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An Empirical Assessment of Energy Management Information System Success Using Structural Equation Modeling

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An Empirical Assessment of Energy Management Information System Success Using Structural Equation Modeling

by

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We hereby certify that this dissertation, submitted by Gwendolyn Stripling, conforms to acceptable standards and is fully adequate in scope and quality to fulfill the dissertation requirements for the degree of Doctor of Philosophy.

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Abstract

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The Energy Industry utilizes Energy Management Information Systems (EMIS) smart meters to monitor utility consumers' energy consumption, communicate energy consumption information to consumers, and to collect a plethora of energy consumption data about consumer usage. The EMIS energy consumption information is typically presented to utility consumers via a smart meter web portal. The hope is that EMIS web portal use will aid utility consumers in managing their energy consumption by helping them make effective decisions regarding their energy usage. However, little research exists that evaluates the effectiveness or success of an EMIS smart meter web portal from a utility consumer perspective.

The research goal was to measure EMIS smart meter web portal success based on the DeLone and McLean Information Success Model. The objective of the study was to investigate the success constructs system quality, information quality, service quality, use, and user satisfaction, and determine their contribution to EMIS success, which was measured as net benefits.

The research model used in this study employed Structural Equation Modeling (SEM) based on Partial Least Squares (PLS) to determine the validity and reliability of the measurement model and to evaluate the hypothetical relationships in the structural model. The significant validity and reliability measures obtained in this study indicate that the DeLone and McLean Information Success Model (2003) has the potential for use in future EMIS studies. The determinants responsible for explaining the variance in net benefits were EMIS use and user satisfaction. Based on the research findings, several implications and future research are stated and proposed.

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To my committee members, Dr. Ling Wang and Dr. Steven Zink: Thank you for your service and support of my journey. Thank you for helping to ensure the dissertation research was well written and statistically strong.

To my father, Robert Lee Stripling: You left this earth much too quickly but I have always felt your spirit, faith, and encouragement. To my mother, Ida Anderson: Thank you for instilling in me a “fighting spirit” and the will to “finish what you start.” To my sister, Belinda Stripling: Thank you for being on the “front lines” of care for our beautiful older brother, Robert “Bobby” Stripling, Jr.

To Nada, Saskia, and Christina: All my love.

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Chapter 1

Introduction

Background

Electricity generation accounts for over 40% of the carbon dioxide emitted by the United States (Chen et al., 2015). Currently, United States electricity consumers lose billions of dollars per year by not reducing residential energy usage. Per the United States Energy Information Administration (EIA), the average national price of electricity was 12.00 cents per kilowatt hour in 2014, which is up from 8.00 cents per kilowatt hour in 2003 (EIA, 2014c). While United States residential electricity sales per household declined 7% between 2010 and 2016, electricity sales show an increase of 12% from 1990 to 2016 (EIA, 2017). In 2015, household appliances accounted for 35% of U.S. household energy consumption, up from 24% in 1993 (EIA, 2016). Although appliances have become more energy-efficient over the years, consumers tend to have more energy-consuming appliances than before, which results in a higher combined energy consumption (Bhati et al., 2017).

To implement energy efficiency programs that lead to operational efficiency and to help consumers better monitor their energy consumption, utility service providers upgraded their utility infrastructures from a mechanical-analog based infrastructure to an interconnected-digital Smart Grid infrastructure (NIST, 2016) capable of real-time energy information exchange. An Energy Management Information System (EMIS) is a component of the Smart Grid intelligence infrastructure. Energy Management Information Systems are designed to collect consumer energy consumption data using smart grid monitoring devices and to provide feedback to customers regarding their energy consumption (Piti et al., 2017; Hooke, 2014). Figure 1 illustrates the Smart Grid infrastructure.

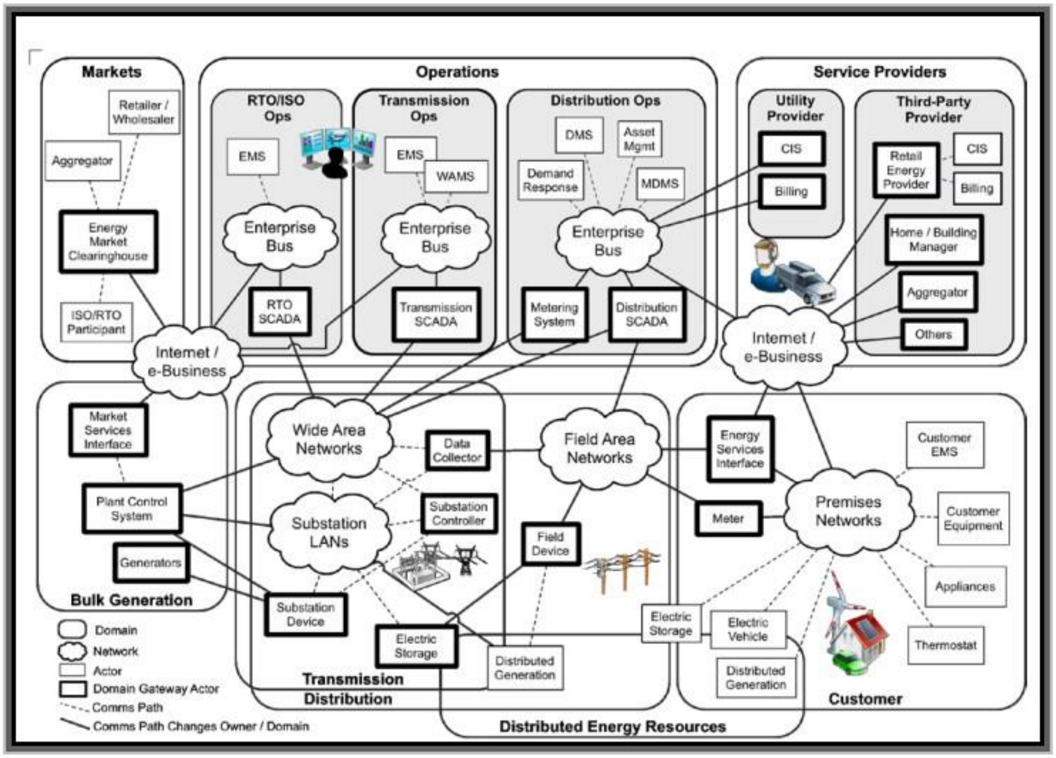

Figure 1. The Smart Grid Infrastructure Service Provider View. Source: (NIST, 2012).

An EMIS utilizes a smart meter installed at the customer's home to collect energy load data (Piti et al., 2017; Hooke, 2014). The smart meter is an essential tool for linking energy consumption measurements and utility production measurements with the customer's identity and Time-of-Use data (Piti et al., 2017). Smart meters (or automated metering infrastructure devices) serve as a gateway between the utility, customer site, and the customer's load controllers.

Smart meters measure, record, display, and transmit data such as energy usage, generation, text messages, and event logs to authorized utility systems (DOE, 2014c). Services that utilities provide to customers via smart meters include utility feedback on different timescales, past (hourly, daily, weekly, monthly), present (or real time), and future (forecasting) to help consumers know when and over what timescale energy was consumed and wasted (Kazmi, O'Grady, Delaney, Ruzzelli, & O'Hare, 2014). This data is typically distributed via online web portals, home energy reports, and downloadable energy usage data (Cooper, 2016). An EMIS can be characterized by its deliverables, features, elements, and support. Deliverables include the early detection of poor performance, effective energy reporting, and support for decision-making.

However, utility energy consumers today have little-to-no experience interacting with a utility service provider's EMIS smart meter web portal as an EMIS is a relatively new technological innovation. An effective EMIS smart meter web portal should have adequate system quality, information quality, and service quality. It should provide an adequate support structure and be reliable and accessible, as utility consumers can only use a system successfully if they can access it and have access to support services when needed. In addition, customers must perceive a utility's EMIS web portal as trustworthy–in terms of data integrity, privacy, and security. Smart meter data should be accurate, relevant, and easily understood, keeping consumers engaged–as energy portals can lose their effectiveness if they fail to keep customers actively engaged (Verkade & Hoffken, 2017; Chen, 2017; Hartman & LeBlanc, 2015).

Problem Statement

An EMIS enables individuals and organizations to plan, make decisions, and take effective action to manage energy use and costs (Sovacool et al., 2017; Piti et al., 2017; Hooke, 2014). The economic value to utility service providers is to adjust the price of electricity depending on the level of demand, since off-peak electricity and gas requires less of an energy load to service than on-peak demands. This time-of-use pricing reduces operating costs because lower energy demand equates to lower energy rates. An EMIS' sustainability value is to influence changes in consumer behavior by providing energy consumption data to utility consumers. Because smart meter web portals are relatively new, there is a dearth of research on which to guide the evaluation of such systems or to outline utility customer expectations of the benefits associated with using them. Although many studies have evaluated information systems success in different organizational settings, how Energy Management Information System success is achieved has not been clearly articulated.

EMIS smart meter web portals are designed to communicate energy consumption information to utility consumers, but few guidelines and little sustainability design research exists to determine the usefulness and satisfaction with these web portals. A major problem utility service providers face is how to develop and deliver effective customer engagement tools to assist energy consumers in understanding EMIS smart meter data output. While massive deployment of metering devices allows collecting a plethora of data, considerable efforts are required to make this data accessible and easy to understand by users, especially when the purpose is addressing energy saving objectives (Pasini et al., 2017; Smith, 2013).

Other problems include customer concerns about system trust, as interconnected systems can increase the amount of private information that is exposed. Privacy concerns include: 1) loss of confidentiality (unauthorized disclosure of information); (2) loss of integrity (the unauthorized modification or destruction of information); and (3) loss of availability (the disruption of access to or use of an information system) (Sovacool, 2017; Rodden et al., 2013; NIST, 2012).

The typical online customer is information seeking, e.g. seeking information on products, services, health, social communications, or entertainment, etc. (Jalal & Al-Debei, 2013). The typical online energy customer may visit a utility web portal to perform a transaction such as paying a utility bill, but does not typically seek information on energy consumption or view their energy usage data (Accenture, 2015). Similar to e-commerce and information-oriented web portals, smart meter web portals employ similar evaluative use cases, e.g. how easy is it to log in, change a password, view usage information, change a customer profile, navigate, get relevant information, or obtain help when using a web portal?

However, EMIS smart meter web portals may also require additional evaluative use cases. For example, does the residential utility consumer have the ability to change the way energy data is visualized, e.g. change chart type from a line chart to a bar chart? Or, change the chart attributes to better accommodate personal preferences? Does the residential customer have the option to download their energy usage data? Does the residential customer have the option to allow authorization to a Third Party to view their usage data? How easy is it to grant this option? Is it easy for the residential customer to change, review, and revoke access of a Third Party that has authorization currently to view the residential customer’s usage data

(Zientara, Rankin, & Wornat, 2016)? Specifying user interface requirements is a key to success in any development activity as the user interface requirements describe system behavior (Shneiderman, Plaisant, Cohen, Jacobs, Elmqvist & Diakopoulos, 2017).

The goal of an energy portal is to encourage the customer to save energy and money, but it is too early in the evolution of smart meter portals to determine which elements are critical to driving energy savings (Gölz et al., 2016; Hartman & LeBlanc, 2015). Vassileva et al. (2016) argued that the real impact of consumer interaction with smart meters and the services obtained from them is still uncertain and limited. Several studies have estimated how much energy conservation is achieved by providing households with real-time information on energy use via in-home displays (Piti et al., 2017; DECC, 2015; Westskog et al., 2015; Alcott et al., 2014; Pierce & Paulos, 2012), but factors that influence EMIS web portal success have not been widely studied in the context of utility customer usage, satisfaction, or net benefits.

To date, insufficient research has been conducted in identifying what quality factors contribute to EMIS success. The quality factors of system quality, information quality, and service quality and their impact on a utility customer's EMIS use and user satisfaction have not been addressed in the literature. The addressable problem of this study was the lack of an established way to measure EMIS web portal usefulness, user satisfaction, and net benefits.

DeLone and McLean (2016) observed that although many research studies have tested and validated IS success measurement instruments, most of them have focused on a single dimension of success, such as system quality, impacts, or user satisfaction. Few studies have measured and accounted for the multiple dimensions of success and the interrelationships among these dimensions. This research study utilized the DeLone and McLean (2003)

Information Systems (IS) Success Model to assess EMIS success using Structural Equation Modeling (SEM). The Information Systems Success Model developed by DeLone and McLean (2003) provides a clear taxonomy for conceptualizing and operationalizing IS success (DeLone & McLean, 2016; Zheng, Zhao, & Stylianou, 2013). A successful EMIS should not only collect energy consumption data but it should also provide good system quality, information quality, and service quality – it should be easy to use, learn, and provide relevant information and functions to aid utility consumers in reducing their energy consumption and the cost of their energy bills.

Research Goal

The goal of this research study was to measure IS success based on the DeLone and McLean IS (2003) success model construct's net benefits. Improved energy management decision-making is the net benefit derived from an efficient and useful EMIS, which may achieve both economic and social benefits for the utility customer and operational efficiencies for the utility service provider. The DeLone and McLean IS Success Model provides a valuable framework for understanding the multi-dimensionality of IS success (DeLone & McLean, 2016). Therefore, the study employed Structural Equation modeling (SEM) based on Partial Least Squares (PLS) to evaluate the model.

Research Questions

Three research questions framed this empirical study.

1. To what degree do information quality, system quality, and service quality influence EMIS use?
2. To what degree do information quality, system quality, and service quality influence user satisfaction with an EMIS?
3. To what degree do EMIS use and user satisfaction benefit utility customers in managing their energy consumption?

Relevance and Significance

Information systems success research evaluates the effective creation, distribution, and use of information via technology (DeLone & McLean, 2016). Failure to account for all six constructs (e.g. system quality, information quality, service quality, use, user satisfaction, and net benefits) can lead to possible confounding results or an incomplete understanding of the system under investigation. Research on IS success that measures only some of these variables (e.g. satisfaction), and fails to measure or control for the others (e.g. service quality), has resulted in the many conflicting reports of success that are found in the IS success literature (Petter et al., 2008). This research measured all six constructs of the DeLone and McLean (2003) IS Success Model at the individual level of analysis. This research is deemed significant as little research has assessed the success of EMIS smart meter web portals as an Information System in delivering benefits to the utility customer using the six constructs in DeLone and McLean's IS Success Model.

Energy consumers need an adequate frame of reference to understand whether their consumption levels are excessive – and this frame of reference depends on system quality, information quality, and service quality. Energy consumption data captured by the smart meter is the heart of an Energy Management Information System. The ability to monitor energy usage effectively provides consumers with an opportunity to develop energy-saving decision-making strategies, which may result in decreased pressure on the power grid, less need to build new power plants, reduced carbon emissions, and lower utility operating costs for utility service providers (Sovacool et al., 2017; Pacific Gas & Electric, 2015; DECC, 2015). The sustainability value of the study to Human Computer Interaction (HCI) design is the utilization of IS theory to investigate EMIS smart meter web portal success based upon information quality, system quality, and service quality – quality factors that can facilitate EMIS web portal design.

This study investigated the perspective of the individual utility consumer, whose energy consumption behavior an EMIS smart meter web portal is designed to affect. A benefit of the study is an evaluative model for EMIS success measures that can aide in the planning, design/re-design, and implementation of an Energy Management Information System smart meter web portal.

Barriers and Issues

There are significant barriers to the adoption of new technologies, especially for the energy consumer with little exposure to an Energy Management Information System. The DOE (2014c) has reported low customer participation in smart meter web portals and Zvingilaite and Togeby's (2015) literature review of feedback studies noted that website visits to smart meter web portals tends to be small. Chen (2017) noted low smart meter technology adoption rates in the United States. There is a learning curve associated with EMIS use. Therefore, a potential issue was that survey respondents may not have been completely honest in their answers to survey questions due to a lack of exposure to smart meter web portals. This issue may impact the generalizability of the study.

Defining and measuring "success" has been a challenge for the IS field. As Information Systems have become more complex, so has the evaluation of the effectiveness or success of those systems. In evaluating the success of an information system, it is paramount to define success based on the context of the information system and its stakeholders (DeLone & McLean, 2016). Thus, the complexity and multidimensional nature of the IS success concept and the measurement of the success constructs may have influenced survey results.

Definition of Terms

The following terms were used throughout this study.

Average Variance Extracted (AVE) – Average variance extracted is a criterion of convergent validity. An AVE value of at least 0.5 indicates sufficient convergent validity, meaning that a latent construct explains more than half of the variance of its indicators on average (Chin, 1998).

British Thermal Unit (BTU) – A BTU is a standard unit of measurement used to denote both the amount of heat energy in fuels and the ability of appliances and air conditioning systems to produce heating or cooling. A BTU is the amount of heat required to increase the temperature of a pint of water (which weighs exactly 16 ounces) by one degree Fahrenheit (EIA, 2014d).

California Alternate Rates for Energy (CARE) – The CARE program gives utility discounts to qualified households with limited income. Limited-income customers enrolled in the CARE program receive a monthly discount on their electric and natural gas bills (Pacific Gas & Electric, 2016).

Electronic Service Quality (E-S-QUAL) – Electronic Service Quality measures the service quality delivered by websites on which customers shop online (Parasuraman et al., 2005).

Energy Management Information System (EMIS) – An EMIS is a component of the Smart Grid intelligence infrastructure. Energy Management Information Systems are designed to collect consumer energy consumption data using smart grid monitoring devices and provide feedback to customers regarding their energy consumption (NIST, 2016).

Endogenous Variables – Endogenous ("of internal origin") variables represent the effects of other variables (i.e., at least one arrow pointing to it). They can be described as a factor in a causal model or causal system whose value is determined by the states of other variables in the system (Chin et al., 2003).

End-User Computing Satisfaction (EUCS) – EUCS is a 12-item instrument developed by Doll and Torkzadeh (1988) to measure end-user satisfaction with information systems.

Exogenous Variables – Exogenous ("of external origin') variables are described as factors in a causal model or causal system whose value is independent from the states of other variables in the system; their value is determined by factors or variables outside the causal system under study (Chin et al., 2003).

Family Electric Rate Assistance Program (FERA) – The FERA program gives qualified households with limited income discounts on a portion of their electricity bills (Pacific Gas & Electric, 2016).

Green Button – The Green Button allows utility customers to download energy usage data from a utility service provider's website. This file is in an Extensible Markup Language (.XML) format and requires an application to properly read and determine the contents of the file.

Human-Computer Interaction (HCI) – HCI is an area of research and practice that emerged in the early 1980s, initially as a specialty area in computer science embracing cognitive science and human factors engineering. HCI now aggregates a collection of semi-autonomous fields of research and practice in human-centered informatics (Carroll,1997).

Information Quality – Information quality is concerned with the timeliness, accuracy, format, accuracy, and relevance of the information (DeLone & McLean, 2003).

Kilowatt Hour – A kWh is unit or measure of electricity supply or consumption of 1,000 Watts over the period of one hour; equivalent to 3,412 BTU (EnergyLens, 2013).

Missing Completely at Random (MCAR) – MCAR means that the probability that an observation (Xi) is missing is unrelated to the value of Xi or to the value of any other variables. Another way to think of MCAR is to note that any piece of data is just as likely to be missing as any other piece of data (Little, 1988).

MySQL – MySQL is an open-source relational database management system.

Net Benefits – Net benefits is defined as the extent to which information systems contribute to the success of individuals, groups, organizations, industries, and government. For example, improved decision-making, improved productivity, increased sales, cost reductions, improved profits, market efficiency, and customer welfare (DeLone & McLean, 2016; Petter et al., 2008).

Partial Least Squares SEM (PLS-SEM) – PLS-SEM is a soft modeling approach to Structural Equation Modeling with no assumptions about data distribution. The partial least squares approach to SEM (or PLS path modeling) offers an alternative to covariance-based Structural Equation Modeling (Hair, Ringle, & Sarstedt, 2011).

Service Quality (SERVQUAL) – The SERVQUAL framework was developed by Parasuraman et al. in 1988 as a method of evaluating service quality for service industries, e.g. a bank, a credit card company, a repair and maintenance firm, and a phone service carrier (Parasuraman et al., 1988).

Structural Equation Modeling (SEM) – SEM is a second-generation multivariate data analysis method that is used in research because it can test theoretically supported linear and additive causal models (Chin et al., 2003; Haenlein & Kaplan, 2004). With SEM, researchers can visually examine the relationships that exist among unobservable, hard-to-measure latent variables. Latent variables are underlying variables that cannot be observed directly (Chin et al., 2003).

System Quality – Important attributes of system quality include usability, availability, reliability, adaptability, system flexibility, system reliability, functionality, and ease of learning (DeLone & McLean, 1992).

System Use – System use is concerned with actual use, the nature of use, frequency, thoroughness, and appropriateness of use (DeLone & McLean, 2016).

Technology Acceptance Model (TAM) – TAM suggests that when users are presented with a new technology, a number of factors influence their decision about how and when they will use or accept it (Davis, 1989).

User Information Satisfaction(UIS) – UIS is a model of user involvement which shows system quality and system use as influenced by user involvement - which are mediated by cognitive factors and motivational factors (Ives & Olson, 1984).

User Satisfaction – User satisfaction is the affective attitude towards a specific computer application of someone who interacts with the application directly (Doll & Torkzadeh, 1988).

Variance Inflation Factors (VIF) – VIF is the degree to which the standard error has been increased due to the presence of collinearity. It is used to describe how much multicollinearity (correlation between predictors) exists in a regression analysis. Multicollinearity is problematic because it can increase the variance of the regression coefficients, making them unstable and difficult to interpret (Allison, 1999).

List of Acronyms

AVE	**Average Variance Extracted**
BTU	**British Thermal Unit**
CARE	**California Alternate Rates for Energy**
EMIS	**Energy Management Information System**
E-S-QUAL	**Electronic Service Quality**
EUCS	**End-User Computing Satisfaction**
FERA	**Family Electric Rate Assistance Program**
HCI	**Human-Computer Interaction**
kWh	**Kilowatt Hour**
MCAR	**Missing Completely at Random**
PLS-SEM	**Partial Least Squares Structural Equation Modeling**

SEM	**Structural Equation Modeling**
SERVQUAL	**Service Quality**
TAM	**Technology Acceptance Model**
UIS	**User Information Satisfaction**
VIF	**Variance Inflation Factors**

Summary

An EMIS is a relatively new technological innovation that is in the nascent stages of technological diffusion, which affords an opportunity to baseline EMIS usefulness and user satisfaction in the residential domain. The residential domain is important because of the significantly high number of end users impacted. In the United States alone, residential energy consumption affects hundreds of millions of homes and other residences (Venkatesh et al., 2013). The energy industry is developing and deploying Energy Management Information Systems to mitigate the problem of unmanaged energy consumption. EMIS communicate energy consumption information to utility consumers to influence their consumption behavior. However, there were few guidelines or little research to determine the usefulness of these systems. Sustainability research integrated with information systems research faces many barriers, one of which includes a potentially steep learning curve. The Information Systems success model developed by DeLone and McLean (2003) was used to gauge EMIS success. This study employed structural equations modeling (SEM) based on partial least square (PLS) to evaluate sample data and model fit.

Chapter 2

Review of the Literature

This chapter presents the literature review and consists of three sections: (1) Energy behavior; (2) Information Systems success; and (3) Energy Management Information Systems.

Theoretical Background: Energy Behavior

A review of the literature revealed that technologies developed to encourage sustainability awareness through human interaction with technological devices has increased. Human Computer Interaction sustainability research has centered on homes that adaptively control energy systems for consumers and persuasive technology interfaces that attempt to persuade people to conserve energy (D'Oca, Corgnati, & Buso, 2014; Bonanni, Arroyo, Lee, & Selker, 2005; Beckmann, Consolvo, & LaMarca, 2004).

Prior empirical research also ranged from a focus on basic interactions within the home (e.g., accounting for energy reductions in terms of specific appliances and interactions) to more complex issues (e.g., the subjective experiences of using and living with energy feedback systems) (Pierce & Paulos, 2012; Pierce, Fan, Lomas, Marcu, & Paulos, 2010). Residential energy sustainability studies of any scale tend to implement one prototype, usually monitoring one utility, and mainly focus on outcome measures of consumption and savings (Ma et al., 2017; Bager & Mundaca, 2017; Ghazal et al., 2016; D'Oca, Corgnati, & Buso, 2014; Fitzpatrick & Smith, 2009).

