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Usability of Real Time Data for Cold Chain Monitoring Systems

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USABILITY OF REAL TIME DATA

FOR COLD CHAIN MONITORING SYSTEMS

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TABLE OF CONTENTS

LIST OF FIGURES

Figure Page

LIST OF TABLES

CHAPTER 1. INTRODUCTION

One in every nine people on earth do not have enough food to lead a healthy life, according to The World Food Programme. That's nearly 800 million people. In addition to that, billions of tons of perishable food products are wasted during transportation and logistics before it reaches the end consumers as thousands of people die every day due to hunger related causes. Perishable foods, medicine and other goods impose severe challenges on inventory management. Businesses debate on whether to keep limited stock just to meet demand and fear losing additional customers or keep excess stock and face the risk of expiry of goods.

Unlike the transportation of other goods, perishable food products and medicines undergo tremendous degradation in quality as a function of environmental conditions over time. Figure 1.1 describes the amount of food wasted in different regions of the world. Perishable food products are usually stored in

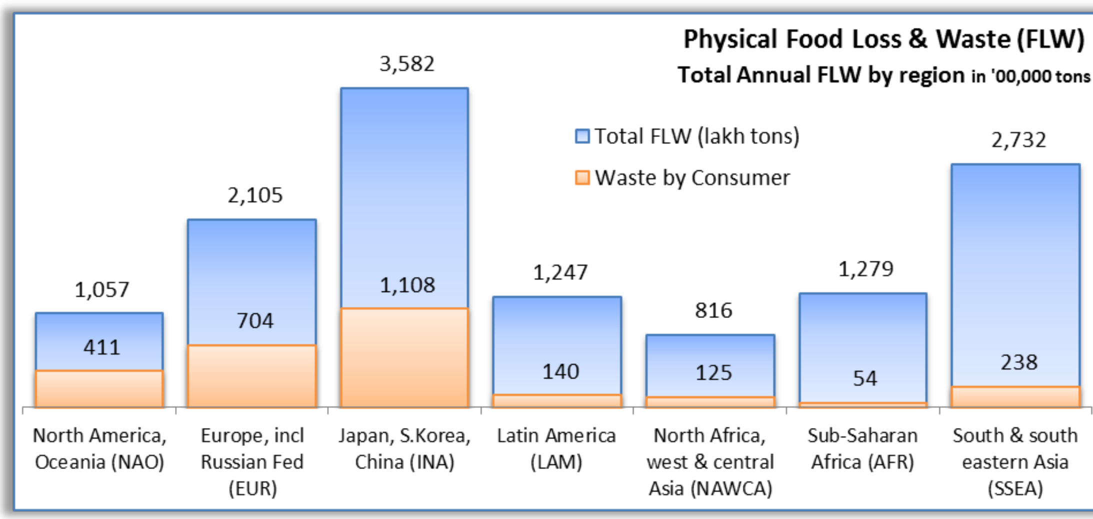


Figure 1.1.: Physical food loss and Waste. Kohli (2014)

frozen and refrigerated condition at the distribution centers, supermarkets and during the transit in order to preserve the quality of food and extend the shelf life. Even though, temperature controlled supply chain in the food retail sector has become commonplace, there is one major limitation of the current practice in the chilled food chain management. The printed 'sell-by-date' is not a true indicator of the quality of the product as it does not reflect the temperature variations during distribution at the different stages of the food supply chain (Blackburn and Scudder, 2009). The food quality is severely compromised when actual environmental conditions deviate from the expected conditions.

No Federal regulations are currently in place with regards to transportation of food, but several states regulate the food safety during transportation. The Indiana State Department of Health (ISDH) conducts Indiana Food Transportation Assessment Projects (IFTAP) with assistance from agencies such as Indiana State Police (ISP) for ensuring food safety during transportation. Since 2007, ISDH has found 43 trucks in violation (8%) out of the 532 food trucks inspected, and disposed nearly 30,000 lbs. of food. Violations include food products being out of acceptable temperature range, cross-contamination, and mislabeling of food.

Albert Einstein once said, "Any fool can know. The point is to understand". For organizations across the globe, knowing what has happened and why it happened is no longer adequate. The modern era requires organizations to understand what's happening in real-time, predict what will happen next, and devise strategies and actions to implement data driven decision making. Top performing organizations are using data visualization solutions, internet of things, big data and predictive analytics to improve their processes and enhance decision making capabilities.. In spite of the number of advantages proposed by the use of big data and predictive analytics, more than 55 percent of big data projects fail (Rijmenam, 2014). Contrary to belief, quality of data, lack of available technology or getting the data are not the major reasons behind the failure of big data projects.

The biggest challenges in big data analytics projects are related to technology adoption, managerial and cultural bandwidth and usability.

This research proposes the use of real-time sensor data to support supply chain decisions and describe a model for improving usability on the real-time sensor data.. Data reported through the wireless sensor networks could help in predicting the shelf-life of perishable food products and preventing them from spoilage. Use of sensor data would encourage data driven decision making rather than intuition. The findings would encourage businesses operating in the cold chain environment in exploring value added innovation opportunities through internet of things use cases and improve the usability experience and competitiveness of their supply chains via warehouse workers and truck drivers.

1.1 Scope

The application of big data analytics and internet of things in perishable goods cold supply chain is experimental and this research is highly exploratory for further development. As per the *Harvard Business Review*, big data is the new management revolution and it is proposed to solve big problems that organizations face today (2014). However, there are quite a few bottlenecks in its path to achieve the true value that big data entails. Some of these issues are managerial, cultural and related to organizational change and technology adoption. This research provides a framework for improving the operational efficiency and enhancing the usability experience of workers and other entities involved in the supply chain process management, but is limited in addressing issues with management bandwidth, executive sponsorship and commitment.

The research is restricted within the realm of cold supply chain systems catering to perishable food products and focuses on enhancing the usability experience for warehouse personnel and truck drivers. The goal is to improve the user experience that would enable the people to gain insights and make effective decisions based on the data collected from sensors. The research is also restricted in developing predictive optimization models and decision trees that would advise the businesses to gain more value from the data collected from sensors.

1.2 Significance

There are endless opportunities available with the ability to analyze the condition of food products in real time. Sensor data could be used to make effective supply chain decisions. Some of the benefits and use cases are listed below:

- Monitor the food containers in real-time
- Food quality and inspection report team would have real time information on status of arriving food products
- Dashboards showing refrigeration failures and food spoilage in real time
- Service execution based on real-time sensor data
- Reduce costs by minimizing food waste and increase margins
- Increased maintenance planning effectiveness
- Predictive maintenance and identification of cause of failure

Most of the issues associated with big data and analytics projects today are related to usability, technology adoption, management and organizational culture. With the myriad of disruptive technologies at our disposal today, there is a need to lay more emphasis on improving the usability of the technology and develop a successful model for technology adoption. A tremendous technology with a novel idea would fail if the technology doesn't have a good user experience. In adopting the use cases mentioned above, the goal of the research is to combine different aspects of a great user design and design an application that would reduce food quality and traceability issues. The results and findings from the study would help explain the usability dimensions that are important for the acceptance of a real-time food quality monitoring mobile application. The improvements suggested by users could be implemented on similar mobile applications in future to enhance the user's perceived usefulness and ease of use. As a result, there could be a considerable reduction in food wastage.

1.3 Research Question

How do truck drivers and warehouse personnel in the cold chain perceive the usability of a real-time food quality monitoring application in terms of usefulness and ease of use?

1.4 Assumptions

The assumptions for this study include:

- The research utilizes simulated data in lieu of data coming from the sensor networks deployed in trucks, warehouses and distribution centers and considers it to be free from quality and reporting issues.
- The study assumes that the users' experience with the mobile application while driving is equivalent to the users' experience at a standstill position.
- The research assumes that there is a continuous uninterrupted streaming of data and there aren't any internet connectivity and power issues for the end user.
- The study assumes that by improving the usability experience on the data coming through the sensors alone, we could significantly improve operational effectiveness and protect perishable food products from spoilage.

1.5 Limitations

The limitations of this study include:

- The research only looks into cold storage supply chain systems for perishable food products.
- Due to limited accessibility to truck driver's and warehouse personnel's time, they only use the application for 5-10 minutes.
- The study is only concerned with optimizing the usability of the application and the digital artifact related to it.
- The research took a small sample size of 18 trucker drivers and warehouse personnel to generalize the usability of the application.
- The warehouses and trucks under study are based in Indiana.
- The research is limited in addressing impact of road and weather conditions in optimizing the perishable goods cold supply chain.
- The study does not address food wastage due to inadequate market facilities, poor packaging and planning.

1.6 Delimitations

The delimitations for this study include:

- The digital artifacts other than simulated sensor data and survey responses on human interaction with the application are not considered.
- The distribution of the simulated sensor data is normal with a mean and standard deviation of 30.02 and 5.86 respectively.
- The research does not include other factors which might enhance food quality and preservation like storage, handling etc.

- The study does not capture the user's behavior while participating in the study ex. facial expression, speech etc.
- The research does not look into the users' (participating truck drivers' and warehouse supervisors' and managers') personal information like name, ID, contact details, past records etc. that is protected legally to see the correlation between user's attitude and application usage behavior.
- Quality issues in food preparation and production are not analyzed.
- The research is also delimited in developing predictive optimization models and decision trees that would advise the businesses to gain more value from the data collected from sensors.

1.7 Definitions

Adoption: A decision to make full use of an innovation as the best course of action available (Rogers, 2003, p. 473)

Analytics: These are the applications, tools and utilities designed for users to access, interact, analyze and make decisions using data in relational databases and warehouses (Dull, 2014).

Big Data: It refers to a wide range of large data sets almost impossible to manage and process using traditional data management tools due to their size, but also their complexity (Magoulas, 2005)

Big Data Analytics: is where advanced analytic techniques operate on big data sets (Russom, 2011).

Business Intelligence: Business intelligence systems combine operational data with analytical tools to present complex and competitive information to planners and decision makers (Negash, 2004).

Business Process Management: It is a structured approach to performance improvement that centers on the disciplined design and careful execution of a company's end-to-end business processes (Hammer, 2002).

Cold Chain: A cold chain is a temperature-controlled supply chain. An unbroken cold chain is an uninterrupted series of storage and distribution activities which maintain a given temperature range (Ashby, 1995).

Compatibility: The degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters (Rogers, 2003, p. 240).

Complexity: The degree to which an innovation is perceived as relatively difficult to understand and use (Rogers, 2003, p. 257).

Cloud Computing: It refers to the on-demand delivery of IT resources and applications via the Internet with pay-as-you-go pricing (Amazon Glossary, 2014).

Data Mining: It shows how to quickly and easily tap the gold mine of business solutions lying dormant in an organization's information systems (Berry, Linoff, 1997)

Data Science: It is the application of qualitative and quantitative methods to solve relevant problems and predict outcomes (Waller, Fawcett, 2013).

Diffusion: The process in which an innovation is communicated through certain channels over time among the members of a social system (Rogers, 2003, p. 474).

Effectiveness: The completeness and accuracy with which users achieve their goals (Quesenbery, 2003, p. 83).

Efficiency: The speed (with accuracy) with which users can complete their tasks (Quesenbery, 2003, p. 84).

Engagement: The degree to which the tone and style of the interface makes the product pleasant or satisfying to use (Quesenbery, 2003, p. 86).

Error tolerance: How well the product prevents errors, or helps with recovery from those that do occur (Quesenbery, 2003, p. 87).

Easy of learning: How well the product supports both initial orientation and deepening understanding of its capabilities (Quesenbery, 2003, p. 88).

Enterprise Data Warehouse: is a repository of integrated data from multiple structured data sources used for reporting and data analysis (Dull, 2014).

Extract, Transform, Load (ETL): A process that involves extracting data from sources, transforming the data to fit operational needs, and loading the data into the end target, typically a database or data warehouse (Cloudera Glossary, 2014).

Food Safety: The assurance that food will not cause any sort of harm to the consumer while it is prepared and/or eaten (WHO, 2001).

Food Quality: The totality of features and characteristics of a product that bear on its ability to satisfy the implied or stated needs

Hadoop: A free, open source software framework that supports data-intensive distributed applications (Cloudera Glossary, 2014).

Internet of Things (IoT) or Internet of Everything: It is the network of physical objects or "things" embedded with electronics, software, sensors, and network connectivity, which enables these objects to collect and exchange data (Microsoft Glossary, 2014).

Machine Learning: It is a rich source of ideas for algorithms that can be trained to perform the extraction of information from informal text of the sort commonly found in the online environment, such as email, Usenet posts, and plan files (Freitag, 2000).

MapReduce: A distributed processing framework for processing and generating large data sets and an implementation that runs on large clusters of industry-standard machines (Cloudera Glossary, 2014).

Process Improvement: The breakthrough strategy for total quality, productivity, and competitiveness (Harrington, 1991).

Predictive Analytics: Predictive analytics uses confirmed relationships between explanatory and criterion variables from past occurrences to predict future outcomes (Hair, 2007).

Relative Advantage the degree to which an innovation is perceived as being better than the idea it supersedes (Rogers, 2003, p. 229).

Supply Chain Management: The integration of key business processes from end user through original suppliers that provides products, services, and information that add value for customers and other stakeholders (Lambert et al., 1998, p. 1)

SQL: A declarative programming language designed for managing data in relational database management systems. Originally based upon relational algebra and tuple relational calculus, its scope includes data insert, query, update and delete, schema creation and modification, and data access control (Cloudera Glossary, 2014).

Technology acceptance model (TAM): It is an information systems theory that models how users come to accept and use a technology (Davis, 1989).

Traceability: The ability to trace the history, location or application of an entity by means of recorded identification (Van Dorp, 2002).

Trialability: The degree to which an innovation may be experimented with on a limited basis (Rogers, 2003, p. 258).

Usability: It is the ease of use and learnability of a human-made object. The object of use can be a software application, website, book, tool, machine, process, or anything a human interacts with (Bias, 2005).

1.8 Acronyms

3PL : 3rd Party Logistics

BI: Behavioral Intention to Use

CMPL: Compatibility

CPLX: Complexity

DOI: Diffusion of Innovation

EFFE: Effectiveness

EFFI: Efficiency

EN: Engagement

EOL: Ease of Learning

IDT: Innovation Diffusion Theory

IOT : Internet of Things

IOE : Internet of Everything

PEU: Perceived Ease of Use

PU: Perceived Usefulness

RA: Relative Advantage

SUS : System Usability Scale

TAM : Technology Acceptance Model

WSN : Wireless Sensor Network

1.9 Summary

This chapter explained the motivation behind conducting this research study. It presented the scope, significance and research question. It also provided a list of assumptions, limitations and delimitations. The next chapter presents a brief summary of relevant literature on perishable food products supply chain, big data and internet of things in cold supply chain systems, and technology adoption and usability.

CHAPTER 2. REVIEW OF RELEVANT LITERATURE

Food safety, quality and traceability concerns are increasing at an alarmingly high rate across the globe. Perishable food products and pharmaceuticals are sensitive to heat and time and must be kept at the prescribed standard temperature right from the time that they are manufactured until the food products are eventually consumed by the end customer. The current metrics adopted to ensure quality of perishable products (for ex. "use by date", "sell by date") are oblivious to the conditions that these perishable products are typically subjected to like freezer failures, material handling issues, leakages, parasites etc. The lifetime of perishable products can degrade substantially due to any of these issues, even though the current metrics may indicate otherwise. As a result, consumption of these spoiled perishable goods severely affect safety and health of a human being. Internet of Things (IoT) provides a disruptive solution for cold chain execution through real-time monitoring of the condition of a perishable product.

FRAMEWORK

This chapter is divided into four major sections. The first section provides a comprehensive review of challenges and issues in perishable food health monitoring and growing importance on cold chain. The second section covers the current traceability systems and emerging developments. The third section walks through the new digital age of big data, sensors and Internet of Things and defines them in the context of perishable goods and traceability systems. Finally, the fourth section analyzes the importance of usability scales, technology acceptance model and adoption of a real-time mobile application in a cold chain environment.

2.1 Introduction to Cold Chain

The Global Supply Chain Forum defines supply chain management as a cross-functional discipline that combines key business processes from original suppliers through the end user while providing products, services and information that create value for the consumers and stakeholders involved (Lambert et al., 1998, p. 1). The supply chain of food products is comprised of entities and business units involved in producing, preserving and distributing food products.

There has been a rising concern about the sustainability of the food supply chain(Smith, 2008). With the impact of globalization in food trade, the distance that food travels from producers to the end consumers has increased tremendously. Consumers today call for longer shelf lives and are highly concerned about food safety. Hence, ensuring safety and quality at different stages of the food supply chain has become an even bigger challenge for the perishable foods and pharmaceutical industry players. With the rapid increase in demand for the products requiring temperature control, cold chain systems have gained popularity in the global economy today.

Cold chain systems are temperature-controlled supply chains comprising of an uninterrupted series of storage and distribution activities maintaining the prescribed temperature range. The shelf life and spoilage of perishable goods are a function of several factors, internal and external, like pH vale, salt content, pressure, humidity and temperature. There is a common belief that temperature is the most crucial factor (Branscheid et al., 2007). If perishable products are stored beyond the individual prescribed temperature limits, rapid microbiological development occurs and the product faces danger of being spoiled even before the estimated best before date'. Such an incident causes severe economic loss (Kreyenschmidt et al., 2007).

The credibility of the perishable foods industry has been severely challenged and called to question in the last couple of decades following a sudden rise in the number of food crises, such as mad cow disease, food-borne illness such as salmonella, Dioxin in chicken feed, and Food-and-Mouth Diseases (FMD) (Aung et al. 2014). . As per the World Health Organization (WHO, 2002) records, about 2.2 million people die annually because of food and water-borne. According to Scharff (2010, pp. 1e28), the annual economic impact of illness and diseases caused due to poor quality of food across the nation has been estimated to be approximately 152 billion. The economic value of discarded spoiled food products in the US is approximately 35 billion dollars annually(Aung et al., 2014).

2.2 Traceability in perishable goods supply chain

The two major terms in the food traceability system are food safety and quality. Food safety has been defined by the CAC (2003) as an assurance that there won't be any sort of harm to the consumer while the food product is prepared and/or consumed by the customer. ISO defines quality as the complete set of products' features and characteristics that allow it to satisfy the desired demands and needs(Van Reeuwijk, 1998). According to ISO 8402 (1994), traceability is defined as the capability to trace the location, history or application of a package unit through means of recorded identification.

Customers today call for higher standards and quality of food products following a series of food scandals. Perishable foods traceability systems have gained tremendous importance recently, particularly following a number of incidents questioning food safety where they were proven to be absent or severely weak (FSA, 2002). The traceability systems should provide information on origin of the goods, when they were processed, retail and final destination of the goods to be transported. The three main characteristics of traceability systems, as defined by the Food Standard Agency (FSA, 2002) are as follows:

- Identifying constituent ingredients' and products' batches.
- Collecting and analyzing information on where and when the products are moved to.

- An information system that links these data points.

Golan (2004) in their research have suggested that an efficient traceability system should have breadth, depth and precision. Breadth signifies the volume of information collected. Depth denotes how far forward or backward the system tracks the information. And precision refers to the degree of assurance. Traceability helps in building trust with the customers, and improves confidence and peace of mind in the food products they consume. Cold chains including perishables such as fresh produce, milk, meat and fish are significantly different from other chains in the sense that the quality changes continuously with time (Apaiah et al., 2005). Traceability could be categorized into qualitative traceability and logistics traceability. Qualitative traceability integrates information regarding consumer safety and product quality, such as storage and distribution conditions, pre-harvest and post-harvest techniques, etc. (Folinas et al., 2006). On the other hand, logistics traceability treats food as a commodity and follows only the physical movement of the product.

