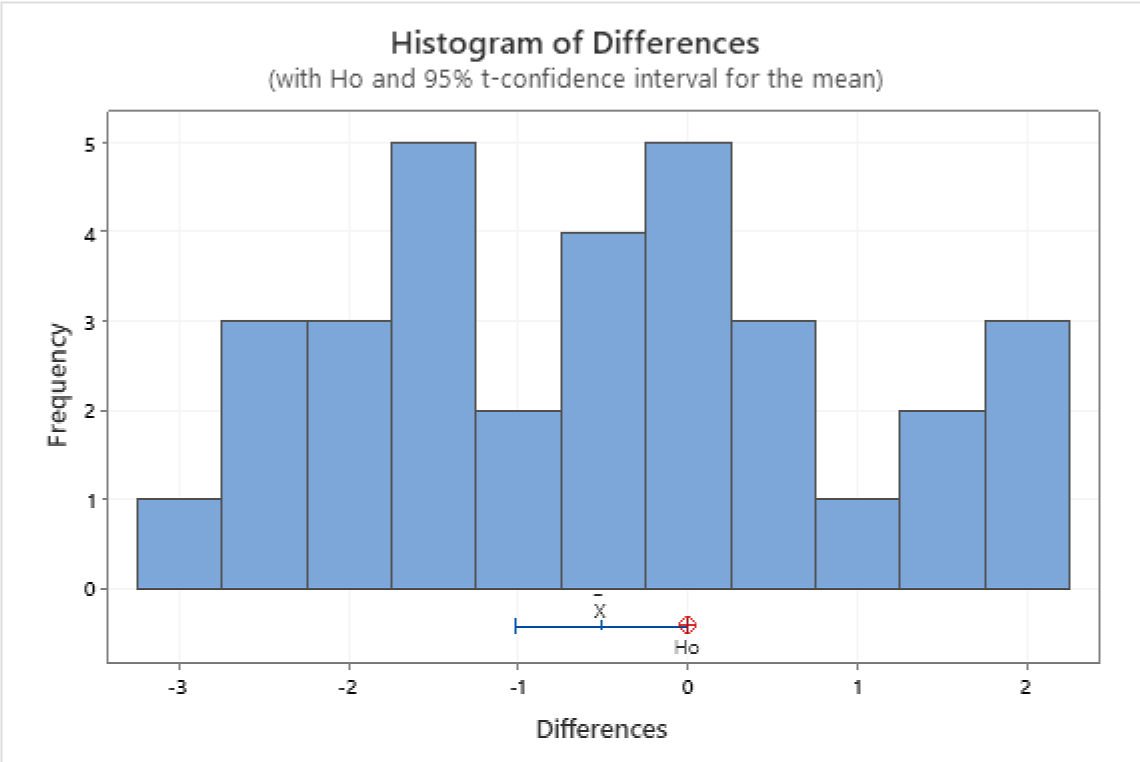
Mean	StDev	SE Mean	95% CI for μ_difference
-0.513	1.414	0.250	(-1.022, -0.003)

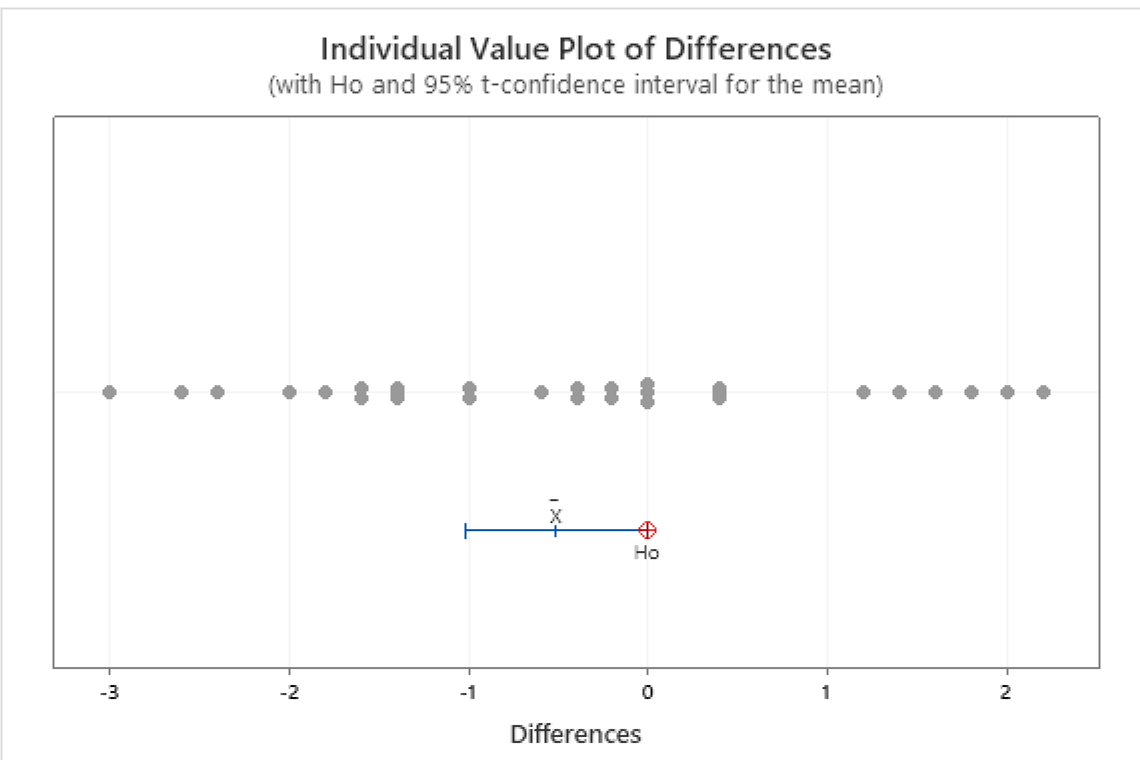
μ_difference: population mean of (DM B - DM A)