The Rational/Irrational Energy Consumer

Changes in energy management behavior are primarily a function of technological innovation and technological diffusion as determined by income, price, payback, profitability (Darby, 2006; Ehrhardt-Martinez, 2008; Owen & Ward, 2006), and educational attainment. The primary approach to understanding energy management has been the assumption of a rational actor model in which individuals make rational choices regarding the adoption of new, more energy efficient technologies for use in home, business, or industry (Verkade & Höffken, 2017; Darby, 2006; Ehrhardt-Martinez, 2008). This framework identified the individual in terms of his/her role as a rational economic actor making rational choices regarding the adoption of efficient technologies and behaviors (Verkade & Höffken, 2017; Darby, 2006; Ehrhardt-Martinez, 2008).

Previous research has highlighted the many ways in which energy use is particularly prone to what traditional economics would deem "irrational" behavior. Factors that influence irrational behavior include: the effective invisibility of electricity and heat, the abstract and unfamiliar units used to delineate their prices, and the temporal distance between usage and receipt of monthly billing statements (Davis, 2011). Although managing energy consumption would benefit the energy consumer in terms of cost savings, the "invisibility" of this commodity leads to an irrational economic actor making irrational decisions or choices. Rational decision making models involve a cognitive process where each step follows a progression in a logical order from the one before. Cognitive here means the thinking through and weighing of all the alternatives to arrive at the best potential result.

Kahneman (2003) observed that the fundamental assumption aligned with rational choice theory is that when people make rational preferences among outcomes, they always strive to maximize utility, and thus will act based on full and relevant information. Based on this assumption, traditional economic models predict that people will make decisions that yield the optimal result given budget constraints, and that behavioral choices can be improved by providing people with more information (i.e., by increasing knowledge/awareness) and/or more options (i.e., by increasing choices).

Frederiks, Stenner, and Hobman (2015) noted that consumers are far from the purely rational decision-makers assumed by traditional economic models; there is often a wide gap between peoples' values, material interests, and their actual behavior. Put simply, people often act in ways that both fail to align with their knowledge, values, attitudes, and intentions, and fall short of maximizing their material interests. A growing body of research indicates that consumer choices and behavior are largely driven by cognitive biases, heuristics, and other predictably irrational tendencies—for example, people tend to use mental shortcuts to cut through complexity.

According to Kahneman (2011), when you think, your mind uses two cognitive systems. System 1 works easily and automatically and does not take much effort; it makes quick judgments based on familiar patterns. System 2 takes more effort; it requires intense focus and operates methodically. These two systems interact continually, but not always smoothly. For example, [a consumer’s] use of electricity depends on what [the consumer] chooses to do, e.g. whether to heat a room, toast a piece of bread or do nothing at all. If the consumer decides to accept the gain that electricity provides for the risk of monetary loss, then System 1 makes that decision easier, as there is no effort expended to decide whether we want to be warm or hungry (Kahneman, 2011).

System 2 takes more effort, as it would require calculation or at least the consideration that there is a cost for the energy associated with our decision. System 1 makes the decision to turn on the heat. System 2 reads/views the electrical bill and tries to make sense of what the numbers and graphs mean. The two systems are two sides of the same coin. Intuitive System 1 does the fast thinking while the slower and effortful System 2 monitors System 1 and maintains decision control as best it can within its limited resources (Kahneman, 2011). Ecologic (2013) suggested that energy consumers value the immediate future too highly and do not value the distant future enough and that there is a tendency to favor immediate rewards and avoid immediate costs.

As March (1994) observed, the most common and best-established elaboration of pure theories of rational choice is one that recognizes the uncertainty surrounding future consequences of present action. Decision-makers are assumed to choose among alternatives based on their expected consequences, but those consequences are not known with certainty. Information is seen to reduce decision-maker uncertainty. Information that is perceived as valuable allows decision-makers to know the likelihood of various possible outcomes and thus make better-informed decisions. Ecologic (2013) noted that when consumers make decisions, they are caught between two competing thought processes: (1) slow, reflective thinking, which enables them to consider some of the costs and benefits of a choice before making it; or (2) emotive thoughts, which often persuade them to buy things that might not be beneficial in the long term.

Frederiks, Stenner, and Hobman (2015) argued that consumers seem to be gaining greater awareness of the value and need for sustainable energy practices, yet even with adequate knowledge of how to save energy and a professed desire to do so, many consumers still fail to take noticeable steps towards energy efficiency and conservation. There is often a sizeable discrepancy between consumers' self-reported knowledge, values, attitudes, intentions, and their observable behavior. Examples include the well-known "knowledge-action gap" and "value-action gap."

Ploderer, Reitberger, Oinas-Kukkonen, and Gemert-Pijnen (2014) suggested two approaches to behavior change: (1) reflection-in-action; and (2) reflection-on-action. Reflection-in-action is supported by systems that provide feedback at the time of action. These systems can be effective as they offer resources for reflection at the right time. Reflection-on-action is encouraged by systems where resources for reflection are offered after the activity has ended. A key challenge is how to best represent data for a particular activity, i.e. activities yield many data points; the challenge is to understand what data to choose for representation, the extent of concreteness (or ambiguity) in its representation, and how different sources of data are structured and related to one another (Costanza, Ramchurn, & Jennings, 2012; Ploderer, Reitberger, Oinas-Kukkonen, & Gemert-Pijnen, 2014).

Verkade and Höffken (2017) argued that the paradigm of a "rational actor" when provided energy information through technological interventions will change behavior is a false paradigm. Energy monitoring devices operate on the basis that when they provide new information and/or instructions, individuals will change their respective energy usage behavior accordingly. This individual, positivist, and technology centered approach to understanding energy usage envisages homeowners as smart energy users who can be persuaded to take control of' energy consumption through monitors and apps. Using ever more accurate energy data, the smart energy consumer makes conscious and informed consumption decisions to be more economical and sustainable. This vision can be quite different for most people where there is a lack of engagement with energy monitoring in their daily lives.

Behavior Change through Technological Interventions

Energy savings based on technology enabled feedback devices may not be as effective in reducing energy consumption (Fabi et al., 2017; Carroll, Lyons, & Denny, 2014; Darby, 2001; Hargreaves, Nye, & Burgess, 2013; Pierce et al., 2010**).** Other studies show the effectiveness of feedback devices in reducing energy consumption (Gans et al., 2013; Grønhøj & Thøgersen, 2013; Darby, 2001). Darby (2006) noted that savings in the region of five to fifteen percent for technology enabled feedback devices have been observed.

Pierce and Paulos (2012) argued that energy consumption feedback research is focused on a specific type of intervention while energy awareness and conservation behavior research is focused on a specific goal, namely promoting individual energy conservation behavior and/or cognitive awareness of energy consumption. Smart meters and in-home displays (see Figure 2) clearly dovetail with the types of home energy monitoring displays and visualizations characteristic of current energy consumption feedback research (Fabi et al., 2017; DECC, 2015).

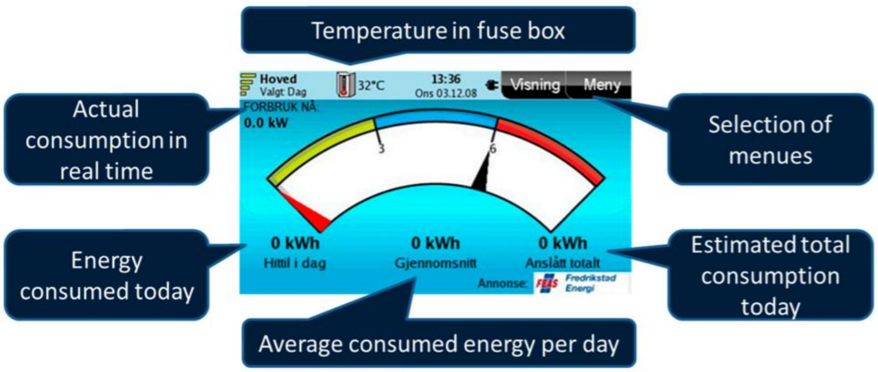

Figure 2. e-Wave In-Home Display. Source: (Westskog, 2015).

Fabi et al. (2017) observed that current electricity consumption feedback models only convey the monitored information in data records and statistical charts. Feedback models that emphasize and enhance the visualization of feedback information could persuade energy consumers into practicing behavior that would reduce electricity consumption. The process of persuasion is derived from the characteristics and tendencies of the user. As such, feedback models should attempt to gauge the strength of user interaction with the system.

The literature reveals that there is not a clear picture of an ideal design for or how to assess the effectiveness of energy technology device research (Pepermans, 2014). Suppers and Apperley (2014) argued that to design effective and useful residential energy usage visualizations aimed at greater awareness and better management, there is a need to understand user type. The authors suggested analyzing individual personal characteristics influencing and motivating behavior as well as the impact of social effects to understand how to create successful domestic energy use visualizations.

For example, Pepermans (2014) assessed to what extent consumers are willing to make use of the features and capabilities smart meters offer. Experimental households were offered the choice between a set of smart meters, described by five attributes: impact on the comfort and privacy level, functionality, visibility, cost savings, and investment outlay. The results indicated that households have heterogeneous preferences for some attributes but not for others, suggesting that sufficient effort be devoted to designing smart metering devices.

Technology systems that deliver current, relevant, and well-coordinated information has greater potential to create attitude or behavior change (Fogg, 2003). In a study of factors related to household energy use and information, Abrahamse, Steg, and Rothengatter (2005) found that users who received tailored energy information via an easy to navigate website interface adopted more energy-savings measures and had more knowledge of energy conservation compared to a control group who received traditional paper-based billing information. The literature supports the effectiveness of information feedback that is specific (e.g. personalized) to the customer and allows the customer to control their energy use more effectively (Pasini et al., 2017; Chen et al., 2014; Chiang et al., 2014; Darby, 2001).

Johnson et al. (2017) reviewed 25 research studies to assess the effectiveness of gamification and serious (non-entertainment) games in impacting domestic energy consumption. Their findings indicate that gamification and serious games appear to provide information value, with varying degrees of evidence of positive influence found for behavior, knowledge and learning and the user experience. Morganti et al. (2017) found that both serious games and gamification can foster energy-saving behaviors and vary widely in terms of type of games and of features that might be appealing and motivating. Ro et al. (2017) designed a game-based sustainability intervention and tested its effectiveness in two large-scale field studies. In study one, the sustainability game significantly reduced people's household electricity consumption six months after the game. In study two, the authors found that high-energy (digitally engaged) consumers changed their environmental behaviors and attitudes more than hypothesized.

Digital Customer Engagement

Utilities have typically interacted with customers on a limited basis—usually to start or stop service, troubleshoot service issues, or process monthly bills. However, unlike other smart grid investments, customer-facing technologies require effective communications and new interactions between utilities and customers to maximize the value of new capabilities. Smart meters (and the services they provide via web portals) involve complicated equipment and require customers to “climb learning curves” that require extensive communication and education (DOE, 2014a).

Although many energy providers have invested in improving website designs, developing mobile applications, and building social media engagement, 56% of energy customers are not digitally engaged, e.g. they have not interacted with their utilities online at least once during the past 12 months (Accenture, 2015). Just 44% are digitally engaged. Even fewer have an electric-company-provided energy app. Consumers have passed a tipping point of mass adoption of self-serve and digital engagement, yet in the energy industry consumers are not adopting digital at the same levels. Per Accenture (2015), 41% of energy consumers believe their digital experience with their energy providers is more difficult than with other types of providers—with younger consumers more likely to have that perception.

Design is critical when engaging digital consumers. A critical step in engaging customers in smart meter data is presenting smart meter data as effective information, which can be accomplished via website portals that are compelling, actionable, scalable, secure, and available on customers' preferred communications channels. However, wrangling smart meter data and consolidating it into a comprehensive, searchable, relational database from which utility service providers can implement a customer engagement platform is challenging. Typically, data is stored across multiple divisions and departments within a utility. However, as many utilities seek to replace aging, legacy customer information systems, there are increasing opportunities to provide a holistic customer engagement platform (Orfanedes et al., 2016).

Cooper (2016) notes that utility companies are providing the following enhanced services to customers with smart meters – with varying degrees of engagement: (1) budget setting options that allow customers to set spending goals and that provide weekly updates to show how they are performing against their goals; (2) high usage alerts that provide customers an early warning if their bill is projected to be higher than normal; (3) power alerts that notify customers if their power is out and provide an estimated time to restore service; and (4) time-based pricing and load management services that provide an economic incentive to customers to shift usage and/or respond to price signals**.** Utilities also provide the ability for customers to download energy usage data from a smart meter website. This file is in an Extensible Markup Language (.XML) format and requires an application to properly read and determine the contents of the file.

Theoretical Background: Information Systems Success Models

Researchers and practitioners alike face a daunting challenge when evaluating the "success" of information systems (DeLone & McLean, 2016; Behrens, Jamieson, Jones, & Cranston, 2005). This may be in part due to the complex nature of IS success measurement driven by the constantly changing role and use of information technology (DeLone & McLean, 2016). There are numerous IS success definitions (e.g. individual or organizational performance, increased productivity, cost reductions, user acceptance or user satisfaction), and a plethora of models (e.g. Zmud's Individual Differences Model (1979), Ives and Olson's User Involvement Success Model (1984), Doll and Torkzadeh's (1988) End-User Computing Satisfaction Model, Davis' Technology Acceptance Model (1989), DeLone and McLean's IS success model (1992, 2003), and Gable's IS Impact Model (2008).

Zmud's Individual Differences Affect MIS Success

Seeking to understand the determinants of IS success, Zmud (1979) synthesized the literature of more than 100 multidisciplinary empirical studies examining decision behavior and its effect on the successful development of an organization's Management Information System (MIS). The author concluded that individual differences exert a major force in determining MIS success.

Zmud (1979) developed a model that portrays the manner in which individual differences influence MIS success. Two distinct paths are conceptualized. An upper path finds individual differences amplifying or dampening limitations in human information processing and decision behavior, which in turn impose or suggest MIS design alternatives directed toward motivating or facilitating MIS usage. A lower path reflects the impact of individual differences upon the attitudes held by potential MIS users and upon the tendencies for MIS users to involve themselves in the MIS development effort. These paths can thus be characterized as representing the cognitive and attitudinal influences of individual differences upon MIS success (Chen, 2011).

Zmud (1979) categorized individual differences into three different classes: cognitive style, personality, and demographic/situational variables. Demographic variables are personal characteristics such as gender, education, age, and experience with computers. Personality variables relate to the cognitive and affective structures maintained by individuals to facilitate their adjustments (or to understand) events, people, and situations encountered in life. The cognitive behavior as it affects MIS success refers to the human limitations in cognition; these limitations, the author argues, are directly related to how an information system is designed. Thus, the author concluded that individual differences influence information systems success. There are seven components in the model. Individual differences influence cognitive behavior, which influence MIS design characteristics, which then influence MIS success. Attitude of the user towards the MIS system before and after the use also affects MIS success or failure. Figure 3 illustrates Zmud's (1979) MIS Success Model.

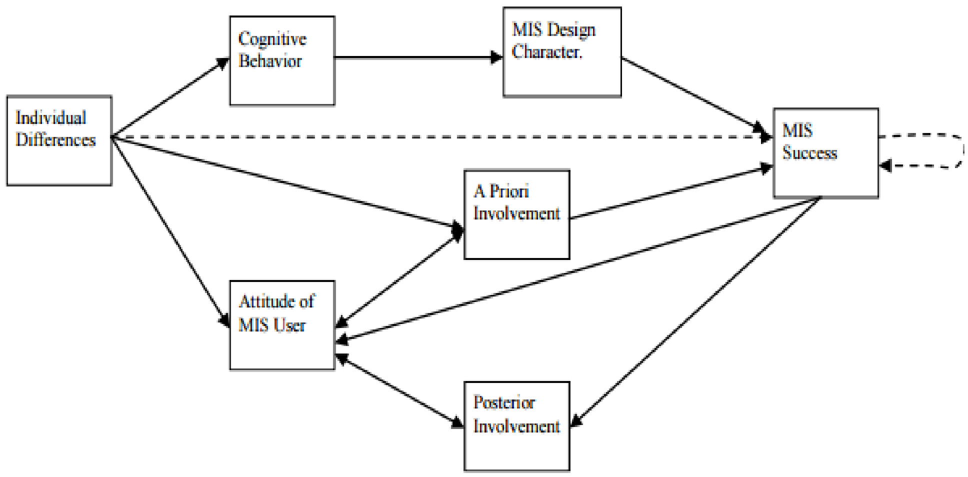

Figure 3. Zmud's Individual Differences MIS Success Model (1979).

Huber (1983) rejected Zmud’s (1979) conclusions, noting that there are many individual differences related to an individual’s decision to use a management information system. Huber (1983) argued that the task of constructing empirically based normative design models that accounts for all their individual effects is overwhelming. Dishaw (1998) concurred, noting that other important individual differences (or confounding factors) may influence MIS design. Huber (1983) noted that the matter of an *a priori* determination of the user’s style as a basis for identifying the most appropriate design becomes largely irrelevant because of multiple differences that exist between individuals. However, what is notable about Zmud’s (1979) research are his observations regarding how MIS design characteristics may affect MIS success.

According to Zmud (1979), users are more satisfied if the information presented is exactly matched with the user’s information needs and also if the information presented is dynamic (e.g. reports could be modified by the user). The author’s research also revealed that graphical, color-coded reports help to improve decision-making, and that an easy to use system interface is positively related to user satisfaction. If the MIS system is accessible and reliable, the author observed, online usage is more consistent.

Ives and Olson's User Involvement Success Model

Five years after Zmud's (1979) research on the importance of individual differences in MIS success, Ives and Olson (1984) challenged the prevailing assumptions regarding the importance of user involvement in systems development as a factor for system success. Ives and Olson's (1984) IS literature review suggested that the relationship between user involvement in information system development and system success was not strongly supported. According to Ives and Olson (1984), research on participation and involvement yielded mixed results, as there was no clear positive relationship between user participation and various outcome variables. The authors argued that there are systems that cannot be developed without the input of the user and there are systems where the input of the user would not be necessary at all.

Ives and Olson (1984) developed a model of user involvement (as shown in Figure 4) which shows system quality and system use as influenced by user involvement - which are mediated by cognitive factors and motivational factors. Cognitive factors refer to improved understanding of the system, system needs, and improved evaluation of system features. The motivational factors that lead to system acceptance (e.g. user satisfaction) are increased ownership, decreased resistance to change, and increased commitment.

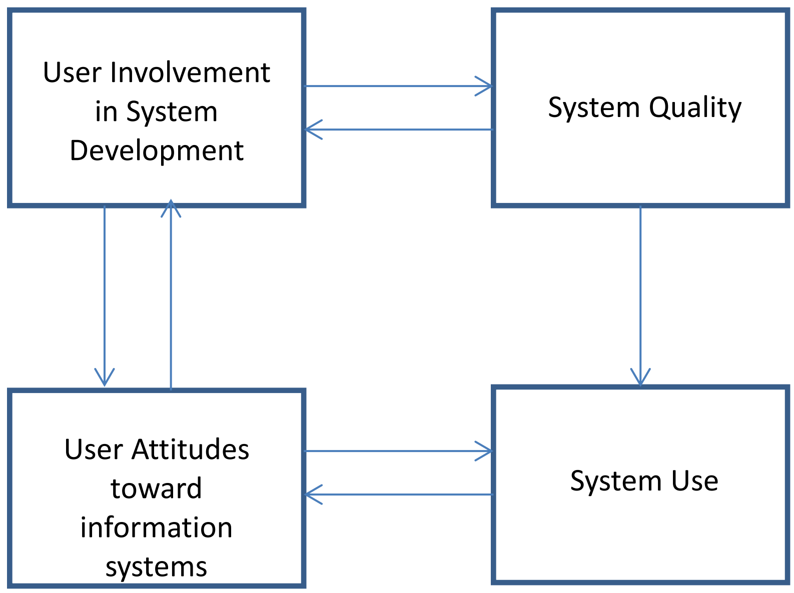

Figure 4. Ives & Olson's User Information Satisfaction Model (1984).

According to Ives and Olson (1984), user participation is a critical success factor during the definition stage and becomes less important in the installations stages. The authors suggested that future research on system success should focus on the conditions under which user involvement may or may not be appropriate. Using meta-analytical techniques, Hwang and Thorn (1999) reviewed information systems literature and concluded that user participation has a positive correlation with system success as measured by system quality, use, and user satisfaction.

However, Ives and Olson's (1984) model, which is based on a study in a data processing computing environment, where the emphasis was on computing tasks that were carried out by the data processing group in an organization, is not considered an adequate measure of user satisfaction. Due to this context limitation, the end user satisfaction instrument developed by Doll and Torkzadeh (1988) is often used as a measure of end user satisfaction.

Doll and Torkzadeh End-User Computing Satisfaction Model

Doll and Torkzadeh (1988) noted that user participation will not yield the expected results if users do not desire to participate and thus proposed an “end-user computing model” where the end-user interacts directly with the IS to obtain information. The authors developed a 12-item End-User Computing Satisfaction (EUCS) instrument by contrasting traditional data processing environments and end-user computing environments (Figure 5).

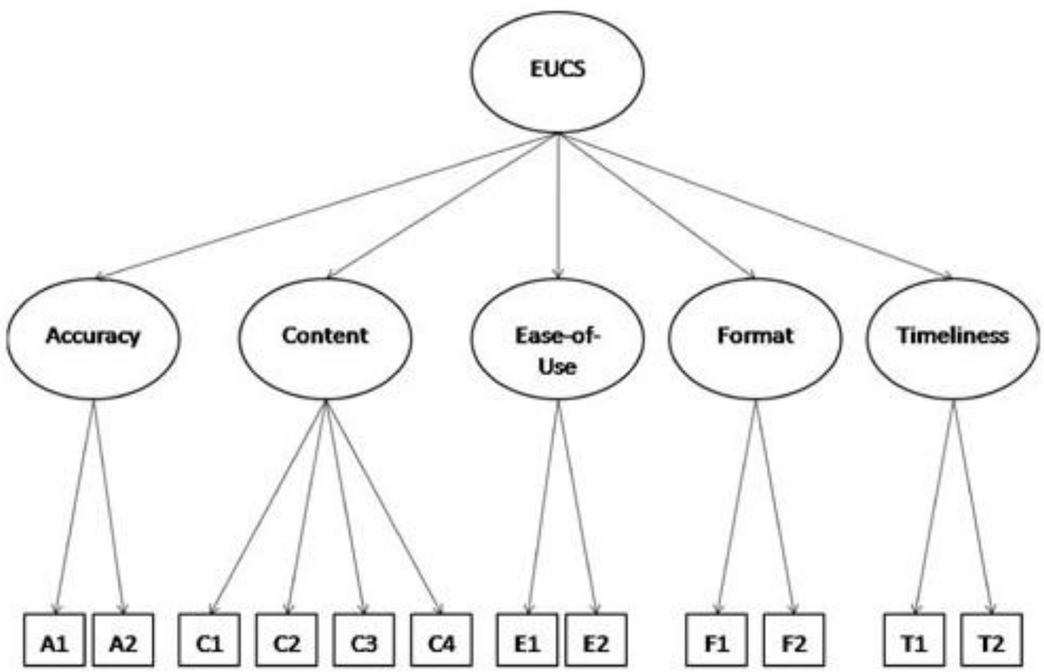

Figure 5. Doll and Torkzadeh’s End-User Computing Satisfaction Instrument (1988).

Doll and Torkzadeh’s (1988) model evaluated the following context items shown in Table 1.

Table 1

End-User Computing Satisfaction

Construct	**Items**
Accuracy	A1: Is the system accurate? A2: Are you satisfied with the accuracy of the system?
Content	C1: Does the system provide the precise information you need? C2: Does the information content meet your needs? C3: Does the system provide reports that seem to be about exactly what you need? C4: Does the system provide sufficient information?
Ease of Use	E1: Is the system user friendly? E2: Is the system easy to use?
Format	F1: Do you think the output is presented in a useful format? F2: Is the information clear?
Timeliness	T1: Do you get the information you need in time? T2: Does the system provide up-to-date information?

Doll and Torkzadeh (1988) posited that their 12-item instrument has adequate reliability and validity because they reviewed previous work on user satisfaction in their search for a comprehensive list of items. The authors also included a measurement of “ease of use,” which was not included in earlier IS research. Thus, the authors noted, their 12-item instrument is a convenient measure to evaluate the efficiency and effectiveness of an Information System.

However, Etezadi-Amoli and Farhoomand (1996) argued that different weights be applied to the 12-items according to the scale of responses. In Doll and Torkzadeh’s

(1988) model, each item receives an equal weight. The authors argued that the instrument is intended to evaluate the level of end-user satisfaction as a dependent variable of user perception on the successful development and implementation of an IS; the instrument is not intended to predict the psychological behavior of end-users. Doll, Xia, and Torkzadeh (1994) conducted a confirmatory analysis using a test-retest of reliability of the EUCS instrument, indicating the instrument was reliable over time.