2.3 Current food traceability systems, recent advances and technological trends

An effective traceability system is one that can help reduce cost of recall since it provides the capability to have a prospective product recalled before the product gets spoiled. Also, it can help in identifying what caused the problem (Regattieri et al., 2007). On the basis of requirements of traceability in the food chain, Aung et al. (2014) developed a conceptual framework for an efficient food traceability system as shown in Figure 2.1. According to this framework, all entities in the supply chain are considered to have both external and internal traceability in order to achieve traceability in the entire supply chain.

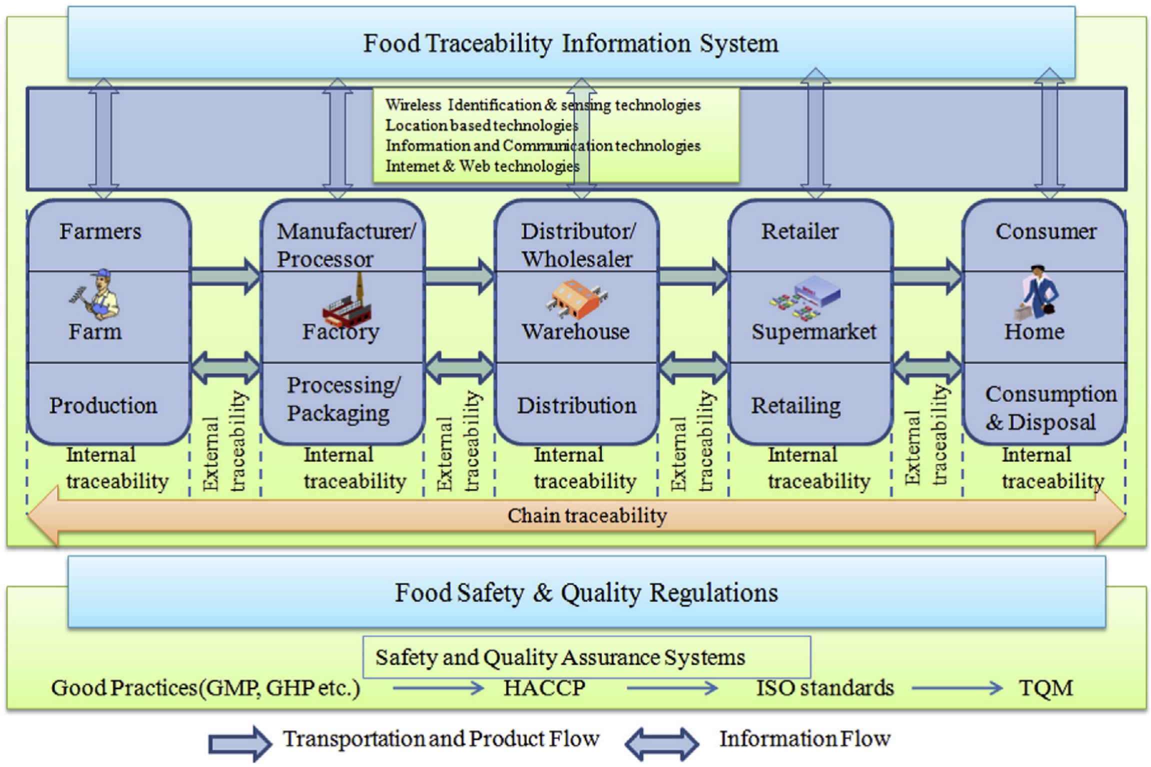


Figure 2.1.: Food Traceability Information System (Aung et al., 2014)

Currently, a wide variety of technologies are used in the food traceability systems. These include alphanumeric codes, bar codes, RFID, WSN, NFC, Isotopic analysis, chemometrics and DNA barcoding. Many researchers have designed highly efficient food traceability frameworks with these technologies as core foundations. Regattieri et al. (2007) proposed a framework based on identification of products, routing, and use of sophisticated tools for traceability of food products. Their traceability system used an alphanumeric code and RFID tags to trace cheese products and apply any possible recall strategies rapidly. Shanahan et al. (2009) suggested another RFID based framework for traceability of beef from the farms to slaughter houses. The integrated system used RFID for identifying each cattle, and biometric identifiers (e.g. Retina Scan) for verifying each cattle's identity. It was proposed as a solution to address the fraudulent activities, loss of ear tags and the inaccessibility of traceability records. RFID can enhance the efficiency of perishable cold chain by storing information like production area and process, methods of plantation, and any other information that the customers may desire when they buy the products (Zhang et al., 2012).

Folinas et al. (2006) suggested a framework for the management of traceability information based upon Physical Markup Language (PML), a simple and flexible information exchange format which is well suited for supporting web enabled business applications. Mattoli et al. (2010) developed a Flexible Tag Datalogger (FTD) for the wine logistics chain. The FTD is hooked to the wine bottles and it collects data on their transit environmental conditions like temperature, humidity and light. This helps in tracing the wine bottles as they are transported from the producer cellar to a shop. FTD's have the capability to transmit the stored data to a smart phone or Personal Digital Assistant (PDA) using infrared rays. The smart phone or PDA can then evaluate the safety of the wine bottles.

Abad et al. (2009) attempted to validate an RFID smart tag (with integrated relative humidity and temperature sensors) to develop an automated system for real-time cold chain monitoring and traceability of fresh fish. Zhang et al. (2009) designed a temperature-controlled traceability system for chilled and frozen food during transportation and storage by integrating GPS, RFID and mobile communication.

Wang et al. (2010) designed a real-time monitoring and decision support system combining WSN, RFID, GPS and rule-based decisions to improve the distribution and delivery system for perishable food products. Their system was equipped with a forecast module that could predict the quality of perishable food products, based on the application of mathematical models on the data collected from the sensor network and RFID. Future innovations in DNA finger-printing, facial recognition and iris scanning have great untapped potential for improving the speed and precision of traceability in the food industry (Smith et al. 2008). Figure

2.2 provides a brief summary of the technology currently in use and recent advancements in food traceability.

Current traceability systems lack the ability to link food chains records (Pizzuti et al., 2014).Aarnisalo et al. (2007) mentioned that there is an increasing need for the use and adoption of sensors reporting real-time data for improving the safety and quality assurance processes in the perishable foods industry.

Technological advancements.

Technology	Concept	Author
RFID	Higher reading rate than traditional barcodes.	Hong et al. (2011)
	RFID proved better than lot numbering.	Kelepouris et al. (2007)
	Cold traceability for combat feeding logistics.	Amador and Emond (2010)
	Cold traceability for temperature sensitive products.	Ruiz-Garcia et al. (2010)
	Wheat Flour Milling Traceability System.	Qian et al. (2012)
	Integration of RFID and Barcode printer for cattle/beef supply chain.	Feng et al. (2013)
	Cheese wheels tracking.	Barge et al. (2014)
	Enhance the traceability of the white wine.	Catarinucci et al. (2011)
	Intelligent food logistics.	Zou et al. (2014)
NFC	End consumer knows the history of the product.	Mainetti, Mele, et al. (2013)
	IV gama products traceability information.	Mainetti, Patrono, et al. (2013)
	Safely purchase the food.	Yu-Yi Chen et al. (2014)
	Gas detector in NFC tag.	Trafton MIT (2014)
Unique identification and quality of livestock	Quality tracing model for vacuum-packed lamb.	Mack et al. (2014)
	RFID, biometrics and identifiers for verification of cattle identity.	Shanahan et al.(2009)
	Farm-to-fork traceability using GS1-128 barcode.	Mc Carthy et al. (2011)
	DataMatrix barcodes onto the beaks of chickens.	Mc Inerney et al. (2010)
Isotope analysis	Approach for agro-product authenticity and traceability using isotope analysis.	Zhao et al. (2014)
	Identification of isotopes of beef and lamb.	Horacek and Min (2010); Perini et al. (2009)
	Classification of milk, rice, wine and olive oil.	Molkentin and Giesemann (2007); Suzuki et al. (2008); Dutra et al. (2011); Camin et al. (2010)
Chemometrics and NIRS	Traceability of cereals, olive oil, tea and wheat grain using NIR and MIR.	Cozzolino (2014); Bevilacqua et al. (2012); Ren et al. (2013); Gonzalez-Martin et al. (2014).
	Near Magnetic Resonance for geographical origin and quality of traditional food products.	Consonni and Cagliani (2010)
	Chemometrics analysis for wine identification.	Versari et al. (2014)
DNA barcoding	DNA analysis applied for traceability of seafood, meat, milk, edible plants and processed food and fruit residues.	Becker et al. (2011); Cai et al. (2011); Arcuri et al. (2013); De Mattia et al. (2011)

Figure 2.2.: Technological advancements in food traceability(Badia-Melis et al., 2015)

The growing diffusion of new emerging technologies into the food traceability systems coupled together with the availability of new machine learning based computational models and tools could improve the current and future value of food traceability.

The notion of intelligent food logistics has started becoming quite a popular subject in perishable cold chain. Jedermann et al. (2014) suggested that intelligent food logistics would significantly reduce the waste of perishable foods by reducing the deviations from the expected optimal cold chain conditions. For real-time

Table 1. Evolution of key IoT technologies

	Before 2010	2010—2015	2015—2020	Beyond 2020
Network	• Sensor networks	• Self-aware and self-organizing networks • Sensor network location transparency • Delay-tolerant networks • Storage networks and power networks • Hybrid networking technologies	• Network context awareness	• Network cognition • Self-learning, self-repairing networks
Software and Algorithms	• Relational database integration • IoT-oriented RDBMS • Event-based platforms • Sensor middleware • Sensor networks middleware • Proximity/ Localization algorithms	• Large-scale, open semantic software modules • Composable algorithms • Next generation IoT-based social software • Next generation IoT-based enterprise applications	• Goal-oriented software • Distributed intelligence, problem solving • Things-to-Things collaboration environments	• User-oriented software • The invisible IoT • Easy-to-deploy IoT software • Things-to-Humans collaboration • IoT 4 All
Hardware	• RFID tags and some sensors • Sensors built into mobile devices • NFC in mobile phones • Smaller and cheaper MEMs technology	• Multiprotocol, multistandards readers • More sensors and actuators • Secure, low-cost tags (e.g., Silent Tags)	• Smart sensors (biochemical) • More sensors and actuators (tiny sensors)	• Nanotechnology and new materials
Data Processing	• Serial data processing • Parallel data processing • Quality of services	• Energy, frequency spectrum-aware data processing • Data processing context adaptable	• Context-aware data processing and data responses	• Cognitive processing and optimization

Figure 2.3.: Evolution of key IoT technologies. Adapted from Sundmaeker et al.(2010, p. 74)

remote monitoring, it is important to quantify and minimize these deviations and predict variations in shelf life.

2.4 The new digital age: Internet of Things and Big data analytics

The disrupting innovation through Internet of Things (IoT) has its roots in Mark Weiser's vision of "Ubiquitous Computing" where computers disappear from the users' perception as they are seamlessly integrated into machines and into the environment. IoT also called the Internet of Everything or the Industrial Internet, could be defined as a network of sensors, devices and machines that possess the capability of interacting with each other (Lee, 2015). It's not entirely a new concept. PLC and automation machines, the earliest form of IoT date back to 1970's. However, with the widespread increase in the devices that are connected to the network, and a steep decrease in the price of sensors and cloud based infrastructure services, the term IoT has significantly increased in popularity. In the last four years, the price of embedded modules which connect things to the internet has dropped by 80 percent, making many business uses vital, which have failed earlier due to cost of hardware or unreliable and pricey connections. Figure 2.3 provides a brief summary of evolution of IoT technologies

The Economist Intelligence Unit (EIU) foresees 12-50bn devices to be connected to the internet by 2020, excluding smartphones (Gartner, 2014). Gartner predicts a 40-50 percent compound annual growth rate for the Machine-to-Machine market until 2020 (Kubach, 2013). Over the past 10 years, the cost of bandwidth for data transfer has decreased by 40 times. Wi-Fi coverage is now ubiquitously available for free or at a very low cost. Similarly, the cost for data processing has decreased by 60 times over the past 10 years. Sensors, on an average cost nearly $1.25 today and their sizes have drastically diminished as well making it easier to install and embed (Jankowski, 2014). Enterprises are driving towards adoption of Machine to Machine/IoT solutions.

The key facilitator to IoT has been the emergence of cloud computing and tools and techniques to manage big data and derive insights from it. Big data is characterized by 3 V's; volume, variety and velocity of data. At present, five exabytes of data, i.e. five billion gigabytes of data is generated each day. Almost 80 percent of the data today is unstructured (images, videos, emails etc). In the present era of IoT, the velocity aspect of data is even more significant than the volume of data for certain applications. In a cold chain environment, there is continuous streaming of data from sensors and other smart devices to the cloud where advanced analytic techniques could be applied to derive insights from the data. Organizations across the globe are building use cases leveraging real-time or nearly real-time information to stay one step ahead of their competitors McAfee and Brynjolfsson (2012, p. 5).

One of the major reasons, even small scale businesses are moving towards IoT is cloud computing. Cloud computing has helped them overcome the cost barrier of technology adoption to a great extent, as the user only pays for the services it makes use of rather than having its own independent server and managing all the cost by itself.

Mcafee and Brynjolfsson (2012) interviewed executives from over 300 US companies. The interviews were based on the organizational and technology management practices adopted by these companies, and gathered their performance data. It was found that not every organization was embracing a data driven approach. The organizations having better financial and operational results were more data driven than their counterparts. Their work provides examples of an airline company and other companies unleashing the power of big data. In these examples, big data analytics helped them make better decisions and accurate predictions at a large scale. In spite of the number of advantages proposed by the use of big data analytics, 32 percent of the respondents were rated quite low on the scale of being data driven.

2.5 Internet of Things in cold chain

Current food traceability systems are severely challenged in the ability to track issues, errors and inaccuracy in records and delays in a cold chain environment. This is highly crucial when a major food outbreak disease occurs. Truck drivers don’t have real-time information on the time they have available to deliver the food products, best possible routes and if the drivers could afford a break. Loss to the perishable food industry today is worth billions of dollars. The updates at the distribution centers, retail stores and transportation units regarding location and movement of goods are more frequent now. The updates are not only about where the truck and perishable products are, but its environmental conditions (e.g. temperatures, growth of bacteria etc), what is close to it etc. (Ruiz-Garcia et al., 2008). Agricultural technologies using IoT are proposed to improve the yield of crops globally by approximately 65%. With the capability of real-time remote monitoring, IoT based use cases could optimize the production process and help in reducing food prices by nearly 50% by 2050 (Rai, 2014). Cold chains traceability systems are being severely challenged today due to food wastage and quality issues, poor inventory management, demand and supply. In addition, pricing strategies for degrading perishable products is a major area of concern. We could use the capabilities of intelligent cloud based systems to mitigate these challenges. As explained in the previous chapter, IoT based scenarios often prove to be a solution to the problems related to quality, inventory management and pricing. But, eventually it is up to the humans/end users to leverage the capabilities of a smart IoT based system to solve the issues discussed above. The implementation of an intelligent IoT based system for perishable food products' quality control requires executive sponsorship, followed by a buy-in and support from middle managers, quality professionals, warehouse workers and truck drivers. Here is a summary of the potential users that could benefit from this study:

- Truck drivers (Part-time and full-time)
- Warehouse Receiving Inspection Quality supervisors and managers
- Warehouse workers
- Food manufacturers and processors
- 3rd Party Logistics organizations
- Executive board

Following are the different areas where IoT could be leveraged in the perishable food products cold chain:

- Temperature and humidity sensors in warehouse bins. This has multiple usage scenarios.

  1. Temperature + Humidity + Product Characteristics (Enterprise Resource Planning/ Enterprise Warehouse Management/ Warehouse Management): Here, the use of IoT and decision management could lead to decision outcomes like Inspection documents, Blocking Stock, Alert Mechanism to Supervisors Etc.

  2. Energy savings solutions is a huge business opportunity in cold storage or pharmaceutical businesses. Different products require different temperatures. Businesses can't add or remove bins dynamically. For example, vegetables are stored at 45F, dairy products at 34F, meat is stored at freezing temperatures. Similarly in the pharmaceutical industry, variety of temperature ranges are required for different drugs. Configuring bins with so much variety is a difficult task. When bins go empty, adjusting bins to make them suitable for different products is a heavy labor intensive process. For example, inbound deliveries are planned for diary, vegetables, frozen goods and make bins ready can be automated with much higher accuracy and reduced power.

     The process could be enhanced to apply to the above business scenarios based on planned outgoing and planned receiving. Consider a dairy storage and distribution system. Once the bin where it is stored could be done, switching the power to make bin suitable for other products. From a 3PL standpoint, it is a business opportunity.

  3. In case of 3PL providers who serve a lot of clients with variety of storage requirements.

Reconfiguring space is very difficult in a cold storage environment, because of temperature and optimization limitations. For example, the following are bins in the warehouse with current temperatures B1 55F B3 50F B5 60F B2 80F B4 40F B6 45F

To store products with X number of deliveries, required temperatures are as follows: (All are possible bins to store in this scenario and all are in one storage type suitable for products). 2 bins with 62F, 1 bin with 32F, 1 bin with 50F , 2 bins with 82F. The challenge is knowing the most economical way to increase and decrease bin temperatures with optimal power usage. For example, increasing temperature is more economical than decreasing and changing from 55F to 32 F costs more than 40F to 32F. Think of a scenario for a warehouse with more than 200 bins and 50 different variety of products. It is a complex problem to solve but there is a huge potential for savings. This is a true application of IoT and in-memory database optimization algorithms.

- Preventing accidents in warehouse

  This may not be a direct IoT application for cold chain. But it has great value for warehouse management. Accidents in warehouse are costly. Most of the accidents happen due to forklifts, whether they hit the pedestrians or when they tilt trying to lift heavy materials. Here, IoT can be used to avoid these accidents in warehouse. Sensors can alert pedestrians and forklift drivers when other fork lift drivers are in their vicinity. This requires real-time streaming and high processing of data and fast networks. Similarly, pressure sensors are available and when warehouse resource tries to lift/change angle, it should have the capability to give a warning. Angle of tilt, stacking factor is very important.

- Efficient decision trees based on real-time location updates and traffic.

> Warehouse managers need to increase efficiency and must know the ETA of trucks more accurately, and quality of incoming food products. There is a need for IoT driven network hub that facilitates communication between different business units that usually don't have a direct one-one business relationship. This would allow real-time transparency into the transportation progress using GPS data. By optimizing inbound and outbound product flow, we can increase goods throughput and optimize infrastructure for maximum productivity in the cold chain. Automating different processes would result in a huge boost in efficiency. This would eventually shrink waiting times and the need for manual monitoring. Advising truck drivers on optimal routes would reduce the distance travelled which would help reduce emissions and make an environmental impact.

According to Gartner (2014), the uninterrupted stream of data from sensors would impose a severe challenge for the data centers' security and storage management. But one of the biggest concern areas is technology adoption and usability of applications that consume real-time data. The next section provides a summary of measures of usability, the Technology Acceptance Model (TAM) and the integrated TAM and IDT model for evaluating the usability and acceptance of a new innovation.

2.6 Technology adoption and usability

Bob Dylan said in his song, "The Times They Are a-Changin". We live in the digital age where technology is changing at a pace much faster than it ever has before. According to Rodgers (2010), there are five customer segments with respect to technology adoption. He identified the personality traits that map an individual into one of the segments. These customer segments are:

- Innovators (2.5%): They are the first individuals/organizations to adopt an innovation. They possess the highest social class and great financial lucidity.

- Early adopters (13.5%): They are the fastest category of individuals after innovators to adopt an innovation. They possess opinion leadership and more financial lucidity

- Early Majority(34%): They adopt an innovation after a varying degree of time; have above average social status and seldom hold position of opinion leadership.