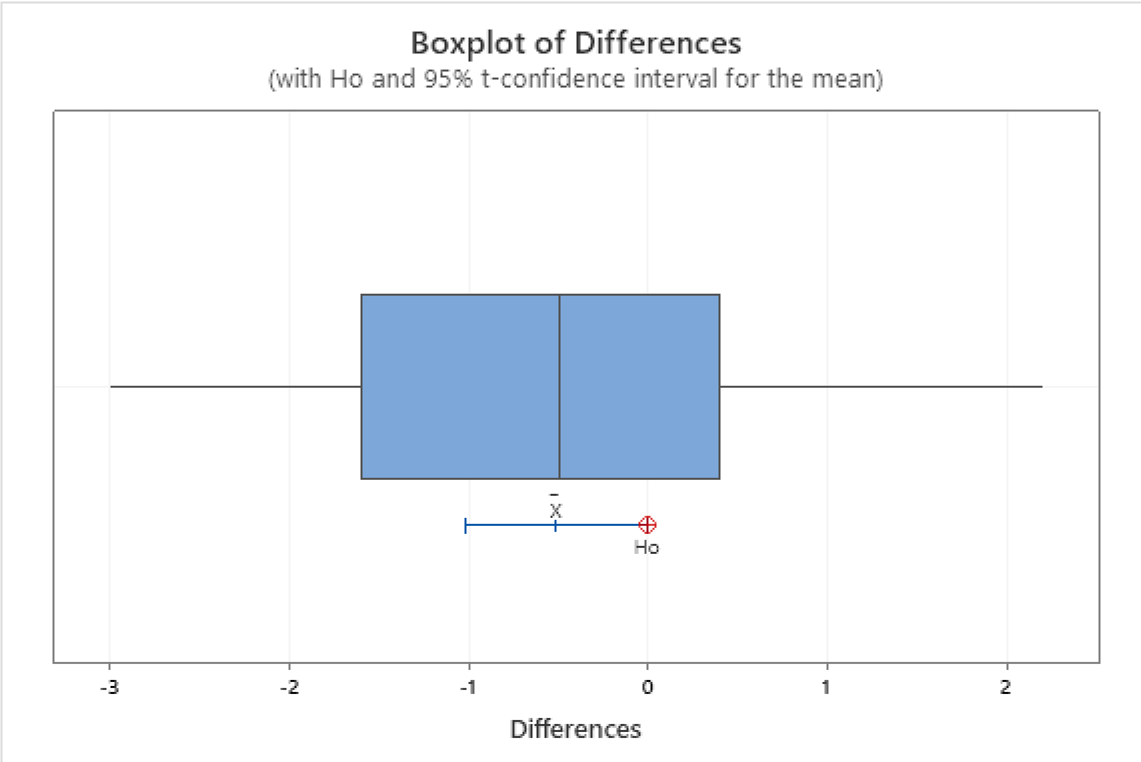
Test

Null hypothesis	H_0: μ_difference = 0
Alternative hypothesis	H_1: μ_difference ≠ 0

T-Value	P-Value
-2.05	0.049


Histogram of Differences
(with Ho and 95% t-confidence interval for the mean)
Frequency
0
1
2
3
4
5
X̄
Ho
-3
-2
-1
0
1
2
Differences


Individual Value Plot of Differences
(with Ho and 95% t-confidence interval for the mean)
X̄
Ho
-3
-2
-1
0
1
2
Differences



Paired T-test: Perceived Usefulness:

WORKSHEET 1

Paired T-Test and CI: PU B, PU A

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
PU B	32	5.292	1.063	0.188
PU A	32	5.766	1.373	0.243

Estimation for Paired Difference

Mean	StDev	SE Mean	95% CI for μ_difference
-0.474	1.620	0.286	(-1.058, 0.110)

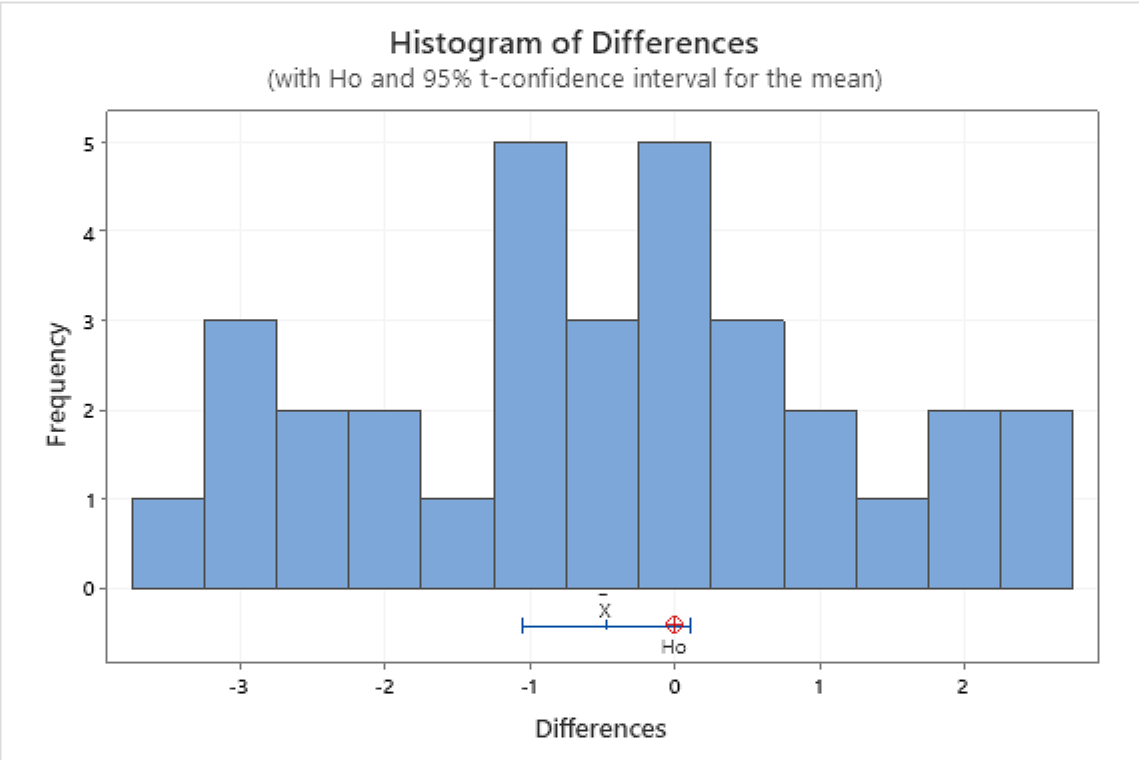
μ_difference: population mean of (PU B - PU A)