Davis' Technology Acceptance Model

Davis' (1989) Technology Acceptance Model (TAM) is a widely accepted theoretical framework used to measure system acceptance. The Technology Acceptance Model is based on the premise that if a system is accepted it will have a higher likelihood of being used and therefore positively encourage success. Based on Fishbein and Ajzen's (1975) Theory of Reasoned Action, Davis (1989) developed the Technology Acceptance Model to ascertain what factors cause people to accept or reject an information technology.

The Technology Acceptance Model suggests that when users encounter a new IS innovation two main factors influence how and when they will use it - perceived usefulness and perceived ease of use. Perceived usefulness is the degree to which a person believes that using a particular system would enhance his or her job performance. Perceived ease of use is the degree to which a person believes that using a particular system would be free from effort (Davis 1989).

According to TAM (see Figure 6), perceived usefulness and perceived ease of use affect a users' motivation and behavioral intentions. Perceived usefulness, followed by the perceived ease of use, has proven to be the major direct motivator to behavioral intention and technology adoption (Petter et al., 2008; Dias, Silva, Schmitz, & Dias, 2009).

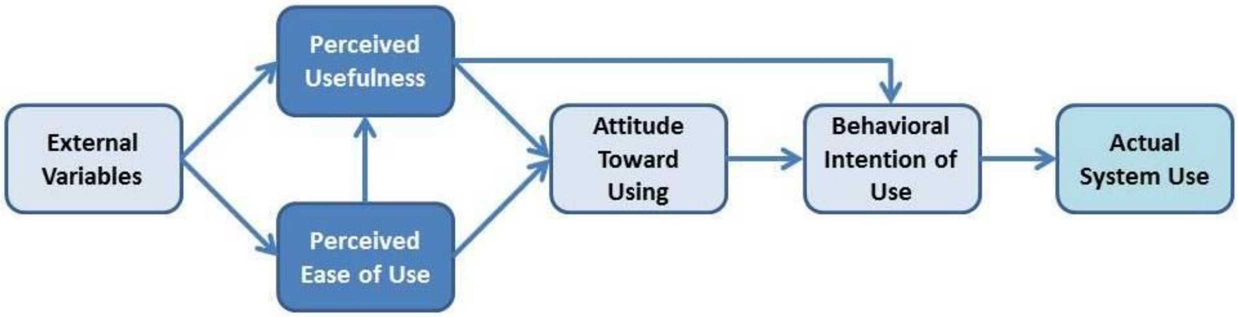

Figure 6. Davis' Technology Acceptance Model (1989).

The Technology Acceptance Model's impact on IS research is well recognized. Numerous studies have validated TAM and confirmed the relationship between behavioral intentions and actual system use (Benbasat & Barki, 2007; Lee et al., 2007; Yousafzai et al., 2007). Davis' (1989) perceived ease of use is the most common measure of system quality because of the large volume of empirical research devoted to TAM (Petter et al., 2008; Rai, Lang, & Welker, 2002). According to Behrens et al., (2005), TAM measures of perceived usefulness and perceived ease of use are effective predictors of systems success.

However, the TAM does not include some of the quality factors of an IS, e.g. output quality or some of the social influences (e.g. subjective norm or voluntariness) in the model. Venkatesh and Davis (2000) extended TAM and developed TAM2 by adding social influences (subjective norm, voluntariness, and image) and cognitive instrumental processes (job relevance, output quality, result demonstrability, and perceived ease of use) to predict the adoption of an information technology and therefore impact positively on success.

DeLone and McLean's Model of IS Success

Early attempts to define information system success were ill-defined due to the complex, interdependent, and multi-dimensional nature of IS success. To address this problem, DeLone and McLean (1992), performed a review of the research published during the period 1981–1990 and created a taxonomy of IS success (DeLone & McLean, 2016). DeLone and McLean's (1992) IS Success Model was based on research work in communications by Shannon and Weaver (1949) and Mason's (1978) research on measuring information output. Seeking to synthesize and provide a framework for communications theory, Shannon and Weaver (1949) posited that information (as the output of an information system) can be measured at different levels: the technical level, the semantic level, and the effectiveness level. The technical level is defined as the accuracy and efficiency of the system that produces the information, the semantic level is defined as the success of the information in conveying the intended meaning, and the effectiveness level is defined as the effect of the information on the receiver.

Seeking to synthesize previous IS research efforts with Shannon and Weaver's Information Theory communications work, DeLone and McLean (1992) introduced six major variables that define information system success: *System Quality*, *Information Quality*, *Use*, *User Satisfaction*, *Individual Impact*, and *Organizational Impact*. The model suggests causal rather than process relationships between the variables. Unlike a process model, which merely states that B *follows* A, a causal model postulates that A *causes* B; i.e., increasing A will cause B to increase (or decrease). For example, higher system quality leads to increased user satisfaction and use, which affects individual and organizational impacts.

DeLone and McLean (1992) characterized system quality as desired characteristics of the information system itself, and information quality as desired characteristics of the information product. More concretely, they incorporated four scales from the Bailey-Pearson (1983) instrument into system quality (convenience of access, flexibility of the system, integration of the system, and response time) and nine scales into information quality (accuracy, precision, currency, timeliness, reliability, completeness, conciseness, format, and relevance).

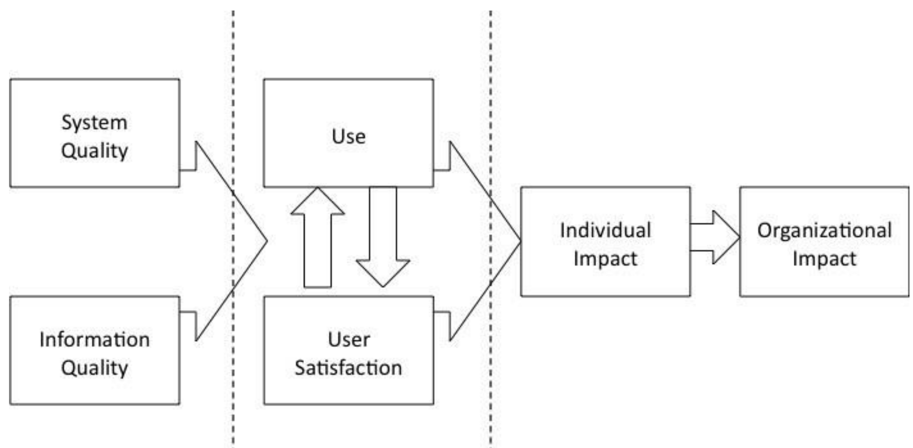

Figure 7. DeLone and McLean's IS Success Model (1992).

The model (as shown in Figure 7), is to be interpreted in the following ways: system quality and information quality singularly and jointly affect both use and user satisfaction. Additionally, the amount of use can affect the degree of user satisfaction –

positively or negatively – as well as the reverse being true. Use and user satisfaction are direct antecedents of individual impact; and lastly this impact on individual performance should eventually have some organizational impact (Delone & McLean, 1992).

The primary conclusions of DeLone and McLean (1992) were: (1) the multidimensional and interdependent nature of IS success requires careful attention to the definition and measurement of each aspect of the dependent variable; (2) it is important to measure the possible interactions among each of the success dimensions in order to isolate the effect of various independent variables with one or more of these dependent success dimensions; and (3) selection of success dimensions and measures should be contingent on objectives and context of the empirical investigation; but, where possible, tested and proven measures should be used.

Seddon's Respecified IS Success Model

In 1997, Seddon wrote that the value of DeLone and McLean's (1992) IS Success Model is diminished due to its inclusion of both variance and process interpretations:

> "After working with this model for some years, it has become apparent that the inclusion of both variance and process interpretations in their model leads to so many potentially confusing meanings that the value of the model is diminished" (p. 240).

Seddon (1997) argued that the confusion that such overloading of meanings can cause requires that the model be "respecified." Seddon (1997) thus respecified and slightly extended DeLone and McLean's (1992) model.

The original DeLone and McLean model (1992) specified *use* as a measure of success and defined *use* as the degree and manner in which staff and consumers utilize the capabilities of an information system. Seddon (1997) criticized DeLone and McLean's (1992) *use* construct as ambiguous. Seddon (1997) suggested that system *use* was not an IS success measure. Seddon defined system *use* as using the system for everyday work and tasks purposes.

Seddon wrote:

> DeLone and McLean's (1992) Model is really a combination of three different models. The four success-construct categories on the right-hand side of the model are just ways of classifying variables that attempt to measure benefits from use. Two of these variables, IS Use and User Satisfaction, have been used so often in the past that DeLone and McLean have placed them in special classes. The other two are just convenient classifications of the remaining variables. *Prima facie* there is no reason for expecting any variance-model relationship between these four types of measures; they are just different ways of tapping into the one underlying construct, Benefits from Use (Seddon, 1997, p. 243).

Seddon (1997) also asserted that the merger of causal and process concepts in the IS success model proposed by DeLone and McLean's (1992) model could become a source of confusion and therefore proposed three classes of variables in his respecified model **(**Figure 8).

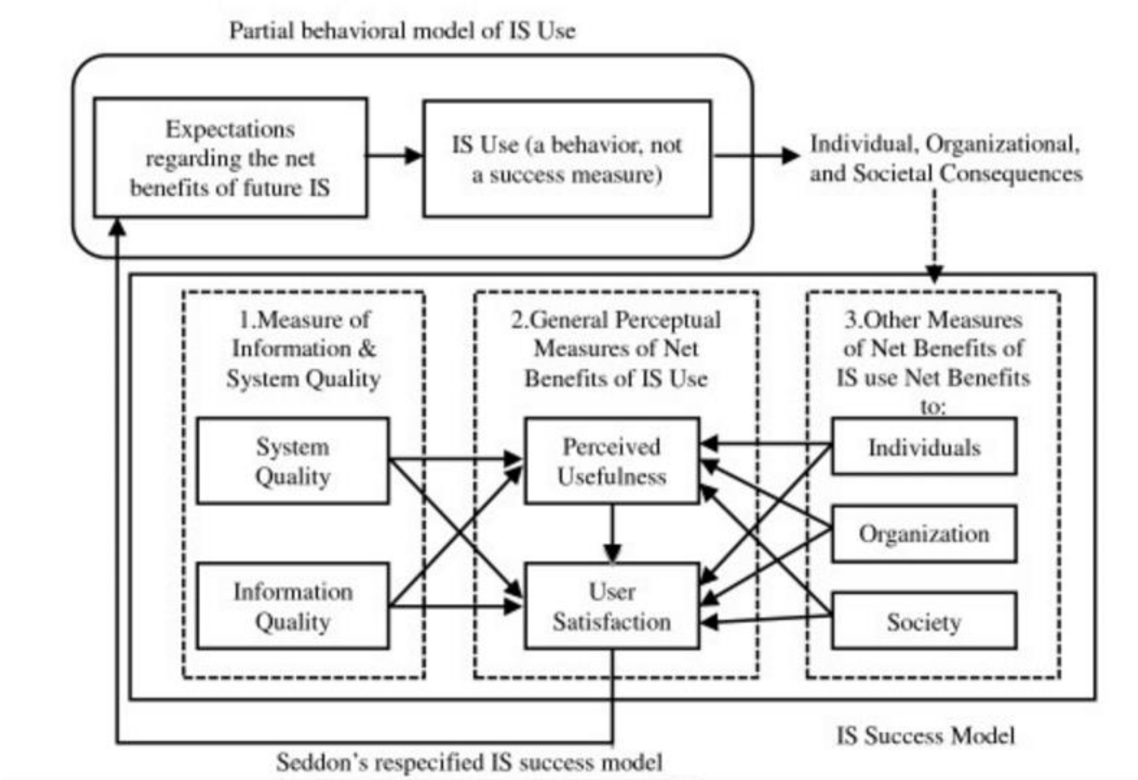

Figure 8. Seddon's Respecified IS Success Model (1997).

Seddon (1997) viewed IS use as a behavioral outcome manifest as an anticipation of net benefits from utilizing an IS. This latter definition of IS use implied that IS use resulted from IS success, rather than being an innate feature of IS success. Seddon's (1997) model included a direct path leading from system quality and information quality to perceived usefulness and user satisfaction. In addition, perceived usefulness was felt to influence user satisfaction.

In Seddon's (1997) model, the process interpretation of DeLone and McLean's (1992) model has been eliminated, and the remainder of their model has been split into the two distinct variance models. The first of these two variable models is the partial behavioral model of IS Use. According to Seddon (1997), only a partial behavioral model is presented because the goal of the paper is to interpret and clarify the DeLone and McLean (1992) model, not to extend it significantly. The second variance model is the IS Success model. The two variance models are linked through the path down from Consequences of IS Use to the IS Success Model, and the feedback path from User Satisfaction (in the IS success model) up to revised expectations about the net benefits of future use.

DeLone and McLean's Model of IS Success

DeLone and McLean (2003) "respecified" their original IS Success Model based on criticism by Seddon (1997). The updated IS Success Model is shown in Figure 9.

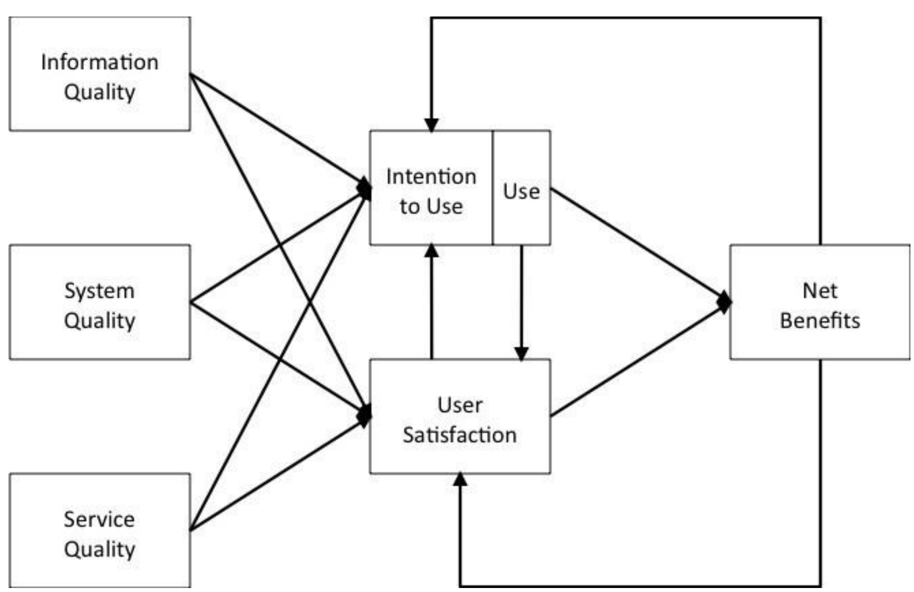

Figure 9. DeLone and McLean IS Success Model (2003).

This updated IS success model accepted the Pitt, et al. (1995) recommendation to include service quality as a construct. Another update to the model addressed the criticism that an information system can affect levels other than those at the individual and organizational level. Because IS success affects workgroups, industries, and even societies (Petter, et al., 2008; Seddon, 1997), DeLone and McLean replaced the variables, individual impact and organizational impact, with net benefits. This revision allowed the model to be applied to whatever level of analysis the researcher considers most relevant (Petter, et al., 2008).

A final enhancement made to the updated DeLone and McLean model was a further clarification of the use construct (Petter, et al., 2008). In Seddon and Kiew's (1996) view, for voluntary systems, use is an appropriate measure but if system use is obligatory, usefulness is a better measure of IS success than use. Seddow and Kiew (1996) suggested eliminating the use construct altogether. However, DeLone and McLean's (2003) response was that the *use* construct be retained because there can still be considerable variability of *use* even if the systems are mandatory to use. *Use*, the authors argued, must precede "User Satisfaction" in a *process* sense, but positive experience with "Use" will lead to greater "User Satisfaction" in a *causal* sense. Therefore, according to the authors, increased "User Satisfaction" will lead to a higher Intention to "Use", which will subsequently affect use.

The key modifications in the updated model in 2003 can be summarized as follows: (1) the inclusion of "Service Quality" as an additional aspect of IS success; (2) the elimination of "Individual Impact" and "Organizational Impact" as separate variables, and their replacement with “Net Benefits”; and (3) the clarification of the “Use” construct, by measuring “Intention to Use” (i.e., an attitude) rather than “Use” (i.e., a behavior) (DeLone & McLean, 2003).

Among the numerous studies examining IS success over the years, DeLone and McLean's (1992, 2003) IS Success Model is considered the most comprehensive information system assessment model available in IS literature (Petter et al., (2008). To date, the dimensions of IS success include the following definitions and operational measurements.

System Quality

DeLone and McLean (1992) suggested that system quality is the desired characteristic of an information system, of which the main objective of the system is to produce information that can be used by users to aid in decision-making. Important attributes of system quality include usability, availability, reliability, adaptability, system flexibility, system reliability, functionality, and ease of learning. System quality also includes system features of intuitiveness, sophistication, flexibility, and response times (Petter et al., 2008). Other constructs to measure system quality include portability, economy, maintainability, verifiability, network infrastructure reliability, stability, and user-friendly interfaces (see Table 2).

Table 2

Validated System Quality Measures Used in Past Research

Item	**Literature Sources**
Access	Gable et al. (2008), McKinney et al. (2002)
Adaptability	DeLone & McLean (2002)
Convenience	Bailey & Pearson (1983), Iivari (2005)
Customization	Gable et al. (2008), Sedera & Gable (2004)
Data accuracy	Gable et al. (2008), Doll & Torkzadeh (1988)
Data currency	Gable et al. (2008)
Ease of learning	Gable et al. (2008), Sedera & Gable (2004)
Ease of use	Doll & Torkzadeh (1988), Gable et al. (2008), McKinney et al. (2002), Sedera & Gable (2004), Seddon & Kiew (1996), Davis (1989)
Efficiency	Gable et al. (2008)
Flexibility	Bailey & Pearson (1983), Gable et al. (2008), Iivari (2005), Sedera & Gable (2004)
Functionality	Estrada & Romero (2016), DeLone & McLean (2016)
Integration	Bailey & Pearson (1983), Gable et al. (2008), Iivari (2005), Sedera & Gable (2004)
Interactivity	McKinney et al. (2002)
Navigation	McKinney et al. (2002)
Relevant	Doll & Torkzadeh (1988)
Reliability	Gable et al. (2008), DeLone & McLean (2003)
Response time	Iivari (2005), Bailey & Pearson (1983), DeLone & McLean (2003)
Sophistication	Gable et al. (2008), Sedera & Gable (2004)
System accuracy	Doll & Torkzadeh (1988), Gable et al. (2008), Sedera & Gable (2004)
System features	Gable et al. (2008), Sedera & Gable (2004)
System security	DeLone & McLean (2016)
Usability	DeLone & McLean (2003)

Perceived ease of use is the most common measure of system quality because of the large amount of research relating to the TAM (Davis, 1989). However, as previously stated, perceived ease of use does not capture the system quality construct as a whole. Other researchers have created indexes of system quality using the dimensions identified by DeLone and McLean (1992) in their original model or through their review of the system quality literature (Gable et al., 2003).

Information Quality

Shannon and Weaver (1949) posited that information quality belongs to the semantic level of information and is more concerned with interpretation of the meaning by the receiver than the intended meaning of the sender. According to DeLone and McLean (2003), the most common measures of information quality are timeliness, completeness, consistency, understandability, accuracy, and relevance. In a traditional IS sense, information quality depends on how the data is generated and used within the organization. Substantial empirical research in different studies have measured information quality. Rai et al. (2002) suggests that information quality is related to content and format. As previously mentioned, the Doll and Torkzadeh (1988) instrument included measures of accuracy, content, format, and timeliness. For measuring e-commerce systems success, DeLone and McLean (2003) propose additional attributes of ease of understanding, personalization, and security. The most common dimension of information quality is accuracy, which is usually defined in terms of number of errors, i.e., in a database. Many additional measures have been proposed and used to capture the information quality construct as a whole (see Table 3).

Table 3

Validated Information Quality Measures Used in Past Research

Item	**Literature Sources**
Accuracy	Bailey & Pearson (1983), Gable et al. (2008), Iivari (2005), Doll & Torkzadeh (1988), DeLone & McLean (2003), Seddon & Kiew (1996)
Adequacy	McKinney et al. (2002)
Availability	Gable et al. (2008), Sedera & Gable (2004) , DeLone & McLean (2003)
Completeness	Bailey & Pearson (1983), Iivari (2005), Doll & Torkzadeh (1988), DeLone & McLean (2003)
Conciseness	Gable et al. (2008), Sedera & Gable (2004)
Consistency	Iivari (2005)
Format	Gable et al. (2008), Iivari (2005), Sedera & Gable (2004), Doll & Torkzadeh (1988)
Precision	Bailey & Pearson (1983), Iivari (2005)
Relevance	Seddon & Kiew (1996), Gable et al. (2008), McKinney et al. (2002), Sedera & Gable (2004), DeLone & McLean (2003)
Reliability	Bailey & Pearson (1983), McKinney et al. (2002), DeLone & McLean (2003)
Scope	McKinney et al. (2002)
Timeliness	Bailey & Pearson (1983), Gable et al. (2008), Iivari (2005), Doll & Torkzadeh (1988), McKinney et al. (2002)
Understandability	Gable et al. (2008), McKinney et al. (2002), Sedera & Gable (2004), Bailey & Pearson (1983)
Uniqueness	Gable et al. (2008)
Usability	Gable et al. (2008), Sedera & Gable (2004)
Usefulness	McKinney et al. (2002)

Service Quality

DeLone and McLean (2003) define service quality as the overall support delivered by a service provider regardless of whether this support is provided by an internal IS department, a new organizational unit or outsourced to an Internet Service Provider. Other measures of service quality include quick responsiveness, assurance, empathy, follow-up service, and technical support (Parasuraman et al.,1988; Pitt et al., 1995). Adapted from the field of marketing, the original service quality construct measured service quality as a discrepancy between what the customer feels should be offered and what is actually provided (Parasuraman et al.,1988).

Parasuraman, Zeithaml, and Berry (1988) conducted empirical studies in several industry sectors to develop and refine SERVQUAL, a multiple-item instrument to quantify customers' global (as opposed to transaction-specific) assessment of a company's service quality. This scale measures service quality along five dimensions: reliability, responsiveness, assurance, empathy, and tangibles. The SERVQUAL framework developed by Parasuraman et al. in 1988 is a method of evaluating service quality for service industries, e.g. a bank, a credit card company, a repair and maintenance firm, and a phone service carrier.

Parasuraman et al. (2005) developed a multiple-item scale (E-S-QUAL) for measuring the website service quality as perceived by online shoppers. The basic E-S-QUAL scale developed in the research is a 22-item scale of four dimensions: efficiency, fulfillment, system availability, and privacy. E-Service quality refers to the evaluation of website design, dependability, security, and customer value of the service offered to ensure that the client finds the best solution (Muhammad et. al, 2015).

According to Petter et al. (2008), service quality is the degree to which a service meets the expectations of customers based upon the quality of the support that system users receive from a provider's support structure. A service-oriented perspective views an organization as a collection of multiple processes with the goal of providing consumers with high-quality service (Lee, Jeoungkun, & Kim, 2007). Jiang et al. (2002) found SERVQUAL a satisfactory instrument for measuring IS service quality. However, researchers argue that a distinction needs to be made between online service quality attributes and traditional service quality attributes (Han et al., 2004; Yang & Jun, 2002). Han et al. (2004) investigated the usefulness and applicability of SERVQUAL in measuring online service quality and its relationships to customer satisfaction and found that the level of service quality has a positive impact on customer satisfaction. Many additional measures have been proposed and used to capture the service quality construct as a whole, including measures that capture the overall "user experience" (see Table 4).

Table 4

Validated Service Quality Measures in Past Research

Item	**Literature Sources**
Assurance	Parasuraman et al. (2005); Pitt et al. (1995), DeLone & McLean (2003), Han et al. (2004)
Empathy	Parasuraman et al. (1988, 2005), Pitt et al. (1995), Han et al. (2004)
Flexibility	Parasuraman et al. (1988, 2005)
Interactivity	Estrada & Romero (2016), Wan (2000), Liu & Arnett (2000)
Privacy	Parasuraman et al. (2005)
Reliability	Pitt et al. (1995), Parasuraman et al. (2005), Han et al. (2004)
Responsiveness	Pitt et al. (1995), DeLone & McLean (2003), Jiang (2002), Han et al. (2004)
User Experience	Aizpurua et al. (2016), Rau, et al. (2015), Boothe et al. (2011)
Web assistance	Zeithaml et al. (2002), Han et al. (2004)

Use

The original DeLone and McLean model (1992) specified the degree of system use as a measure of success and defined system use as the degree and manner in which staff and consumers utilize the capabilities of an information system. As previously mentioned, Seddon (1997) criticized DeLone and McLean's (1992) use construct as ambiguous. Seddon (1997) suggested that system use was not an IS success measure. The author defined system use as using the system for everyday work and tasks purposes. DeLone and McLean (2002) disagreed, arguing that system use should be considered in context, e.g. the extent, nature, quality, and appropriateness of use. DeLone and McLean

(2002) also argued that simply measuring the amount of time a system is in use is not enough; informed and effective use is an important indication of IS success.