- Late Majority (34%): They adopt an innovation after it's become commonplace among the majority of the society. They have little financial ludity and opinion leadership.

- Laggards (16%): They are the last to adopt an innovation, and have little or no opinion leadership and financial fluidity.

The research subjects in this study would constitute users from the Late Majority and Laggard customer segment groups.

According to McGrath (2013), the rate of technology adoption in US has increased considerably in the previous decade.From Figure 2.5, we could understand that nearly 90% of U.S households have a cellular phone and over 60% use the internet.

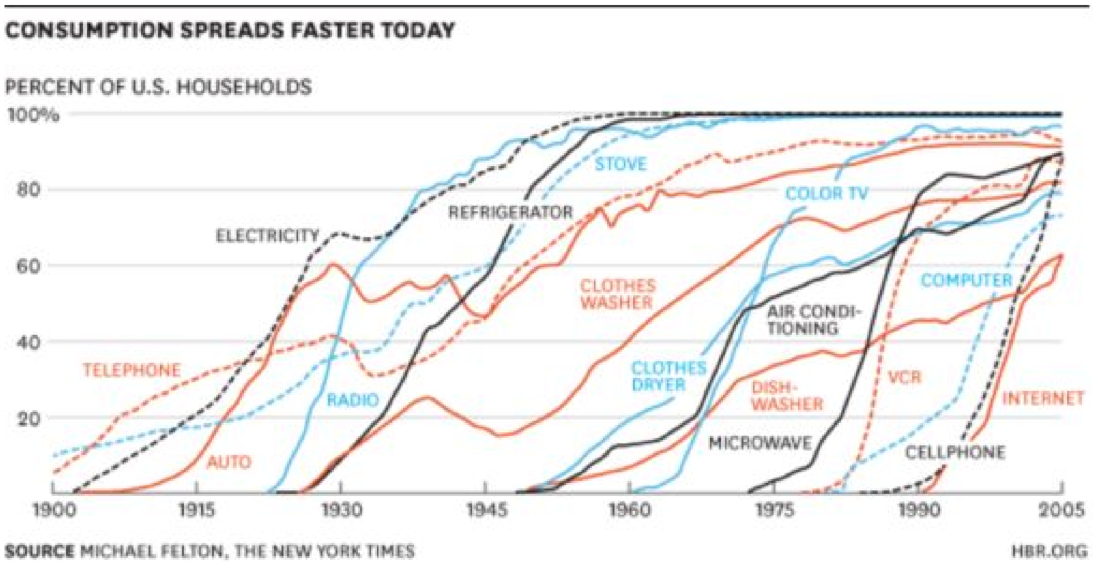


Figure 2.4.: Consumption Spreads. (Mcgrath, 2013)

Atlas Van Lines (2013) conducted a survey to analyze trends and preferences among their professional truck drivers. They found that about 66% of truckers used smart phones at that time, an increase of 6% from the year before. Also, 58% of the drivers that use smart phone preferred iPhone in comparison to 38% Android users.

The truck drivers represent the late majority and laggard customer segment of technology adoption. The usability of mobile devices and the prospect of smart IoT based applications differs significantly from other computer systems, because they have different characteristics. The IoT based smart application for perishable food health monitoring should be simple and easy to use, in order to seamlessly integrate it with the truck drivers and warehouse workers ecosystem.

Usability is context specific and doesn't have an absolute sense. It's only relative. Brooke (2011) describes usability as a general quality of being appropriate to the defined purpose of any particular artifact. The research suggests that, in addition to a great user design, incorporation of gamification, feedback and performance statistics services are great ways to enhance the user experience. The present food traceability systems don't lay much emphasis on the user experience.

The design of the instruments the users use is very complex and primitive for example flexible tag dataloggers, RFID's etc. Introduction of gamification in the real-time cold chain monitoring application would allow the end users (truck drivers and warehouse personnel) earn merit points on the basis of their interaction and outcome from the application. This would both increase their productivity and reward them for their efforts. There is a great need for user-centric applications to enhance the efficiency of food traceability systems.

According to Brooke (2011), ISO 9241-11 recommends that usability measures should cover effectiveness, efficiency and user satisfaction. Effectiveness could be defined as the quality of the work performed by the users while using the system. Effectiveness describes the amount of resources the user used in performing the work on the system. And user satisfaction can be expressed as the user's reaction on using the system.

There are five main characteristics of a usable software, as defined by Quesenbery (2003, 2004). They are effectiveness, efficiency, engagement, ease of learning and error tolerance. One of the widely used scales to measure usability has been the System Usability Scale (SUS). According to Bangor (2008), it has several notable attributes which make it a great choice for different applications. Both novice and advanced users find it quite easy and relatively quick to use. It's flexible to use across a wide variety of interfaces ranging from computer interfaces, websites, interactive voice responses etc. Figure 2.5 shows the SUS with the SUS score. The SUS scores range between 0 and 100 and should be only considered in terms of percentile rankings. Research shows that a score above 68 is considered above average.

The Technology Acceptance Model (TAM) states that the actual use of an application/system could be determined by the user's behavioral intention to use it (Davis, 1989). This behavioral intention to use the system covers effectiveness and efficiency as explained above and is described by the system's perceived ease of use and perceived usefulness. . TAM is a very popular model for evaluating new

System Usability Scale

	Strongly disagree 1	2	3	4	Strongly agree 5	
1. I think that I would like to use this system frequently					√	4
2. I found the system unnecessarily complex				√		1
3. I thought the system was easy to use		√				1
4. I think that I would need the support of a technical person to be able to use this system	√					4
5. I found the various functions in this system were well integrated		√				1
6. I thought there was too much inconsistency in this system			√			2
7. I would imagine that most people would learn to use this system very quickly		√				1
8. I found the system very cumbersome to use				√		1
9. I felt very confident using the system					√	4
10. I needed to learn a lot of things before I could get going with this system		√				3

Total score = 22

SUS Score = 22 *22.5 = 55

Figure 2.5.: System Usability Scale. (Brooke, 2011)

systems to estimate their adoption and use in the future. TAM also helps to anticipate user acceptance problems if any with the new system. Most studies on technology acceptance have used TAM to evaluate the acceptance of a new system, but haven't addressed the adoption of the new system which is different from acceptance (Lin, 2014). The factors that impact the adoption and acceptance of a new information system/application are different. Lin and Lin (2014), in their research indicated that about 43.7% of the logistics industry is open to the use of RFID technology and have high degree of acceptance, but the actual adoption of RFID technology is only 8%. Hence, there is a significant difference between acceptance and adoption of technologies for the logistics service providers.

Several empirical studies have recommended integrating TAM with Innovation Diffusion Theory because they are similar in some aspects but complement each other to examine the adoption of a new information system/application. Diffusion can be defined as a process where innovation spreads through the members of a social system over time through certain communication channels Rogers (2010). (p. 5). Rogers (2010, p. 12) defined innovation as a new idea, practice, or object that an individual interacts with. The structure of the IDT model explores the acceptance variables of the organization and divides the process of adoption into persuasion, knowledge, decision, implementation and confirmation levels from the psychological to the action level (Lin, 2014). According to Rogers(2010), the different dimensions that affect the adoption rate of a new information system/application are compatibility, complexity, observability, relative advantage and trialability. TAM combined with the IDT theory has been widely adopted and considered useful in different industries.

This research aims to analyze whether truck drivers would adopt a real-time cold chain monitoring application and find it useful and easy to use. This would help evaluate whether a real-time IoT based smart application for perishable food health monitoring could increase value for a business by decreasing food wastage by acting at the right time.

2.7 Summary

After the review of past scholarly works, it is evident that the food traceability systems, especially in the cold chain environment require a major uplifting. The major food wastage occurs during transit and there is a huge opportunity to improve the cold chain operational efficiency through a real-time food quality monitoring application that has a high user acceptance. Per Moores law, computing power doubles every 18 months and the disk capacity grows even faster as defined by Kryders law. Sensors are getting much cheaper and we possess the capability of intelligent cloud based systems that are cost effective and perform real time monitoring. There has been some promising work done in food traceability with IoT based cold chain systems and there's need for further research in the area. However, keeping in mind the challenges of such an intelligent system, we have to design applications that leverage users to benefit and help them make better decisions. If the application interface is too complex and users find it difficult to navigate through it, no matter how innovative the solution seems to be, it won't add value. Iridium satellite mobile phone seemed to be a breakthrough innovation at that time, but it never reached the target audience it intended to and ultimately filed for bankruptcy for this reason. The research on usability of cold chain monitoring through IoT based apps for truck drivers and warehouse workers is still in its nascent stage and is highly exploratory for further development. The literature review helps to justify the need for such an application. It also discusses the key aspects which can be improved in the cold chain systems. The following chapter would discuss the research methodology to test whether the participants and eventually businesses find it useful and easy to use.

CHAPTER 3. FRAMEWORK AND METHODOLOGY

The purpose of the research is to understand the behaviour of users involved in the cold chain and analyze the usability of an IoT based smart application in improving the perishable goods cold chain environment. This would make the cold chain traceability systems more efficient in detecting issues in real-time, preventing spoilage and avoiding wastage. This chapter describes the research framework and methodology used to evaluate the usability, acceptance and adoption of a real-time food quality monitoring application. Also, the chapter describes the participants for the study, data sources and analysis techniques used, and the perspective and bias of the researcher.

3.1 Framework

The goal of the research was to gauge the readiness and identify attributes that may be important to truck drivers and warehouse personnel with respect to usability of a web-based mobile application. This study captured both qualitative and quantitative data to analyze the usability, acceptance and adoption of a real-time mobile application with regards to cold chain monitoring systems.

As explained in the previous chapter and studies, researchers have conducted usability studies in the supply chain environment using TAM and IDT or DOI (Diffusion of Innovation) theory as it encompasses attributes for both acceptance and adoption of a new system. Hence, the integrated TAM and IDT model, along with usabilty dimensions served as the underlying methodology in this study to evaluate the acceptance and adoption of a real-time food quality monitoring application in a cold chain environment.

Table 3.1 highlights the usability and innovation dimensions that were studied for analyzing the usability and adoption of a real-time food quality monitoring application. According to research, user's perception of usability, acceptance and adoption of the application could be determined by their perception of innovation and usability dimension attributes.

Table 3.1: Usability and Innovation Dimensions

Usability Dimensions	**Innovation Dimensions**
Ease of Learning	Compatibility
Effectiveness	Complexity
Efficiency	Relative Advantage
Engagement	
Error Tolerance	

Davis (1989) suggested that user's actual system use depends on the user's behavioral intention to use the system. Perceived Usefulness and Perceived ease of use are determinants to the behavioral intention to use the system. The effectiveness and efficiency usability dimensions might enhance the user's perception of the mobile application's usefulness while the engagement, ease of learning and error tolerance usability dimensions could improve the user's perception of the mobile application's ease of use.

Similarly, compatibility and relative advantage innovation dimensions might enhance the mobile application's perceived usefulness, whereas complexity dimension could improve the mobile application's perceived ease of use. Observability and trialability innovation dimensions were not included in the study analysis because the users used the mobile application for the first time and they did not observe their peers as they used the application.

3.2 Research Methodology

According to TAM described in the previous chapter, the two major factors that affect how and when users use a new technology are Perceived Usefulness and Perceived Ease-of-Use. As explained by Bangor (2008), there are a number of examined usability surveys which have proven to be of great value. They are summarized in figure 3.1.

Although SUS is a popular tool to evaluate the usability of an application, it fails to cover all the usability dimensions, for example effectiveness. Through the course of this research, the researcher combined related survey questions from multiple studies to identify appropriate survey questions for evaluating the usability and innovation adoption dimensions described in Table 3.1.

Summary of Examined Usability Surveys

Survey Name	*Abbreviation*	*Developer*	*Survey Length (Questions)*	*Availability*	*Interface Measured*	*Reliability*
After Scenario Questionnaire	ASQ	IBM	3	Nonproprietary	Any	0.93[a]
Computer System Usability Questionnaire	CSUQ	IBM	19	Nonproprietary	Computer based	0.95[b]
Poststudy System Usability Questionnaire	PSSUQ	IBM	19	Nonproprietary	Computer based	0.96[b]
Software Usability Measurement Inventory	SUMI[c]	HFRG	50	Proprietary	Software	0.89[d]
System Usability Scale	SUS	DEC	10	Nonproprietary	Any	0.85[e]
Usefulness, Satisfaction and Ease of Use	USE	Lund	30	Nonproprietary	Any	Unreported[f]
Web Site Analysis and Measurement Inventory	WAMMI	HFRG	20	Proprietary	Web based	0.96[g]

[a]Lewis (1995). [b]Lewis (2002). [c]Kirakowski and Corbett (1993). [d]Igbaria and Nachman (1991). [e]Kirakowski (1994). [f]Lund (2001). [g]Kirakowski , Claridge, and Whitehand (1998).

Figure 3.1.: Summary of examined usability surveys

The survey questionnaire consisted of questions from SUS designed by Brooke, and survey instruments designed by Davis (1989), Green(2006) and Moore (1991). Three questions from SUS, six questions from Green's survey instrument and a couple of questions designed by the researcher helped in evaluating the five usability dimensions presented in Table 3.1. Five questions from the survey designed by Moore (1991) were used to analyze the three innovation attributes shown in Table 3.1 (Bot, 2013). In order to measure the perceived ease of use, perceived usefulness and behavioral intention to use the real-time food quality monitoring application, a couple of survey questions from the instrument proposed by Davis (1989), and three questions designed by the researcher were used. A complete list of the survey questions used in the study with their codes are highlighted in Appendix A Table A1. The researcher used this set of 21 questions to gather data and analyze the user's experience with the application, and evaluate acceptance and adoption.

A sample size of atleast 30 users is recommended for usability studies. According to Sheehan (2012), a sample size of 10-20 is substantial for gauging the usability acceptance and adoption of mobile applications. For the research study, it was difficult to gather more than 20 participants. It was difficult to engage truck drivers and warehouse/store personnel for the study while they performed their duties as they had a busy schedule. The participating truck drivers didn't have a fixed schedule and they arrived at the destination warehouse/ store at different times of the day. Even after waiting for hours at the store to have an opportunity to talk to the truck drivers, the researcher was able to talk to only 3-4 of them each day. The inclusion criteria for participants involved in the study was, they should be involved in the distribution and quality control of perishable food products in a cold chain environment. Among the truck drivers that the researcher talked to, the percentage of participants that transported temperature controlled food products was fairly low. In order to have more participants, the researcher contacted all the supermarkets in the Lafayette area, Purdue Dining Courts, and Costco Wholesale at Romeoville, and requested their assistance in scheduling meetings with their contracted truck drivers. The researcher visited these stores everyday for 2-3 weeks and talked to the warehouse/store personnel, and truck drivers representing different companies, for example Celedon and Coke. Considering the scope and practicality of getting these participants to get involved with the research study, the researcher managed 18 participants to use the application and complete the survey based on their experience.

The methodology and framework used for data analysis is as follows:

- The quantitative data obtained from the surveys contained demographic information on the participants, for example profession, years of experience, level of experience and comfort with technology etc.

- The participants' response scores on their perception of usefulness and ease of use of the mobile application was categorical.

- Kendall's Tau correlation coefficient was calculated to determine the correlation and association between the individual usability and adoption variables and also between different usability and innovation dimensions. When the sample size is small with multiple tied ranks, Kendall's Tau correlation method is quite useful to analyze the association between ordinal variables.

- The participants' intention to use the application was examined and compared for different demographic groups.

- The dimensions that affect the user's perception of usefulness and ease of use were analyzed.

- Based on the demographic information of the participants, their mean scores on different dimensions were compared based on profession, years of experience, experience with web-based applications etc.

- Kendall's Tau correlation coefficient was calculated to examine the association between Perceived Usefulness, Perceived Ease of Use and Behavioral Intention to use the application.
- Finally, the qualitative responses of the participants to the questions on the perceived usefulness and ease of use of the application suggested improvements to the application.

3.3 Design of real-time cold chain monitoring application

The major components of a real-time cold chain monitoring mobile application include sensors, cloud platform and a mobile device. The architecture of the application is shown in Figure 3.2.

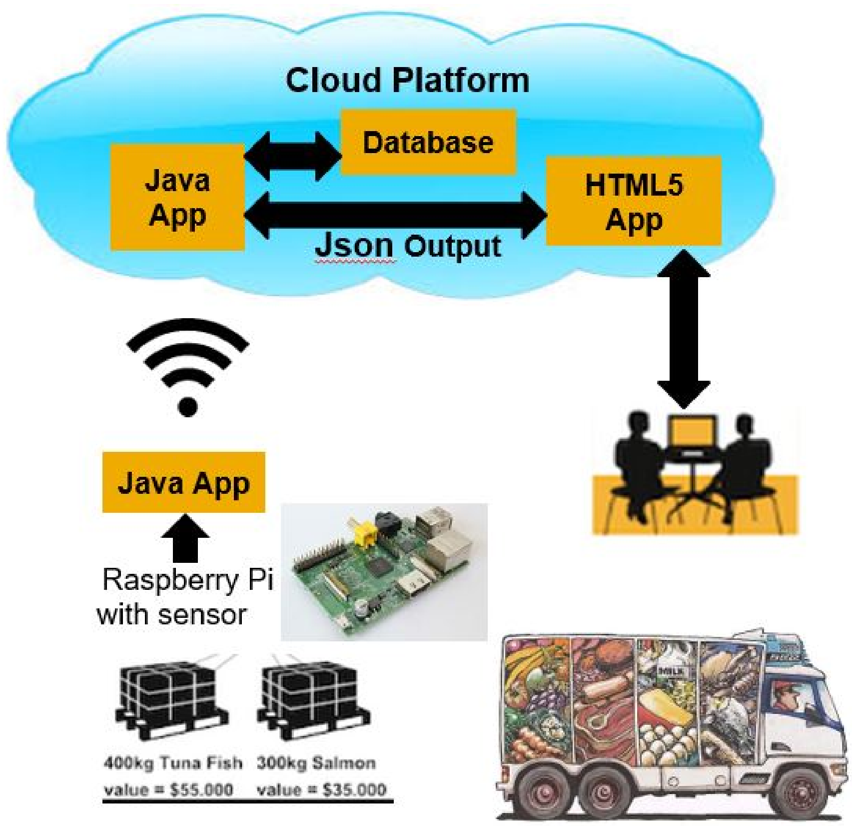


Figure 3.2.: Application architecture

Figure 3.2 describes a truck carrying perishable food products. Each pallet/container in the truck is embedded with sensors, for example temperature sensor. The sensors are connected to the Raspberry Pi and send real-time temperature values for each pallet/container to the Raspberry Pi. Raspberry Pi is a low cost credit card sized computer that is capable of browsing the internet, playing high-definition video, making spreadsheets, word-processing, and playing games. It's useful for integrating data from wide variety of sensors, for example temperature, humidity, motion and light sensors. The Raspberry Pi offers HDMI support, 256 512 MB RAM, 1-4 USB 2.0 ports and 1748 I/O ports based on the Raspberry Pi type.

The researcher developed a Java application that collects data reported on Raspberry Pi's I/O ports and sends it to the database in the cloud. For this study, the researcher simulated the temperature data in lieu of data coming from the sensors. The temperature values are sent to the cloud. The Java application sends a HTTP url request with the information for each sensor, for example sensor ID, sensor value, unit of temperature etc. The url for a sample sensor is as follows:

```
https://username.xxxxxx.com/iotscenario/
?action=addsensorvalue&sensorid=1&unit=Celsius&sensorvalue=
10&sensorvaluemultiplier=0.1&sensorvaluecalibration=0
```

Another Java application deployed in the cloud using the Java Persistence service allows to persist the data in the cloud and feed it to the cloud database instance. The Java application also creates a stream of JavaScript Object Notation (JSON) output, that could be consumed by an HTML5 application. The HTML5 application creates the front end user interface that the users see on the mobile device.