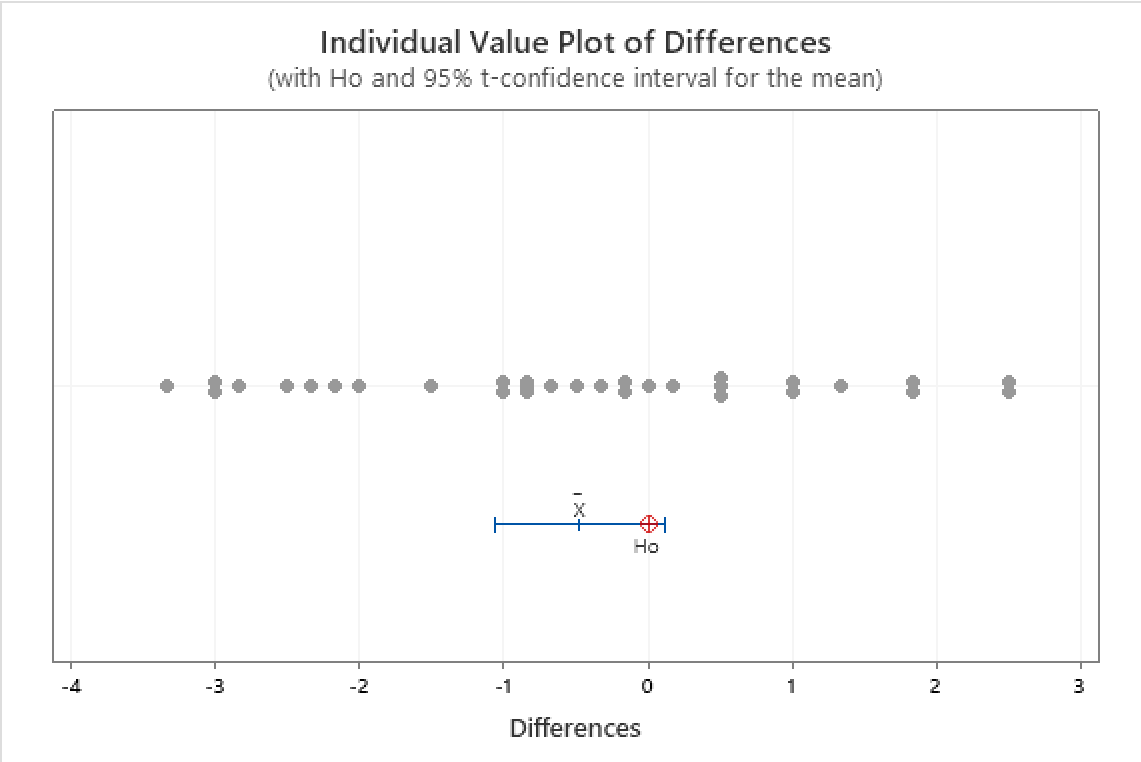
Test

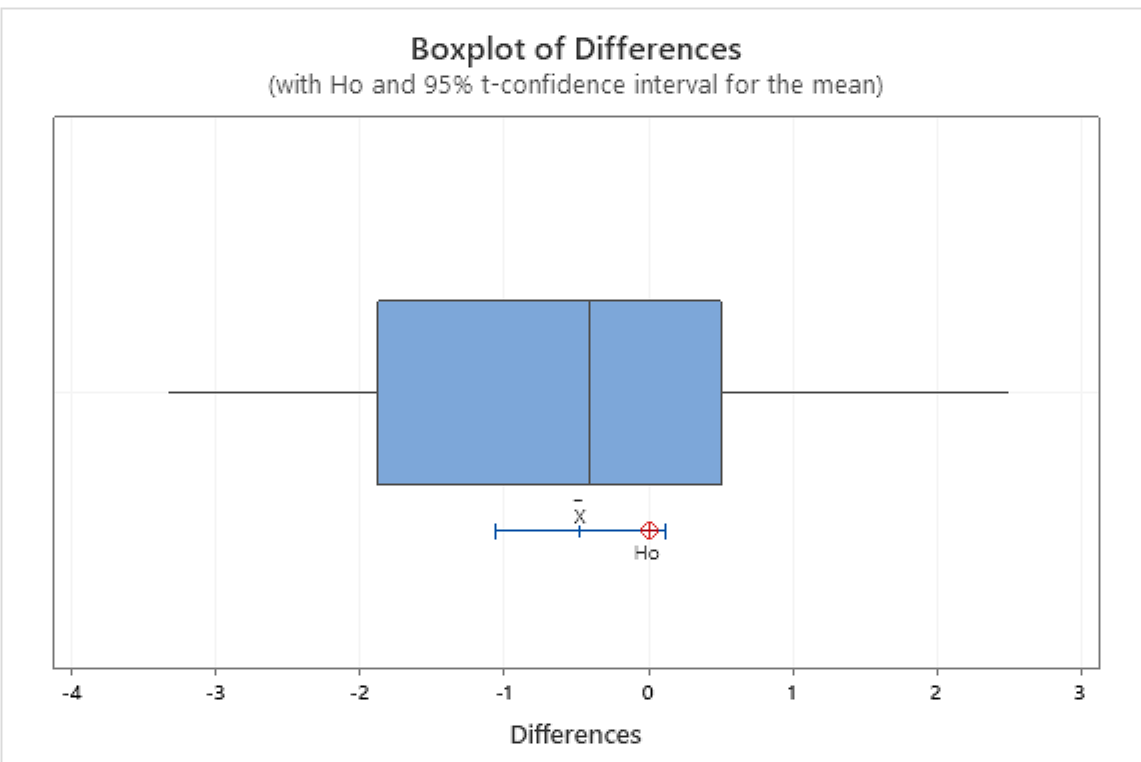
Null hypothesis	H_0: μ_difference = 0

Alternative hypothesis	H_1: µ_difference ≠ 0

T-Value	P-Value
-1.66	0.108




Individual Value Plot of Differences
(with Ho and 95% t-confidence interval for the mean)
X̄
Ho
-4
-3
-2
-1
0
1
2
3
Differences


Boxplot of Differences
(with Ho and 95% t-confidence interval for the mean)
X̄
Ho
-4
-3
-2
-1
0
1
2
3
Differences

Paired T-test: Perceived Ease of Use:

WORKSHEET 1

Paired T-Test and CI: PE B, PE A

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
PE B	32	5.719	0.999	0.177
PE A	32	6.182	0.940	0.166

Estimation for Paired Difference

Mean	StDev	SE Mean	95% CI for μ_difference
-0.464	1.180	0.209	(-0.889, -0.038)

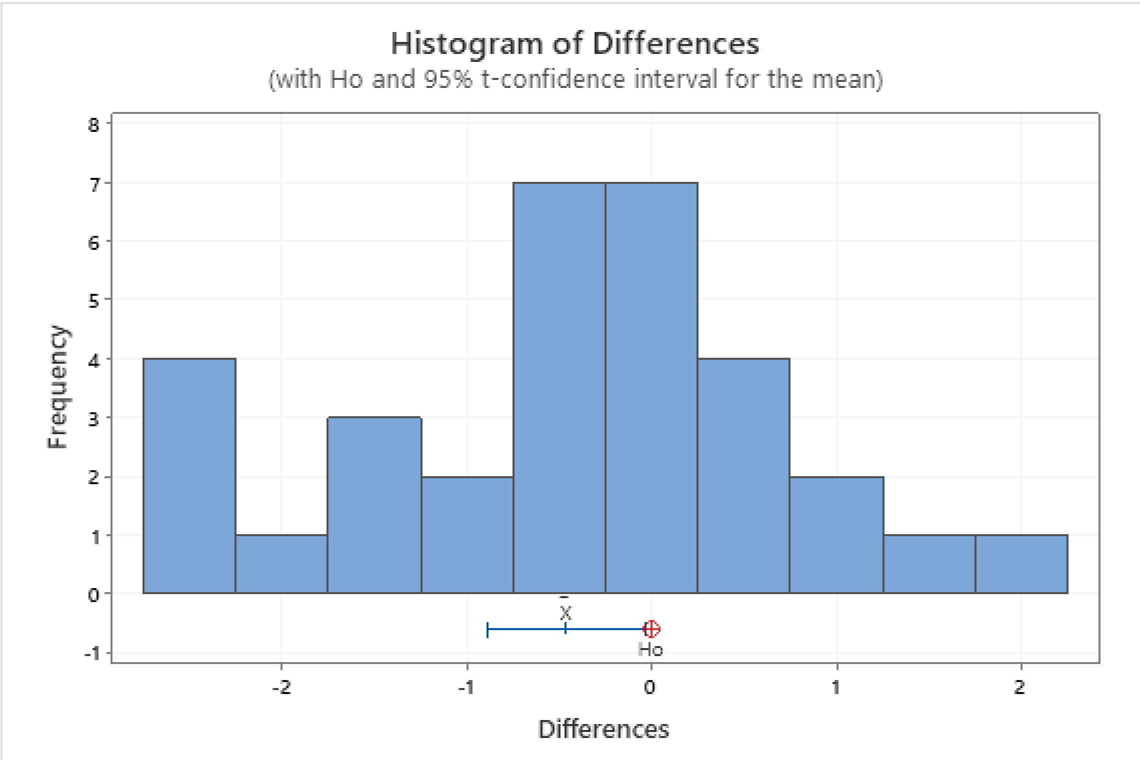
µ_difference: population mean of (PE B - PE A)