Empirical studies have adopted multiple measures of IS use, including intention to use, frequency of use, self-reported use, and actual use (Petter et al., 2008). These different measures could potentially lead to mixed results between use and other constructs in the DeLone and McLean (2003) IS Success Model. For example, heavy users tend to underestimate use, while light users tended to overestimate use. Venkatesh et al. (2003) found a significant relationship between intention to use and actual usage. In addition, frequency of use may not be the best way to measure IS use. Doll and Torkzadeh (1998) suggest that more use is not always better and they developed an instrument to measure use based on the effects of use, rather than by frequency or duration. Many additional measures have been proposed and used to capture the use/intention to use construct (see Table 5).

Table 5

Validated Measures of Use/Intention to Use in Past Research

Item	**Literature Sources**
Actual use	Davis (1989), DeLone & McLean (2003)
Ease of use	Doll & Torkzadeh (1998), Davis (1989)
Daily use	Iivari (2005)
Frequency of use	Iivari (2005), DeLone & McLean (2003), Wu & Wang (2006)
Intention to (re)use	Davis (1989), Wang (2008)
Nature of use	DeLone & McLean (2003)
Navigation patterns	DeLone & McLean (2003)
Number of site visits	DeLone & McLean (2003)
Number of transactions	DeLone & McLean (2003)
Thoroughness	DeLone & McLean (2016)

User Satisfaction

User satisfaction is "the affective attitude towards a specific computer application of someone who interacts with the application directly" (Doll & Torkzadeh, 1988, p. 261). User satisfaction is the most widespread measure of success and researchers have developed and validated different instruments to measure user satisfaction (DeLone & McLean, 1992, 2004; Seddon and Kiew, 1996; Seddon, 1997; Rai et al., 2002; Doll & Torkzadeh, 1988). The most widely used user satisfaction instruments are the Doll et al. (1994) End-User Computing Support (EUCS) instrument and the Ives et al. (1983) User Information Satisfaction (UIS) instrument. Both the EUCS and UIS instruments contain items related to system quality, information quality, and service quality.

According to Doll and Torkzadeh (1988), "user satisfaction" is defined as the opinion of the users about a specific computer application, which they use. Ives et al. (1983) defined "User Information Satisfaction" as "the extent to which users believe the information system available to them meets their information requirements" (p. 785). The authors posited that if a system provides the necessary information, its users will be satisfied. Thus, user satisfaction is a measure that reflects the extent to which users believe that the information provided by the system meets their needs. Seddon and Kiew (1996) observed that user satisfaction is considered the most common measure of IS success.

Xiao et al. (2002) argued that researchers who generally apply the Doll and Torkzadeh (1988) instrument in their studies to measure the extent of user satisfaction assume it is valid and reliable for web-based information systems. However, the authors noted, there are differences between web-based information systems and traditional corporate information systems. For example, with widespread use of the Internet, it is much easier to get access to information that one needs, therefore access may not be an issue for web-based information systems.

Xiao et al. (2002) reviewed the literature in the field of user satisfaction seeking to validate their argument that a distinction be made in measuring user satisfaction in traditional information systems and web-based information systems. After an extensive literature review, the authors decided to adopt the EUCS instrument by Doll and Torkzadeh (1988) and retested the instrument to measure satisfaction in a web-based environment. Xiao et al. (2002) found that with minor revisions, the EUCS instrument by Doll and Torkzadeh (1988) provided a valid measure of user satisfaction. Many additional measures have been proposed and used to capture the user satisfaction construct (see Table 6).

Table 6

Validated Measures of User Satisfaction Used in Past Research

Item	**Literature Sources**
Accuracy	Doll & Torkzadeh, (1988)
Adequacy	Seddon & Yip (1992), Seddon & Kiew (1996), DeLone & McLean (2003)
Content	Doll & Torkzadeh, (1988), Xiao et al. (2002)
Ease of use	Doll & Torkzadeh, (1988), Xiao et al. (2002)
Effectiveness	Seddon & Yip (1992), Seddon & Kiew (1996), DeLone & McLean (2003)
Efficiency	Seddon & Yip (1992), Seddon & Kiew (1996), DeLone & McLean (2003), Doll & Torkzadeh, (1988)
Enjoyment	Gable et al. (2008)
Information satisfaction	Gable et al. (2008), Ives et al. (1983)
Overall satisfaction	Gable et al. (2008), Rai et al. (2002), Seddon & Yip (1992), Seddon & Kiew (1996), DeLone & McLean (2003), Doll & Torkzadeh, (1988)
System satisfaction	Gable et al. (2008), Doll & Torkzadeh, (1988), Ives et al. (1983)
Repeat purchases, repeat visits	DeLone & McLean (2003), Xiao et al. (2002)

Net Benefits/Individual Impact

The original DeLone and McLean (1992) outcome constructs were organizational impact and individual impact. Net benefits replaced both these constructs. According to DeLone and McLean (2003), net benefits is defined as the extent to which information systems contribute to the success of individuals, groups, organizations, industries, and government. For example, improved decision-making, improved productivity, increased sales, cost reductions, improved profits, market efficiency, customer welfare, creation of jobs (Petter et al., 2008) define net benefits at the individual and organizational level of analysis. DeLone and McLean (2003) posit that net benefits is the most important construct since it captures the balance of positive and negative impacts of the information system on customers, suppliers, employees, organizations, markets, industries, economies, and even societies.

When measuring information systems success in terms of net benefits, the objectives of the system, its context, and unit of analysis must be firmly understood (DeLone & McLean, 2003). Because of use and user satisfaction, certain net benefits will occur. If the information system or service is to be continued, it is assumed that the net benefits from the perspective of the owner or sponsor of the system are positive, thus influencing and reinforcing subsequent use and user satisfaction. These feedback loops are still valid, however, even if the net benefits are negative. The lack of positive benefits is likely to lead to decreased use and possible discontinuance of the system.

Empirical studies have adopted multiple measures of net benefits at both the individual and organizational level of analysis. Perceived usefulness or job impact is the most common measure at the individual level (Muhammad, 2015) in an organizational environment. Torkzadeh and Doll (1999) created an instrument to measure different aspects of impact – task productivity, task innovation, customer satisfaction, and management control – to augment their EUCS instrument. However, there has been little consensus on how net benefits should be measured objectively and thus net benefits are usually measured by the perceptions of those who use the information system (Wu & Wang, 2006). The challenge for the researcher is to define clearly and carefully the stakeholders and context in which net benefits are to be measured (DeLone & McLean, 2003). Many additional measures have been proposed and used to capture the net benefits construct (see Table 7).

Table 7

Measures of Net Benefits Used in Past Research

Item	**Literature Sources**
Awareness/Recall	Gable et al. (2008), Sedera & Gable (2004)
Decision effectiveness	Gable et al. (2008), Sedera & Gable (2004)
Individual productivity	Gable et al. (2008), Sedera & Gable (2004), Torkzadeh & Doll (1999)
Job effectiveness	Davis (1989), Iivari (2005)
Job performance	Davis (1989), Iivari (2005)
Job simplification	Davis (1989), Iivari (2005)
Learning	Sedera & Gable (2004), Gable et al. (2008)
Productivity	Davis (1989), Iivari (2005), Torkzadeh & Doll (1999)
Task performance	Davis (1989), Torkzadeh & Doll (1999)
Usefulness	Davis (1989), Iivari (2005)

Gable's IS-Impact Model

Gable and Sedera (2008) introduced the IS-Impact Model, which is based on the DeLone and McLean (2003) model. The IS-Impact model is conceptualized as a formative, multidimensional index, wherein the dimensions have a causal relationship with the overarching measure: IS-Impact. This model differs from other models in various ways. First, it is a measurement model, and not a causal/process model. Second, it does not have a use construct. Third, the overall success measure is satisfaction. Fourth, new measures were added to reflect the IS context and organizational success. The model can be used to measure the complete view of the system and success using all four dimensions (see Figure 10). Gable et al. (2008) define the IS-impact of an Information System (IS) as “a measure at a point in time, of the stream of net benefits from the IS, to date and anticipated, as perceived by all key-user groups” (p. 381).

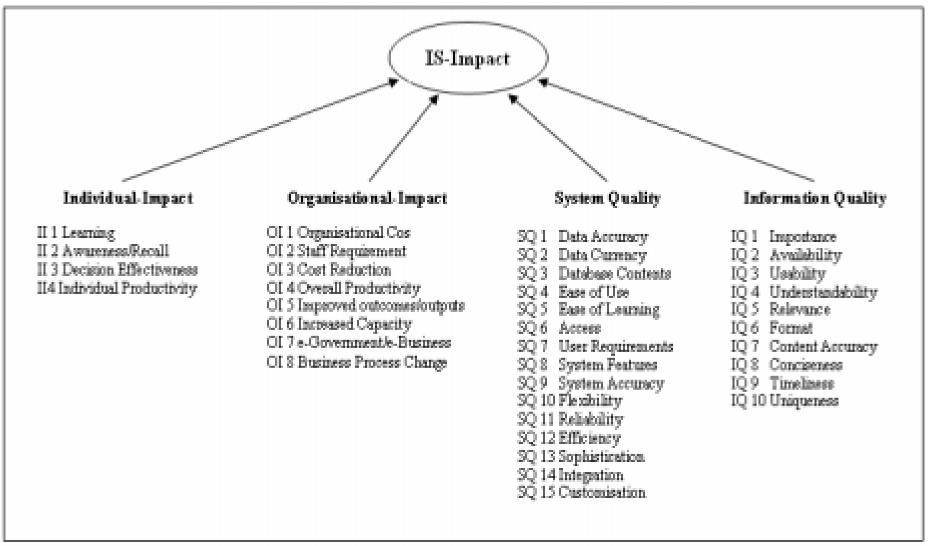

Figure 10. Gable’s IS-Impact Model (2008).

Gable et al. (2008) pointed out that the IS-Impact Model deviates from the traditional DeLone and McLean model in the following ways: (1) it depicts a measurement model and does not purport a causal/process model of success; (2) it omits the use construct; (3) satisfaction is treated as an overall measure of success, rather than as a construct of success; (4) new measures were added to reflect the contemporary IS context and organizational characteristics; and (5) it includes additional measures to probe a more holistic organizational impacts construct.

The DeLone and McLean (2003) IS Success Model is considered the most dominant of the IS success models in use today. Since the DeLone and McLean (1992) IS Success Model was first introduced and published in 1992, researchers have extended the model with more dimensions and relationships, revised the model, examined the relationships, or identified standardized measures to evaluate the specified dimensions. According to Petter et al. (2008), numerous studies have empirically tested and validated the model to improve the understanding of IS success.

Customer-Focused Information Systems Success

DeLone and McLean (2016) posit that IS success is currently in a customer-focused era. In this era, individuals have the potential to receive customized experiences based on their interests, preferences, or roles. In this era, measurement becomes more complex; that is, systems must create value (success) for the customer and the firm concurrently. For customer-facing systems, impact measurement becomes more complex because systems must provide positive "Net Impacts" for the customer as well as for the organization.

As social media, social networking, and peer-to-peer computing as information systems are increasingly used by customers and suppliers, external measures of IS success become more important (DeLone & McLean, 2016). Today the biggest challenges facing IS success measurement is the development of measures that capture the dimension's social value, societal value, and economic value.

Prior methods of evaluating IT success — system, service, and information quality, use, user satisfaction, individual benefits, and organizational impacts — are all still relevant in the customer-focused era, but the context and metrics related to these factors are evolving. As information systems have become more complex, so has the evaluation of the effectiveness or success of those systems. In evaluating the success of an information system, it is paramount to define success based on the context of the information system and its stakeholders (DeLone & McLean, 2016).

Theoretical Background: Energy Management Information Systems

Web portals are a type of information system that provides access to integrated applications and databases and acts as tools that support decision-making. Typically used in a business context, a web portal is a single point of access that provides an aggregated and personalized view of diverse information related to work or personal interests (Al-Debei, Jalal, & Al-Lozi, 2013). A portal's competitive advantage depends on their abilities to filter, target, and categorize information so that users will get only what they need **(**Eckel, 2000). By receiving customized information, users are able to make informed decisions and to be innovative in performing their tasks or achieving their goals.

Energy Management Information System smart meter web portals are designed to offer accurate real-time energy usage data to consumers to affect energy consumption behavior (see Figure 11). Providing utility consumers information about their energy usage is fundamental to energy consumption management. Current EMIS smart meter data includes bill-to-date, bill forecast data, projected month-end tiered rate, a rate calculator, notifications to consumers as they cross rate tiers, detailed personal use patterns of all electrical appliances used by any individual within a customer premise, and information about vehicle charging usage (Chou et al., 2016; NIST, 2012).

Energy usage data is provided via: (1) websites that receive (aggregate or non-aggregate) data from a smart meter and displays consumption information; or (2) a hardware device (e.g. In -Home Display) with a graphical user interface (GUI) that displays consumption information. Information feedback can be in real-time and show current cost, pricing, prior consumption, and an extrapolation of current consumption. The web portal also allows the user to compare energy consumption for a year (comparison of the months), half a year (comparison of the weeks), a month (comparison of the days), or a day (hours) (Chou et al., 2017; Serrenho, Zaugheri, & Bertoldi, 2015; Chen, Delmas, & Kaiser, 2014; Chiang et al., 2014; Fitzpatrick & Smith, 2009).

Energy data can be presented as a cumulative amount for the household or (in some cases) disaggregated by utility or appliance in the form of numeric readouts, graphs, ambient displays, or via the Internet (Feuerriegel et al., 2016; Serrenho et al., 2015; Chen et al., 2014; Chiang et al., 2014; McKenna, Richardson, & Thomson, 2012; Fitzpatrick & Smith, 2009). Figures 11, 12, and 13 show examples of EMIS Smart Meter Web pages for three utilities in the United States.

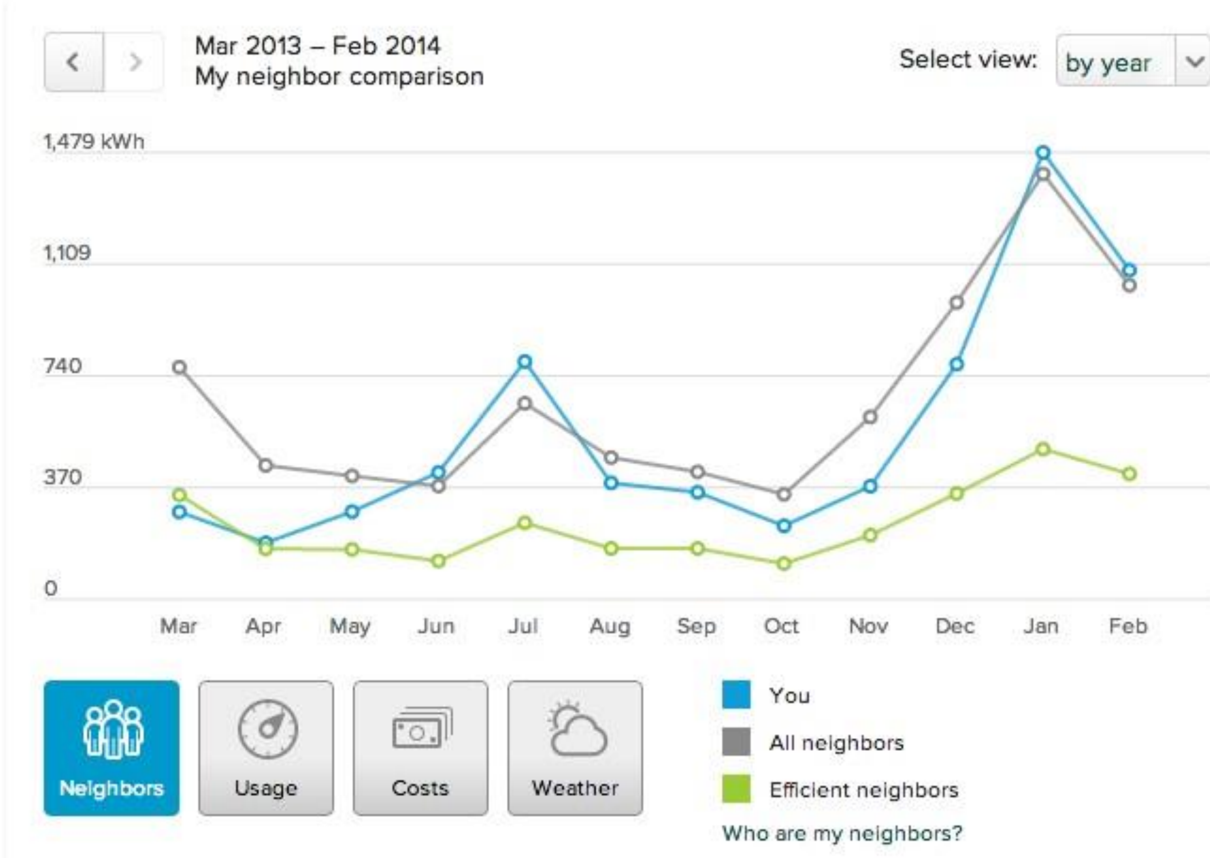

Figure 11. EMIS Smart Meter Web Page. Source: Hawaiian Electric (2016).

Figure 12. EMIS Smart Meter Web Page. Source: Florida Power & Light (2016).

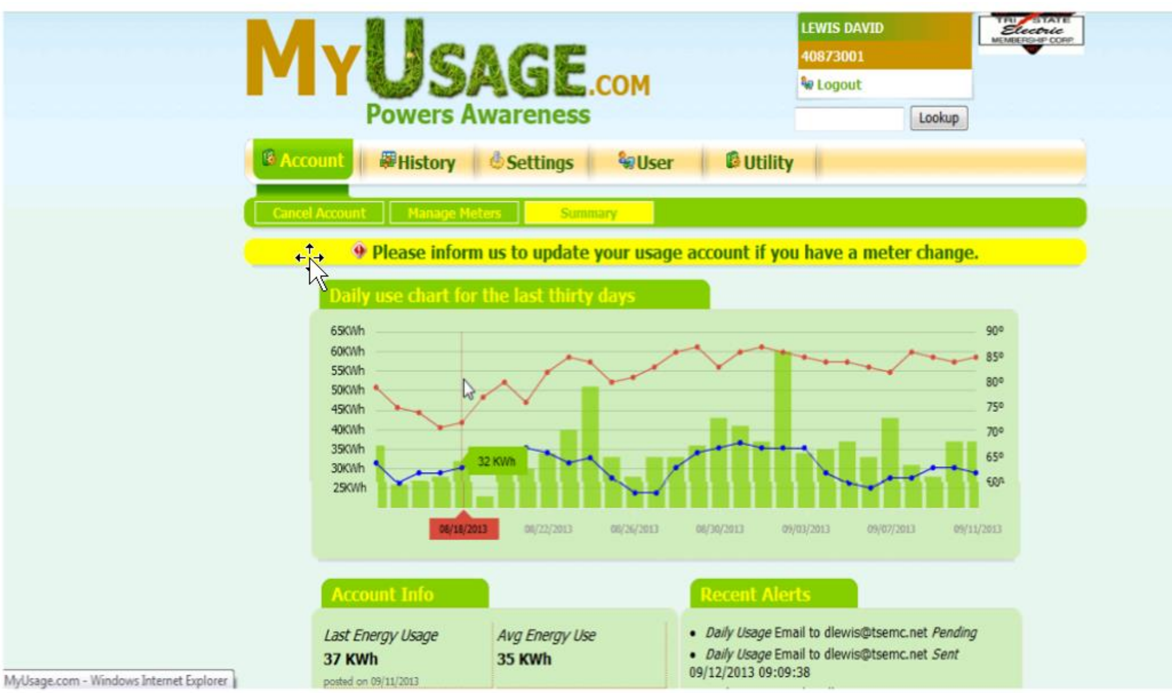

Figure13. EMIS Smart Meter Web Page. Source: Tri-State Electric. DOE (2014b).

Prior energy research work has tended to focus on displays that report aggregated or disaggregated consumption data for an entire household or building. Many utility industry interfaces show aggregated energy data. Research on energy consumer behavior indicate that people are better able to manage their energy consumption when given disaggregated, appliance-by-appliance information instead of aggregated information alone (Fischer, 2008; Schwartz, Stevens, Ramirez, & Wulf, 2013). For example, an individual would find it beneficial to know how much energy their refrigerator used so they could decide whether it would be cost effective to replace it with a more efficient version (Ellegård & Palm, 2011; Kelly & Knottenbelt, 2012). The right information, presented in the right way, will lead people to choose behaviors that will reduce their energy consumption (Arsenio & Delmas, 2015; NIST, 2009).

Asensio and Delmas (2015) found that providing consumers specific, tailored information about the associated environmental and health effects of their electricity consumption could influence and motivate behavioral decision-making about daily electricity use. Jenkins (2014) exported seven months of personal energy data from a smart meter web portal and imported the data into a data analytics software application. The author created line and bar charts to visualize the energy data. The author then analyzed personal household consumption patterns to identify energy consumption and opportunities to improve energy use. Figure 14 presents average weekday electricity consumption for every half-hour period. In the line chart, peaks in consumption in the morning, between 8:00 a.m. and 10:00 a.m., and in the evening, from 6:00 p.m. to 10:00 p.m. is evident.

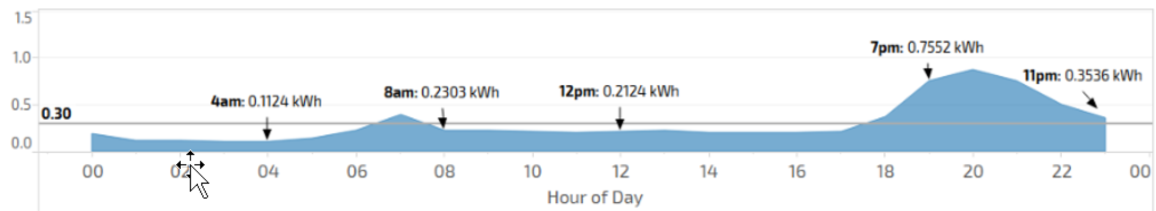

Figure 14. Average Weekday Consumption for Every Half-Hour (kWh). Source: Jenkins (2014).

Jenkins (2014) observed a downward trend in the amount of energy use each day and suggests that by having access to better information, consumers are more likely to make improved decisions about their energy use, helping them to reduce their bills and contribute to carbon emissions reduction. In Figure 15, a bar chart is used to compare total consumption over a seven-month period (March – September).

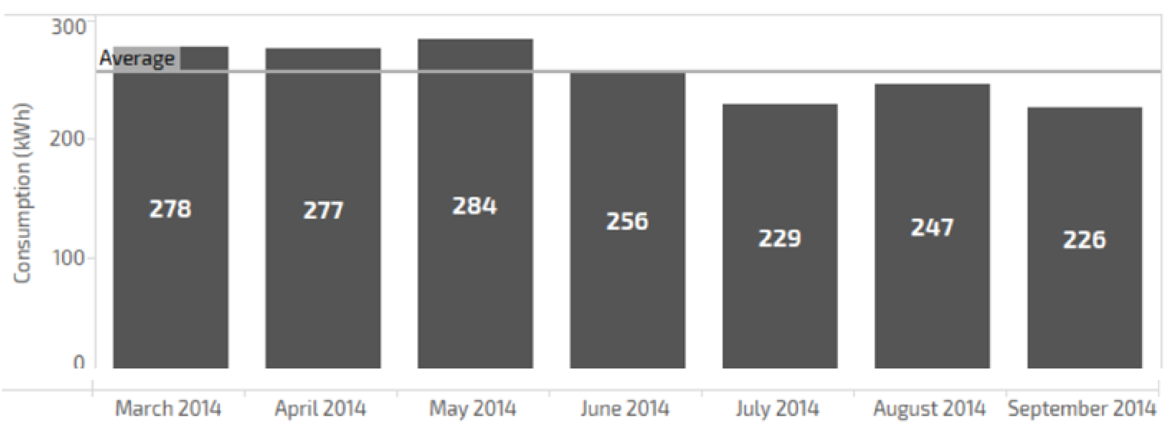

Figure 15. Average Monthly Consumption from March to September. Source: Jenkins (2014).