3.4 Context and Participants

It was important to define the intended use of the application. Figure 3.2 describes the objective of using the application, target users of the application and platform for running the application.

Application Objective	Real-time monitoring of refrigerated food products and preventing food wastage
Application Target Users	Truck drivers and warehouse personnel (18-65 years old)
Application Platform	Any web-based mobile device (smartphones, tablets)

Figure 3.3.: Defining intended use

The inclusion criteria for selecting the participants, steps to identify the participants, risks and benefits to the participants and their rights are as follows:

- As explained in the previous section, the participating truck drivers and warehouse/store personnel were required to be above 18 years in age and involved in distribution and quality control of perishable food products.
- The researcher arranged meetings with the store managers of Purdue Dining Courts, Costco Wholesale at Romeoville, and all the supermarkets in the Lafayette area, and explained the idea of the research, potential benefits and risks of the study. The researcher also discussed with the managers, the best practices used in ensuring good quality of perishable food products. Through discussion with the managers, the researcher discovered widely used intelligent real-time food quality monitoring systems, for example Fast Alert. Despite the busy schedule of the participants, all the supermarkets in the Lafayette area except Fresh City had participants available for the study. Participants constituted truck drivers and warehouse personnel at Marsh Supermarket, Payless Supermarket, Meijer Supermarket, Costco Wholesale, Walmart and Purdue Dining Courts.

- There was no risk to the participants in the study beyond what they face day to day. The survey questions were designed such that the identity of the participants was kept anonymous. Breach of confidentiality was a risk and the safeguards used by the researcher to minimize this risk included storing and maintaining the data at a secured Purdue server. Only the researcher had access to the survey data collected from interaction with the participants.
- The participants had an opportunity to get hands-on experience with a mobile application for monitoring the quality of food products in a refrigerated environment. Monetary compensation was not provided to the participants.
- The participation of truck drivers and warehouse/store personnel was completely voluntary and they had the right to withdraw their participation at any time without penalty or loss of benefits.

The outcomes of this research could be useful to any 3rd party logistics organization responsible for transporting perishable goods from manufacturing plants to distribution centers and end customers. It could also prove to be valuable for manufacturers and processors of bio-pharmaceuticals, milk, vegetables and meat products.

3.5 Data Sources and collection

In an industrial setting of this application, there would be continuous, real-time and uninterrupted streaming of data from sensors and other reporting devices to the data center. For this research, the streaming of the data was simulated, meaning there were no sensors or other information recording and/or reporting devices deployed. The researcher designed a function to feed random temperature values into the application deployed in the cloud. The application simulated 10 different food containers. For the sake of simplicity, the function was written as to generate temperature values between 0 and 40 F for each of the food containers. A threshold temperature was set for each food container depending on its content, for example 35F for Tyson Grilled Chicken Breast container. The application reported alerts through a change in the color of the food container tile to red in addition to the description of the issue. In addition to the temperature values and alerts, the application included a map that showed time and distance to the destination warehouse/store from the truck drivers' current location. The research tracked the user's experience with the application, simulated data and alerts through a survey instrument enclosed in Appendix A. Truck Drivers were requested to use the application as if they were driving and using the application. The user interface of the application was kept simple to avoid any distractions to the truck driver.

The survey consisted a total of six demographics questions and 25 questions measuring usability, innovation and behavioral intention to use a new system/application. This survey was created with the use of Qualtrics. Table 3.2 summarizes the codes and number of survey questions analyzed for each category, i.e Demographics, Usability, Innovation, Perceived Usefulness and Ease of Use, and Behavioral Intention. The responses to the survey questions were coded as numeric ordinal variables. For example, a response of 1 on the profession demographic question indicated truck driver while 2 indicated warehouse/store personnel. The usability and innovation dimensions as described earlier were distributed across the Perceived Usefulness and Perceived Ease of Use attributes. Each dimension had one or more survey questions to gauge the acceptance and adoption of the real-time food quality monitoring application. Survey questions adapted from SUS and other surveys described above were modified to address the real-time food quality monitoring application.

Table 3.2: Survey Questions

Survey Questions	
Demographic Questions (6)	D1, D2, D3, D4, D5, D6
Usability (11)	EFFE1, EFFE2, EFFI1, EN1, EN2, EN3, EOL1, EOL2, EOL3, EOL4, ER1
Innovation (5)	CMPL1, CPLX1, RA1, RA2, RA3
Perceived Usefulness (3)	PU1, PU2, PU3
Perceived Ease of Use (3)	PEU1, PEU2, PEU3
Behavioral Intention (3)	BI1, BI2, BI3

The user's responses to the survey questions except demographic questions were recorded on a seven point Likert Scale ranging from 1 to 7, 1 representing Strongly Disagree and 7 representing Strongly Agree. The average score for each question was used to compute the average score for each dimension. The demographic information provided compare and contrast analysis for the Perceived Usefulness and Perceived Ease of Use attributes. The open ended qualitative questions on the survey assisted in understanding features and issues that participants found easy or complex, and to identify additional features that would enhance the application.

In order to test the acceptance and adoption of a real-time food quality monitoring application, the researcher selected a group of participants from the selected stores as described in the above section, who are involved in the perishable goods cold chain. The user interface for a real-time food quality monitoring application that is presented to the users(truck drivers, warehouse inspection quality supervisors and workers) is shown by figures 3.4 and 3.5. Figures 3.6 and 3.7 shows similar user interface for such an application as proposed by Fiedler (2013).

Figure 3.4 shows a dashboard that truck drivers will see while driving. If an issue was reported by any of the simulated food containers, example freezer failure, seal breaks etc. the corresponding tile of the food container changed to red.

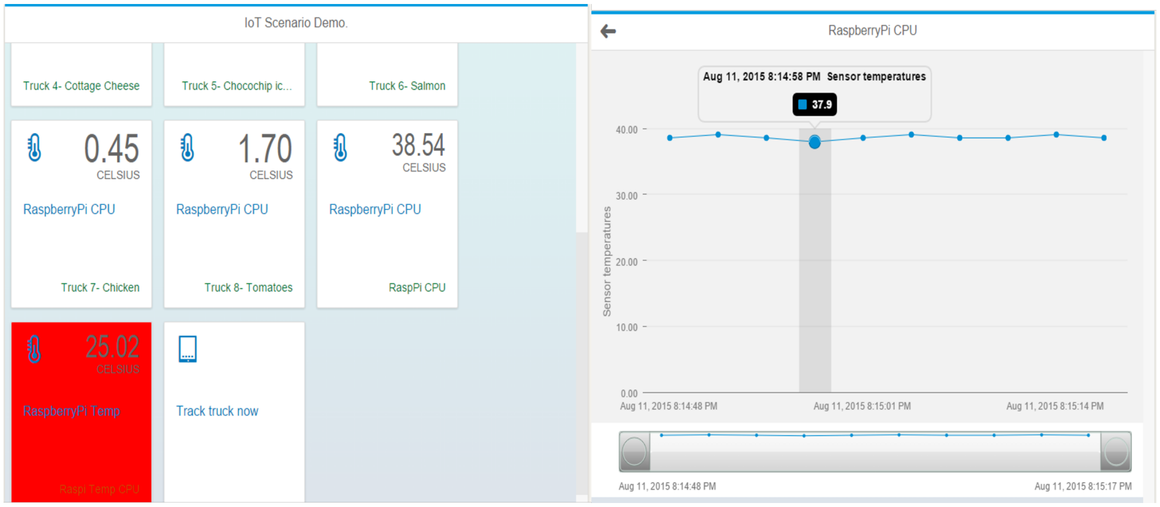


Figure 3.4.: Application User Interface home screen

Figure 3.5 describes the GPS capability of the application. The application estimates the most optimal route for the truck drivers and notifies them of real-time traffic conditions, ongoing construction on the road etc. The drivers can estimate the time it would take them to reach the destination warehouse/store.

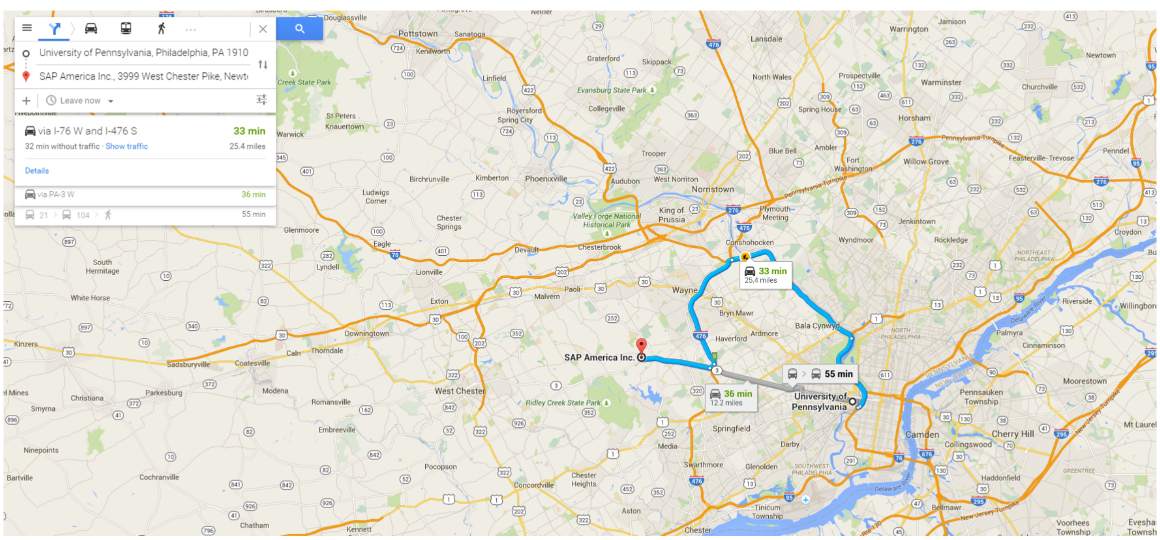


Figure 3.5.: Application user interface for GPS based analytics

Figure 3.6 describes a scenario where the inspection quality managers at the receiving warehouse/store could use the application to check which food products are in good condition, and which products should be rejected based on their real-time monitoring during transit.

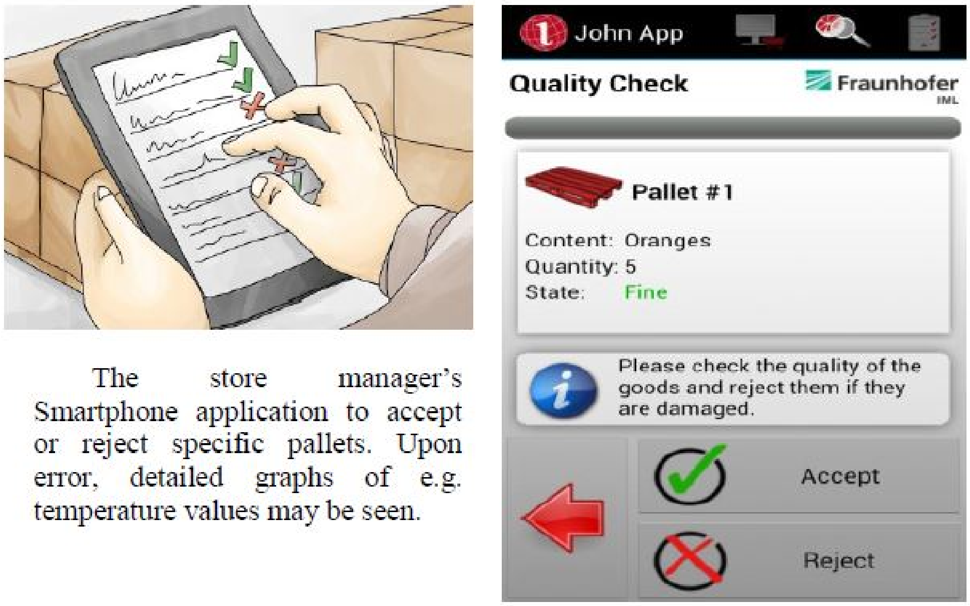


Figure 3.6.: Handover and quality control of goods (Fiedler et al., 2013)

If the managers find an issue with a product, they could explore detailed history of the product's condition during transit, for example past temperature values. This would help them analyze whether the product has remained outside the prescribed temperature zone for only a few hours or the entire course of the journey.

Figure 3.7 depicts the truck drivers' interface with the application while driving (Fiedler et. al, 2013). It is similar to the user interface shown in Figure 3.4

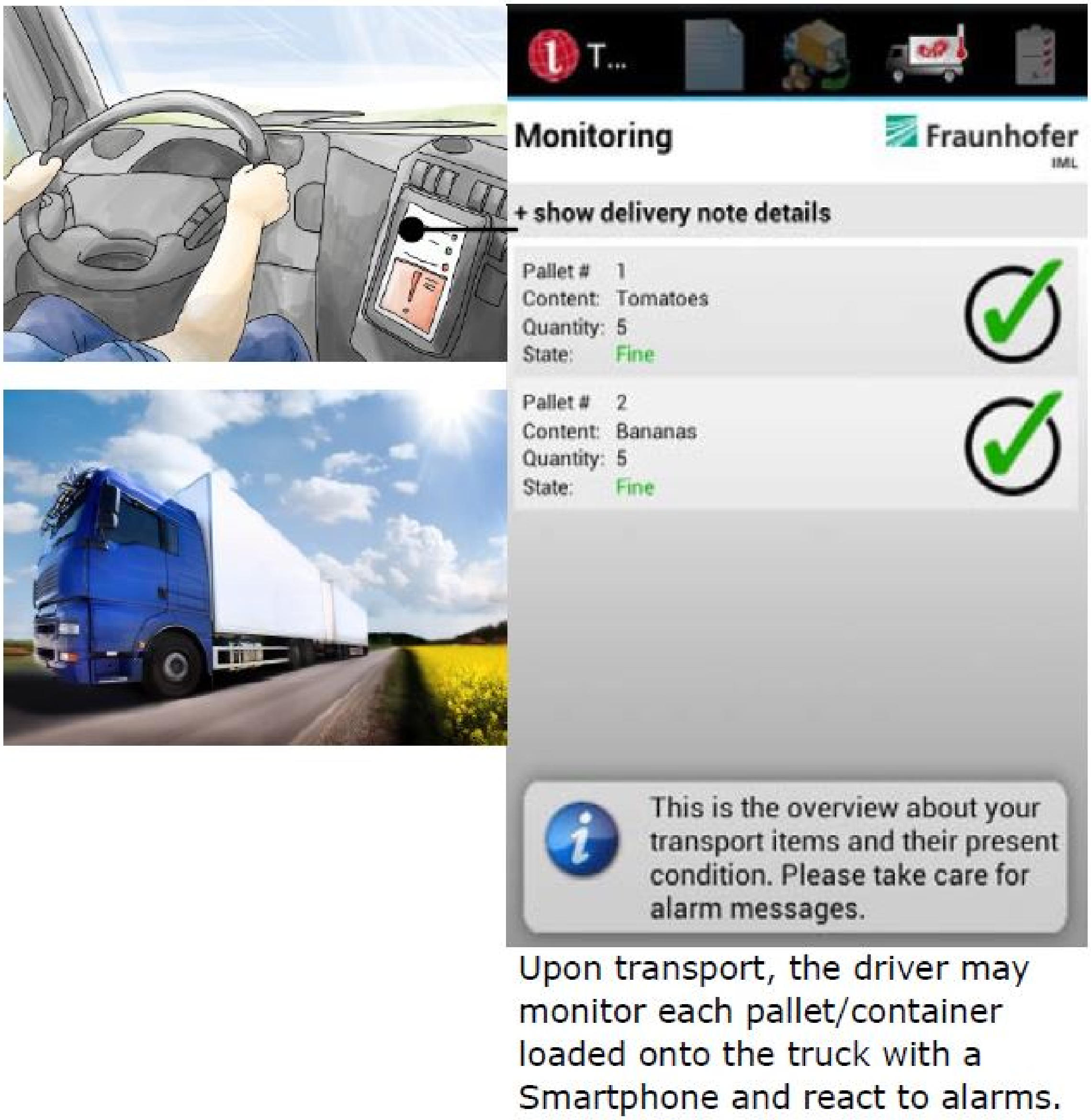


Figure 3.7.: On-the-road monitoring of transported goods (Fiedler et al., 2013)

Institutional Review Board (IRB) approval was required since human subjects were involved in the research. The researcher designed the survey questions such that the users' response was completely anonymous, ensuring the integrity and confidentiality of the participants. A written consent from the store managers of targeted stores highlighted in previous sections, indicating their agreement to participate in the research was obtained. Before the participants used the application, the researcher informed them in person about the IRB protocols. Their participation was completely voluntary. A The researcher completed the CITI training for researching the social behaviour of human subjects as a prerequisite for the IRB approval. The IRB approval is enclosed in Appendix B.

3.6 Data Analysis

The data analysis was both qualitative and quantitative. The researcher sought the guidance of Purdue's Statistical Consulting Service (SCS) to formulate the data analysis methodology. The director of SCS suggested it would be best to do calculate Kendall's Tau correlation coefficient for the usability and innovation dimensions to understand the association between them. Also, he suggested engaging more users to gather more data.

Statistical analysis of the data collected helped identify if there is a consistency in how each user evaluates the acceptance and adoption of a mobile application for real-time perishable food health monitoring. The data analysis was done to analyze if different users could be grouped into clusters in a statistically significant manner based on their responses on the survey questionnaire. The steps followed for data analysis are as follows:

- In the case of exploratory data analysis, descriptive statistics was used to analyze the demographic information, for example age, profession etc. and user's responses on usability and innovation dimensions.
- Quantitative analysis was conducted on the 22 survey questions which had categorical responses.
- Correlation was performed on the responses to these 22 questions. Kendall's Tau correlation coefficient was calculated to measure the association between the usability and innovation dimensions. SPSS was used to compute the Kendall's Tau Correlation Coefficient score p-values.

- The analysis helped to identify survey questions which could be obviated when similar questions had nearly equivalent average scores and strong correlation. For example, EN variables (EN1, EN2 and EN3) had a strong correlation among each other. Therefore, an average of EN1, EN2 and EN3 scores was calculated to represent the EN usability dimension. For the variables that had a weak correlation, for example EFFE 1 and EFFE2, the survey question more relevant based on the context and literature was chosen as a representative for that particular dimension.

- The 6 demographic questions were used to compare the usability and innovation dimensions for different demographic groups.

- Correlation between Perceived Usefulness, Perceived Ease of Use and Behavioral Intention was analyzed using SPSS to validate TAM.

- Qualitative analysis was performed on open ended questions as defined in the survey to evaluate what was useful to participants and what would they like in such an application.

3.7 Perspective

The research aims at decreasing the overall food wastage in the cold chain systems. Having had experience with the technology side of designing this application, the researcher understands the technical architecture and design. Also, through review of relevant literature and interviews, the researcher understands what information is highly desired by truck drivers and inspection quality supervisors for food monitoring, that is not currently delivered to them at the right time.

3.8 Bias

The research is written from the bias of a student and is limited in addressing some of the other perspectives or viewpoints in using a real-time food monitoring application to its full potential, for example, truck drivers and inspection quality supervisors. They are the intended users of the systems. And, the adoption to technology would be less seamless for them.

3.9 Summary

This chapter described the framework and methodology used in the research study, the data sources and collection methods, the data analysis techniques used, the perspective and bias of the researcher.