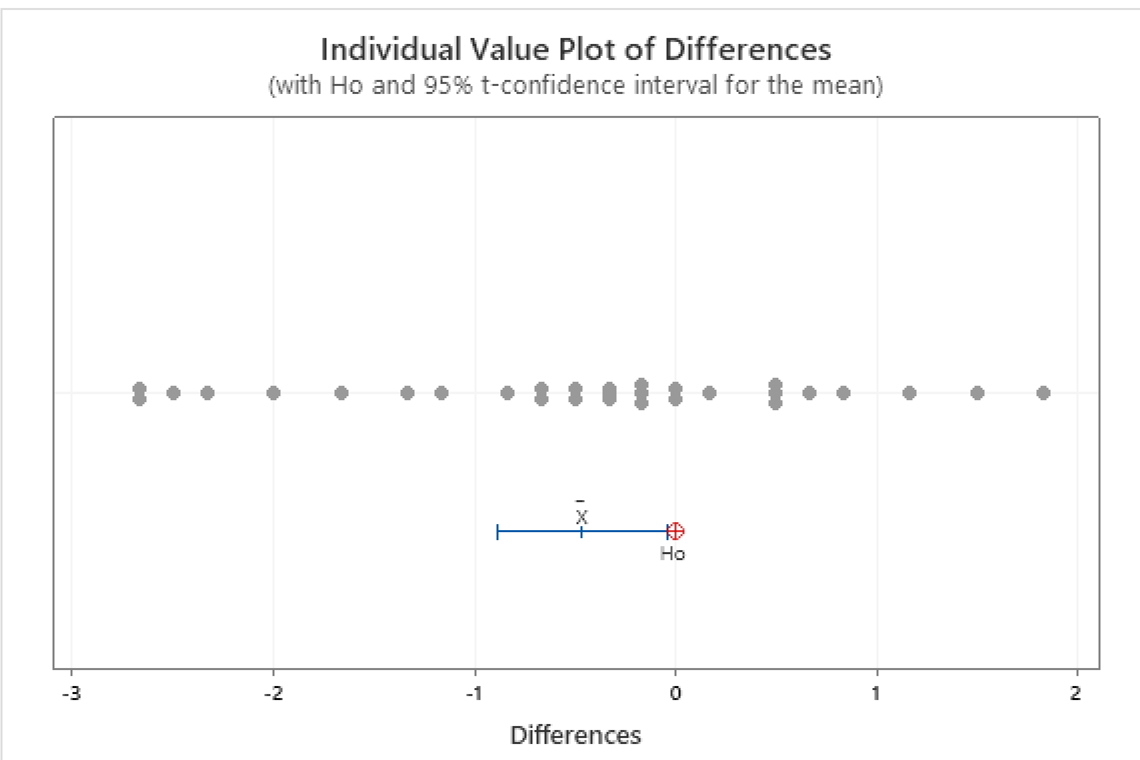
Test

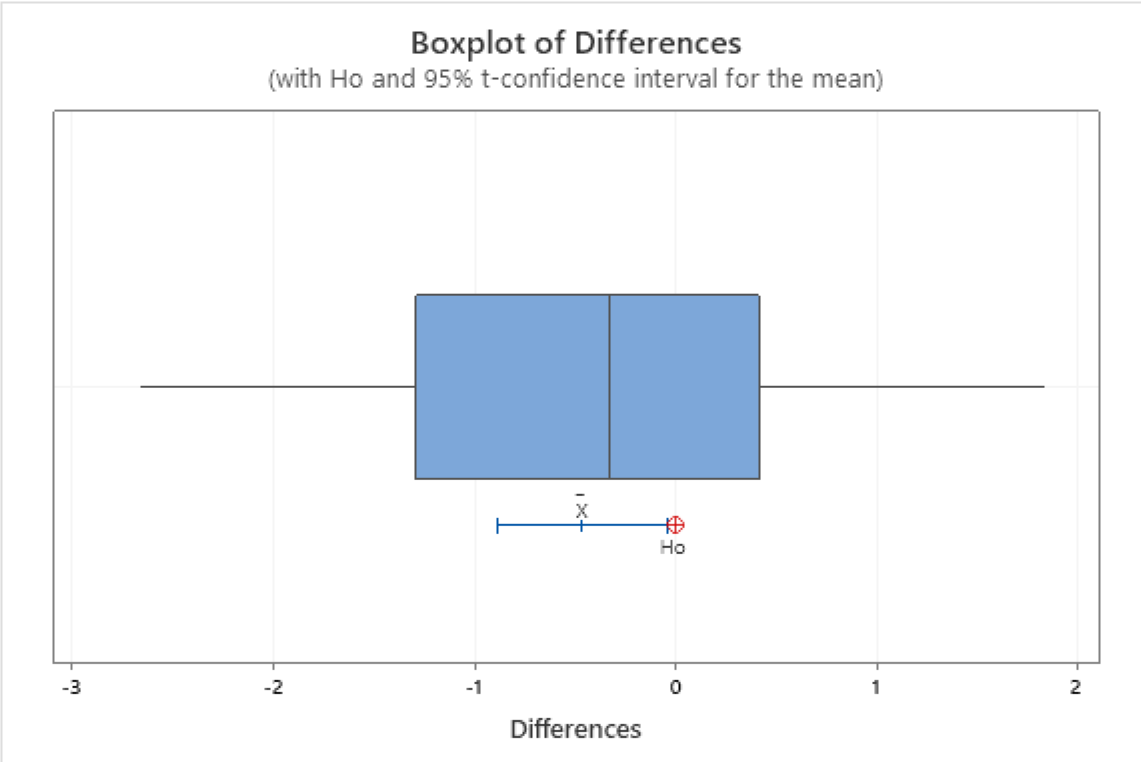
Null hypothesis	H_0: μ_difference = 0
Alternative hypothesis	H_1: μ_difference ≠ 0

T-Value	P-Value

-2.22	0.034


Histogram of Differences
(with Ho and 95% t-confidence interval for the mean)
Frequency
Differences
Ho
8
7
6
5
4
3
2
1
0
-1
-2
-1
0
1
2


Individual Value Plot of Differences
(with Ho and 95% t-confidence interval for the mean)
Differences
Ho
-3
-2
-1
0
1
2


Boxplot of Differences
(with Ho and 95% t-confidence interval for the mean)
X̄
Ho
-3
-2
-1
0
1
2
Differences

WORKSHEET 1

Two-Sample T-Test and CI: End Score, Gender

Method

μ_1: population mean of End Score when Gender = Female

μ_2: population mean of End Score when Gender = Male

Difference: $\mu_1 - \mu_2$

Equal variances are not assumed for this analysis.