In the multi-year study regarding desires and expectations of utility customers, OPower found that customers trust their utility—more than the government or third parties—as the source of energy information (Opalka, 2013). When asked to evaluate a number of types of information about energy use, study participants consistently rated personalized, insight-based options as highly valuable, and much more valuable than any other type of information. The study revealed that customers want their utilities to do the hard work of analyzing the data to give them simple, targeted, and actionable takeaways. Prior to 2011, the residential energy consumption data that feeds the EMIS, smart meters, and third-party devices was difficult for the energy consumer to access. In essence, it was extremely difficult for consumers to download their own energy consumption data. In 2011, the United States government implemented the Green Button initiative, which encouraged utilities to provide electricity customers with easy access to their energy usage data via a Green Button on the service provider's website (Zipperer, Aloise-Young, Suryanarayanan, Roche, Earle, Christensen, & Zimmerle, D., 2013).

The California Public Utilities Commission (CPUC) requires utilities implementing a Green Button to: (1) publicly post monthly sum and average zip code level data so that a comparative analysis can be performed; and (2) protect the privacy of utility customers by anonymizing aggregated customer data. The CPUC also requires utilities to set up a "data request web portal" so customers (or Third Parties) can download energy data (Sandoval, 2014). Haaser (2014) suggested that both smart meter web portals and the Green Button portals suffer from a lack of coordination amongst utilities, e.g. no consistent branding and no collaborative customer outreach.

Hartman and LeBlanc (2015) argued that it is too early in the evolution of smart meter portals to determine which elements are critical to driving energy savings. However, the authors identified nine elements of successful smart meter data portals. These options include: (1) bill payment; (2) energy-saving and budget goals; (3) energy-usage patterns; (4) high-usage alerts; (5) disaggregated usage by appliance; (6) comparisons over a variety of time periods; (7) comparisons with peers; (8) entry into contests and sweepstakes; and (9) gaming.

In addition, the ability to push data to customers rather than expecting them to log in to view their information is critical (Hartman & LeBlanc, 2015). Studies indicate that most customers spend fewer than six minutes per year thinking about energy, making it unlikely that the majority of users will log in to energy-usage portals without a compelling reason to do so (Collier, 2013). The key to customer engagement in smart meter data is presenting this information effectively by using portals that are compelling, actionable, and available to people on the communications channels they prefer to use (Hartman & LeBlanc, 2015).

What constitutes a good user interface? Shneiderman et al., (2017) suggest that a system that can achieve the required reliability of person–computer combinations (e.g. reliability, availability, security, and data integrity) can result in a dramatic difference in user acceptance. Energy portals can lose their effectiveness if they fail to keep customers actively engaged in information. Maintaining this connection requires that portals regularly push out information that people care about in a simple, compelling format on communication channels that they are already using. For example, receiving a short text message alert when the utility bill is due is valuable information for a customer, especially if that message contains a link to the customer’s account login page.

Smart Meter Web Portals

Ma et al. (2017) compared the impact of an eco-feedback system on building occupants with different cultural backgrounds using a smart meter based web portal. Using an experimental design, the authors developed a system that included a data capture component, data processing, and a delivery component (as shown in Figure 16).

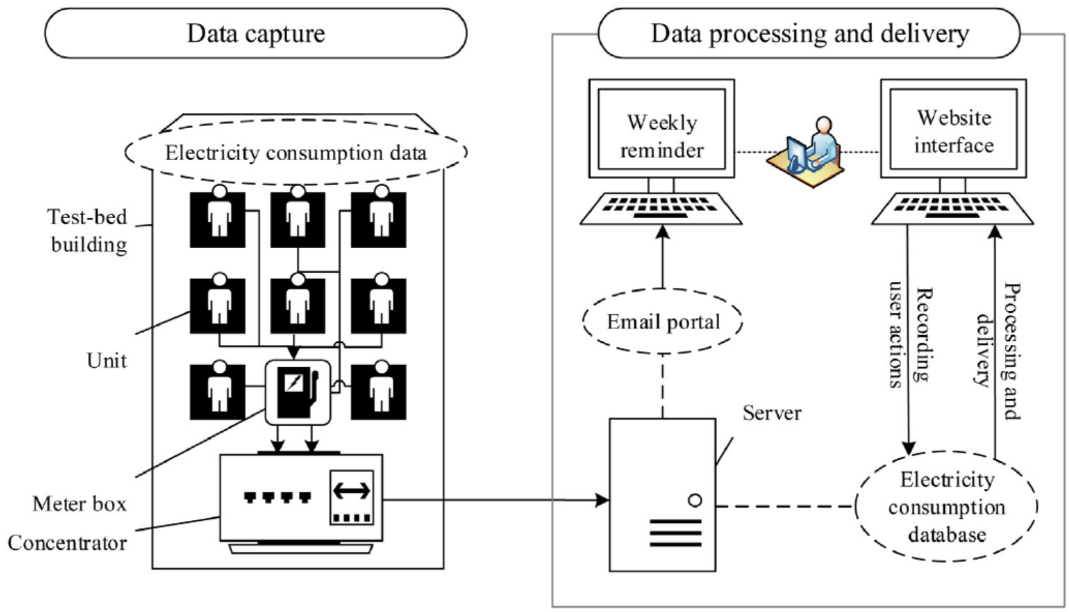

Figure 16. Architecture of the Eco-Feedback System. Source: (Ma et al., 2017).

The data capture component included electric meters, concentrators, and cables. Electric meters, each responsible for monitoring one unit in a building, were connected to a concentrator through cables in each building. The concentrators reported to a server to upload the last readings of energy consumption. The server saved raw energy consumption data on a daily basis in a MySQL database, where the data were analyzed and prepared for delivery to building occupants. The delivery component was composed of an interface website that allowed for online access to eco-feedback information, and an email portal for sending automatic weekly emails to the occupants reminding them of checking eco-feedback information through the smart meter web portal (see Figure 17).

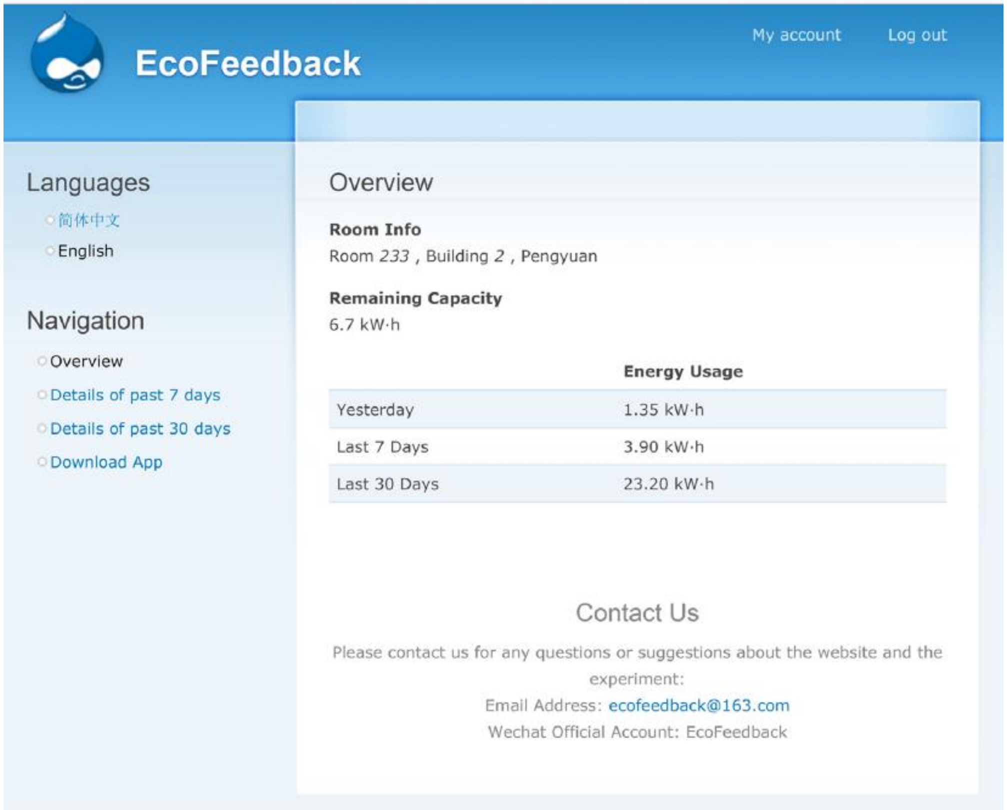

Figure 17. Eco-Feedback Website Interface. Source: (Ma et al., 2017).

Energy consumption information included charts of the occupant's daily energy consumption and previous historical consumption, as well as peer energy consumption data. A list of navigation options, including reviewing the charts, changing display language, and changing account settings were also presented. Energy consumption data collected in the experiment showed that participants from different countries had statistically different behavioral responses to eco-feedback, measured in both daily and cumulative changes of their energy consumption. The results implied that the effectiveness of eco-feedback via a smart meter web portal was dependent on the cultural background of the occupants. To improve their effectiveness in energy conservation, smart meter web portals would require a certain degree of adaptation to the cultural context in which they are implemented (Ma et al., 2017).

Using a smart meter web portal, Bager and Mundaca (2017) explored the potential to induce household energy conservation when salient information is framed as a monetary loss. Taking a behavioral economics perspective, their results suggested that how smart meter information is presented to households has an impact on how the feedback is perceived and acted upon. The experiment had users access consumption information using software installed on their smartphones, tablets, or computers. The reference group received 'standard smart meter' consumption information given in kilowatt-hours (kWh) and Danish Krone (DKK) on an hourly, daily, weekly, monthly, or yearly basis. This information was unframed; the cost of electricity for a day, month and year was simply stated.

The intervention group received the same data, but the information was framed as a salient loss by its presentation in the web portal, which read: "Money lost from electricity consumption" followed by the monetary value. The smart meter web portal displayed the amount spent per day as a running total; this figure was updated every few seconds and reset every day, meaning that it looked like money was flowing out of users' pockets. Estimated weekly cost was updated every 15 min, and consumption data was updated daily. The results revealed that the provision of monetary loss-framed, salient information reduced daily demand by 7–11%, compared to unframed information (Bager & Mundaca, 2017), which had little impact.

Ghazal et al. (2016) collected energy consumption data via a smart plug system. The authors developed a smart plug system consisting of a wireless sensor network interfaced with a mobile application that provided users real-time access to energy consumption information via a smartphone. The smartphone app allowed end users to control consumption by turning on or off loads to devices plugged into an experimental smart plug system (see Figure 18).

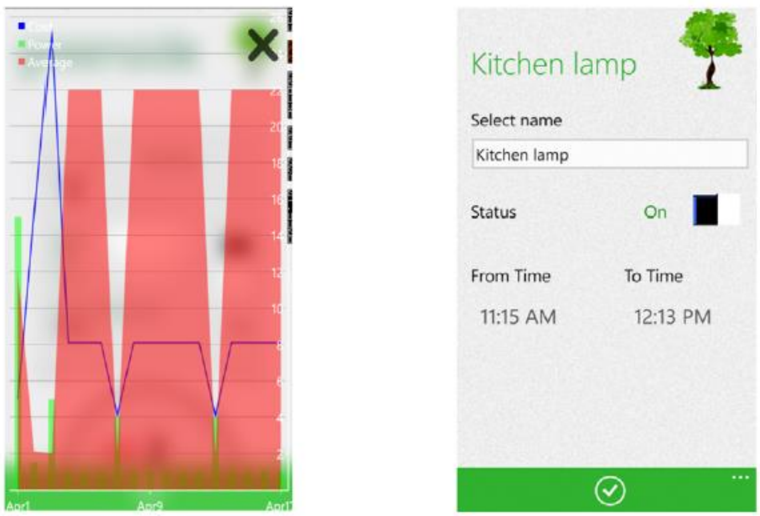

Figure 18. Smart Plug Mobile Application. Source: (Ghazal et al., 2016).

Ghazal et al. (2016) examined the IS constructs of perceived usefulness and user satisfaction as dependent, endogenous variables. Information quality and app usefulness were independent, exogeneous variables. Information quality had a positive and highly significant effect on app usefulness. However, information quality’s direct effect on perceived satisfaction was not significant. The construct environmental concerns had a positive significant effect on perceived usefulness and satisfaction with the system.

Chou et al. (2016) developed a web-based portal that served as the interface layer in an energy-saving smart decision support system (SDSS) framework. Through the identification of consumer usage patterns, the SDSS was expected to enhance energy use efficiency and improve the accuracy of future energy demand estimates using a forecasting model based on historical data. According to the authors, the system would support reduce electricity costs by providing: (1) real-time electricity consumption; (2) monthly consumption records; (3) monthly comparisons; (4) maximum, average, and minimum consumption; (5) consumption forecasts for the current month and the resulting expenditure; (6) alternative operation schedules for home appliances with optimal electricity costs; and (7) the electricity cost saved by using alternative operation schedules.

Al-Debei et al. (2013) investigated the use of web portals in improving job performance at the individual level from the perspective of employees as users. The authors' research was deemed significant as they identified the functions and features of portals and then linked these functions and features to portal quality factors: system quality, information quality, and service quality.

Measuring the Success of Smart Meter Web Portals

To synthesize and cluster the related literature aiming to define and classify the main functions and features of portals, Al-Debei et al. (2013) identified seven portal components:

1. *Content management and tailorability*, which provides users with the ability to adjust and tailor accessed data based on a users' specific requirements and preferences.
2. *Integration*, which aims at bringing, harmonizing and synchronizing data existing in different formats in incompatible applications all together, and then presenting it on a unified interface (i.e., the portal).

3. *Security*, which provides users with a secure access to a diverse range of resources.
4. *Searchability*, which allows users to retrieve required information directly by using search engines, instead of browsing through the different information categories.
5. *Collaboration*, which provides users with collaborative tools needed to enforce and optimize work and process collaboration inside and outside the organization.
6. *Scalability,* which describes the capability of the system to cope and perform under an increasing or expanding workload.
7. *Accessibility,* which describes the ability to access the system from anywhere at any time.

Numerous utility service provider EMIS smart meters provide energy usage data – all with different specifications, functionalities, and interfaces. Numerous design choices exist for both virtual (mobile and web-based) and physical products, yet there are no industry-specific standards from which to choose (Fitzpatrick & Smith, 2009). Customer engagement in EMIS smart meter data is critical. With customer engagement, smart meter data is key to fulfilling the opportunities of the smart grid by enabling utility customers to manage their energy consumption (Pasini, 2017; Orfanedes et al., 2016).

Fan et al. (2017) argued that EMIS systems that offer energy visualizations in the home may lack customer engagement: (1) the visual data is simple so as to make it difficult to personalize the applications; (2) the lack of intelligent data analysis and recommendations results in poor user experience; and (3) the ability to download personal energy data and use it to connect with a third-party system was too difficult.

There is also a lack of standardization of display types and interfaces, since every vendor or utility service provider has developed their own physical and/or web-based interface. As such, there are no agreed upon design principles amongst utility service providers and utility equipment vendors who manufacture energy feedback products. Interface design quality relates to the virtual manifestation of the data via a channel option (e.g. email, mobile, or web-based interface) and how energy data is displayed in the EMIS interface (e.g. formats, colors, and graphs versus tables to illustrate kWh).

Utility customers need effective EMIS web portals to encourage reduced energy consumption. These web portals must have a high degree of perceived system quality, information quality, and service quality to increase utility customer use and satisfaction, which will lead to improved decision-making behavior and reduced energy costs. Measuring the influence of quality factors is critical to gauging the success of an Energy Management Information System. Following the massive investment that utilities have made in EMIS smart meter installations, engaging customers in the data with effective energy-usage portals is essential (Hartman & LeBlanc, 2015).

Summary

This chapter presented the literature on utility customer energy behavior, IS success models, and Energy Management Information Systems. The relationship between energy, technology, and customer behavior is complex and multi-faceted (Burgess & Nye, 2008; Harland, Staats, & Wilke, 1999). Interventions act as technological tools to inform and persuade energy consumers to change behavior. EMIS are information systems designed to influence human beliefs and behaviors by aiding decision-making.

There are numerous information system success definitions (e.g. improved decision-making, individual or organizational performance, increased productivity, cost reductions, user acceptance or user satisfaction), and a variety of models (e.g. Zmud's Individual Differences Model (1979), Ives and Olson’s User Involvement Success Model (1984), Doll and Torkzadeh’s (1988) End-User Computing Satisfaction Model, Davis’ Technology Acceptance Model (1989), DeLone and McLean’s IS success models (1992, 2003), and Gable’s IS-Impact Model (2008).

Numerous empirical studies have utilized the DeLone and McLean (1992, 2003) IS Success Models to evaluate the success of various types of information systems, such as web-based portals (Urbach et al., 2010), government to citizen (G2C) e-government systems (Wang & Liao, 2008), e-commerce (Molla & Licker, 2001), decision support systems (Manchanda et al., 2014); knowledge management systems (Wu & Wang, 2006), and mobile banking systems (Lee et al., 2009).

DeLone and McLean (2003) proposed six dimensions of Information Systems success (e.g. system quality, information quality, service quality, use/intention to use, user satisfaction, and net benefits). Numerous studies have empirically tested these dimensions. Researchers have extended the DeLone and McLean (2003) IS Success Model with more dimensions and relationships, revised them, examined the relationships or identified standardized measures to evaluate the specified dimensions (Petter, DeLone, & McLean, 2008). Yet, in a review of the literature, no empirical research on the use of the DeLone and McLean (2003) IS Success Model to assess Energy Management Information System success was found. The literature search also indicated that there is a general scarcity of models and frameworks for measuring EMIS success.

Research studies that have empirically tested the DeLone and McLean (1992, 2003) IS Success Models have typically focused on a single part of success - such as information quality or user satisfaction or service quality as a dependent variable (Petter et al., 2008). In a review of the IS success literature, no study aimed specifically at comprehensively examining the success of an Energy Management Information System utilizing all the DeLone and McLean (1992, 2003) success constructs was found.

DeLone and McLean (2003) advised that IS success dimensions be framed by context - where the level of analysis is situational and contextual. In a review of the literature, no documented empirical research using the complete DeLone and McLean (2003) IS Success Model in an Energy Management Information System context at the individual level of analysis was found. Although customer-facing EMIS are now widespread, there is no known comprehensive, integrated theoretical framework for measuring the quality factors that contribute to EMIS success. Therefore, there is a need for empirical studies to assess the quality factors that influence EMIS success.

Chapter 3

Methodology

Introduction

In this chapter, the methodology for the study is presented. This chapter begins with an overview of the research methods, which describes the research questions, hypotheses, and the theoretical model. This is followed by instrument development, population, the data collection methods, and an explanation of the statistical data analysis used for the study.

Approach

This quantitative study used PLS-SEM to validate the DeLone and McLean (2003) IS Success Model to the context of an EMIS smart meter web portal. An online questionnaire was used to collect responses regarding the overall use of the system, user satisfaction with the system, and any derived net benefits.

Research Questions and Hypotheses

Three research questions framed this empirical quantitative study.

1. To what degree do information quality, system quality, and service quality influence EMIS use?
2. To what degree do information quality, system quality, and service quality influence user satisfaction with an EMIS?
3. To what degree do EMIS use and user satisfaction benefit utility customers in managing their energy consumption?

Based on the research questions, the following hypotheses were proposed.

H_1: System quality will positively affect use.

H_2: System quality will positively affect user satisfaction.

H_3: Information quality will positively affect use.

H_4: Information quality will positively affect user satisfaction.

H_5: Service quality will positively affect use.

H_6: Service quality will positively affect user satisfaction.

H_7: Use will positively affect perceived net benefits.

H_8: User satisfaction will positively affect perceived net benefits.

Theoretical Model

The objective of this study was to identify the determinants of EMIS success. The relationship between the constructs were examined to understand the effect on the dependent variable net benefits. The approach to this study is depicted in Figure 19.

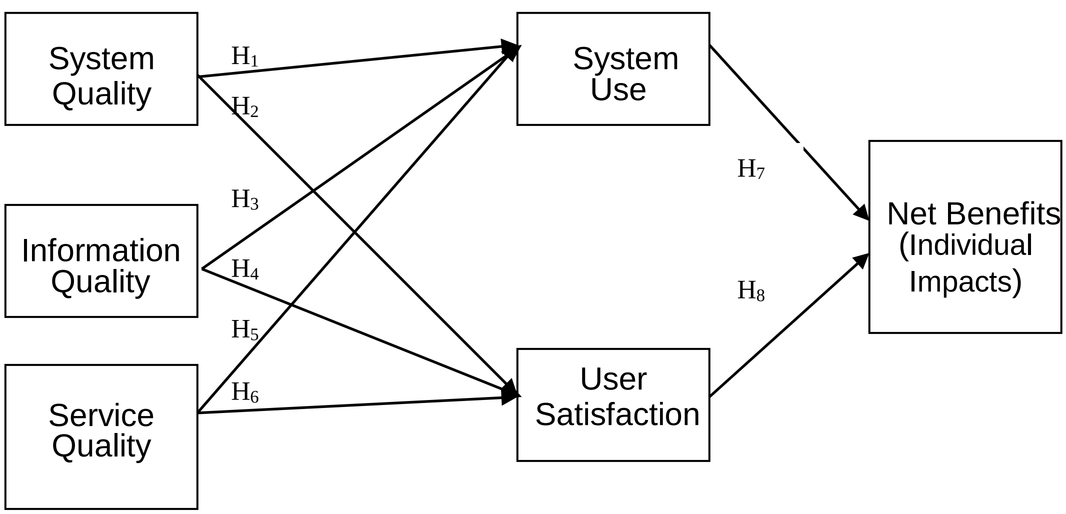

Figure 19. Research Model.

The dependent variables in this study are system use, user satisfaction, and net benefits. The independent variables are system quality, information quality, and service quality.

Instrumentation

Several factors determine the best data collection strategy for a research study. Surveys and experiments are more suitable for collecting quantitative data whereas in-depth interviews and participant observations may be more suitable for collecting qualitative data (Oates, 2006). The idea of using a research survey is to generalize from a sample to a population so inferences can be made about characteristic, attitude, or behavior of the population (Babbie, 1990). Oates (2006) observed that experiments are not often feasible for Information Systems research, thus surveys are widely accepted and used in the Information Systems field for empirical research.

Depending on the target population, web-based surveys are more accessible, are easier to complete, and are less time consuming for the respondent; the researcher can benefit from faster response rates and easier data collection and analysis due to automatic coding (Kiernan, Kiernan, Oyler, & Gilles, 2005). Online survey methods have some disadvantages. These disadvantages can include uncertainty over the validity of the data and sampling, as well as issues regarding design, implementation, and evaluation. The disadvantages from a respondent perspective include requiring computer literacy and access to Internet services. Since the goal of this research was to assess the effectiveness of an online EMIS, an online survey was an appropriate match with the target population. Respondents without Internet service could access the survey via a web browser on a cell phone.

The survey used a Likert scale to measure utility customer's perceptions of system quality, information quality, service quality, use, user satisfaction, and net benefits. The survey required respondents to indicate to what extent they agreed or disagreed with statements on a five-point Likert scale. The primary purpose of a Likert scale was to obtain the ideas, opinions, beliefs, and attitudes of the users towards the EMIS smart meter web portal.

A review by Krosnick and Fabrigar (1997) found that scales between five- and seven-points were more reliable than scales with fewer points or more points. A higher point Likert scale increases the time required for the survey respondent to discriminate between the different options. In addition, with a five-point scale, there is "centering," giving the respondent a neutral opinion option. Krosnick and Fabrigar (1997) suggested that a five-point scale appears to be less confusing and increases response rates. Therefore, a five-point Likert scale was used in the survey.

The selection of measures and constructs was based on a review of the literature on measurement of IS success. The technological factors (i.e., system quality, information quality, and service quality) and the social/human factors (i.e., usefulness, user satisfaction, and perceived net benefits) were practical constructs for measuring the success of smart meter web portals. To ensure the content validity of the scales proposed in the research study, the items chosen for the constructs are from previous IS studies reviewed in the literature. Thus, the researcher adapted validated scales from existing literature where psychometric properties have already been established.