CHAPTER 4. RESULTS

This chapter describes the findings and results of the analysis conducted in the study, according to the framework and methodology explained in the previous chapter. The chapter begins with a summary of the demographic characteristics of the participating truck drivers and warehouse/store personnel, for example age, experience and level of comfort with web based technology/tools/applications etc. The second section analyzes the correlation between the ordinal variables under the usability and innovation dimensions. The following section analyzes the correlation between usability and innovation adoption dimensions, and the participant's perception of usefulness and ease of use. The subsequent section summarizes the results of the qualitative analysis and validation of Technology Acceptance Model (TAM). The chapter concludes with a summary of notable findings of the research study.

4.1 Demographic Profile

Tables 4.1 through 4.8 highlight the demographic information of the participants involved in the research. The research analyzes the usability and acceptance of a real-time food quality monitoring application by truck drivers and warehouse/store personnel. The demographic information captured the participants' age, years of experience, profession, gender, and level of experience and comfort with technology. The profession of the participants was either truck drivers or warehouse/store personnel. Age of the participants ranged between 20 and 60. Participants reported their level of experience with technology on a 5 point Likert Scale that varied from Very Inexperienced to Very Experienced. Similarly, level of comfort with technology varied from Very uncomfortable to Very Comfortable.

As shown in Table 4.1, a total of 18 participants were studied. But, since most of the food waste occurs during transit as described in the previous chapters, the population consisted mostly of truck drivers. Nearly 67% of them were truck drivers while the remaining 33% participants constituted warehouse/store personnel.

Table 4.1: Demographic Profile of Participants

Participants	Frequency	Percent
Truck Drivers	12	66.7
Warehouse/ Store Personnel	6	33.3
Total	18	100.0

The age of the participants ranged between 20 and 60. As shown in Table 4.2, almost 75% of the truck drivers who participated in the research were between 30 and 50 years in age.

Table 4.2: Age of Participants

Variable			Profession		Total
			Truck Driver	Warehouse/ Store Personnel	
Age	20-30	Count	1	2	3
		Percentage	8.3%	33.3%	16.7%
	30-40	Count	5	2	7
		Percentage	41.7%	33.3%	38.9%
	40-50	Count	4	0	4
		Percentage	33.3%	0.0%	22.2%
	50-60	Count	2	2	4
		Percentage	16.7%	33.3%	22.2%
Total		Count	12	6	18
		Percentage	100.0%	100.0%	100.0%

Table 4.3 highlights the years of experience for the research participants. The distribution of truck drivers based on the years of experience is nearly uniform, with

all the groups (5-10,10-15,15-20 and 20+) except the first group (0-5) having equal distribution. And nearly 67% of the warehouse/store personnel had between 5 and 15 years of work experience.

Table 4.3: Participants' years of experience

Variable			Profession		Total
			Truck Driver	Warehouse/ Store Personnel	
Years of experience	0-5	Count	4	0	4
		Percentage	33.3%	0.0%	22.2%
	5-10	Count	2	3	5
		Percentage	16.7%	50.0%	27.8%
	10-15	Count	2	1	3
		Percentage	16.7%	16.7%	16.7%
	15-20	Count	2	0	2
		Percentage	16.7%	0.0%	11.1%
	20+	Count	2	2	4
		Percentage	16.7%	33.3%	22.2%
Total		Count	12	6	18
		Percentage	100.0%	100.0%	100.0%

According to Table 4.4, almost 75% of the research participants reported themselves as experienced or very experienced in using web based technology, tools and applications. Among the participants, warehouse/store personnel were observed to be more experienced with web based technology, tools and applications in comparison to truck drivers. Nearly 84% of warehouse/store personnel in contrast to 65% truck drivers identified themselves as experienced or very experienced with technology.

Table 4.4: Participants' experience with web based technology/tools/applications based on profession

Variable			Profession		Total
			Truck Driver	Warehouse/ Store Personnel	
Experience using Web based technology/ tools/ applications	Undecided	Count	3	0	3
		Percentage	25.0%	0.0%	16.7%
	Inexperienced	Count	1	1	2
		Percentage	8.3%	16.7%	11.1%
	Experienced	Count	7	4	11
		Percentage	58.3%	66.7%	61.1%
	Very Experienced	Count	1	1	2
		Percentage	8.3%	16.7%	11.1%
Total		Count	12	6	18
		Percentage	100.0%	100.0%	100.0%

Of the 18 participants, almost 84% were comfortable or very comfortable with the use of web based tools, technology and applications as shown in Table 4.5. Even while using the application, they were at ease with the mobile platform.

Table 4.7 highlights the participants' experience with web based technology, tools and applications based on their age. All the participants in age groups 20-30 and 30-40 reported themselves as experienced or very experienced in using technology. On the other hand, 28% of the population that expressed their proficiency with technology as undecided or inexperienced were aged above 40.

Table 4.5: Participants' comfort with web based technology/tools/applications based on profession

Variable			Profession: Truck Driver	Profession: Warehouse/ Store Personnel	Total
Level of comfort with Web based technology/ tools /applications	Very Uncomfortable	Count	1	1	2
		Percentage	8.3%	16.7%	11.1%
	Neither Uncomfortable nor Comfortable	Count	3	0	3
		Percentage	8.3%	0.0%	5.6%
	Comfortable	Count	9	4	13
		Percentage	75.0%	66.7%	72.2%
	Very Comfortable	Count	1	1	2
		Percentage	8.3%	16.7%	11.1%
Total		Count	12	6	18
		Percentage	100.0%	100.0%	100.0%

Table 4.6: Gender Profile of Participants

Variable			Profession: Truck Driver	Profession: Warehouse/ Store Personnel	Total
Gender	M	Count	12	5	17
		Percentage	100.0%	83.3%	94.4%
	F	Count	0	1	1
		Percentage	0.0%	16.7%	5.6%
Total		Count	12	6	18
		Percentage	100.0%	100.0%	100.0%

Similarly, as described in Table 4.8, all the participants below 50 years in age expressed themselves as being comfortable or very comfortable with the use of technological solutions, while only 25% of the participants above the age of 50 were comfortable with the use of technological solutions.

Table 4.7: Participants' experience with web based technology/tools/applications based on age

			Age				Total
			20-30	30-40	40-50	50-60	
Experience using Web based technology/ tools/ applications	Undecided	Count	0	0	2	1	3
		Percentage	0.0%	0.0%	50.0%	25.0%	16.7%
	Inexperienced	Count	0	0	0	2	2
		Percentage	0.0%	0.0%	0.0%	50.0%	11.1%
	Experienced	Count	1	7	2	1	11
		Percentage	33.3%	100.0%	50.0%	25.0%	61.1%
	Very Experienced	Count	2	0	0	0	2
		Percentage	66.7%	0.0%	0.0%	0.0%	11.1%
Total		Count	3	7	4	4	18
		Percentage	100.0%	100.0%	100.0%	100.0%	100.0%

Table 4.8: Participants' comfort with web based technology/tools/applications based on age

			Age				Total
			20-30	30-40	40-50	50-60	
Level of comfort with Web based technology/ tools /applications	Very Uncomfortable	Count	0	0	0	2	2
		Percentage	0.0%	0.0%	0.0%	50.0%	11.1%
	Neither Uncomfortable nor Comfortable	Count	0	0	2	1	1
		Percentage	0.0%	0.0%	0.0%	25.0%	5.6%
	Comfortable	Count	1	7	4	1	13
		Percentage	33.3%	100.0%	100.0%	25.0%	72.2%
	Very Comfortable	Count	2	0	0	0	2
		Percentage	66.7%	0.0%	0.0%	0.0%	11.1%
Total		Count	3	7	4	4	18
		Percentage	100.0%	100.0%	100.0%	100.0%	100.0%

4.2 Usability Study

A total of 11 survey questions gauged user's experience with the application in terms of usability. Participants expressed their responses to factors gauging usability of a real-time food quality monitoring application on a seven point likert scale, ranging from 1 to 7. A score of 1 denoted strongly disagree and a score of 7 indicated strongly agree. Since the responses of the participants were ordinal and not continuous, the researcher calculated Kendall's Tau correlation coefficient to analyze the association between survey questions within each dimension. Kendall's Tau-b is calculated as:

$$Kendall'sTau - b = \frac{P - Q}{\sqrt{(P + Q + T_R)(P + Q + T_C)}}$$

Where, P = Number of concordant pairs

Q = Number of discordant pairs

Tr = Number of ties in the row variable

Tc = Number of ties in the column variable

Goodman - Kruskal Gamma is calculated as:

$$Gamma = \frac{P - Q}{P + Q}$$

Gamma is defined as the surplus of the concordant pairs over the discordant pairs, as a percentage of all the pairs, excluding ties.

The five dimensions for analyzing the usability of the application are EFFE,EFFI, EN, EOL and ER. Please refer Appendix A for survey questions used for analyzing these dimensions. For the usability dimensions (sub-questions) with strong correlation, an average of the participants' responses to different sub-questions within the same dimension was computed to represent the entire usability dimension. This also helped to reduce the number of regressors. And for the sub questions which have a weak correlation with each other, the survey question more relevant based on the context and literature was chosen as a representative for that particular dimension.

4.2.1 Usability Dimensions and Variables

According to Table 4.9, the null hypothesis states that there is no correlation between the responses to two survey questions gauging Perceived Usefulness. Since the p-value = 0.036 i.e less than 0.05 for 95% confidence interval and Kendall's Tau-b coefficient = .434, we reject the null hypothesis and accept the alternative. An average of participants' responses to PU1 and PU2 were calculated to create a new score for the PU dimension.

Table 4.9: Correlation between PU1 and PU2

PU1 vs PU2

Count

		PU2			
		Somewhat Agree	Agree	Strongly Agree	Total
PU1	Agree	1	8	4	13
	Strongly Agree	0	1	4	5
Total		1	9	8	18

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Ordinal by Ordinal	Kendall's tau-b	.434	.186	2.096	.036
	Gamma	.805	.219	2.096	.036
N of Valid Cases		18			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

For the Effectiveness usability dimension as shown in Table 4.10, the p-value is greater than 0.05. This means that we fail to reject the null hypothesis that there is no correlation among the survey questions. EFFE1 analyzed the degree of satisfaction for the participants on receiving the results they expected from the application. EFFE2 analyzed if the participants found the information on the application useful. In this case, EFFE1 variable is chosen as it suited the context of study and has been widely used in previous usability studies as mentioned by Green & Pearson (2006).

Table 4.10: Correlation between EFFE1 and EFFE2

EFFE1 vs EFFE2

Count

		EFFE2			
		Somewhat Agree	Agree	Strongly Agree	Total
EFFE1	Neither Disagree nor Agree	1	0	0	1
	Somewhat Agree	1	0	0	1
	Agree	0	9	5	14
	Strongly Agree	0	1	1	2
Total		2	10	6	18

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Ordinal by Ordinal	Kendall's tau-b	.481	.214	1.716	.086
	Gamma	.783	.233	1.716	.086
N of Valid Cases		18			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

Similarly, Kendall's Tau correlation coefficient was calculated for other sub questions between the remaining usability dimensions to identify variables for calculating the average response scores for different usability dimensions. The results are summarized in tables 4.11 - 4.19.

EN1 and EN3 had a strong correlation with a Kendall's Tau correlation coefficient of .746 and gamma value of .957 as shown in Table 4.13. The significance or the p-value is 0.022 which is less than 0.05 for 95% confidence interval. Therefore, we can reject the null hypothesis that there is no correlation between EN1 and EN3.

Table 4.11: Correlation between EN1 and EN2

EN1 vs EN2

Count

		EN2		
		Somewhat Agree	Agree	Total
EN1	Somewhat Agree	0	1	1
	Agree	2	11	13
	Strongly Agree	0	3	3
Total		2	15	17

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Ordinal by Ordinal	Kendall's tau-b	.098	.096	.889	.374
	Gamma	.500	.433	.889	.374
N of Valid Cases		17			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

Table 4.12: Correlation between EN2 and EN3

EN2 vs EN3

Count

		EN3			
		Neither Agree nor Disagree	Agree	Strongly Agree	Total
EN2	Somewhat Agree	0	2	0	2
	Agree	1	11	3	15
Total		1	13	3	17

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Ordinal by Ordinal	Kendall's tau-b	.098	.096	.889	.374
	Gamma	.500	.433	.889	.374
N of Valid Cases		17			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

Table 4.13: Correlation between EN3 and EN1

EN3 vs EN1

Count

		EN1			
		Somewhat Agree	Agree	Strongly Agree	Total
EN3	Neither Disagree nor Agree	0	1	0	1
	Agree	1	13	0	14
	Strongly Agree	0	0	3	3
Total		1	14	3	18

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Ordinal by Ordinal	Kendall's tau-b	.746	.179	2.288	.022
	Gamma	.957	.062	2.288	.022
N of Valid Cases		18			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

EOL1 analyzed if the layout of the application was predictable. There is a significantly weak correlation between EOL1 and other Ease of Learning variables. The strongest correlation is observed between EOL2 and EOL4 as shown in Table 4.18. EOL2 measured the confidence of participants in using the application because of their previous knowledge of mobile applications. And EOL4 asked the participants if they felt they needed to learn a lot of things before using the application. For questions EOL3 and EOL4, the scales were reversed as a low score on these questions represents a high ease of learning and vice versa.

Table 4.14: Correlation between EOL1 and EOL2

EOL1 vs EOL2

Count

		EOL2			
		Somewhat Agree	Agree	Strongly Agree	Total
EOL1	Neither Disagree nor Agree	0	2	0	2
	Somewhat Agree	3	4	0	7
	Agree	3	4	0	7
	Strongly Agree	0	1	1	2
Total		6	11	1	18

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Ordinal by Ordinal	Kendall's tau-b	.105	.230	.449	.653
	Gamma	.172	.369	.449	.653
N of Valid Cases		18			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

Table 4.15: Correlation between EOL1 and EOL3

EOL1 vs EOL3 (scale reversed)

Count

		EOL3 (scale reversed)					
		Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree	Total
EOL1	Neither Disagree nor Agree	0	0	0	2	0	2
	Somewhat Agree	1	0	1	3	2	7
	Agree	0	1	1	4	1	7
	Strongly Agree	0	0	0	0	2	2
Total		1	1	2	9	5	18

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Ordinal by Ordinal	Kendall's tau-b	.186	.195	.935	.350
	Gamma	.270	.275	.935	.350
N of Valid Cases		18			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

Table 4.16: Correlation between EOL1 and EOL4

EOL1 vs EOL4 (Scales Reversed)

Count

		EOL4 (Scales Reversed)				
		Somewhat Disagree	Neither Disagree nor Agree	Somewhat Agree	Agree	Total
EOL1	Neither Disagree nor Agree	1	0	0	1	2
	Somewhat Agree	2	1	1	3	7
	Agree	3	0	1	3	7
	Strongly Agree	0	0	0	2	2
Total		6	1	2	9	18

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Ordinal by Ordinal	Kendall's tau-b	.152	.212	.711	.477
	Gamma	.235	.324	.711	.477
N of Valid Cases		18			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

Table 4.17: Correlation between EOL2 and EOL3

EOL2 vs EOL3 (Scales Reversed)

Count

		EOL3 (Scales Reversed)					
		Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree	Total
EOL2	Somewhat Agree	0	0	1	5	0	6
	Agree	1	1	1	4	4	11
	Strongly Agree	0	0	0	0	1	1
Total		1	1	2	9	5	18

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Ordinal by Ordinal	Kendall's tau-b	.256	.190	1.309	.190
	Gamma	.414	.296	1.309	.190
N of Valid Cases		18			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

Table 4.18: Correlation between EOL2 and EOL4

EOL2 vs EOL4 (Scales Reversed)

Count

		EOL4 (Scales Reversed)				
		Somewhat Agree	Neither Disagree nor Agree	Somewhat Agree	Agree	Total
EOL2	Somewhat Agree	3	1	1	1	6
	Agree	3	0	1	7	11
	Strongly Agree	0	0	0	1	1
Total		6	1	2	9	18

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Ordinal by Ordinal	Kendall's tau-b	.415	.174	2.258	.024
	Gamma	.655	.228	2.258	.024
N of Valid Cases		18			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

Table 4.19: Correlation between EOL3 and EOL4

EOL3 vs EOL4

Count

		EOL4				
		Somewhat Disagree	Neither Disagree nor Agree	Somewhat Agree	Agree	Total
EOL3	Disagree	0	0	1	0	1
	Somewhat Disagree	1	0	0	0	1
	Somewhat Agree	0	1	0	1	2
	Agree	5	0	1	3	9
	Strongly Agree	0	0	0	5	5
Total		6	1	2	9	18

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Ordinal by Ordinal	Kendall's tau-b	.396	.156	2.591	.010
	Gamma	.532	.212	2.591	.010
N of Valid Cases		18			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

After applying the similar approach to all the usability dimensions, the final list of variables used for analyzing correlations between EFFE, EFFI, ERT, EN and EOL are as shown in Table 4.20.

Table 4.20: Usability dimensions and variables chosen for further analysis

Usability Dimension	Variable
Ease of Learning	EOL2 EOL3 EOL4
Effectiveness	EFFE1
Efficiency	EFFI1
Engagement	EN1 EN3
Error Tolerance	ER1
Perceived Usefulness	PU1 PU2
Perceived Ease of Use	PEU1

4.2.2 Correlation between Usability dimensions

Once the average scores for all the usability dimensions were calculated, the researcher computed the ordinal correlation between the five usability dimensions considered for the study i.e EFFE, EFFI, EN, EOL and ER. Table 4.21 describes the results of the calculated Kendall's Tau correlation coefficient. Among the five usability dimensions, there is weak correlation between ER and the other dimensions. Also, EFFI and EOL have a weak correlation with EFFE. But, there is a significant positive association between the remaining pairs. The strongest correlation of .58 present at 99% confidence interval is between EOL and EN. Also, the correlation between EN and EFFI is quite strong, .51 at 99% confidence interval.

Table 4.21: Correlations between Usability dimensions

Ordinal

Variable	EFFE	EFFI	EN	EOL	ER	PU
Usability						
EFFE	1.00					
EFFI	.19	1.00				
EN	.42**	.51*	1.00			
EOL	.32	.45*	.58*	1.00		
ER	.20	-.20	.25	-.15	1.00	
Perceived Usefulness						
PU	.38	.42**	.14	.40*	.10	1.00
Perceived Ease of Use						
PEU	.44**	.81**	.74**	.58**	-.05	.456

**. Correlation is significant at the 0.01 level (2-tailed). $p < 0.05$

*. Correlation is significant at the 0.05 level (2-tailed). $p < 0.01$

The researcher also calculated correlation between the usability dimensions and users' perceptions to better understand the relationship between them. PU and PEU measured the participant's perception of the ease of use and usefulness of the real-time food quality monitoring application. As shown in Table 4.21, EFFI and EOL have a significant positive correlation with PU, while all the usability dimensions except ER have a significant positive correlation with PEU. The strongest correlation is between PEU and EFFI, and PEU and EN. However, only 6 warehouse personnel participated in the study.

The research focuses on reducing food waste both during transit and at the store/warehouse. Hence, it was important to discover and compare the usability tests for both the participant groups. Therefore, the researcher further examined the mean values for the usability dimensions between the truck drivers and warehouse/store professionals. The results are summarized in Figure 4.1. The score of 5 on a likert scale used in the study represented "Somewhat Agree". Both, the truck drivers and warehouse/store personnel reported similar scores on all the usability dimensions analyzed. The scores across all the dimensions ranged from 5.30 to 6.17. From Figure 4.1, we could conclude that all the participants were in favour of the usability of the mobile application.