Descriptive Statistics: End Score

Gender	N	Mean	StDev	SE Mean
Female	16	10418	2391	598
Male	13	11972	1817	504

Estimation for Difference

Difference	95% CI for Difference
-1554	(-3160, 53)

Test

Null hypothesis	$H_0: \mu_1 - \mu_2 = 0$
Alternative hypothesis	$H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-1.99	26	0.058

WORKSHEET 1

Descriptive Statistics: End Score

Statistics

Variable	Gender	N	N*	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3	Maximum
End Score		3	0	9287	1067	1848	7446	7446	9273	11141	11141
	Female	16	0	10418	598	2391	4825	9700	10607	11698	13645
	Male	13	0	11972	504	1817	8383	11056	11908	13473	14695

APPENDIX I: LAB EXPERIMENT RECRUITMENT MATERIALS

Novel Device User Study

Participants Needed for Fall 2020!

Seeking students for a research study investigating how new devices can be used to help workers process information and make decisions. Participants will use one of a series of tools to evaluate metrics to make decisions.

The duration of this experiment will be 45 to 60 minutes and you will be compensated a **$20 Amazon gift card** for your time.

Participants must be:

- Business or Industrial Engineering Majors
- 18 years or older
- Currently enrolled UCF student
- Not knowingly pregnant
- Not a felon or prisoner
- Not epileptic
- No pre-existing vision disorders (Color blind, Blind, etc.)
- No pre-existing balance issues

*Researchers and participants will follow the COVID-19 Standard Safety Plan while participating in the study.

Interested in participating?

Scan the QR or follow the link below to sign up for a time slot!

https://www.signupgenius.com/go/10C0D4DA9A82DA5FDC07-ucfiems

SCAN ME

Recruitment email to send to ESI 4221 students:

Recruitment Email:

Dr. Keathley and her PhD Candidate, Joshua Nelson, are now recruiting students to participate in a research study investigating the effects of different technologies on a person's ability to effectively use information. Participants will use a tablet to evaluate metrics to make decisions.

The duration of this experiment will be 45 to 60 minutes and you will receive extra credit for course ESI-4221 for your time. Researchers and participants will follow the COVID-19 Standard Safety Plan while participating in the study.

Below is the sign-up link:

https://www.signupgenius.com/go/10C0D4DA9A82DA5FDC07-ucfiems

If you have any questions or concerns, please email Joshua Nelson at joshuanelson@knights.ucf.edu.

APPENDIX J: LAB EXPERIMENT SURVEY QUESTIONS

Pre-Survey

Introductory Questions:
- Participant Number:

The following questions ask about your perspectives regarding the tablet/tool. Please note that we are interested in your opinions and there are no right or wrong answers to any of the questions.

Perceived Usefulness
Q1: Using the tablet/tool will enable me to accomplish this task more quickly.
Q2: Using the tablet/tool will improve my ability to complete this task.
Q3: Using the tablet/tool will increase my productivity on this task.
Q4: Using the tablet/tool will enhance my effectiveness on this task.
Q5: Using the tablet/tool will make it easier to do this task.
Q6: I will find the tablet/tool useful in this task.

Perceived Ease of Use:
Q1: Learning to operate the tablet/tool will be easy for me.
Q2: I will find it easy to get the tablet/tool to do what I want it to do.
Q3: My interaction with the tablet/tool will be clear and understandable.
Q4: I will find the tablet/tool to be flexible to interact with.
Q5: It will be easy for me to become comfortable using this tablet/tool.
Q6: I will find the tablet/tool easy to use.

Decision Making:
Q1: This tablet/tool will help me maximize profit.
Q2: This tablet/tool will help me understand if I am making good decisions.
Q3: This tablet/tool will help me make decisions faster.
Q4: This tablet/tool will help me to achieve my goals(s).
Q5: This tablet/tool will help me use resources more effectively.
Q6: I trust my intuition more than data when making decisions.

Other:
Q1: I will be able to perform the experiment better by first having a practice run.

Post-Survey

Introductory Questions:

- Participant Number:
- Gender:
- Age:
- Class Standing:
- What's you primary major?

The following questions ask about your perspectives regarding the tablet/tool. Please note that we are interested in your opinions and there are no right or wrong answers to any of the questions.

Perceived Usefulness

Q1: Using the tablet/tool enabled me to accomplish this task more quickly.
Q2: Using the tablet/tool improved my ability to complete this task.
Q3: Using the tablet/tool increased my productivity on this task.
Q4: Using the tablet/tool enhanced my effectiveness on this task.
Q5: Using the tablet/tool made it easier to do this task.
Q6: I found the tablet/tool useful for this task.

Perceived Ease of Use:

Q1: Learning to operate the tablet/tool was easy for me.
Q2: I found it easy to get the tablet/tool to do what I wanted it to do.
Q3: My interaction with the tablet/tool was clear and understandable.
Q4: I found the tablet/tool to be flexible to interact with.
Q5: It was easy for me to become comfortable with this tablet/tool.
Q6: I found the tablet/tool easy to use.

Behavioral Intention to Use

Q1: If grocery store managers had access to a similar tool, they would use it.
Q2: Grocery store managers would use a tool like this.
Q3: Grocery store managers will probably use a tool like this in the future.

Decision Making:

Q1: This tablet/tool helped me maximize profit.
Q2: This tablet/tool helped me understand if I was making good decisions.
Q3: This tablet/tool helped me make decisions faster.
Q4: This tablet/tool helped me to achieve my goal(s).
Q5: This tablet/tool helped me use resources more effectively.
Q6: I trusted my intuition more than data when making decisions.

Other:

Q1: I was able to perform the experiment better by first having a practice run.

APPENDIX K: LAB EXPERIMENT IRB FORMS

UNIVERSITY OF CENTRAL FLORIDA

Title of research study: ***Leveraging Augmented Reality for Real-Time Operational Performance Management***

Investigator: ***Joshua Nelson***

Key Information: The following is a short summary of this study to help you decide whether or not to be a part of this study. More detailed information is listed later on in this form.

Why am I being invited to take part in a research study?

We invite you to take part in a research study as a student at UCF who meets the following criteria:

- Business or Industrial Engineering major
- Aged 18 years or older
- Currently enrolled UCF student
- Not currently pregnant (unless incidental)
- Not a prisoner
- Not epileptic
- No pre-existing vision disorders
- No pre-existing balance issues

Why is this research being done?

The purpose of this study is to investigate the effects of different technologies on a person's ability to effectively use information as part of a doctoral study being conducted at the University of Central Florida.

How long will the research last and what will I need to do?

It is expected that you will be in this research study for approximately 35- 60 minutes. An introductory PowerPoint will guide you through your part in the study and then you will be asked to complete an online pre-survey at the beginning of the study. After the survey is complete, you will be asked to complete a short simulation using a tablet where you will be making decisions on inventory management and staffing. Once you finish the simulation, you will then be asked to complete an online post-survey regarding your experience.

More detailed information about the study procedures can be found under ***"What happens if I say yes, I want to be in this research?"***

Is there any way being in this study could be bad for me?

The risks to participation are minimal and do not exceed the risks associated with activities found in daily life.

Will being in this study help me in any way?

There are no benefits to you from your taking part in this research. We cannot promise any benefits to others from your taking part in this research.

What happens if I do not want to be in this research?

Your participation in this study is voluntary. You are free to withdraw your consent and discontinue participation in this study at any time without prejudice or penalty. Your decision to participate or not participate in this study will in no way affect your continued enrollment, grades, employment or your relationship with UCF or the individuals who may have an interest in this study.

Detailed Information: The following is more detailed information about this study in addition to the information listed above.

What should I know about a research study?