In the context of an EMIS smart meter web portal, an effective portal must be accessible and provide relevant functions to support tasks performed by the utility customer. System quality was measured as ease of use, response time, privacy, and functionality. DeLone and McLean (2016) contend that privacy (security) is a system quality dimension and not a service quality dimension. In the context of an EMIS, privacy was measured as a system quality construct. Providing utility consumers information about their energy usage is a primary factor in energy consumption behavior. In the context of an EMIS, information quality was measured as data format, data accuracy, understandability, and relevancy.

Service quality was measured as web assistance, reliability, and interactivity. Web assistance was measured as the ability of the EMIS web portal to offer online help. Reliability was measured as the expectation that the portal will provide energy information. Interactivity means that the site will respond to the user's commands, such as clicking, typing, drag and dropping, or any other action done by the user to manipulate the website. In this case, the primary measure of interactivity is the ability to download energy data via the Green Button.

In the context of an EMIS smart meter web portal, use was measured as the nature of use and appropriateness of use. The nature of use was measured as using the portal to obtain information about home energy use while appropriateness of use was measured as using the portal to understand energy terms. User satisfaction was measured as overall satisfaction and system satisfaction, e.g. the degree of satisfaction and continued use. The net impacts (benefits) construct measures the system’s outcomes and is therefore inevitably compared to the system’s purpose. For this reason, the net impacts construct is the most contextual dependent and varied of the six success dimensions (DeLone & McLean, 2016). Net benefits was measured as decision effectiveness, learning, and usefulness. Measures used in the study are presented in Table 8.

Table 8

Measures used in study.

Construct		**Measures**
System Quality	Ease of use	Doll & Torkzadeh (1988), Gable et al. (2008), McKinney et al. (2002), Sedera & Gable (2004), Seddon & Kiew (1996), Davis (1989)
	Response time	Bailey & Pearson (1983), DeLone & McLean (2003)
	Privacy	DeLone & McLean (2016), Parasuraman et al. (2005); (Molla & Licker 2001)
	Functionality	Estrada & Romero (2016), DeLone & McLean (2016)
Information Quality	Format	Gable et al. (2008), Iivari (2005), Sedera & Gable (2004), Doll & Torkzadeh (1988)
	Accuracy	Bailey & Pearson (1983), Gable et al. (2008), Iivari (2005), Doll & Torkzadeh (1988), DeLone & McLean (2003), Seddon & Kiew (1996)
	Understandability	Gable et al. (2008), McKinney et al. (2002), Sedera & Gable (2004), Bailey & Pearson (1983)
	Relevance	Seddon & Kiew (1996), Gable et al. (2008), McKinney et al. (2002), Sedera & Gable (2004), DeLone & McLean (2003)
Service Quality	Web assistance	Zeithaml et al. (2002), Han et al. (2004)
	Reliability	Pitt et al. (1995), Parasuraman et al. (2005), Han et al. (2004)
	Interactivity	Estrada & Romero (2016), Wan (2000), Liu & Arnett (2000)
Use	Nature of use	DeLone & McLean (2003); DeLone & McLean (2016)
	Appropriateness	DeLone & McLean (2016)

Table 8 *(Continued)*

Construct		Measures
User Satisfaction	Overall satisfaction	Gable et al. (2008), Rai et al. (2002), Seddon & Yip (1992), Seddon & Kiew (1996), DeLone & McLean (2003), Doll & Torkzadeh, (1988)
	System satisfaction	Gable et al. (2008), Doll & Torkzadeh, (1988), Ives et al. (1983)
Net Benefits	Decision effectiveness	Gable et al. (2008), Sedera & Gable (2004)
	Learning	Sedera & Gable (2004), Gable et al. (2008)
	Usefulness	Davis (1989), Iivari (2005)

Population and Sample

The population of all utility customers in California is too large to study in its entirety. Therefore, a sampling of the population was employed to draw conclusions about the larger group. This research study relied on random sampling, snowball sampling, and network sampling as an approach for the collection of responses from participants. The target population for this study includes individuals who are residential utility customers in the Pacific Gas & Electric (PG&E) service area in the State of California. The unit of analysis focuses on what or who is being studied, across some spatio-temporal extent (Babbie, 1989).

This was a cross-sectional study of a population of utility customers who may use the PG&E EMIS smart meter web portal. The sampling frame for this research were individuals who were residential utility customers in the Pacific Gas & Electric

California service area. The study did not include households enrolled in Pacific Gas & Electric's California Alternate Rates for Energy (CARE) or the Pacific Gas & Electric's Family Electric Rate Assistance (FERA) program, which gives utility discounts to qualified households with limited income. The survey included two "yes" or "no" filter questions on the CARE and FERA programs. No respondents answered "yes".

Sample size was based on the recommendations when using PLS-SEM for data analysis. Sample size requirements for PLS-SEM vary among research studies. Hair et al. (2011) and Urbach and Ahlemann (2010) both recommend at least 10 times the greatest number of constructs leading to a single variable in the model. Sekaran (2003) notes that sample sizes larger than 30 and less than 500 are appropriate for most research.

Although PLS-SEM is well known for its capability in handling small sample sizes, it does not mean the goal should be merely to fulfill the minimum sample size requirement. Prior IS research suggests that a sample size of 100 to 200 is usually a good starting point in carrying out path modeling (Chin, 1998). A rule of thumb for the required sample size in PLS-SEM is that the sample should be at least 10 times the number of independent variables in the most complicated multiple regression of the model (Wong, 2013). Three independent variables were used in this study. The original sample size of the dataset was 135. The sample size fell to 126 after removing the cases with missing values, which still met the criteria for PLS-SEM analysis.

Data Collection

Pilot Survey

Following the recommendations of van Teijlingen and Hundley (2001), a pilot study was conducted with representatives of the target population to test the overall quality of the survey. The researcher sent an email invitation using SurveyMonkey to five participants clarifying the purpose of the pilot survey. The screening process did not show any major functional issues with the survey instrument. Based upon feedback from the pilot study participants, formatting and presentation improvements were made. To improve readability, the survey was divided into one page per question. Pilot data was not included with the main study data due to possible contamination.

Survey Administration

SurveyMonkey was used to develop the online survey instrument, which included the consent form. SurveyMonkey was then granted permission to begin solicitation. SurveyMonkey selected random members of their panel using the Invite Algorithm to participate in the survey. Members of the panel receiving the email link had the opportunity to participate or decline to participate. Those individuals choosing to participate clicked on the link provided in the email to access the survey. In addition, the researcher used social media and email to elicit responses. NextDoor Crocker Highlands, LinkedIn, and email was used to obtain the requisite respondent minimum. Email messages and social media posts were posted at intervals when responses decreased to remind possible participants to complete the survey. One hundred and thirty-five responses of survey data were collected. The data files with survey responses was downloaded as a Microsoft Excel file onto the researcher's computer on June 25th, 2017. After data screening, sample size was reduced to 126 respondents.

Data Preparation and Screening

The following data preparation and screening procedures were conducted prior to data analysis. Processing (non-sampling) errors were mitigated due to the nature of survey administration. Processing errors occur where data are incorrectly recorded or incorrectly transferred from recording forms, such as from questionnaires to computer files. SurveyMonkey administration permitted downloading survey responses into Microsoft Excel or a comma separated file format. Therefore, the process of transformation of collected responses to computer files was mitigated, which removed the possibility of processing errors being introduced.

After data collection, the survey data was exported from SurveyMonkey into a Microsoft Excel file and saved in a *.xlsx format. The data set was converted from the *.xlsx format to a .csv (Comma Delimited) file format for import into SmartPLS 3.2.6. The raw data file was then imported into SmartPLS 3.2.6 with the item indicators placed in the first row of the dataset separated by commas. The data was screened for missing values, suspicious response patterns, outliers, and data distribution (Hair et al., 2014).

The screening process revealed missing values. To explain the incomplete cases, a missing value analysis procedure was conducted using SmartPLS 3.2.6. Little's Missing Completely at Random (MCAR) test was used to assess the presence of random missing values (Little, 1988). A significant Little's MCAR test implies that missing values do not occur at random. If there is a missing value in the dataset, PLS-SEM allows the researcher to choose

"Mean Value Replacement" rather than "Case Wise Deletion," as it is the recommended option for PLS-SEM (Wong, 2013). A mean-replacement was selected to replace missing values, e.g. the missing values are replaced with the mean of their associated item values.

Data analysis using Structural Equation Modeling Approach

This study applied PLS-SEM to validate the study constructs and test the hypotheses. The PLS-SEM technique is based on a combination of principal component analysis and regression analysis, with the main aim of explaining the variance of the constructs of the model (Chin, 1998). PLS-SEM can simultaneously evaluate the measurement model (the relationships between constructs and their corresponding indicators), and the structural model (the relationship among constructs) with the aim to minimize error variance (Petter et al., 2007; Wong, 2013; Hair et al., 2011; Davcik, 2014).

PLS-SEM generates loadings between reflective constructs and their indicators, standardize regression coefficients between constructs, and coefficients of multiple determination (R^2) for dependent variables (Davcik, 2014). PLS-SEM has been deployed in numerous Management Information Systems research studies (Gefen & Straub, 2000; Chin et al., 2003; Petter et al., 2007; Urbach et al., 2010; Alshehri et al., 2012). Petter et al. (2007) observed that reflective constructs are used throughout the information systems literature for concepts such as perceived ease of use, perceived usefulness, and satisfaction. Such reflective constructs have observed measures that are affected by an underlying latent, unobservable construct. When measures are used to examine an underlying construct that is unobservable (i.e., a latent variable), the measures can be referred to as reflective indicators or effect indicators (Davcik, 2014). The unobservable construct, which consists of the reflective indicators and the error term for each indicator, is called a reflective construct (Petter et al., 2007).

There are two sub-models in a structural equation model: (1) the inner model specifies the relationships between the independent and dependent latent variables; and (2) the outer model specifies the relationships between the latent variables and their observed indicators. The inner model is also known as a structural model; the outer model is known as a measurement model. The measurement model shows the relations between the latent variables and their indicators, and the structural model shows the potential causal dependencies between endogenous and exogenous variables (Chin et al., 2003; Haenlein & Kaplan, 2004). In SEM, a variable is either exogenous or endogenous. An exogenous variable has path arrows pointing outwards and none leading to it. An endogenous variable has at least one path leading to it and represents the effects of another variable(s).

The research model for data analysis was created using SmartPLS 3.2.6. In a PLS-SEM model, no circular relationships, causal loops, or otherwise recursive relationships (Hair et al., 2014) should exist. Figure 20 depicts the structural model used to test the impact of IS success quality factors on net benefits. This model consists of three exogenous constructs – system quality, information quality, and service quality, and three endogeneous constructs – use, satisfaction, and net benefits. All six constructs were measured by means of multiple indicators. Paths from the exogenous variables to the endogenous variables provided a platform for analysis to determine support for the hypotheses. A positive relationship was expected for each of the outlined paths.

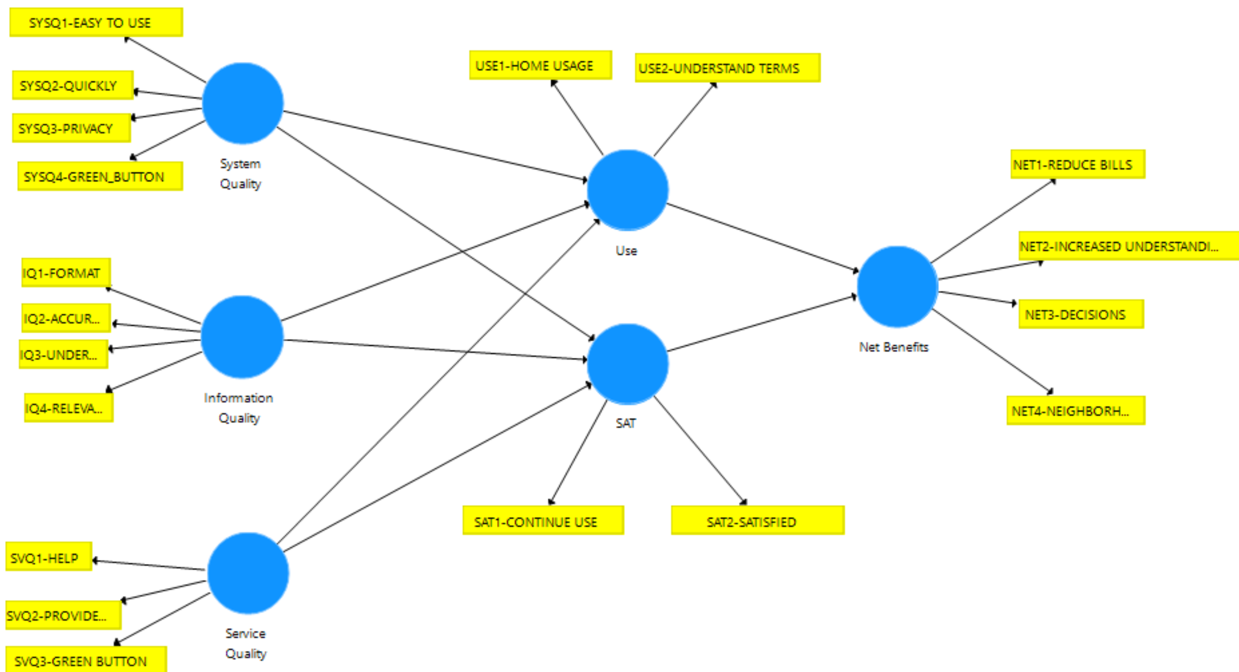

Figure 20. EMIS Model.

It is important to note that PLS-SEM is not appropriate for all kinds of statistical analysis. Wong (2013) notes that researchers need to be aware of some weaknesses of PLS-SEM, including: (1) the need for high-valued structural path coefficients if the sample size is small; (2) the creation of large mean square errors in the estimation of path coefficient loading; (3) the potential lack of complete consistency in scores on latent variables, which may result in biased component estimation, loadings, and path coefficients; and (4) the problem of multicollinearity - if not handled well (Wong, 2013).

Multicollinearity exists when two or more of the predictors in a regression model are moderately or highly correlated, e.g. meaning predictor variables are correlated with each other, making it harder to determine the role each of the correlated variables is playing. This means that mathematically, the standard errors are increased. Multicollinearity occurs when there are high correlations among predictor variables, leading to unreliable and unstable estimates of regression coefficients.

Multicollinearity can limit the research conclusions that can be drawn. Allison (1999) argues that moderate multicollinearity may not be problematic. However, severe multicollinearity is a problem as it can increase the variance of the coefficient estimates and make the estimates highly sensitive to minor changes in the model. The result is that the coefficient estimates are unstable and difficult to interpret. Multicollinearity reduces the statistical power of the analysis, can cause the coefficients to switch signs, and makes it more difficult to specify the correct model.

Despite the limitations mentioned above, PLS-SEM was appropriate for structural equation modeling in the current research study. As Petter et al. (2007) observed, with the increasing popularity of SEM techniques, information systems researchers can examine measurement and structural models simultaneously.

A PLS-SEM analysis involves two stages (Chin., et al., 2003): (1) the assessment of the measurement model, including the individual item reliability, internal consistency, and discriminant validity of the measures; and (2) the assessment of the structural model to test the research hypotheses and the suitability of the model. As previously mentioned, the measurement model describes how each construct is measured by corresponding manifest indicators, whereas the structural model shows how the latent variables are related to each other - it shows the constructs and the path relationships between them in the structural model.

Assessment of the Measurement Model

A two-stage approach was employed to test the validity of the measurement (outer) and structural (inner) model. A two-stage analysis ensures the reliability of the measurement items of each construct and avoids any interaction between the measurement and structural model. It also ensures that instrument reliability and construct validity is adequate before analyzing the path coefficients. The first stage of the analysis specified the causal link between the manifest variables (measurement items) and its underlying latent variables in the outer model. Thus, the measurement model was analyzed first on item reliability and validity prior to analyzing the relationships proposed in the structural model. The adequacy of the measurement model was assessed using individual item reliability analysis (indicator reliability), convergent validity, and discriminant validity of the measurement instrument following the validation guidelines suggested by Hair et al. (2014).

Measurement Model

Multicollinearity: Each set of predictors in the structural model was examined for multicollinearity. As previously mentioned, multicollinearity arises when two indicators are highly correlated. Multicollinearity does not affect how well the model fits. If the model satisfies the residual assumptions and has a satisfactory predicted R^2, even a model with severe multicollinearity can produce acceptable predictions. The variance inflation factor (VIF), defined as the degree to which the standard error has been increased due to the presence of collinearity, was used to diagnose multicollinearity. After collinearity assessment, the adequacy of the measurement model was evaluated.

Internal Consistency Reliability: Assessment instruments must be both reliable and valid for study results to be credible. Reliability is defined as the degree of stability exhibited when a measurement is repeated under identical conditions. Does the instrument consistently measure what it is intended to measure? Reliability refers to whether an assessment instrument yields the same results each time it is used in the same setting with the same type of subjects. Reliability essentially means consistent or dependable results. According to Babbie (1989) and Sekaran (2003), internal consistency reliability is applied to groups of items thought to measure different aspects of the same concept. Since internal consistency is not applied to one item but among a group of items combined to form a single scale, the degree of consistency of results across items was interpreted as a correlation coefficient using ≥ 0.70 as a benchmark.

Convergent Validity: The convergent validity of the measured constructs was assessed by composite reliability scores and Average Variance Extracted values (Fornell & Larcker, 1981). Convergent validity is the degree to which multiple items measuring the same concept are in agreement, e.g. the extent to which the items under each construct are actually measuring the same construct. Validity is defined as how well (or the degree) a survey measures what it sets out to measure. For outcome measures such as surveys or tests, validity refers to the accuracy of measurement. Here validity refers to how well the assessment tool measures the underlying outcome of interest.

Composite reliability ranges from 0 to 1, with 1 being perfect estimated reliability. Hair et al. (2010) recommends 0.70 as a cut-off point for composite reliability. According to Henseler et al. (2009), the composite reliability must not be lower than .60. The recommended value for

AVE should be greater than 0.50 (Hair et al., 2011), which means that at least 50% of measurement variance is captured by the latent variable. This research employed Wong's (2013) suggestion of using factor loadings and the average variance extracted (AVE) to assess convergent validity. An AVE value of at least 0.5 indicated sufficient convergent validity, meaning that a latent construct is able to explain more than half of the variance of its indicators on average.

Discriminant Validity: Discriminant validity examines the degree to which the constructs diverge from each other and are empirically separate (Hair et al., 2010). Discriminant validity is assumed when the items correlate weakly with all other constructs except the one it is theoretically associated (Wong, 2013). Discriminant validity examines the loading of each indicator, which is expected to be greater than all of its cross loadings (Chin, 1998). Discriminant validity was assessed by: (1) examining the AVE of the latent constructs to see if they are greater than the square of the correlations among the latent constructs; and (2) examining the loadings and cross-loadings between the individual indicators and the constructs.

According to Fornell and Larcker (1981), the square root of AVE should be greater than the correlations among the constructs; that is, the amount of variance shared between a latent variable and its block of indicators should be greater than the shared variance between the latent variables. For example, in a matrix showing AVE for each construct, the diagonal of the matrix contains the square roots of the AVEs, which must be greater than off-diagonal elements in the corresponding row and columns (i.e. correlation of two latent variables) to confirm with discriminant validity. Although the Fornell et al., (1981) criterion assesses discriminant validity on the construct level, the cross-loadings allow this kind of evaluation on the indicator level (Henseler et al., 2009).

Indicator Item Reliability: Outer model loadings are the focus in reflective models, representing the paths from a factor to its representative indicator variables. Outer loadings represent the absolute contribution of the indicator to the definition of its latent variable (Garson, 2016). Individual item reliability can be assessed by looking at the standardized loadings of the measurement items with respect to their latent construct. Reliability can be assured when a scale produces consistent results every time repeated measurements are made on the variables of concern.

While manifest variables with outer loading 0.70 or higher are considered highly satisfactory, Hulland (1999) suggested that 0.40 is an acceptable loading value, while items with loadings of less than 0.40 should be dropped. Henseler et al. (2009) suggested that manifest variables with loading values between 0.40 and 0.70 be reviewed before elimination. If elimination of these indicators increases the composite reliability, then discard or otherwise maintain the factors. One indicator loading (USE3) loaded at 0.213. Following the recommendations of Hulland (1999), USE3 was eliminated from the model, as it did not increase the composite reliability of the use construct.

Wong (2013) provides a set of guidelines for checking reliability and validity when using PLS-SEM. Table 9 presents Wong's (2013) recommendations.

Table 9

Reliability Checks. Source (Wong, 2013).

What to check?	**What to look for in SmartPLS?**	**Where is it in the report?**	**Is it OK?**
Indicator Reliability	"Outer loadings" numbers	PLS calculation Results -Outer Loadings	Square each of the outer loadings to find the indicator reliability value. **0.70 or higher** is preferred. If it is an exploratory research, 0.40 or higher is acceptable. (Hulland, 1999)
Internal Consistency Reliability	"Reliability" numbers	PLS-Quality Criteria-Overview	Composite reliability should be **0.70 or higher**. If it is an exploratory research, 0.6 or higher is acceptable. (Bagozzi and Yi,1988)
Convergent validity	"AVE"numbers	PLS Quality Criteria-Overview	It should be **0.50 or higher** (Bagozzi and Yi, 1988)
Discriminant validity	"AVE" numbers and Latent Variable Correlations	PLS-Quality Criteria-Overview (for the AVE number as shown above) PLS-Quality Criteria-Latent Variable Correlations	Fornell and Larcker (1981) suggest that the "**square root**" of AVE of each latent variable should be greater than the correlations among the latent variables

Lastly, the distributional properties of the variables were examined for skewness and kurtosis. Skewness is used to determine whether the distribution is normal, while kurtosis is used to determine the relative concentration of data values (Hair et al., 2014). According to Hair et al., (2014) both skewness and kurtosis measures should be close to 1. Values greater than 1 or less than –1 for either measure indicates the distribution is non-normal.

Structural Model

Two measures were used to assess the structural model: the statistical significance (*t*-tests) of the estimated path coefficients (β), and the ability of the model to explain the variance (R^2) in the dependent variables (Chin, 1998). Path coefficients indicate the strengths of the relationships between the dependent and independent variables, whereas R^2 values represent the amount of variance explained by the independent variable (Hair et al., 2010).

Coefficient of Determination. In assessing the PLS model, the squared multiple correlations (R^2) for each endogenous latent variable was initially examined and the significance of the structural paths was evaluated. R^2 results represent the amount of variance in the endogeneous/exogeneous construct that is explained by the model (Chin et al., 2003). The R^2 value provided the amount of variance in the endogenous constructs that were explained by all of the exogenous constructs with paths to it (Hair et al., 2011; Urbach & Ahlemann, 2010). The proposed relationships were considered to be supported if the corresponding path coefficients had the proposed sign and were significant.

Change in R^2. The change in R^2 for net benefits (with use omitted) was also examined. Hair et al. (2014) recommends calculating the *change in R^2* value when a construct is omitted from the model to determine the impact on the endogenous construct. The constructs use and satisfaction were each eliminated from the structural model and the PLS algorithm run in SmartPLS 3.2.6.

Path Estimation and Significance. The path coefficients (β) and the path significance (*t*-values) were used for hypotheses testing. Path estimation was performed to examine the significance of the path values (β value) in the structural model. The highest β value symbolized the strongest effect of predictor (exogenous) latent variable towards the dependent (endogenous) latent variable (Hair et al., 2014). The path coefficients, or betas (β s), were indicated on the paths between two constructs, along with their direction. The model β values were tested for significance level through a *t*-statistic test using the PLS bootstrap procedure. Bootstrapping duplicates the sample and retrieves the *t*-value (Garson, 2016). The complete bootstrapping process included 5000 subsamples.

Significance of Effect. The significance of effect size (f^2), an additional criterion for assessing structural models in PLS, was also examined. The effect size f^2 allows assessing an exogenous construct's contribution to an endogenous latent variable's R^2 value, e.g. it is used to evaluate whether an omitted construct has a substantive impact on the endogenous constructs (Hair et al., 2011). Effect size assesses the magnitude or strength of relationship between the latent variables. Such discussion can be important because effect size helps researchers to assess the overall contribution of a research study. According to Hair et al., (2011), the f^2 values of 0.02, 0.15, and 0.35 indicate an exogenous construct's small, medium, or large effect, respectively, on an endogenous construct.

Stone-Geisser (Q^2). The model's predictive relevance was tested with a non-parametric Stone-Geisser test (Geisser, 1975; Stone, 1974). This test used a blindfolding procedure to create estimates of residual variances. By systematically assuming that a certain number of cases are missing from the sample, the model parameters are estimated and used to predict the omitted values. Q^2 is a measure of the extent to which this prediction is successful. Q^2 values above zero confirm the predictive relevance of the model.