Usability Dimensions	Truck Drivers		Warehouse/ Store Personnel	
	Mean Scores	Std Deviation	Mean Scores	Std Deviation
EFFE	5.92	0.79	6.00	0.64
EFFI	6.17	0.39	5.50	1.11
EN	6.13	0.43	6.00	0.49
ER	5.42	0.67	5.83	0.62
EOL	5.31	0.77	5.67	0.82

Figure 4.1.: Usability dimensions mean scores

The subsequent sections 4.2.3 - 4.2.7 study the users responses to each usability dimension considered for the research.

4.2.3 Effectiveness

Figure 4.2 demonstrates the distribution of the user's responses on EFFE1 variable for truck drivers and warehouse/store professionals. EFFE1 analyzed the degree of satisfaction for the participants on receiving the results they expected from the application and it was chosen as a representative of the effectiveness usability dimension. The results are clustered around the higher end of the likert scale, with most of the participants expressing a strong favorable opinion about the effectiveness of the application. The mean EFFE scores for truck drivers and warehouse/store personnel as described in Figure 4.1 are around 6.

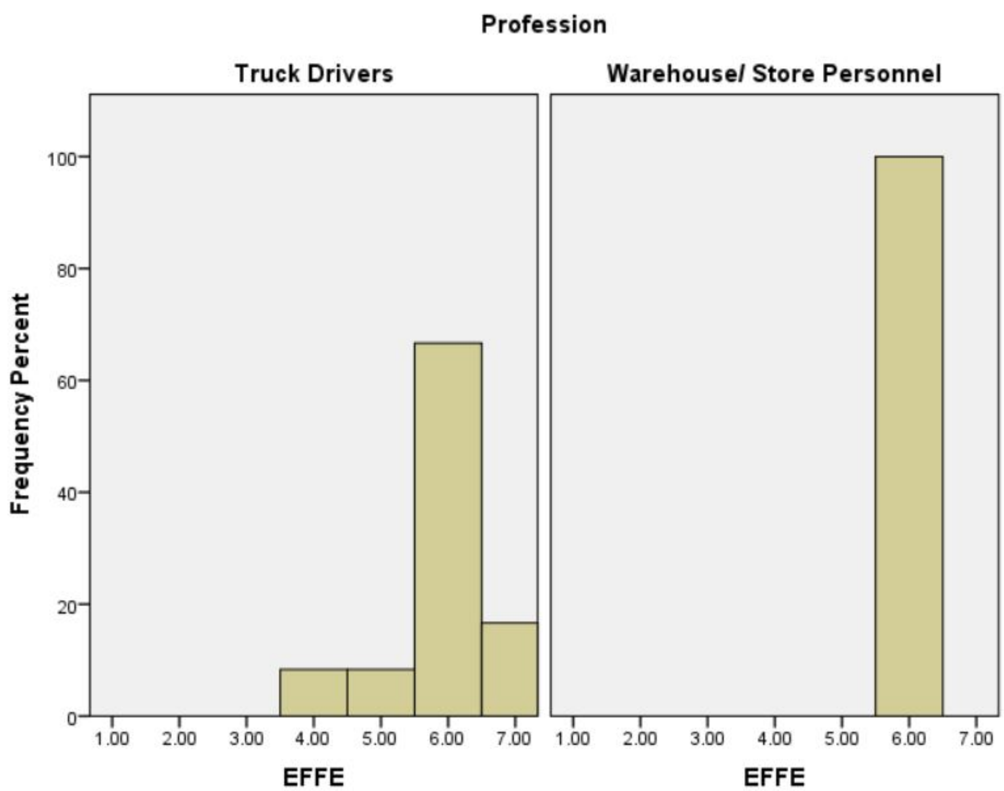


Figure 4.2.: Effectiveness distribution

4.2.4 Efficiency

EFFI1 measured the ability of the participants to navigate through the application and find the information quickly. It was taken as a representative of the efficiency usability dimension. All the truck drivers and store/warehouse personnel considered the application to be very efficient, with majority of their responses being above 6. 100% of the truck drivers and more than 70% of the store/warehouse professional reported EFFI scores above 6 as highlighted in Figure 4.3. The mean of the EFFI scores for truck drivers and warehouse/store personnel as highlighted in Figure 4.1 is 6.17 and 5.50 respectively. Only one warehouse/store personnel didn't have a favorable opinion about the efficiency of the application.

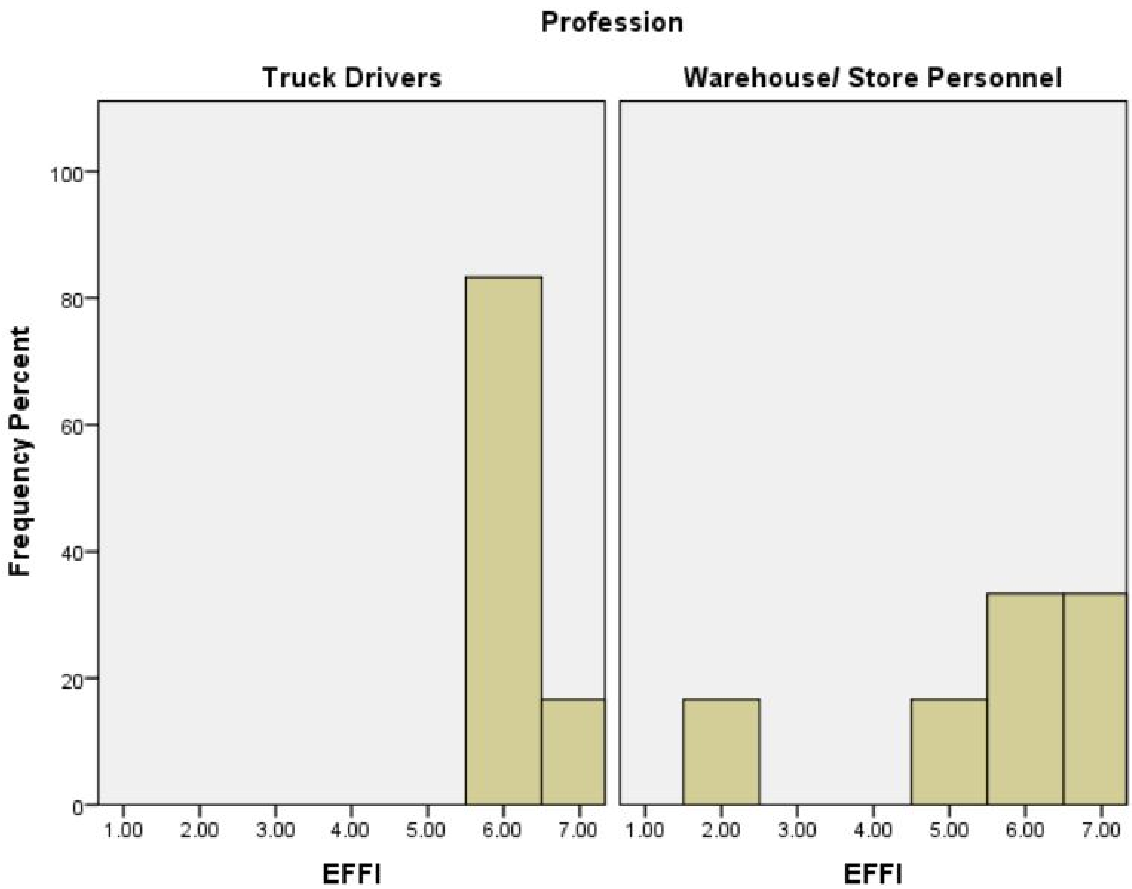


Figure 4.3.: Efficiency distribution

4.2.5 Engagement

According to Figure 4.4, nearly 20% of truck drivers and warehouse/store personnel strongly agreed on the positive engagement with the application. And almost 80% of truck drivers and 70% of warehouse/store personnel agreed that they were engaged with the application. The mean scores on engagement for both type of participants, the truck drivers and warehouse/store personnel is around 6. As described through the variables EN1 and EN3, the participants had a positive experience with the application and had a favorable opinion of the user interface.

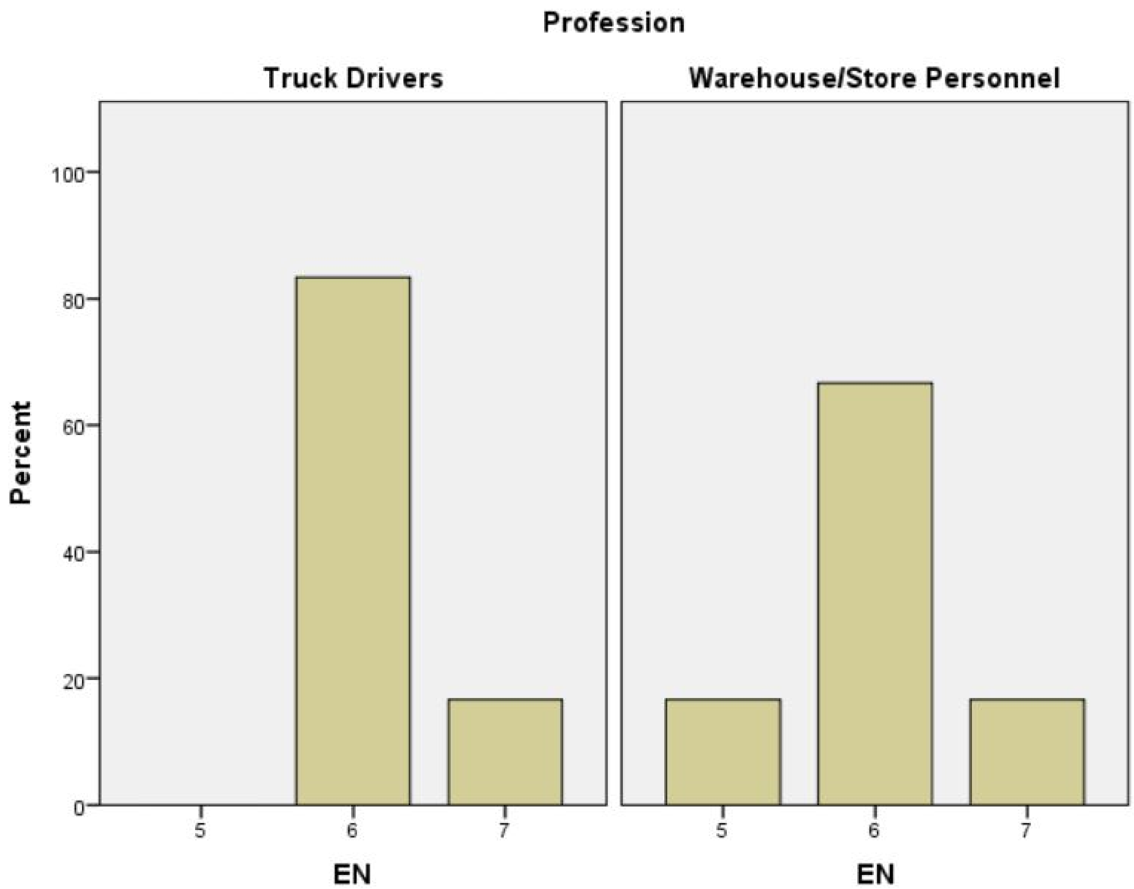


Figure 4.4.: Engagement distribution

4.2.6 Ease of Learning

For the ease of learning dimension, the mean scores for both participant groups as depicted in Figure 4.1 are lower than the mean scores of majority of the other usability dimensions. But in general, Figure 4.5 shows that around 95% of the population either “somewhat agreed”, “agreed” or “strongly agreed” about the ease of learning of how to use the mobile application. Only two participants somewhat agreed that they would need the support of a technical person to use the application. On analyzing their experience and level of comfort with web based tools, technology and applications and comparing with other participants, it was discovered that they reported being comfortable with the use of technology. One of these two participants reported them as being experienced, while the other participant reported them as inexperienced in using technology. On the other hand, 30% of the participants somewhat agreed that they would need to learn a lot of things before they could use the application.

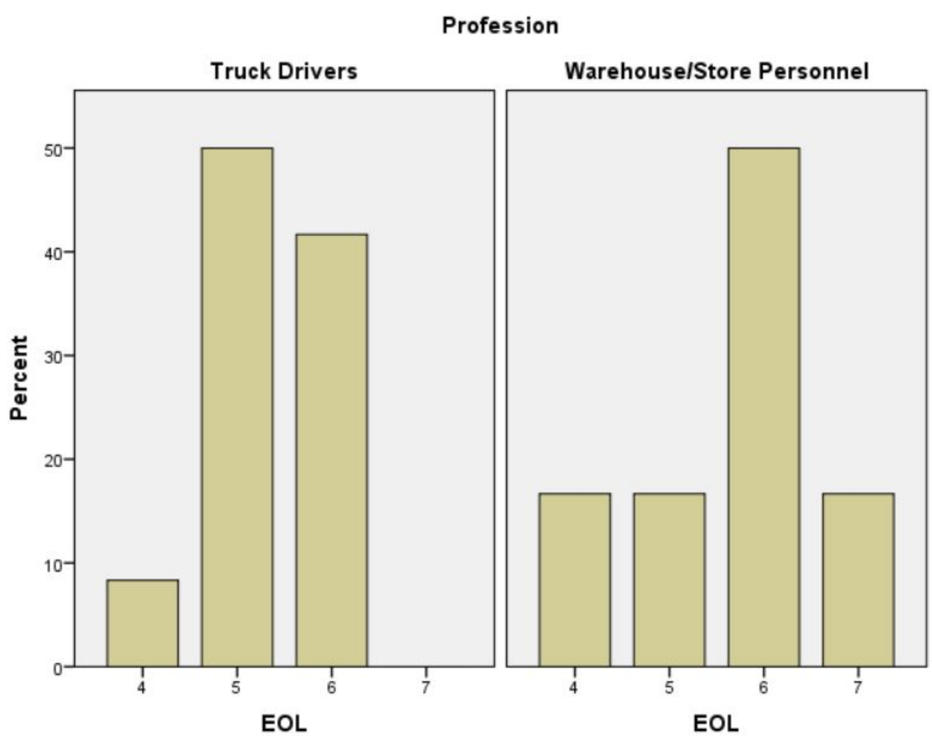


Figure 4.5.: Ease of Learning distribution

4.2.7 Error Tolerance

ER1 is a representative of the Error Tolerance dimension and it analyzed if the user interface helped the participants to avoid making errors. Figure 4.6 highlights the distribution of error tolerance scores for the participants. As seen in figure 4.1, the mean score for error tolerance usability dimension 5.83 and 5.42 for warehouse/store personnel and truck drivers respectively.

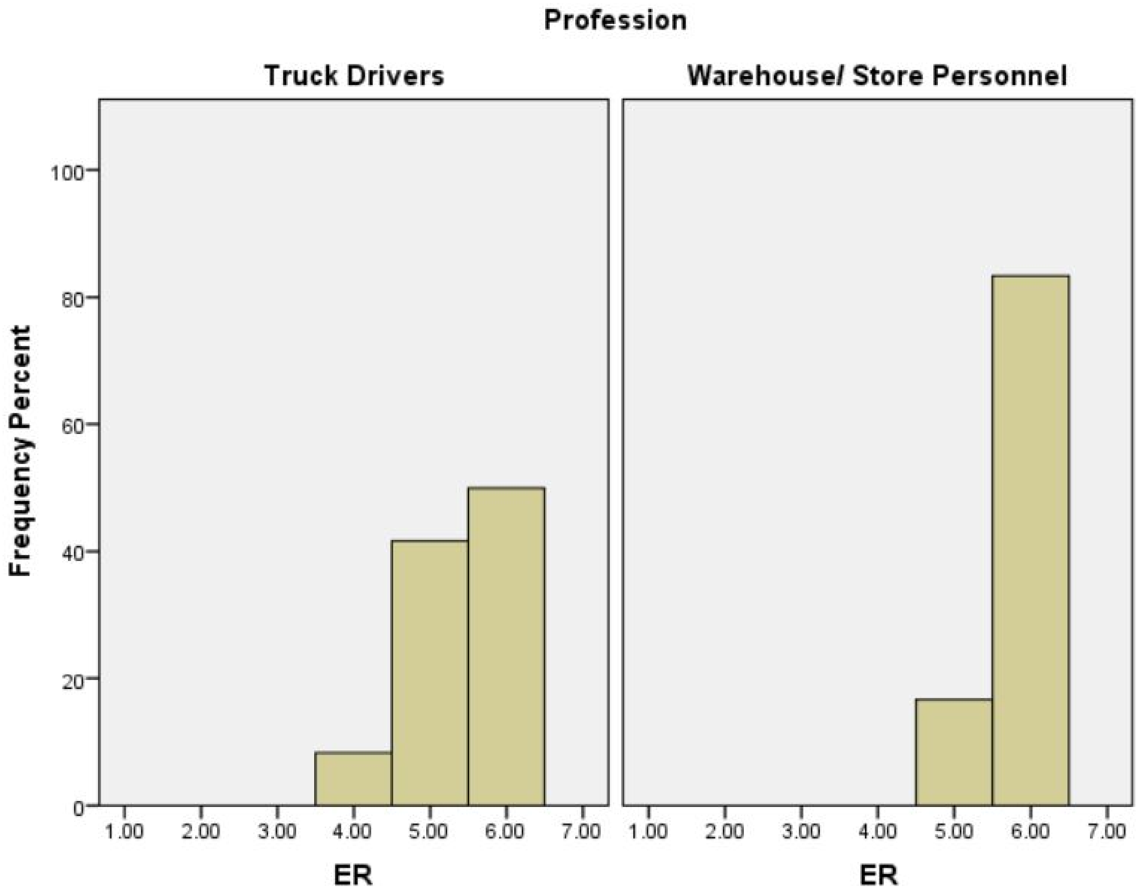


Figure 4.6.: Error Tolerance distribution

4.2.8 Usability analysis between participant groups

The researcher was interested in analyzing whether the profession of the participant affects their response scores on the usability dimensions. Thus, the means of usability dimension scores for the two participant groups, truck drivers and warehouse/store personnel, were compared. The mean scores on usability dimensions for the two participant groups was quite similar. As explained in previous subsections, all the 18 participants except one warehouse/store personnel were either undecided or had a positive opinion about the effectiveness, efficiency, engagement, ease of learning and error tolerance of the real-time food quality monitoring mobile application. The mean scores of usability dimensions for the two participant groups were quite high on the likert scale and similar ranging from a low of 5.30 to a high of 6.17.

4.3 Adoption of Innovation

A total of five survey questions analyzed participants' experience with the real-time food quality monitoring application in terms of adoption. As explained in the section above in the usability study, survey questions gauging innovation dimension attributes were analyzed and Kendall's Tau correlation coefficient between questions within each innovation dimension was calculated. The five dimensions considered in the study are CMPL, CPLX and RA. Based on the level of correlation between variables within each dimension, variables were selected as a representative of that innovation dimension and their average was calculated.

4.3.1 Innovation Dimensions and Variables

For the Relative Advantage innovation dimension, there is a strong correlation among all the three survey questions and the p-value is less than 0.05 in each case. The Kendall's Tau correlation coefficient and Gamma values are significantly high. Thus, as explained in the usability study in the previous section, average of the user's responses to RA1, RA2 and RA3 was computed to define a new variable RA. This variable represents the Relative Advantage dimension and has the score equal to the average of RA1, RA2 and RA3 scores.