- Someone will explain this research study to you.
- Whether or not you take part is up to you.
- You can choose not to take part.
- You can agree to take part and later change your mind.
- Your decision will not be held against you.
- You can ask all the questions you want before you decide.

Who can I talk to?

If you have questions, concerns, or complaints, or think the research has hurt you, talk to the research team: **Joshua Nelson**, Graduate Student, Industrial Engineering, College of Engineering and Computer Science, (407) 409-6636 or by email at joshua.nelson@knights.ucf.edu or **Dr. Heather Keathley**, Faculty Supervisor, Department of Industrial Engineering and Management Systems at (407) 823-4745 or by email at heather.keathley@ucf.edu.

This research has been reviewed and approved by an Institutional Review Board ("IRB"). You may talk to them at 407-823-2901or irb@ucf.edu if:

- Your questions, concerns, or complaints are not being answered by the research team.
- You cannot reach the research team.
- You want to talk to someone besides the research team.
- You have questions about your rights as a research subject.
- You want to get information or provide input about this research.

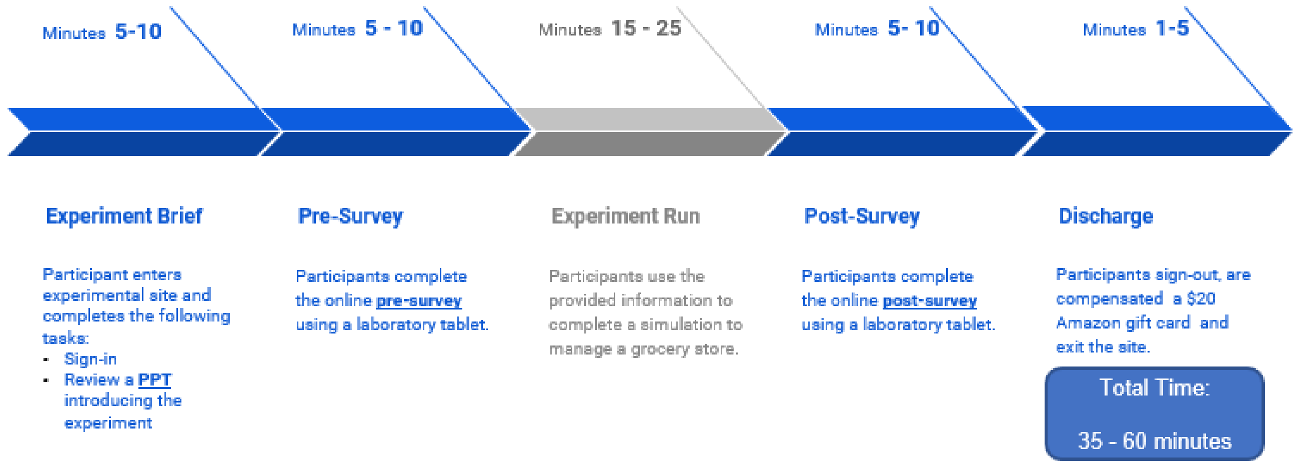
How many people will be studied?

We expect about 40-60 UCF students will participate in this research study.

What happens if I say yes, I want to be in this research?

At random, you will be assigned 1 of 4 treatments to participate in. 4 different devices are described below. Each device will either run the experiment in real-time data or historical data making up a total of 4 treatments. A brief PowerPoint will be shown to introduce the experiment and then you will be asked to complete an online pre-survey on one of the lab's computers. You will then start the experiment, which should take about 15-25 minutes to complete. Once you are done with the experiment, you will complete the online post-survey, sign out, and be compensated a $20 Amazon e-gift card.

The experimental procedure is summarized below:



The total duration of the study will be 35-60 minutes. You will interact with undergraduate and graduate researchers as part of this study in a lab environment.

The research study will be held on the main UCF campus in room ENG 2 Room 323.

Various technologies will be used as part of this study. You will interact with one of the following devices:

- Android Tablet (Augmented Reality): You will use Augmented Reality on an android tablet to view and interact with 3D images in your surroundings.
- Android Tablet (Traditional App): You will use a traditional app and dashboard on an android tablet to interact with the simulation.

Based on the results of this study, future research may be conducted to extend this study.

What happens if I say yes, but I change my mind later?

You can leave the research at any time it will not be held against you. If you decide to leave the research, contact the investigator so that the investigator can remove your data from the database.

Is there any way being in this study could be bad for me? (Detailed Risks)

Side effects of VE (virtual environment) use may include stomach discomfort, headaches, sleepiness, dizziness and decreased balance. However, these risks are no greater than the sickness risks participants may be exposed to if they were to visit an amusement park such as Disney Quest (Disney Quest is a VE based theme park), Disney World or Universal Studios parks and ride attractions such as roller coasters. If you experience any of the symptoms mentioned, please tell the researcher and remain seated until the symptoms disappear.

What happens to the information collected for the research?

Efforts will be made to limit the use and disclosure of your personal information, including research study data, to people who have a need to review this information. We cannot promise complete secrecy. Organizations that may inspect and copy your information include the IRB and other representatives of UCF.

Each participant will be assigned a participant ID and all study information will be linked to this ID ensuring that individual participant's responses are anonymous and cannot be identified. Your identifiable information (full name, gender, PID, and UCF major) will be stored separately from the study data in an encrypted file until all data has been collected. Once data collection is complete, the identifiers will be permanently destroyed. Anonymized data will be stored in encrypted spreadsheets on a protected UCF OneDrive account for at least five years following the completion of the study. The faculty and PI will have direct access and the anonymized data may also be processed using statistical analyses by UCF graduate and undergraduate students.

What else do I need to know?

If you agree to take part in this research study, we will compensate you a $20 Amazon e-gift card for your time and effort. This compensation will be provided after completion of the exit survey.

Your de-identified information may be used to create products or to deliver services, including some that may be sold and/or make money for others. If this happens, there are no plans to tell you, or to pay you, or to give any compensation to you or your family.

UCF UNIVERSITY OF CENTRAL FLORIDA

PROTOCOL TITLE:

Leveraging Augmented Reality for Real-Time Operational Performance Management

PRINCIPAL INVESTIGATOR:

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Industrial Engineering and Management Systems
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VERSION NUMBER/DATE:

Version 1:3-16-2020

REVISION HISTORY

Revision #	Version Date	Summary of Changes	Consent Change?
1	3-16-2020	Initial Release	No

Table of Contents

Study Summary

Study Title	Leveraging Augmented Reality for Real-Time Operational Performance Management
Study Design	Lab experiment featuring human subjects and utilizing a design of experiments (DOE) approach.
Primary Objective	The purpose of this study is to investigate the effects of different technologies on a person's ability to effectively use information as part of a doctoral study being conducted at the University of Central Florida. The primary objective is to conduct an experiment featuring a series of simulations and pre/post surveys.
Secondary Objective(s)	Analyze survey results from experiment.
Research Intervention(s)/ Investigational Agent(s)	Computer Simulation Models
IND/IDE #	NA
Study Population	UCF Students
Sample Size	40- 60 students
Study Duration for individual participants	35- 60 minutes
Study Specific Abbreviations/ Definitions	AR (Augmented Reality) OPM (Operational performance management) DOE (Design of Experiments)

Objectives*

1.1 The objectives of the study are to conduct a series of experiments consisting of eight treatment combinations and to execute pre\post surveys to assess participant experience.