Resources

SurveyMonkey was used to develop the survey and collect the data from the survey participants. The survey was distributed through SurveyMonkey, NextDoor Crocker Highlands, LinkedIn and researcher's email. Once the data were collected, Microsoft Excel was used to convert the raw data and SmartPLS 3.2.6 was used to analyze the data.

Ethical Considerations

Permission to conduct this study was obtained from the Institutional Review Board. Following the ethical considerations for a study, the researcher followed the IRB standards for collecting data. The survey link provided the following information to all participants:

1. Purpose of the research.
2. No request for sensitive or confidential information.
3. Participation in this survey is completely voluntary.
4. Estimated time to complete this survey.

5. Researcher name and email.
6. School name and email.

Participation in this survey was strictly voluntary. All participants were informed about the nature of the study, the extent of dangers, if any, and any obligations related to the study. In addition, all participants were guaranteed confidentiality and anonymity.

Summary

This chapter included a description of the research design, methodology, an explanation of the survey instrument, and measures that were used for this study. The type of investigation was correlational. The research used a descriptive, non-experimental quantitative survey approach to examine the determinants of EMIS success. The time horizon was "one-shot" or cross-sectional. This research study relied on random sampling, network sampling, and snowball sampling as an approach for the collection of responses from 126 participants. Participants were utility customers in Northern California. SurveyMonkey was used to collect survey data. A link to a web-based survey was used to solicit participation of utility customers to gather anonymous data on their perceptions.

The research approach leveraged quantitative methodology, based on statistical analysis, to describe and explain associations between independent and dependent constructs. Since PLS-SEM is extensively used in MIS research (Gefen & Straub, 2000; Urbach et al., 2010), PLS-SEM was used to evaluate both the measurement and structural models.

Chapter 4

Results

Introduction

This chapter presents the results of the statistical analysis methods described in the previous chapter to test the research hypotheses. First, the chapter presents the demographic analysis of the study respondents. The chapter then presents the two-stage data analysis process used to evaluate the theoretical model and test the research hypotheses.

Demographic Analysis

Demographic analysis revealed 84% of the survey respondents were female, while 16% were male. Respondents aged between 18 years of age to over 55. Respondents over the age of 55 formed most of the sample, with a percentage of 42.86%. Respondents aged 18 to 30 accounted for 17.14%, respondents aged 31 to 45 accounted for 20.95%, followed by those aged 46 to 55 (19.05%). Respondents earning over $150,000 dollars account for 14.14%. Respondents earning between $125,000 to $149,999 accounted for 1.7%. Respondents earning income from $100,000 to $124,999 accounted for 10.71%. Respondents earning between $75,000 to $99,000 accounted for 12.50%. Respondents earning between $50,000 and $74,999 accounted for $10.07%. Respondents earning between $25,000 and $49,000 accounted for $10.17%. Respondents earning between $10,000 and $24,999 accounted for $14.29%. Respondents earning less than $9,999 dollars accounted for 10.70%. Thirty of 126 respondents did not provide an answer to the income question.

Assessment of the Measurement Model

Indicator Item Reliability

All outer model indicator loading values loaded within the acceptable range of .40 to .70 (Hulland, 1999). Table 10 shows the final indicator outer loadings for the outer measurement model.

Table 10

Initial Outer Model Indicator Loadings.

	Information Quality	**Net Benefits**	**Satisfaction**	**Service Quality**	**System Quality**	**Use**
IQ1	0.799					
IQ2	0.763					
IQ3	0.804					
IQ4	0.696					
NET1		0.886				
NET2		0.828				
NET3		0.801				
NET4		0.413				
SAT1			0.866			
SAT2			0.870			
SVQ1				0.727		
SVQ2				0.645		
SVQ3				0.795		
SYSQ1					0.855	
SYSQ2					0.720	
SYSQ3					0.606	
SYSQ4					0.579	
USE1						0.851
USE2						0.804

Convergent Validity

The computed AVE values and the composite reliability scores for all variables are shown in Table 11. The results from this internal consistency and reliability test of the measurement model showed that all the scores are above the suggested thresholds. The composite reliability values exceeded the recommended 0.70 level (Hair et al., 2011; Wong, 2013), and ranged from 0.857 to 0.929. The computed AVE values ranged from 0.547 to 0.868 for all latent variables. Thus, this confirmed the convergent validity of the measurement model.

Table 11

Average Variance Extracted and Composite Reliability.

Variables	**Average Variance Extracted (AVE)**	**Composite Reliability**
Information Quality	0.600	0.857
Net Benefits	0.661	0.880
Satisfaction	0.868	0.929
Service Quality	0.582	0.806
System Quality	0.547	0.825
Use	0.781	0.877

Discriminant Validity

As shown in Table 12, the square roots of the AVE's (in bold) for each item are greater than their correlation with the other constructs, which indicates the constructs measure different concepts. This, in turn, indicates validity of the measurement model (Henseler et al., 2009).

Table 12

*Fornell–Larcker Criterion Confirming Discriminant Validity***.**

	Info Quality	Net Benefits	SAT	Service Quality	System Quality	Use
Information Quality	**0.775**					
Net Benefits	0.366	**0.813**				
Satisfaction	0.287	0.660	**0.932**			
Service Quality	0.502	0.528	0.494	**0.763**		
System Quality	0.637	0.466	0.417	0.643	**0.740**	
Use	0.368	0.611	0.622	0.521	0.516	**0.884**

Another check for discriminant validity is to examine indicator cross loadings. Table 13 shows factor loadings and cross loadings for each construct and its indicators. The discriminant validity table shows that each indicator is well correlated with the construct it is connected to as each indicator loads higher on its own latent constructs than on the others.

Table 13

Factor Loadings and Cross-Loadings for the Measurement Model.

	Information Quality	Net Benefits	Satisfaction	Service Quality	System Quality	Use
IQ1	**0.807**	0.261	0.226	0.325	0.511	0.257
IQ2	**0.771**	0.256	0.211	0.520	0.562	0.340
IQ3	**0.812**	0.235	0.202	0.333	0.515	0.247
IQ4	**0.703**	0.376	0.249	0.350	0.372	0.280
NET1	0.244	**0.953**	0.533	0.492	0.422	0.569
NET2	0.392	**0.891**	0.690	0.460	0.439	0.636
NET3	0.285	**0.862**	0.521	0.389	0.331	0.399
NET4	0.247	**0.445**	0.312	0.368	0.297	0.289
SAT1	0.306	0.631	**0.930**	0.466	0.328	0.459
SAT2	0.229	0.598	**0.934**	0.454	0.449	0.699
SVQ1	0.612	0.481	0.383	**0.765**	0.646	0.412
SVQ2	0.177	0.291	0.402	**0.679**	0.240	0.379
SVQ3	0.327	0.422	0.341	**0.837**	0.561	0.394
SYSQ1	0.537	0.457	0.452	0.548	**0.905**	0.564
SYSQ2	0.577	0.317	0.291	0.518	**0.762**	0.311
SYSQ3	0.430	0.277	0.234	0.377	**0.641**	0.349
SYSQ4	0.286	0.304	0.171	0.485	**0.613**	0.192
USE1	0.404	0.514	0.655	0.598	0.493	**0.908**
USE2	0.228	0.576	0.422	0.293	0.412	**0.859**

Assessment of the Structural Model

Multicollinearity Assessment

To assess collinearity, both the tolerance level and the VIF values of the research model were evaluated (Hair et al., 2014). Multicollinearity results in Table 14 show that both the tolerance level and the VIF values are within the acceptable guidelines, e.g. a tolerance level greater than 0.20 and a VIF value less than five.

Table 14

Variance Inflation Factor Values and Tolerance Level.

	Variance Inflation Factor (VIF)	Tolerance Level
IQ1-FORMAT	2.022	>0.2
IQ2-ACCURATE	1.484	>0.2
IQ3-UNDERSTAND	2.153	>0.2
IQ4-RELEVANT	1.283	>0.2
NET1-REDUCE BILLS	2.785	>0.2
NET2-INCREASED UNDERSTANDING	1.686	>0.2
NET3-DECISIONS	2.132	>0.2
NET4-NEIGHBORHOOD	1.063	>0.2
SAT1-CONTINUE USE	1.353	>0.2
SAT2-SATISFIED	1.353	>0.2
SVQ1-HELP	1.238	>0.2
SVQ2-PROVIDES ENERGY INFO	1.130	>0.2
SVQ3-GREEN BUTTON	1.375	>0.2
SYSQ1-EASY TO USE	1.510	>0.2
SYSQ2-QUICKLY	1.551	>0.2
SYSQ3-PRIVACY	1.187	>0.2
SYSQ4-GREEN_BUTTON	1.274	>0.2
USE1-HOME USAGE	1.182	>0.2
USE2-UNDERSTAND TERMS	1.182	>0.2

Coefficient of Determination, R^2

As shown in Figure 21, R^2 for the overall model is 0.501. *R*-squared values of around 0.670 are considered substantial, values around 0.333 are considered moderate, and values of 0.190 and lower are considered weak (Chin, 1998).

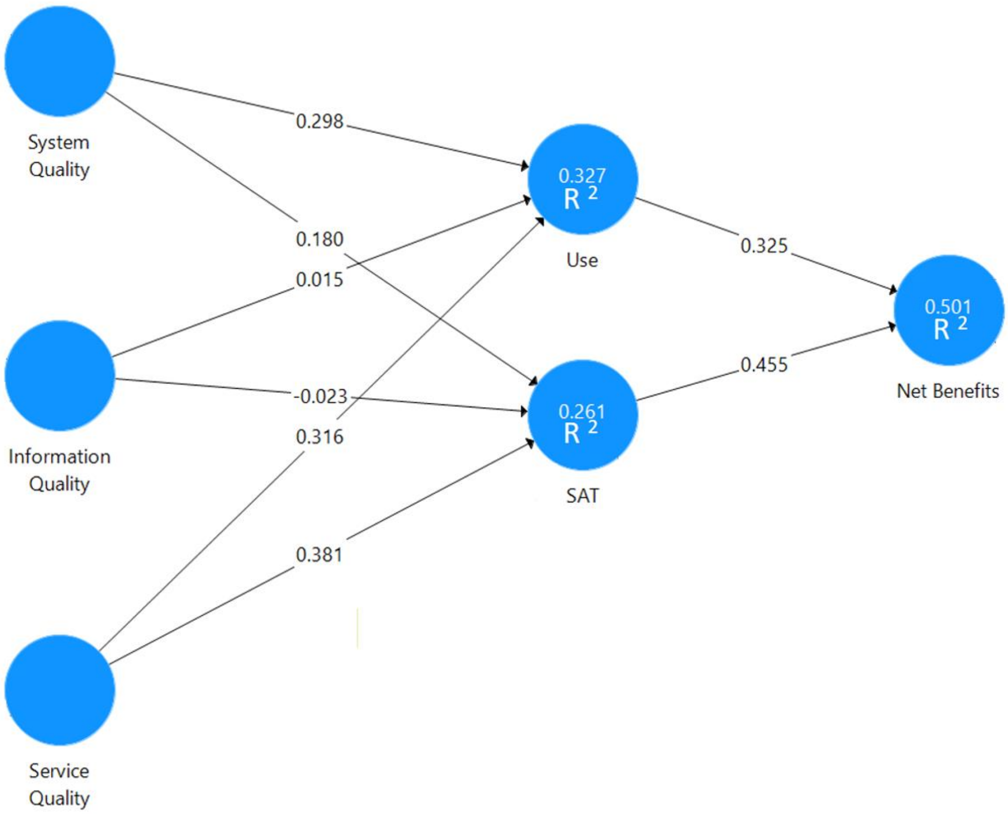

Figure 21. Co-efficient of Determination for each Latent Construct.

Change in R^2

The constructs use and satisfaction were each eliminated from the structural model and the PLS algorithm run in SmartPLS 3.2.6. The change in R^2 for net benefits (with use omitted) was 0.437, as shown in Figure 22. This indicated that satisfaction accounted for 43.70% of the variance in net benefits.

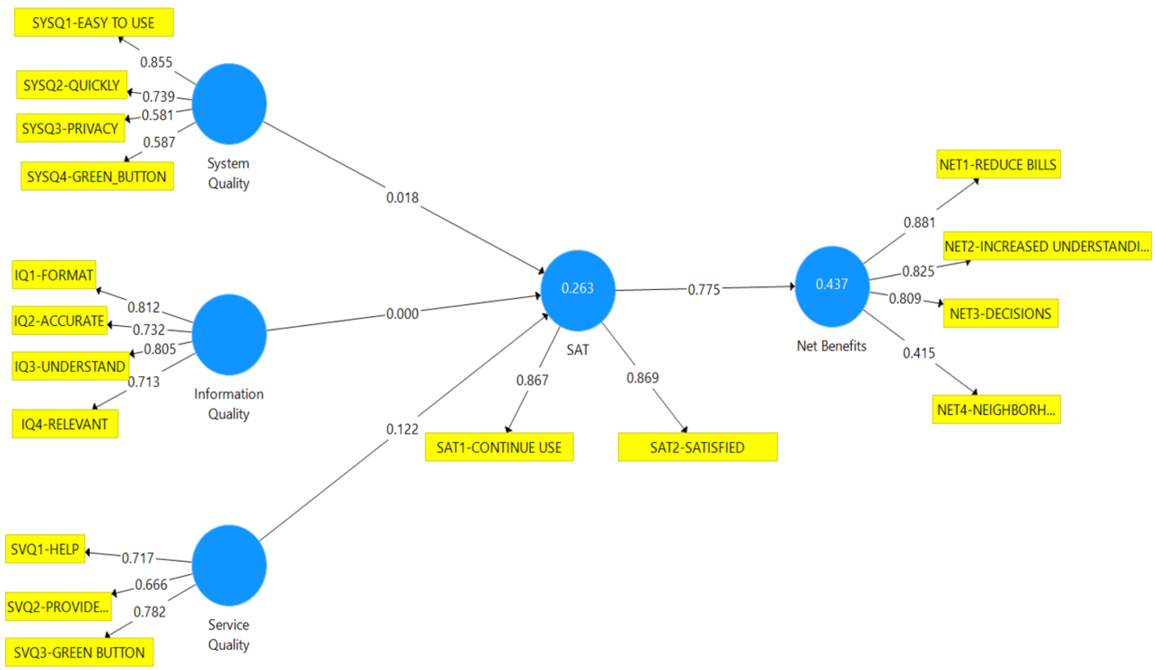

Figure 22. Use Construct Omitted.

The change in R^2 for net benefits (with satisfaction omitted) was 0.373, as shown in Figure 23. This indicated that use accounted for 37.3% of the variance in net benefits.

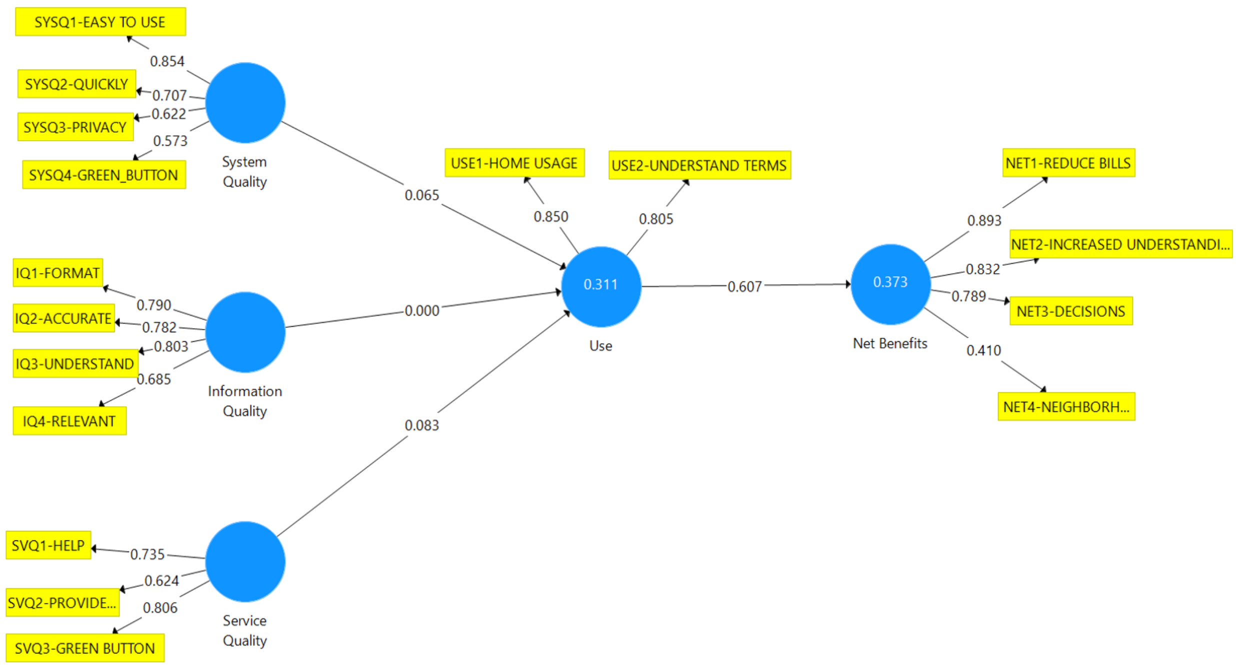

Figure 23. Satisfaction Construct Omitted

Significance of Effect f^2

The effect size f^2 assessed the magnitude or strength of relationship between the latent variables and was used to evaluate whether an omitted construct had a substantive impact on the endogenous constructs. Effect size results are shown in Table 19.

Stone-Geisser (Q^2) Test of Predictive Relevance

Positive Q^2 values (above zero) confirm the predictive relevance of the model in respect of a construct. The test results show positive values for use (Q^2 = .192), user satisfaction (Q^2 = .168), and net benefits (Q^2 = .252).

Structural Path Significance in Bootstrapping

The bootstrapping results from the *t* statistics confirmed that *t*-statistics for paths *Service Quality -> Satisfaction (3.734), Satisfaction -> Net Benefits (3.647), Service Quality -> Use*

(2.525), Use -> Net Benefits (2.333), and *System Quality -> Use (2.146)* are greater than 1.96 and are statistically significant. Path coefficients for *System Quality -> Satisfaction (1.250), Information Quality -> Satisfaction (0.164),* and *Information Quality -> Use (0.158)* values are less than 1.96 and are not statistically significant. Table 15 summarizes the path coefficients, *t*-values, and effect sizes.

Table 15

Structural Model Path Coefficients, t-statistics, and Effect size.

	Path Coefficients	***t* Statistics**	**Effect Size f^2**
Service Quality -> Satisfaction	0.381	3.734	0.117
Satisfaction -> Net Benefits	0.455	3.647	0.256
Service Quality -> Use	0.316	2.525	0.087
Use -> Net Benefits	0.325	2.333	0.132
System Quality -> Use	0.298	2.146	0.061
System Quality -> Satisfaction	0.180	1.250	0.021
Information Quality -> Satisfaction	-0.023	0.164	0
Information Quality -> Use	0.015	0.158	0

Most of the path coefficients were positive. However, the path coefficient for information quality to satisfaction was slightly negative at -0.023. Satisfaction, as the dependent construct, is known to depend on information quality, but the reflective indicators used to generate the data does not have sufficient power to detect that dependence. Further analysis of the information quality indicators revealed that only format and relevance alone had a slightly positive, yet still insignificant effect on satisfaction.

The model showed no collinearity problems. The result of this research indicated that both the tolerance level and the VIF values are within the acceptable guidelines recommended by

Hair et al. (2014). The predictive capability of the model was deemed satisfactory because all R^2 values are higher than 0.10 and they can be interpreted as moderate for net benefits (R^2=0.501), moderate for use (R^2 =0.327) and moderate for satisfaction (R^2 =0.261). Figure 24 presents the EMIS model.

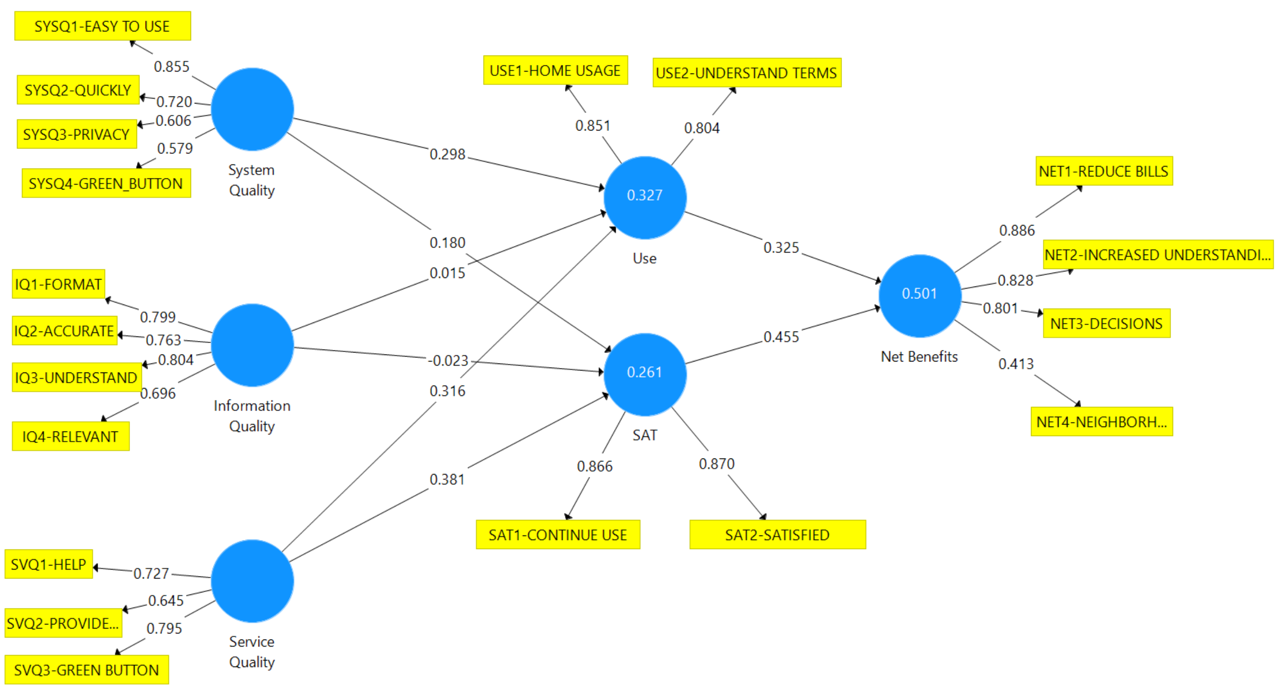

Figure 24. EMIS Model with Path Co-efficients and Variance.

The determinants (predictors) of systems use explain 32.7% of the variance in system use, the determinants (predictors) of user satisfaction explain 26.1% of the variance in user satisfaction. Both use and user satisfaction explain 50.1% of the variance in net benefits. The detailed coefficients of direct effects and their *t*-values for each path are summarized in Table 16.

Table 16

Explanatory Power of the Model and Strength of Individual Paths.

	R^2	***Direct Effects*** *(β)*	***t*** **Statistics**
Effect on Use	0.327		
System Quality		0.298	2.146
Information Quality		0.015	0.158
Service Quality		0.316	2.525
Effect on Satisfaction	0.261		
System Quality		0.180	1.250
Information Quality		-0.023	0.164
Service Quality		0.381	3.734
Effect on Net Benefits	0.501		
System Quality		-	-
Information Quality		-	-
Service Quality		-	-
Use		0.325	2.333
User Satisfaction		0.455	3.647

Hypotheses Testing

The path coefficients (*β*) and the path significance (*t*-values) were used for hypotheses testing. Figure 25 shows the inner structural model with path coefficients, *t*-statistic values (in parenthesis), and the research hypotheses.