Table 4.22: Correlation between RA1 and RA2

RA1 vs RA2

Count

		RA2					
		Disagree	Neither Disagree nor Agree	Somewhat Agree	Agree	Strongly Agree	Total
RA1	Somewhat Agree	0	0	2	1	0	3
	Agree	1	1	1	10	0	13
	Strongly Agree	0	0	0	0	2	2
Total		1	1	3	11	2	18

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Ordinal by Ordinal	Kendall's tau-b	.551	.202	2.180	.029
	Gamma	.763	.178	2.180	.029
N of Valid Cases		18			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

Table 4.23: Correlation between RA2 and RA3

RA2 vs RA3

Count

		RA3					
		Somewhat Disagree	Neither Disagree nor Agree	Somewhat Agree	Agree	Strongly Agree	Total
RA2	Disagree	0	0	0	1	0	1
	Neither Disagree nor Agree	0	0	1	0	0	1
	Somewhat Agree	0	0	3	0	0	3
	Agree	1	1	1	8	0	11
	Strongly Agree	0	0	0	1	1	2
Total		1	1	5	10	1	18

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Ordinal by Ordinal	Kendall's tau-b	.417	.204	1.999	.046
	Gamma	.571	.249	1.999	.046
N of Valid Cases		18			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

Table 4.24: Correlation between RA3 and RA1

RA3 vs RA1

Count

		RA1			
		Somewhat Agree	Agree	Strongly Agree	Total
RA3	Somewhat Disagree	1	0	0	1
	Neither Disagree nor Disagree	0	1	0	1
	Somewhat Agree	2	3	0	5
	Agree	0	9	1	10
	Strongly Agree	0	0	1	1
Total		3	13	2	18

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Ordinal by Ordinal	Kendall's tau-b	.623	.122	2.997	.003
	Gamma	.929	.079	2.997	.003
N of Valid Cases		18			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

After applying the similar approach to other innovation dimensions, the final list of variables used for analyzing correlations between CMPL, CPLX and RA are shown in Table 4.25.

Table 4.25: Innovation dimensions and variables chosen for further analysis

Innovation Dimension	**Variable**
Compatibility	CMPL1
Complexity	CPLX1
Relative Advantage	RA1 RA2 RA3
Perceived Usefulness	PU1 PU2
Perceived Ease of Use	PEU1

4.3.2 Correlation between Adoption dimensions

The researcher computed the ordinal correlation between the three adoption dimensions considered for the study i.e CMPL, CPLX and RA after evaluating the association between the 3 RA variables. Table 4.26 describes the results of the calculated Kendall's Tau correlation coefficient between the adoption dimensions. Among the three innovation dimensions, CMPL and CPLX have a weak correlation, whereas both CMPL and CPLX have a significant positive correlation of .56 and .51 with RA at 95% and 99% confidence intervals respectively.

The researcher also calculated correlation between the adoption dimensions and users' perceptions of usefulness and ease of use to better understand the relationship between them for a real-time food quality monitoring application.

Table 4.26: Correlations between Adoption dimensions

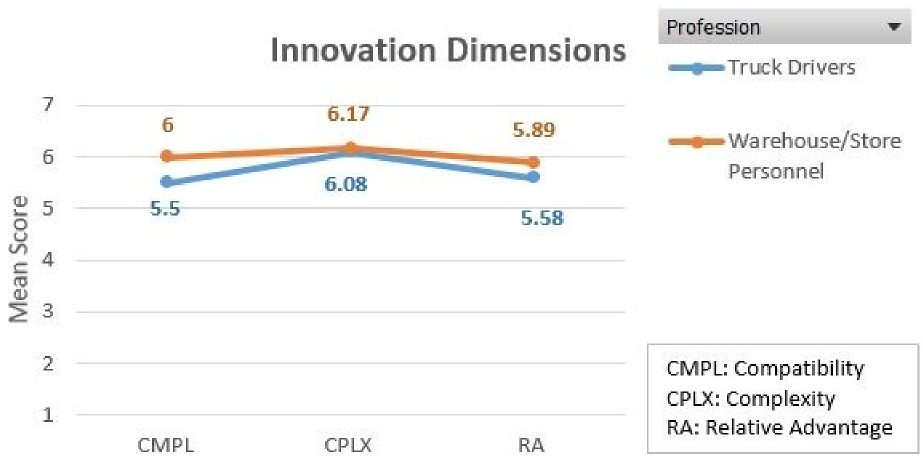
Variable	CMPL	CPLX	RA	PU
Adoption				
CMPL	1.00			
CPLX	.34	1.00		
RA	.56**	.51*	1.00	
Perceived Usefulness				
PU	.54*	.47*	.40*	1.00
Perceived Ease of Use				
PEU	.42	.52*	.50*	.456

**. Correlation is significant at the 0.01 level (2-tailed). $p < 0.05$

*. Correlation is significant at the 0.05 level (2-tailed). $p < 0.01$

As shown in Table 4.26, PU has a significant positive correlation with all the adoption dimensions at 99% confidence interval, while PEU has a significant positive correlation with CPLX and RA at 99% confidence interval. The strongest correlation is between PU and CMPL.

Similar to the usability study explained above, mean scores for the adoption dimension between the two participant groups were examined. The mean scores for the adoption dimensions followed a similar trend for both the participant groups.



Innovation Dimensions	Truck Drivers		Warehouse/ Store Personnel	
	Mean Scores	Std Deviation	Mean Scores	Std Deviation
CMPL	5.50	1.09	6.00	0.00
CPLX	6.08	0.29	6.17	0.41
RA	5.58	0.61	5.89	0.75

Figure 4.7.: Innovation dimensions mean scores

The mean values for both the groups were quite similar and high, ranging from 5.5 to 6.17 and there weren't any significant differences. Figure 4.7 suggests a positive attitude of the participants towards the adoption of a real-time food quality monitoring application. The subsequent sections 4.3.3 - 4.3.5 examine the users responses to each adoption dimension considered for the research.

4.3.3 Compatibility

Figure 4.8 describes the distribution of the user's responses on CMPL1 variable for truck drivers and warehouse/store professionals. CMPL1 evaluates whether using the application fits the work style of the participants, and it is chosen as a representative of the compatibility dimension. About 25% of the participants neither agreed or disagreed about the compatibility of the application, while the remaining population either somewhat agreed, agreed or strongly agreed that the application is compatible with their needs. The mean CMPL scores for truck drivers and warehouse/store personnel as described in Figure 4.7 are 5.5 and 6 respectively. None of the participants had an unfavorable opinion about the compatibility of the application.

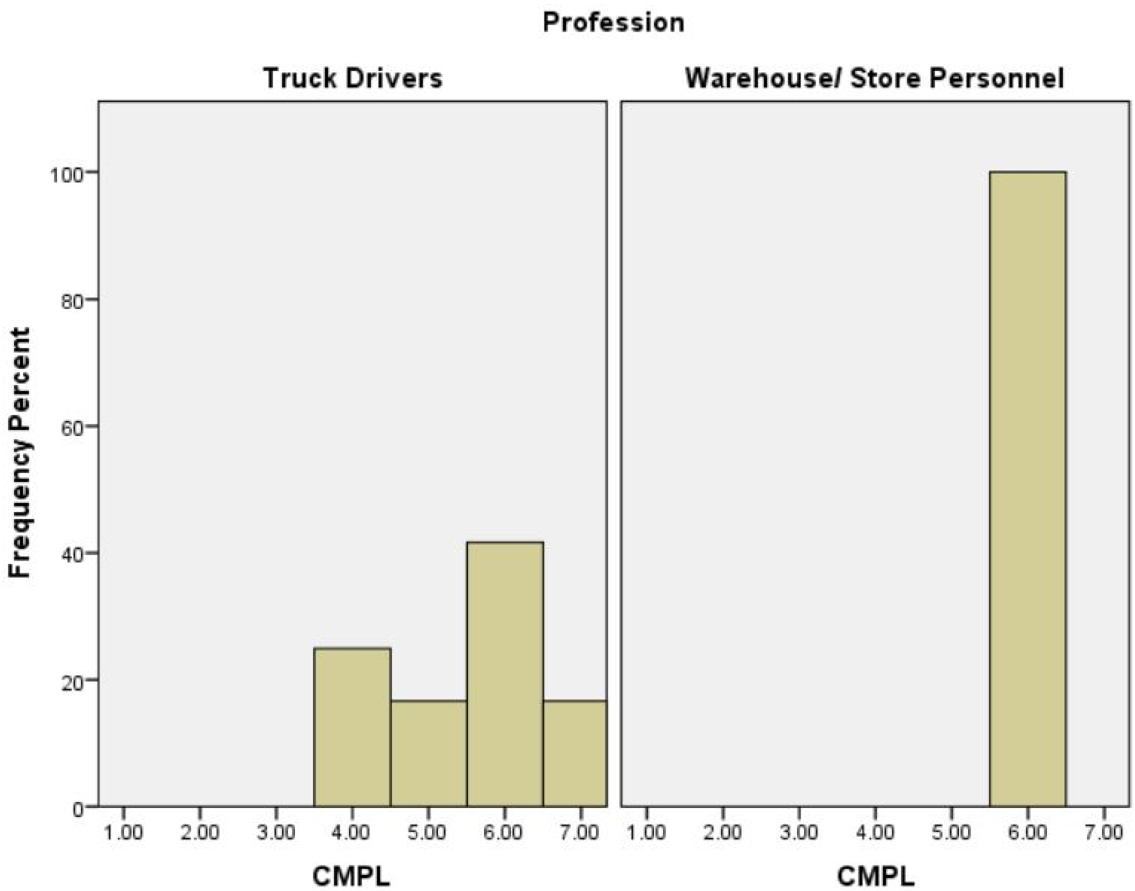


Figure 4.8.: Compatibility distribution

4.3.4 Complexity

Figure 4.9 presents the scores reported by truck drivers and warehouse/store professionals about the complexity of a real-time food quality monitoring application. CPLX1 is chosen as a representative of the complexity dimension of adoption. CPLX1 measured whether it was easy to get the application to do what the participants wanted it to do. High values for CPLX indicate a low level of complexity experienced by the participants. None of the truck drivers and warehouse/store personnel found the application to be complex and reported low levels of complexity, as all the scores for CPLX were above 6.

Figure 4.9.: Complexity distribution

4.3.5 Relative Advantage

As shown in Figure 4.10, the entire population had a favorable opinion about the relative advantage of the real-time food quality monitoring application over previous known solutions. RA2 measured the ability of the application to help the participants do their work easily. Only one warehouse/store personnel disagreed that the application would help them do the work easily. That participant is aged above 50 and reported themself as very uncomfortable with technological solutions.

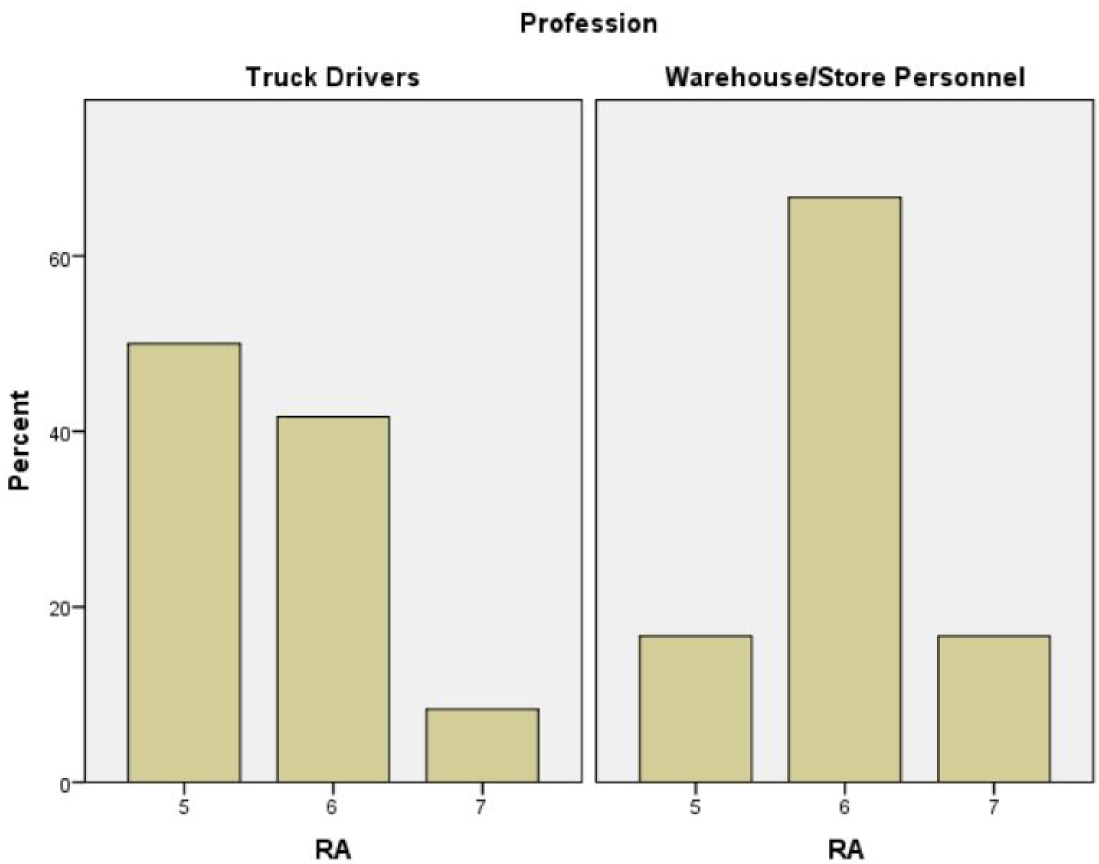


Figure 4.10.: Relative Advantage distribution

RA3 analyzed whether the application would help the participants with their daily work. One truck driver disagreed with the statement. They reported themself as experienced and comfortable with the use of technological solutions. But, this participant experiences minimal food and beverage waste in delivering the products and travels relatively shorter distances. Hence, the participant somewhat disagreed that the application would help them with their daily work. The mean RA scores for truck drivers and warehouse/store personnel as presented in Figure 4.7 are 5.58 and 5.89 respectively.

4.3.6 Adoption analysis between participant groups

The researcher was interested in examining the effect of the profession of the participant on response scores of the adoption dimensions. Thus, the means of adoption dimension scores for the two participant groups, truck drivers and warehouse/store personnel, were compared. The mean scores on innovation dimensions for the two participant groups was quite similar.

As explained in previous subsections in adoption study, none of the 18 participants had an unfavorable opinion about the compatibility, complexity and relative advantage of the real-time food quality monitoring mobile application. Around 25% of truck drivers were undecided about the compatibility of the application with their work style. The mean scores of adoption dimensions for the two participant groups were quite high on the likert scale and similar ranging from a low of 5.50 to a high of 6.17.

4.3.7 Future Adoption

A real-time food quality monitoring mobile application is not currently widely used. And users typically take some time to adapt to a new technology. In addition to evaluating the participants' responses to the adoption dimensions, three survey questions were designed to allow the participants to self predict, whether they would use the application in the future.

The three variables considered that examine the future adoption of the application are BI1, BI2 and BI3. The first survey question BI1 examined the participants' responses to whether they would like to receive additional training. Figure 4.11 describes the distribution of BI1 scores.

All the participants were in favor of receiving additional training on the application. For both the participant groups, around 80% of the participants either "agreed" or "strongly agreed" on getting more hands-on experience and learning additional features of the application.

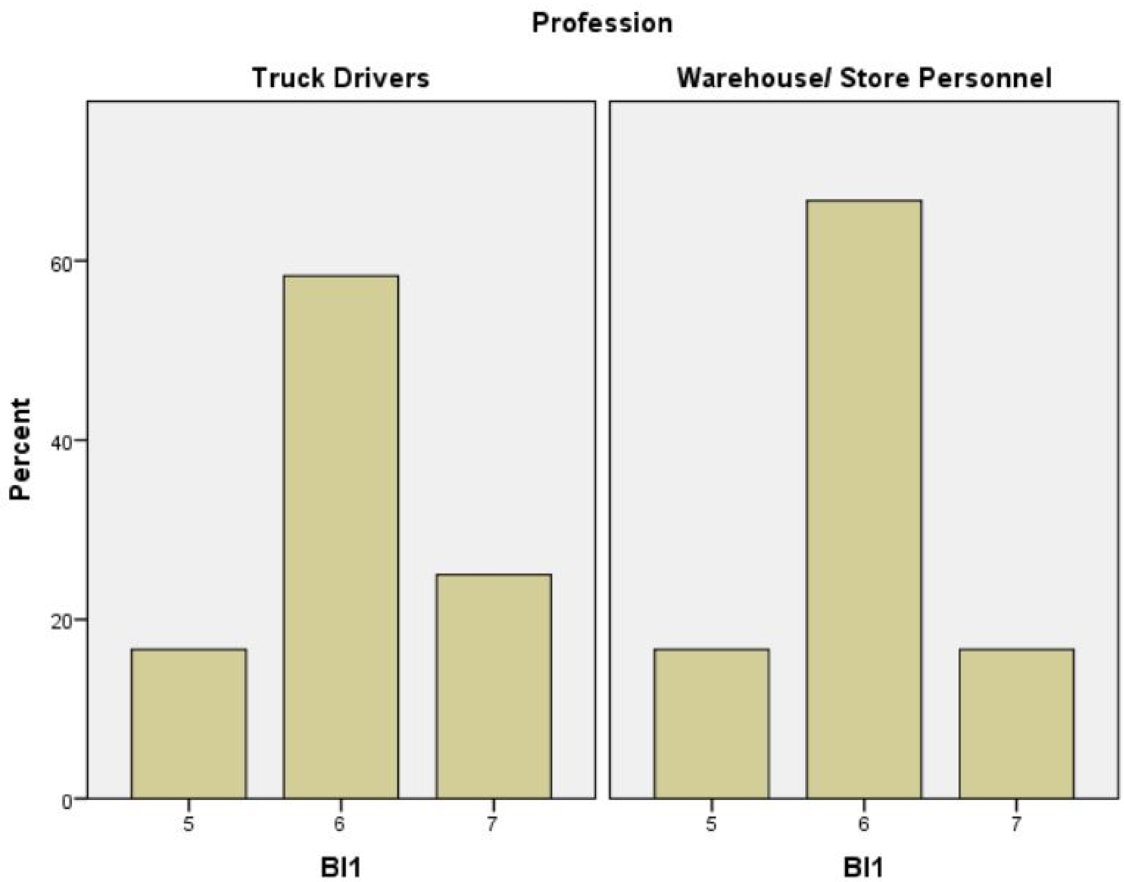


Figure 4.11.: BI1 distribution

The second survey question BI2 determined the participants' intention to use the application frequently. Around 20% of warehouse/store personnel were undecided whether they would use such an application frequently. Through interviews with the participants, the researcher discovered that similar food quality monitoring applications are currently being used by warehouse and store personnel. On the other hand, truck drivers don't use such an application currently. An important finding as shown in Figure 4.12, is that no participant expressed disagreement on using the application frequently. Also, almost 90% of the population had a favorable opinion about using the application frequently.

Figure 4.12.: BI2 distribution

The third survey question BI3 measured the willingness of participants to recommend the application to their peers. Figure 4.13 presents the distribution of BI3 scores. Similar to the BI1 distribution, all the participants had a favorable opinion on recommending the application to their peers. The BI3 scores for both the participant groups, truck drivers and warehouse/store personnel were high.

Figure 4.13.: BI3 distribution

4.4 Technology Acceptance

Previous sections explained the justification for choosing the selected variables and correlation between the usability dimensions and adoption dimensions. It also described the participating truck drivers' and warehouse/store personnel's intention to use the application in the future. The researcher performed both quantitative and qualitative analysis in order to evaluate the participants' perception regarding the usefulness and ease of use, and its effect on their intention to use a real-time food quality monitoring application in the future.

4.4.1 Quantitative Analysis

Results from Table 4.21 and Table 4.26 suggest that Compatibility and Efficiency significantly affect the participants' perception of the Usefulness of the application, and Complexity, Efficiency, Engagement, and Relative Advantage significantly affect the participant's perception of the Ease of Use of the application.