The following hypotheses will be investigated (tested via DOE analytic approaches):

Use of real-time data will have a positive effect on real-time decision making

Use of AR will have a positive effect on real-time decision making

Interaction of real-time data and AR technology will have a significant positive effect on real-time decision making

Technology acceptance and usability will be predictors of decision-making effectiveness

Background*

1.2 The PhD candidate's experience includes leading Augmented Reality (AR) implementation in local manufacturing as well as researching novel AR applications. The PhD advisor's experience includes research in Design of Experiments (DOE) and system implementation/integration. A gap exists in the research of how AR affects decision making for Operational Performance Management.

No preliminary data/pilot testing has occurred for the experiment. A systematic literature review was conducted to evaluate the current application areas related to management practices such as monitoring work practices, process control, and providing feedback. This review did not identify any studies related to the application of AR to support OPM, but did identify many applications relevant to management activities that empirically demonstrate the benefit of adopting such a technology such as reducing errors and improving the efficiency of the decision-making process for an organization or individual (Kim, Park, Lim, & Kim, 2013). The review analyzes the current development in this research area and how it has matured over the last ten years including evaluating the applications discussed in the identified publications to demonstrate the existing gap in the research related to OPM applications.

A DOE is being designed to analyze the research experiment. An Expert Study is being conducted as part of another research project and its results will feed into this.

1.3 Technologies such as artificial intelligence, machine learning, and augmented reality were once considered novelties. However, recent advances have led to the emergence of a variety of practical applications across all industries. This trend is also reflected in management science, which has seen the development of tools that support operational and strategic activities such as project management as well as complex work tasks such as enhanced visualization and motor skills.

A brief review of the literature shows that the amount of research that specifically pertains to using AR as a performance measurement tool is limited. There is evidence of using AR to monitor assembly lines and to analyze Quality Process Control (Segovia et al., 2015), but these areas are also not well developed. Potential contributions that could be made in this area include leveraging this technology to improve OPM best practices. Improving OPM will lead to improvements in organizational performance and sustainability. Further, using AR technology with OPM is an innovative solution that can add to the current literature in the field.

References:

Kim, C., Park, T., Lim, H., & Kim, H. (2013). On-site construction management using mobile computing technology. *Automation in Construction*, *35*, 415–423. https://doi.org/10.1016/j.autcon.2013.05.027

Segovia, D., Mendoza, M., Mendoza, E., & González, E. (2015). ScienceDirect 2015 International Conference on Virtual and Augmented Reality in Education Augmented Reality as a Tool for Production and Quality Monitoring. *Procedia - Procedia Computer Science*, *75*, 291–300. https://doi.org/10.1016/j.procs.2015.12.250

Study Endpoints*

1.4 NA

1.5 NA

Study Intervention/Investigational Agent

1.6 NA

1.7 Devices to be used include an Android tablet. This device will be stored in the advising faculties office and only made available by request to the faculty.

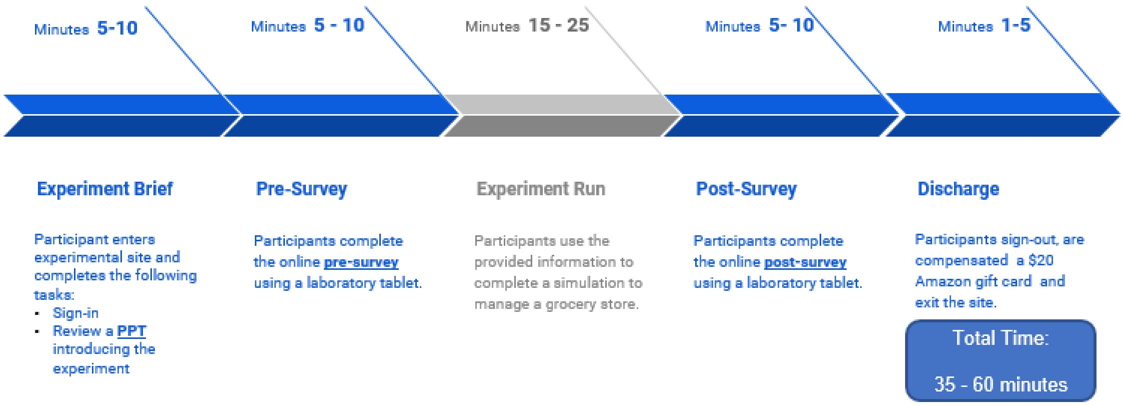
1.8 NA

	Applicable to:		
FDA Regulation	***IND Studies***	***IDE studies***	***Abbreviated IDE studies***
21 CFR 11	***X***	***X***	
21 CFR 54	***X***	***X***	
21 CFR 210	***X***		
21 CFR 211	***X***		
21 CFR 312	***X***		
21 CFR 812		***X***	***X***
21 CFR 820		***X***	

Procedures Involved*

1.9 A classical Design of Experiments (DOE) will be utilized for this experiment. There are 4 treatments will be included in the experiment. The experiment will need 10 observations for each treatment to have a minimum of 40 observations. The results will be analyzed in a 2^2 statistical model. Additional rounds of data collection will be conducted to achieve an appropriate statistical power. There will be 4 different treatments as part of this experiment. The treatment is just the unique combination of either real time data, historical data, Augmented Reality, or not using Augmented Reality. Real time data is data that is updating throughout the data based on decisions made that day. Historical data is data that is more than one day in the past and does not update throughout the day based on decisions being made. Augmented Reality projects a 3D image into the real world that mimics a hologram. 2 will use Real Time data, 2 will use historical data. 2 treatments will utilize Augmented Reality, 2 will not. Not all participants will run the same treatments, there will be different permutations for different participants. 10 participants will run the same treatment resulting in a total of 40 participants.

The experiment simulation will consist of a participant using the device in managing a grocery store. The participant will be given data on food inventory in various departments, expired food rates, cash register utilization, and overall store profit. They will use this data to guide different decisions they can make while managing the store. They can allow more employees to be actively working, they can buy more food (or less food) to stock, and they can assign resources in the grocery store to try to maximize profit.



1.10 Various technologies will be used as part of this study. The participant will interact with the following devices:

a) Android Tablet (Augmented Reality): You will use Augmented Reality on an android tablet to view and interact with 3D images in your surroundings.

b) Android Tablet (Traditional App): You will use a traditional app and dashboard on an android tablet to interact with the simulation.

1.11 Describe:

- The study will be screening participants for visual and balance issues as well as epilepsy. Anonymizing data so that no participants can be directly identified
- An Android tablet will be used in the research. This is a commercially available device that we be used to compare participant data from the experiment.
- The following records will be used to provide information of collect from the participant:
    - Pre-Survey.pdf
    - Post-Survey.pdf
    - Flyer_Recruitment_jmn.docx
    - Video Brief.pptx
    - Study signup link: *https://www.signupgenius.com/go/30e084ba9ac2aa0fd0-pilot*

1.12 Survey data will be collected electronically. The simulation will track the participant's actions that will be exported to Excel files and analyzed. Participant actions will be observed by experimentalists captured by note taking during the experiment.

1.13 NA

1.14 NA

Data and Specimen Banking*

1.15 Anonymized data will be stored in excel files on a protected UCF OneDrive account for at least five years following the completion of the study. The faculty and PI will have direct access and the anonymized data may also be processed using statistical analyses by UCF graduate and undergraduate students.

1.16 Pre/post survey data (collected via Qualtrics and stored in excel files) and simulation capture data (collected via the computer simulations and stored in excel files).

1.17 The data will not be made public and will not be available outside of the research group other than for study result or publication verification

Sharing of Results with Subjects*

1.18 The raw data will not be provided to participants though the results of analysis of the aggregate results will be documented in a final report, which may be made available to study participants upon request.

Study Timelines*

1.19 The experimental procedure is summarized below:

- The total duration of the study will be 35-60 minutes. You will interact with undergraduate and graduate researchers as part of this study in a lab environment.
- Study enrollment will be open until all participants are collected and is expected to be conducted from August through September 2020.

Inclusion and Exclusion Criteria*

1.20 When a student makes an appointment, we will send an email with criteria to confirm whether the potential participant meets the required criteria prior to scheduling their visit.

1.21 We invite individuals to take part in a research study who meets the following criteria:

- Business or Industrial Engineering Majors
- Aged 18 years or older
- Currently enrolled UCF student
- Must not be currently pregnant (unless incidental)
- Must not be a prisoner
- Must not be epileptic

- Must not have pre-existing vision disorders
- Must not have pre-existing balance issues

1.22 The study will exclude each of the following special populations:

- Adults unable to consent
- Individuals who are not yet adults (infants, children, teenagers)
- Pregnant women (unless incidental)
- Prisoners

Vulnerable Populations*

11.1 NA

Local Number of Subjects

1.23 40- 60 participants

1.24 NA

Recruitment Methods

1.25 Potential subjects will be recruited with flyers around UCF with a code/link to more information and the scheduling site to be conducted Summer 2020. Potential subjects will also be recruited by providing UCF professors a recruitment email to distribute to their summer 2020 classes. Researchers will not have access to direct email addresses.

1.26 Source of subjects are UCF students on campus.

1.27 Methods that will be used to identify potential subjects include flyers posted around UCF, information on the scheduling website, and an email distributed by UCF professors to students.

1.28 See attached flyer. Scheduling website is located at *https://www.signupgenius.com/go/30e084ba9ac2aa0fd0-pilot*.

1.29 Participants will be given a $20 Amazon e-gift card at the completion of their experiment (directly following completion of the post-hoc survey).

Withdrawal of Subjects*

1.30 If subjects are found to violate the inclusion criteria they will be withdrawn from the study. The data cannot be used if the observation is found to be flawed or incomplete.

1.31 Considerations have been made to clear a space to walk, provide low distraction space, developed inclusion and exclusion criteria, and using commercially available devices. The participant may terminate their participation at any time throughout the study.

1.32 Any participants that withdrawal from the research experiment will have associated data discarded and not included in the final sample set.

Risks to Subjects*

1.33 The participant has potential for disorientation, headaches, nausea, discomfort, dizziness, and bumping into objects in the study space while walking around the test space. If the participant experiences any of the symptoms mentioned, they will be asked to remain seated until the symptoms disappear.

1.34 NA

1.35 NA

1.36 NA

Potential Benefits to Subjects*

1.37 Students will be compensated a $20 Amazon e-gift card.

1.38 No direct benefit

Data Management* and Confidentiality

1.39 Conduct pilot study, power analysis, then full analysis of statistics including DOE (ANOVA), hypothesis testing (F, t,) and regression modeling.

1.40 Data will be anonymized at the time of collection. Participants will be assigned a participant ID where the list of names/IDs will only be available to the PI and faculty advisor and encrypted. This information will be stored on a UCF owned OneDrive account owned by the faculty advisor. (assigning participant IDs – where the list of names/ids will only be available to PI and faculty advisor and encrypted) and stored on a UCF owned OneDrive account owned by the faculty advisor. Identifiable information to be collected includes Full name, gender, PID, and UCF major.

- Participants will be randomly assigned a participant ID.
- Identifiers will be destroyed after the data collection is complete.
- Recordings (audio or video) will be stored until data collection is complete

- Data will be de-identified immediately and then stored for at least five years.

1.41 NA

1.42 Data will be anonymized at the time of collection. Participants will be assigned a participant ID where the list of names/IDs will only be available to the PI and faculty advisor and encrypted. This information will be stored on a UCF owned OneDrive account owned by the faculty advisor. (assigning participant IDs – where the list of names/ids will only be available to PI and faculty advisor and encrypted) and stored on a UCF owned OneDrive account owned by the faculty advisor. Data will be de-identified immediately and then stored for at least five years.

Provisions to Monitor the Data to Ensure the Safety of Subjects*

This study poses no more than minimal risk.

Provisions to Protect the Privacy Interests of Subjects

1.43 All the data will be de-identified immediately. No private data is requested from the participant.

1.44 A pre-brief will explain the study and objectives to the participant. This will give details to show the room and type of device being used.

1.45 Data is stored in an encrypted file only accessible by the PI and faculty advisor. Subject privacy will be maintained within the complete study activities as well as the surveys. Subject privacy will be maintained when participants are physically in the lab completing study activities by only have CITI trained researchers' part of this research study in the lab.

Compensation for Research-Related Injury

1.46 NA

1.47 NA

Economic Burden to Subjects

1.48 NA

Consent Process

1.49 The participant will be given a pre-brief to review.

- Consent process will take place in the research study location.

- A waiting period will be available between informing the prospective subject and obtaining the consent during the pre-brief with Q&A.
- Participants may withdraw at any time during the experiment.
- Additional information as follows:
    - The individuals listed in the application will directly be involved in the consent process by given an experiment brief and consent form to review.
    - 5-10 minutes will be devoted to the consent discussion.
    - The study will remain consistent to all participants and results will be anonymized to help reduce possibility of coercion or undue influence.
    - A brief and video presentation will be provided to the participant to ensure the subjects' understanding of the experiment.

Process to Document Consent in Writing

1.50 We would like to submit a Waiver of Written Documentation of Consent to remove the signature lines from the Informed Consent.

1.51 The study is minimal risk and this is why the waiver is being requested.

Setting

1.52 The research study will be held on the main UCF campus in room Eng. 2 323. Desks are moveable. The room has a TV and tables will be used to place AR markers.

- *The research team will identify and recruit potential subjects from the main UCF campus.*
- *Research procedures will be performed at the main UCF campus.*
- *No involvement of any community advisory board.*

Resources Available

1.53 Resources available include the room to conduct the experiment, devices, money for compensation, personal computers, and subscriptions to statistical software such as Minitab.

- Recruitment flyers will be posted in UCF buildings. Any participant that meets the required criteria is eligible to participate.
- Fall semester 2020 is devoted to conducting and completing the research.
- The research study will be held on the main UCF campus in room Eng. 2 323. Desks are moveable. The room has a TV and tables will be used to place AR markers.
- All persons assisting with the research will be adequately informed about the protocol, the research procedures, and their duties and functions as part of meeting for EIN 4912.
- All researchers will also be CITI trained

1.54 NA

26.0 Multi-Site Research*

26.1 All procedures will be conducted on UCF campus.
26.2 NA
26.3 NA
26.4 NA