Next step was to calculate the Kendall's Tau correlation between Perceived Usefulness, Perceived Ease of Use and Behavioral Intention to use the application. BI2 measures the participants' intention to use the application frequently. Table 4.27 shows that PU and PEU have a strong correlation with BI2 significant at 99% and 95% confidence interval respectively. Davis (1989) suggested that Ease of Use may indirectly affect usefulness. However, association between PU and PEU is not significant. Hence, results partially supported TAM for the real-time monitoring mobile application.

Table 4.27: Correlation between PU, PEU and BI2 for TAM

Correlations

			PU	PEU	BI2
Kendall's tau_b	PU	Correlation Coefficient	1.000	.456	.526*
		Sig. (2-tailed)	.	.055	.020
		N	18	18	18
	PEU	Correlation Coefficient	.456	1.000	.573**
		Sig. (2-tailed)	.055	.	.009
		N	18	18	18
	BI2	Correlation Coefficient	.526*	.573**	1.000
		Sig. (2-tailed)	.020	.009	.
		N	18	18	18

4.4.2 Qualitative Analysis

A total of three open ended survey questions were designed to gather participants' sentiment on the usefulness and ease of use of a real-time food quality monitoring mobile application. These qualitative questions helped in identifying the potential features/enhancements that could be added to the application and the features participants found easy and cumbersome to use. Majority of the participants were running on a busy schedule, as explained earlier. Therefore, limited number of participants answered the open-ended qualitative questions. Hence, in addition to collecting the participants feedback on the survey questions, the researcher discussed verbally with the truck drivers and warehouse/store personnel, how a real-time food quality monitoring application could add more value.

The first survey question asked the participants, what features on the application would be useful to them. As shown in Table 4.28, the participants felt that the following features/enhancements would be quite useful for them to do their daily work quickly and easily:

Table 4.28: Features useful for the truck drivers and warehouse/store personnel

Category	**Feedback**
Traffic Information	• Real-time traffic information • Alerts for accidents and construction work on truck drivers route
Data Presentation	• Map layout of the store with each food container and their real-time status in addition to the current tile layout in user interface (Warehouse/Store personnel) • Graphs showing variation of temperature over time
Measures	• Knowing the critical time available to take action
Help	• Help messages and suggestive actions in case of an issue
Issue History	• Tracking previous malfunctions and errors reported, who addressed the issues and the action taken by the store personnel
Notifications	• Knowledge of real-time temperature and refrigeration issues • Voice alerts regarding issues • Notification of product mechanical breakdowns, vacuum seal cracks
Product Status	• Information on quality of food products over time

The second survey question gauged participants' perception on the attributes and features of the application that were particularly easy to use. Table 4.29 provides the summary of the participants' feedback.

Table 4.29: Features easy to use for the truck drivers and warehouse/store personnel

Category	Feedback
Traffic Information	• Navigating through maps showing real-time traffic information (truck drivers) with estimated time to destination and best possible routes
Data Presentation	• Simple user interface with minimal yet complete information • Graphs showing temperature variation • Ability to move the time window on the graph to see previous temperature measurements
Notifications	• Alerts if something went wrong with a food container
Product Status	• Knowing real-time status of food containers

The third survey question analyzed the attributes and features of the application that were not particularly easy to use for the participants. All the participants agreed that the application was very simple and easy to use. None of the participants reported any aspect of the application that was not particularly easy to use.

A few participants experienced the application to be slow. But, that was due to poor internet connectivity at the time and location that they used the application. Another participant mentioned that this application would be great for real-time monitoring of small quantities of food products, but was unsure about its significance for larger quantities.

One of the participants remarked, “It’s a no-brainer that anyone would find the application not easy to use and not use it”. Overall, the participants reported that the application seemed fairly easy to navigate and they didn’t see much of an issue with the application.

4.5 Findings of the study

The results of the analysis performed on the usability and adoption of a real-time food quality monitoring application are summarized below:

- A total of 18 participants, 12 truck drivers and 6 warehouse/store personnel were studied in this research.
- Nearly 72% of the participants reported being experienced with web based technology, and almost 83% of the participants expressed being comfortable with the use of web based technology.
- The younger participants reported being more experienced and comfortable with the use of web based tools, technology and applications in comparison to older participants.
- There is a significant positive correlation among most of the usability and adoption variables. Error Tolerance had a weak correlation with the other usability variables. Also, Efficiency and Ease of Learning experienced a weak correlation with Effectiveness. Compatibility and Complexity also had a weak association between them. The strongest correlation of .58 present at 99% confidence interval is between Ease of Learning and Engagement. Also,the correlation between Engagement and Efficiency is quite significant, .51 at 99% confidence interval.
- All the usability dimensions except Error Tolerance significantly correlated with participants' perception of Ease of Use, while their perception of Usefulness had a favorable association with Efficiency and Ease of Learning.
- All the 18 participants except one warehouse/store personnel were either undecided or had a positive opinion about the effectiveness, efficiency, engagement, ease of learning and error tolerance of the real-time food quality monitoring mobile application. And they reported high mean scores for all the usability dimensions.

- Engagement dimension reported the highest mean scores among all the usability dimensions for both the participant groups.

- None of the 18 participants had an unfavorable opinion about the compatibility, complexity and relative advantage of the real-time food quality monitoring mobile application. Around 25% of truck drivers were undecided about the compatibility of the application with their work style. The mean scores of adoption dimensions for the two participant groups were quite high on the likert scale and similar ranging from a low of 5.50 to a high of 6.17.

- All the participants were in favor of receiving additional training on the application. For both the participant groups, around 80% of the participants either agreed or strongly agreed on getting more hands-on experience and learning additional features of the application.

- Almost 90% of the population had a favorable opinion about using the application frequently.

- Participants who reported higher levels of experience and comfort with technology had higher scores for behavioral intention to use the application.

- Compatibility and Efficiency of the mobile application were found to significantly affect its perceived usefulness, whereas Complexity, Efficiency, Engagement, and Relative Advantage of the mobile application significantly affects its Perceived Ease of Use.

- Both Perceived Usefulness and Perceived Ease of Use significantly affect the user's behavioral intention to use the application in the future.

4.6 Summary

This chapter presented the overall results of the research study carried out on the usability, acceptance and adoption of a real-time food quality monitoring application. The researcher carried out both qualitative and quantitative analysis in the study. First, the correlation between survey questions within each usability and adoption dimension was analyzed. Then, association between different usability dimensions and adoption dimensions were explored. Also, the effect of participants' perceptions of usefulness and ease of use on their intention to use the application in the future was examined. Finally, the chapter concluded with a brief summary of the relevant findings in the section above. The following chapter would discuss the major findings and contributions of the research study, and next steps for future studies on the subject.

CHAPTER 5. DISCUSSION

This chapter presents the summary of the research study on usability of real-time data for cold chain monitoring. Recommendations based on the results from the previous chapters, and next steps for future studies in the area are also discussed.

5.1 Discussion

A significant number of studies in the area of Technology Acceptance Model (TAM) suggest that the acceptance of a new technological solution could be determined by the user's perceptions about its usefulness and ease of use. The research study analyzed the truck drivers' and warehouse personnel's perception of usefulness and ease of use of a real-time food quality monitoring application and discovered factors that affect their usability and adoption of the mobile application. The lessons from Innovation Diffusion theory (IDT) and TAM served as the underlying framework for this research.

Both qualitative and quantitative analysis to gauge the usability, acceptance and adoption of a real-time food quality monitoring application were conducted. A total of 25 survey questions examined the participant's feedback on the usability and adoption attributes considered in the study. Before exploring the relationship between the usability and innovation adoption dimensions, the researcher analyzed the correlation among survey questions response scores within each dimension. The analysis was carried out in two phases. The first phase analyzed the correlation between the usability dimensions and their association with Perceived Usefulness and Perceived Ease of Use. And the second phase evaluated the correlation between the innovation adoption dimensions and their association with Perceived Ease of Use and Perceived Usefulness.

The participants had a strong favorable opinion about the usability of the mobile application, where they reported high mean scores on effectiveness, efficiency, engagement, ease of learning and error tolerance. Error tolerance had a weak correlation with the other usability dimensions, while ease of learning and engagement had a strong association ($r = .58$ significant at 99% confidence interval). All the participants reported a very high level of engagement with the application. Hence, we could infer from the quantitative results and participants qualitative feedback that the real-time food quality monitoring application is usable.

Similar analysis for the innovation adoption dimensions (compatibility, complexity and relative advantage) was performed. Relative Advantage reported a strong correlation with compatibility and complexity, while correlation between compatibility and complexity wasn't significant. All the dimensions significantly correlated with perceived usefulness and ease of use. Also, as observed for the usability dimensions, the mean scores of participants on the innovation adoption dimensions was quite high. The level of complexity experienced by the participants was very low. Thus, we could conclude that features of the application positively influence its rate of adoption and truck drivers and warehouse/store personnel would adopt this application.

To further support this claim, truck drivers' and warehouse/store personnel's intention to use the application in the future was analyzed. The participants (Nearly 90%) expressed a favorable opinion to use such a mobile application frequently in the future. Also 80% of the participants either "agreed" or "strongly agreed" on getting more hands-on experience with the application. All the participants showed a strong intention to recommend the application to their peers. Moreover, regarding their intention to use the application frequently and recommending it to peers, the researcher discovered that there is a statistically significant difference in mean scores between participants reporting different experience and comfort level with web based tools, technology and applications.

5.2 Recommendations

Billions of tons of perishable food products are wasted every year globally during transportation and logistics before it reaches the end consumers. Thousands of trucks carrying perishable food products travel through Indiana alone every day. The Indiana State Police spend much time stopping an alarmingly high number of hot trucks. The use and acceptance of a real-time cold chain monitoring application would reduce a significant amount of food waste, while ensuring healthy food products reach the customers.

The current food traceability systems are evolving, but real-time monitoring applications aren't still commonplace. Sensors are getting much cheaper and we possess the capability of intelligent cloud based systems that are cost effective and perform real time monitoring. There has been some promising work done in food traceability with IoT based cold chain systems, but there's need for further research in the area with emphasis on usability and user acceptance.

According to the findings of this research, certain features of the real-time food quality monitoring application had a significant effect on the participants' intention to use the application in the future. Compatibility, Complexity, Efficiency, Engagement, and Relative Advantage were found to be the determinants affecting the participants' use of the mobile application in the future. Similar applications for cold chain monitoring should incorporate enhancements that focus on these usability and innovation adoption dimensions. Future similar mobile applications should research the feedback provided by the participants. None of the participants reported any features that were difficult to use. However, in this research no real sensors were deployed. So, participants didn't get to experience the technical issues that may arise in a practical use , like issues related to network performance, data integration, power outage, sensor failures etc which may cause certain features to not work effectively. Section 4.4.2 highlights the features that the participants reported particularly useful and easy to use. It also describes the additional features that the participants would like to see in the application. Some of the features included voice alerts regarding issues, critical time available to take action, real-time traffic information etc. Their valuable feedback would be extremely useful for the development of similar mobile applications intended for real-time cold chain monitoring.

The research also suggests that demographic characteristics of participants like level of experience and comfort with technology affects their intention to use the application and their mean response score to different usability and innovation adoption dimensions. Participants that reported being more experienced and comfortable with technology showed more interest in adopting the mobile application. Whereas, there is no statistically significant difference for the two profession groups. Hence, development of similar mobile applications in the future should focus on features and attributes most relevant to the targeted population. Although these findings may not be directly applicable, they could have a significant effect on the usability and acceptance of the mobile application and hence should be considered in future studies and development of real-time cold chain monitoring applications.

According to Rogers(2003), the five steps that users follow in the innovation-decision process are knowledge, persuasion, decision, implementation and confirmation. Truck Drivers and Warehouse/store personnel involved in this research study had very limited knowledge and experience with a real-time cold chain monitoring mobile application and could be categorized into the “knowledge” stage.

5.3 Future Research

The proposed framework should be tested with more participants and different organizations to understand if results could be applied and be useful to other settings. Some stores have already employed alert systems using modern tools and techniques for real-time cold chain monitoring, while some stores don't have a real-time alert system and their personnel go and check the temperature and quality of the food every now and then. Also, truck drivers use either a thermometer that could be seen through the rear mirror or portable devices that record the status of the product, but don't use a real-time alert system. Through discussion with the truck drivers, the researcher discovered that depending on the organization they are in and the goods they are transporting, they have different levels of trainings on quality. It would be interesting to see how the scale and technology maturity level of the organization affects the usability and adoption attributes of a real-time food quality monitoring application. Future research should emphasize on generalizing the findings.

As explained in the qualitative analysis section in the chapter above, there are notable insights on the features that the participants would like to see in the application, and the features that were and weren't easy to use. Hence, future research should incorporate the suggested changes in the application and repeat the usability and innovation adoption study for a real-time food quality monitoring application. This would help in analyzing the effect of these improvements on the user's attitude towards use and acceptance of the mobile application.

Since the participants were running on a tight schedule, they couldn't spend much time on the application. However, if similar future studies are sponsored by the organization and are part of their training for example, the application with suggested improvements could be presented to them and their use and acceptance of the mobile application could be validated with higher degree of certainty.

5.4 Conclusion

Perishable food products undergo tremendous degradation in quality as a function of environmental conditions over time. A real-time cold chain monitoring application is pivotal for reducing food waste during transportation and improving the operational efficiency of businesses operating in a cold chain environment. Truck Drivers are currently in the 'knowledge' phase of the Roger's innovation decision process and have very limited knowledge and experience with a real-time cold chain monitoring mobile application.

This study evaluated the truck drivers' and warehouse personnel's intention to use a real-time cold chain monitoring application. The research proposed a model for evaluating the usability, acceptance and adoption of the real-time cold chain monitoring application by consolidating lessons from the TAM model, DoI theory and usability principles. The results from the study indicate that the participants consider the application to be very useful and easy to use. Almost 90% of the participants expressed a favorable opinion about using the application frequently in the future. With the help of Kendall's Tau Correlation coefficient, the researcher identified the usability and innovation adoption attributes that affect the user's perceptions of usefulness and ease of use.

While truck drivers and warehouse/store personnel have different levels of exposure to real-time cold chain monitoring systems and applications, the research suggests that we fail to reject the hypothesis that there is no statistically significant difference between their response scores on the usability and innovation dimension attributes, and ultimately their behavior intention to use the application. However, there is a statistically significant difference in mean response scores on usability and innovation dimension attributes, and intention to use the application between users reporting different levels of experience and comfort with web based tools, technology and applications.

The researcher discovered that Compatibility and Efficiency of the mobile application significantly affect its perceived usefulness, whereas Complexity, Efficiency, Engagement, and Relative Advantage of the mobile application significantly affects its Perceived Ease of Use. Results suggest that perceived attributes of usability dimensions and innovation affect truck drivers' and warehouse personnel's perceptions of usefulness and ease of use, and hence their intention to use and adopt the real-time cold chain monitoring application in the future.

This chapter discussed the findings of the research study on usability of real-time data for cold chain monitoring. Relevant contributions of the study and recommendations presented in this chapter encourage future studies on the subject.

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LIST OF REFERENCES

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APPENDICES

Appendix A Survey Questions

Table A1 *Usability and Adoption Questions*

Question	Code
Perceived Usefulness	
I find the application quite useful in being able to monitor the quality of food products instantly. [b]	PU1
The use of this kind of mobile application would help me collect real-time information on the quality of food products.	PU2
Perceived Ease of Use	
I found the application very easy to use. [b]	PEU1
Effectiveness	
I received the results I expected from the application. [c]	EFFE1
I believe the information on the application was useful.	EFFE2
Efficiency	
I was able to find the information and navigate through the application quickly. [c]	EFFI1
Engagement	
I had a positive experience with the application when navigating through the information. [c]	EN1
I found the various features in this application were well integrated. [a]	EN2
The user interface was consistent throughout.	EN3
Ease of Learning	
The layout of the application was predictable. [c]	EOL1
I was confident in my ability to use the application because of my previous knowledge of mobile applications. [c]	EOL2
I think that I would need the support of a technical person to be able to use this application. [a]	EOL3
I feel I needed to learn a lot of things before I could use this application. [a]	EOL4

Error Tolerance	
The user interface of the application helped me avoid making errors. [c]	ER1
Compatibility	
Using the application fits into my work style. [d]	CMPL1
Complexity	
I believe that it was easy to get the application to do what I wanted it to do. [b,d]	CPLX1
Relative Advantage	
Using the application would enable me to accomplish the work more quickly. [b,d]	RA1
Using the application would enable me to do the work easily. [b,d]	RA2
The application would help me achieve my day to day work.	RA3
Behavioral Intention to Use	
Training on this application would be useful	BI1
I think that I would like to use this application frequently. [a]	BI2
I would recommend use of this kind of application to my peers	BI3

Table A2 *Qualitative Open Ended Survey Questions*

Question	Code
Perceived Usefulness	
What features on the application would be useful to you	PU3
Perceived Ease of Use	
What features of the application did you find particularly easy to use	PEU2
What features of the application were not easy to use	PEU3

Table A3 *Demographic Questions*

Question	Answer
Profession (D1)	Truck Driver Warehouse/Store Personnel
Age (D2)	20-30 30-40 40-50 50-60 Over 60
Years of Experience (D3)	0-5 5-10 10-15 15-20 20+
Level of experience with web based tools, technology and applications (D4)	Very Inexperienced Inexperienced Undecided Experienced Very Experienced
Level of comfort with web based tools, technology and applications (D5)	Very Uncomfortable Uncomfortable Neither Comfortable nor Uncomfortable Comfortable Very Comfortable
Gender (D6)	Male Female

PURDUE UNIVERSITY

HUMAN RESEARCH PROTECTION PROGRAM
INSTITUTIONAL REVIEW BOARDS

To:	CHAD LAUX YONG
From:	JEANNIE DICLEMENTI, Chair Social Science IRB
Date:	07/07/2016
Committee Action:	**Expedited Approval - Category**(7)
IRB Approval Date	07/06/2016
IRB Protocol #	1606017871
Study Title	Usability of real time data for cold chain monitoring
Expiration Date	07/05/2017
Subjects Approved:	

The above-referenced protocol has been approved by the Purdue IRB. This approval permits the recruitment of subjects up to the number indicated on the application and the conduct of the research as it is approved.

The IRB approved and dated consent, assent, and information form(s) for this protocol are in the Attachments section of this protocol in CoeusLite. Subjects who sign a consent form must be given a signed copy to take home with them. Information forms should not be signed.

Record Keeping: The PI is responsible for keeping all regulated documents, including IRB correspondence such as this letter, approved study documents, and signed consent forms for at least three (3) years following protocol closure for audit purposes. Documents regulated by HIPAA, such as Authorizations, must be maintained for six (6) years. If the PI leaves Purdue during this time, a copy of the regulatory file must be left with a designated records custodian, and the identity of this custodian must be communicated to the IRB.

Change of Institutions: If the PI leaves Purdue, the study must be closed or the PI must be replaced on the study through the Amendment process. If the PI wants to transfer the study to another institution, please contact the IRB to make arrangements for the transfer.

Changes to the approved protocol: A change to any aspect of this protocol must be approved by the IRB before it is implemented, except when necessary to eliminate apparent immediate hazards to the subject. In such situations, the IRB should be notified immediately. To request a change, submit an Amendment to the IRB through CoeusLite.

Continuing Review/Study Closure: No human subject research may be conducted without IRB approval. IRB approval for this study expires on the expiration date set out above. The study must be close or re-reviewed (aka continuing review) and approved by the IRB before the expiration date passes. Both Continuing Review and Closure may be requested through CoeusLite.

Unanticipated Problems/Adverse Events: Unanticipated problems involving risks to subjects or others, serious adverse events, and serious noncompliance with the approved protocol must be reported to the IRB immediately through CoeusLite. All other adverse events and minor protocol deviations should be reported at the time of Continuing Review.