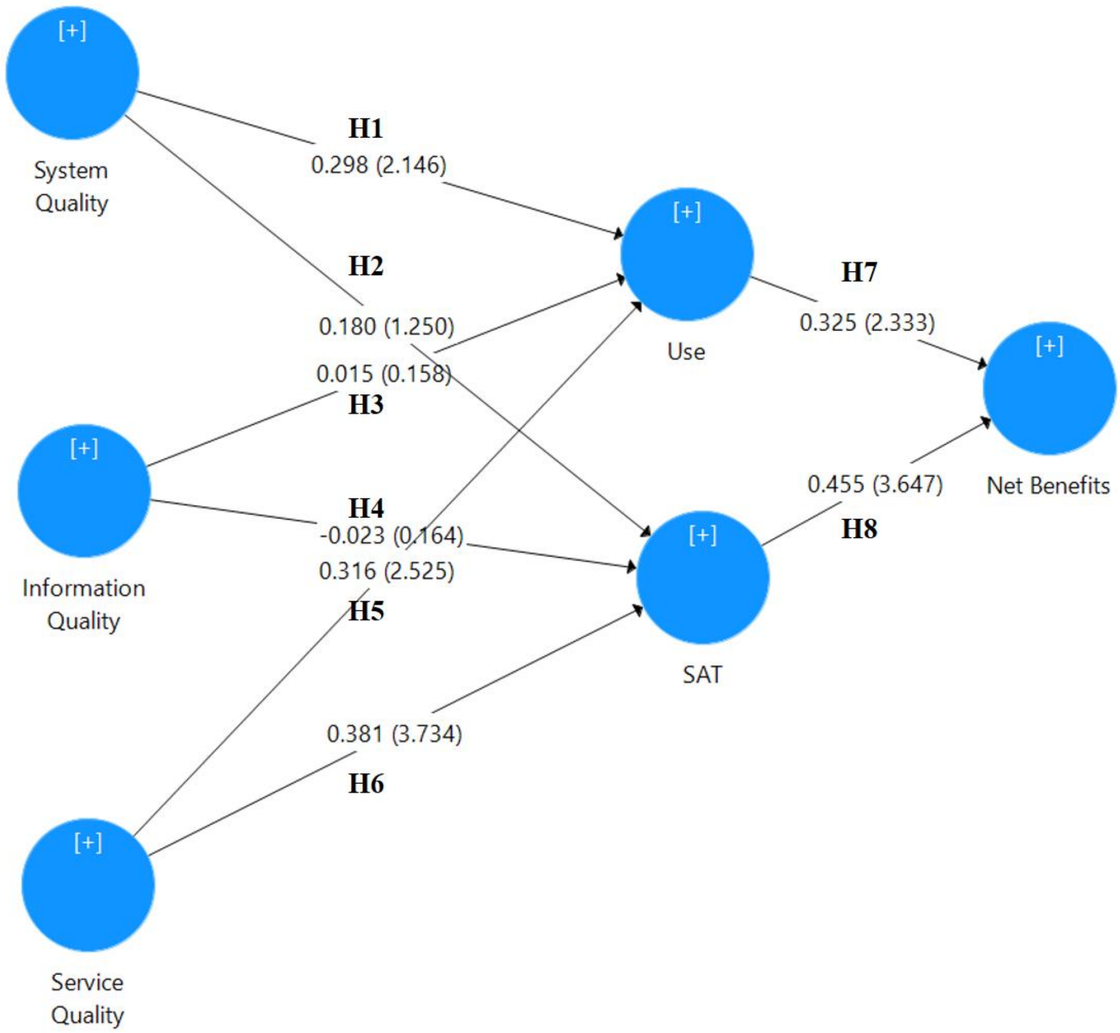

Figure 25. Study Hypotheses.

Based on the PLS-SEM results, the study determined the following:

H_1: EMIS system quality will positively affect use. System quality had a direct significant effect on use (β = 0.298, t = 2.146, *p-value* =0.029, p<.05). Hypothesis one was supported.

H_2: EMIS system quality will positively affect user satisfaction. System quality did not have a direct effect on user satisfaction (β = .180, t =1.250, *p-value* =0.185, p >.05). Therefore, hypothesis two was not supported.

H_3: EMIS information quality will positively affect use. Information quality did not significantly affect use (β = .015, t = 0.158, *p-value* =0.877, p >.05). Therefore, hypothesis three was not supported.

H_4: EMIS information quality will positively affect user satisfaction. Information quality did not significantly affect user satisfaction (β = -.023, t = 0.164, *p-value* =0.861, p >.05). Therefore, hypothesis four was not supported.

H_5: EMIS service quality will positively affect use. Service quality had a direct significant effect on use (β = 0.316, t = 2.525, *p-value* =0.013, p<.05). Therefore, hypothesis five was supported.

H_6: EMIS service quality will positively affect user satisfaction. Service quality had a direct significant effect on user satisfaction (β = 0.381, t = 3.734, *p-value* =0, p < .05). Therefore, hypothesis six was supported.

H_7: Use will positively affect perceived net benefits. Use had a direct significant effect on net benefits (β = 0.325, t = 2.333, *p-value* =0.015, p < .05). Therefore, hypothesis seven was supported.

H_8: User satisfaction will positively affect perceived net benefits. User satisfaction had a direct significant effect on net benefits (β = 0.455, t = 3.647, *p-value* =0, p < .05). Therefore, hypothesis eight was supported. The hypotheses results are noted in Table 17.

Table 17

Hypotheses Testing Results

Hypotheses	β	***p*-value**	**Remarks**
H_1. System Quality -> Use	.298	0.029	Supported
H_2. System Quality -> User Satisfaction	.180	0.185	Not Supported
H_3. Information Quality -> Use	.015	0.877	Not Supported
H_4. Information Quality -> User Satisfaction	-.028	0.861	Not Supported
H_5. Service Quality -> Use	.316	0.013	Supported
H_6. Service Quality -> User Satisfaction	.381	0	Supported
H_7. Use -> Net Benefits	.325	0.015	Supported
H_8. Satisfaction -> Net Benefits	.455	0	Supported

Summary

The goal of this research study was to examine EMIS success at the individual level of analysis using the DeLone and McLean (2003) IS Success Model. Partial Least Squares Structural Equation Modeling was used to validate the theoretical model because it allows for a two-stage validation process of both the measurement model and the structural model. Indicator reliability, convergent validity, and discriminant validity tests validated the measurement model. Indicator item reliability was assessed by looking at the standardized loadings of the measurement items with respect to their latent construct. Results from the internal consistency and reliability test of the measurement model (through composite reliability and AVE) showed that all the scores were above suggested thresholds. Discriminant validity was assessed using AVE and examining the loadings and cross-loadings between the individual indicators and the constructs to ensure that each indicator loads more highly with its own construct than with other constructs.

The structural model was then evaluated for multicollinearity. Study results indicated that both the tolerance level and the VIF values were within the acceptable guidelines recommended by Hair et al. (2014). The explanatory power of the structural model was evaluated by examining the R^2 value in the final dependent variable net benefits. The R^2 for the overall model moderately explained 50.1% of the variance in net benefits. The latent constructs use and user satisfaction were each eliminated from the structural model and the PLS algorithm run in SmartPLS 3.2.6. This process confirmed that use had a large effect on net benefits, though not as large as user satisfaction.

Path estimation was performed using Bootstrapping to examine the significance of the path values (β value) in the structural model. The path coefficients and the path significance (t -values) were used for hypotheses testing. Most of the hypotheses derived from the DeLone and McLean IS Success Model are supported by the research study. Five hypotheses were supported and three non-significant relations were not. In the context of EMIS use, both system quality and service quality had a direct significant effect on use. However, the link between system quality and user satisfaction was not significant. The link between information quality and use and Information quality and user satisfaction was not significant. In the context of user satisfaction with an EMIS, service quality had a stronger significant effect on user satisfaction than system quality. In the context of EMIS individual impact, both use and user satisfaction had a direct significant effect on net benefits.

Chapter 5

Conclusions, Limitations, Implications, Recommendations, and Summary

Introduction

This chapter provides the conclusions, limitations, implications, recommendations for future research, and a summary of the research study. The first section presents the research goal, research questions, and research conclusions, followed by a description of study limitations. The second section provides study implications followed by recommendations for future research. The chapter ends with a summary of the research study.

Conclusions

The Energy Industry utilizes Energy Management Information Systems (EMIS) smart meters to monitor utility consumers' energy consumption, communicate energy consumption information to consumers, and to collect energy consumption data about consumer usage. The hope is that EMIS use will aid utility consumers in managing their energy consumption by helping them make effective decisions regarding their energy usage. Using the DeLone and McLean (2003) IS Success Model, this quantitative survey research examined EMIS success constructs and measures that contribute to EMIS Smart Meter Web Portal effectiveness at the individual level of analysis.

Three research questions framed the study: (1) to what degree do system quality, information quality, and service quality influence EMIS use? (2) to what degree do system quality, information quality, and service quality influence user satisfaction with an EMIS? and

(3) to what degree do EMIS use and user satisfaction benefit utility customers in managing their energy consumption?

Empirical results concerning the effect of system quality on system use is consistent with the findings of other studies (Al-Debei, 2013; DeLone & McLean, 2003; Rai et al., 2002; Venkatesh & Davis, 2000; Seddon & Kiew, 1996). Therefore, hypothesis one (H_1) was supported. However, system quality was not a significant measure of user satisfaction, thus, hypothesis two (H_2) was not supported. As noted above, system quality received mixed support in the model; survey respondents perceived system quality influenced EMIS system use but did not perceive that system quality influenced user satisfaction with an EMIS.

In the context of an EMIS smart meter web portal, an effective portal must be accessible and provide relevant functions to support tasks performed by the utility customer. These tasks include the ability to access the EMIS web portal and navigate the graphical user interfaces that display utility consumption information. System quality also relates to accessibility, ease of use, degree of personalization, and privacy. The ability to have an EMIS system that is easy to use, offers the ability to download customer energy data using the Green Button, and keep utility data private appears to significantly influence utility customer’s use of an EMIS system.

Inconsistent with the results of other studies, system quality was not a significant measure of user satisfaction (Almazán et al., 2017; Petter et al., 2013; Xu et al., 2013; Wixom et al., 2005; Roca et al., 2006; DeLone & McLean, 1992). It was hypothesized that a positive experience with the EMIS web portal would lead to a positive influence on utility customer satisfaction and that satisfaction would be reflected in positive net benefits. However, survey respondents did not perceive that ease of use, a quick system response time, data privacy, and the ability to download home energy data influenced their satisfaction with the EMIS web portal. This may be due to the multidimensionality nature of system quality and the fact that there is no consistent measure of it (DeLone & McLean, 2016). In a comparative study on e-commerce websites, Chen (2013) found that system quality was not a significant measure of user satisfaction. Chen (2013) examined both user satisfaction and attitude toward an e-commerce site. The system quality features included traditional usability attributes of easy to learn, easy to navigate, and easy to use. The authors attributed the lack of significance between system quality and user satisfaction to the different Internet diffusion and usage patterns in the two countries investigated. The authors suggested that e-commerce providers should either tailor their sites to their target market, or adjust the site dynamically to meet the needs of different users. This suggests that quality dimensions may have different weights depending upon the context of analysis (DeLone & McLean, 2003). Thus, it is possible that utility customers do not consider the indicators used to measure system quality in this study relevant to system satisfaction.

However, system quality measures used in the study may indeed be appropriate and may reflect a problem with EMIS smart meter web portals. Only 25.76% of survey respondents agreed that the EMIS portal was easy to navigate to get information about their home's energy usage. In addition, 63.64% neither agreed or disagreed with the previous statement. Only 25.75% agreed that the portal displayed text and graphics quickly. Only 17.39% perceived that their home energy data was kept private, while 11.59% disagreed, and 11.59% strongly disagreed. The perception is that 24% of survey respondents did not trust that their energy data was kept private. Just 12.12% agreed that it was easy to download their energy data to a computer.

Information quality did not have a significant effect on system use, therefore, hypothesis three (H_3) was not supported. However, this finding is inconsistent with other studies, which found information quality to have a significant effect on system use (Al-Debei, 2013; Halawi, et al., 2007, DeLone & McLean, 2003; Rai et al., 2002; Lederer et al., 2000). In addition, information quality did not have a significant effect on user satisfaction, therefore, hypothesis four (H_4) was not supported. This is inconsistent with the findings of other studies (Rouibah, 2015; Rai et al., 2002; Molla & Licker, 2001; Halawi, et al., 2007; Seddon & Kiew, 1996).

Information quality has been considered a typical IS success measure and its relationship with the other IS success measures are generally supported in other studies. Contrary to expectations, its effects on use and user satisfaction was not statistically significant. Survey respondents did not perceive information quality as influencing either user satisfaction or EMIS use. Several reasons may exist to explain the non-significance of information quality.

Although 80% of respondents logged into a utility provider's website to pay a utility bill, and 60% of survey respondents review their energy usage via an EMIS web portal, 40% of survey respondents still review their energy usage via a paper-based bill. This implies that 40% of survey respondents may not spend enough time on the EMIS web portal to render an opinion on the usefulness of the information quality. In addition, only 36.25% of survey respondents felt that the charts and graphs about their home energy usage were easy to understand. In addition, only 31.25% of survey respondents felt that the information provided by their utility service provider's EMIS web portal seemed accurate. However, 41.86% of survey respondents felt that the charts and graphs that showed their home energy usage were relevant. Petter et al. (2008) suggested that information quality is often not distinguished as a unique construct but is measured as a component of user satisfaction. Therefore, measures of this dimension are problematic for IS success studies.

Service quality had a direct significant effect on use, therefore, hypothesis five (H_5) was supported. This result is inconsistent with findings in other studies **(**Al-Debei, 2013; Halawi et al., 2007, Wu & Wang, 2006). Service quality also had a direct significant effect on user satisfaction, therefore hypothesis six (H_6) was supported. This finding is also inconsistent with the findings of other studies (Rouibah, 2015, Al-Debei, 2013, Chiu et al., 2007; Aladwani, 2002).

DeLone and McLean's (1992) original IS Success Model did not include the service quality construct. The author's updated IS success model accepted the Pitt et al. (1995) recommendation to include service quality as a construct (Petter, DeLone, & McLean, 2008). In the context of this study on EMIS web portal effectiveness, service quality exhibited the strongest influence on both system use and user satisfaction. The study results suggest that service quality is the most important factor in increasing EMIS system use and user satisfaction.

Other authors have criticized the inclusion of the service quality construct in a model of IS success that also includes the system quality construct (Rosemann & Vessey, 2008; Seddon, 1997). The research findings indicate that service quality had a significant effect on use and user satisfaction. The higher a utility customer perceives the quality of service, the more likely they are to use the system, and this would reflect in positive net benefits.

Empirical results concerning the effect of use on net benefits are consistent with the findings of other studies (Seddon & Kiew, 1996; Torkzadeh & Doll, 1999; Rai et al., 2002, Wang & Liao, 2008; Urbach et al, 2010). Therefore, hypothesis seven (H_7) was supported. Energy consumers are using the smart meter web portal to learn energy terms, which leads to an increased understanding of energy terminology, which is helping them to better review their energy data provided by the system. Obtaining information about home energy usage appears to contribute toward reducing energy bills and making better energy management decisions.

Empirical results concerning the influence of user satisfaction on net benefits are consistent with the findings of other studies (Torkzadeh & Doll, 1999; Al-Debei, 2013, Rai et al., 2002; Halawi et al., 2007; Wang & Liao, 2008; Urbach et al., 2010). Therefore, hypothesis eight (H_8) was supported, which demonstrates that user satisfaction positively influenced the use–utility of the system, meaning the users feel satisfied enough with some of the qualities of the system and, therefore, were motivated to use it. User satisfaction is widely accepted as a desirable outcome of any product or service experience because it is one of the most significant criteria for measuring IS success. EMIS use and user satisfaction benefit utility customers in managing their energy consumption. The empirical results of this study indicated that use and user satisfaction explain at least 50% of the variance in the overall net benefits measure. Thus, both EMIS use and user satisfaction appear to benefit utility customers in managing their energy consumption.

To summarize, the model explains that the quality of the system and of the service affect both the use–utility of the system as well as user satisfaction. Service quality exhibited the strongest direct effect on both use and user satisfaction. Thus, the quality of the EMIS portal's service features seems to be an important success factor. The direct effect of system quality on use was stronger than the direct effect of system quality on user satisfaction. In fact, system quality had no significant effect on user satisfaction. Interestingly, it was found that the effect of information quality on both use and user satisfaction was not significant. Both use and user satisfaction as the exogenous constructs, had a direct significant effect on the endogenous construct net benefits.

Limitations

There are several limitations to the study that warrant mention. A limitation of this study is that data was not gathered from different utility service provider regions in the United States to develop a comparative analysis. Such comparisons could provide significant insights into the effect of regional differences on the model. Second, the research relied mainly on user perceptions and a single method to elicit those perceptions. Another limitation was that the accuracy of responses to the questions depended on participants' truthfulness in their responses to the survey items, as well as their prior experiences with an EMIS smart meter web portal. Therefore, caution must be exercised in generalizing the results to other contexts and types of EMIS smart meter web portals.

Implications

The results of this study provide implications for utility service providers and for the literature on IS Success. From the academic perspective, the study extends the applicability of the IS success model to the utility industry environment. The study confirms the fitness of the DeLone and McLean (2003) IS success model for an Energy Management Information System. The study results suggest that the DeLone and McLean's (2003) model is robust and applicable to an Energy Management Information System smart meter web portal.

This study also adds to the body of knowledge in the area of IS success. The literature showed that there was a need to conduct EMIS research. This study bridged the gap in literature on the need to conduct EMIS research at the individual level of analysis. The results of this research highlighted the importance of EMIS use and user satisfaction with an EMIS in promoting EMIS success at the individual level. For example, this study contributes to a better understanding of the factors that promote EMIS success at the individual level of analysis.

In addition to its contribution to research, this study has several practical applications for utility service providers. Utility service providers can evaluate their EMIS smart meter web portals by using the success constructs identified in this study to measure and thus improve both their website and the back-end EMIS system. The results of this research are significant because the results can be used to help utility service providers implement methods that could enhance utility customer's EMIS use and satisfaction. Understanding the relative importance of system use and user satisfaction can help utility providers put more emphasis on the quality factors perceived by utility customers to aid them in managing their energy consumption.

For example, this research assessed predictors of system quality, information quality, service quality, use, user satisfaction, and net benefits. These predictors (or item indicators) were analyzed by their item loadings, which indicated the level of agreement or importance of an indicator. In terms of system quality, respondents valued ease of use first, followed by web portal responsiveness, and then privacy of data. In terms of service quality, respondents valued having the Green Button option to download energy data first, followed by having adequate online help, and then having general energy information. In terms of system use, having the ability to obtain energy information about their home energy usage ranked slightly above using an EMIS to understand energy terminology. The study also indicated that both system quality and service quality would influence a utility customer's continued use of an EMIS and their satisfaction with it.

In terms of the net benefits derived from an EMIS, utility service providers can see that respondents ranked reducing energy bills first, increasing their understanding of their energy usage second, helping them make better informed decisions about energy usage third, and using an EMIS to compare neighborhood data last. Thus, EMIS web designers can benefit from the study results by focusing on building EMIS smart meter web portals based on the quality constructs that influence user satisfaction and system use. Three path links may be used by EMIS web designers and utility providers to increase utility customers' net benefits. The first path links system quality and use to net benefits. The second path links service quality and use to net benefits and the third path links service quality and satisfaction to net benefits. These path links can provide an effective diagnostic framework in which to analyze EMIS smart meter web portal features that may increase net benefits (see Table 18).

Table 18

Path Links to Analyze Portal Features

Path Links	**Sample Link Analysis**
System Quality -> Use -> Net Benefits	Which design features would increase portal use, e.g. high-usage alerts, energy savings and budget goals, disaggregated usage by appliance? Should the portal offer customization? Different communication channels – e.g. mobile phone text alerts? Mobile apps that are customizable? Gamification?
Service Quality -> Use -> Net Benefits	What service features would increase portal use, e.g. offering email notifications of loss framed as a monetary value? How can digital engagement be increased using service offerings? Given that an EMIS smart meter web portal may require a steep learning curve, are their learning tools that can be developed to help customers "fast track" their knowledge and learning?
Service Quality -> Satisfaction -> Net Benefits	Would web-based support (both online FAQ help and online chat) increase portal satisfaction? Is help "easy to locate" on the web page? Is online help chat offered twenty-four hours per day, seven days per week?

Recommendations for Future Research

The study provided a solid theoretical foundation from which future studies can build upon. As previously mentioned, a limitation of this study is that data was not gathered from different utility service provider regions in the United States in order to develop a comparative analysis. Such comparisons could provide significant insights into the effect of regional differences on the model. This study encourages researchers to consider all major regions of the

United States as potential locations to test the model. Future research may collect primary data from different utility service provider regions to understand better the relationships and impacts of those factors on EMIS success.

The empirical results of this study indicated that information quality had no significant direct effect on EMIS use or user satisfaction. Essentially, survey respondents did not value EMIS information quality as a predictor of system use or as a predictor of user satisfaction. This was a surprising finding and is a compelling research opportunity to understand why. Furthermore, this study included a predictive investigation. The results of the predictive investigation were statistically significant, as the model accounted for 50% of the variance in net benefits. It is recommended that this predictive study be expanded to evaluate other IS success quality dimensions that would increase the explanatory strength of the model.

Summary

The Energy Industry utilizes Energy Management Information Systems smart meters to monitor utility consumers' energy consumption, communicate energy consumption information to consumers, and to collect a plethora of energy consumption data about consumer usage. The hope is that EMIS use will aid utility consumers in managing their energy consumption by helping them make effective decisions regarding their energy usage. Improved energy management decision-making is the net benefit derived from an efficient and effective EMIS. Utility consumer effective decision-making may achieve both economic and social benefits for the utility consumer and greater operational efficiencies for the utility service provider. As an EMIS is an emerging technology, little research exists that evaluates the effectiveness of an

EMIS from a utility consumer perspective. Issues of system quality, information quality, and service quality may influence consumer use of an Energy Management Information System.

Thus, this study investigated the role of EMIS smart meter web portals in aiding utility customers in managing their energy consumption. This is deemed significant as little research has assessed the success of EMIS smart meter web portals as an information system in delivering benefits to the utility customer. There are few guidelines or little research to determine the usefulness of these systems. The objective of the study was to investigate the success constructs and measures that contribute to EMIS Smart Meter Web Portal effectiveness.

There are numerous information system success definitions and a plethora of models e.g. Zmud's Individual Differences Model (1979), Ives and Olson's User Involvement Success Model (1984), Doll and Torkzadeh's End-User Computing Satisfaction Model (1988), Davis' Technology Acceptance Model (1989), DeLone and McLean's IS success models (1992, 2003), and Gable's IS-Impact Model (2008). Numerous empirical studies have utilized the DeLone and McLean (1992, 2003) IS Success Models to evaluate the success of various types of information systems, such as web-based portals (Urbach et al., 2010), government to citizen (G2C) e-government systems (Wang & Liao, 2008), e-commerce (Molla & Licker, 2001), decision support systems (Manchanda et al., 2014); knowledge management systems (Wu & Wang, 2006), and mobile banking systems (Lee et al., 2009).

Research studies that have empirically tested the DeLone and McLean (1992, 2003) IS Success Models have typically focused on a single part of success - such as information quality or user satisfaction or service quality as a dependent variable (Petter et al., 2008). In a review of the IS success literature, no study aimed specifically at comprehensively examining the success of an Energy Management Information System utilizing all of the DeLone and McLean (1992, 2003) success constructs was found. Although customer-facing EMIS are now widespread, there is no known comprehensive, integrated theoretical framework for measuring the quality factors that contribute to EMIS success.

Thus, there was a need for an empirical study to assess the quality factors that influence EMIS success. This study proposed a comprehensive, multidimensional model of EMIS success, which suggested that information quality, system quality, service quality, use, user satisfaction, and perceived net benefit are success variables in Energy Management Information Systems. Three research questions framed the study: (1) to what degree do system quality, information quality, and service quality influence EMIS use? (2) to what degree do system quality, information quality, and service quality influence user satisfaction with an EMIS? and (3) to what degree do EMIS use and user satisfaction benefit utility customers in managing their energy consumption?

Eight hypotheses were tested to validate the model shown in Figure 19: (1) EMIS system quality will positively affect use; (2) EMIS system quality will positively affect user satisfaction; (3) EMIS information quality will positively affect use; (4) EMIS information quality will positively affect user satisfaction; (5) EMIS service quality will positively affect use; (6) EMIS service quality will positively affect user satisfaction; (7) EMIS use will positively affect perceived net benefits; and (8) EMIS user satisfaction will positively affect perceived net benefits.

To address these research questions and hypotheses, a quantitative methodology was employed. The type of investigation was correlational. The research used a descriptive, non-experimental quantitative survey approach. The time horizon was "one-shot" or cross-sectional. The research study relied on random sampling, snowball sampling, and network sampling as an approach for the collection of responses from 126 participants.

Following the recommendations of van Teijlingen and Hundley (2001), a pilot study was conducted for this study by testing the online survey questions and wording on a small group of participants. Based upon feedback from the pilot study participants, formatting and presentation improvements were made. SurveyMonkey was used to develop the online survey instrument and collect the data. SurveyMonkey selected random members of their panel using the Invite algorithm to participate in the main survey. In addition, the researcher used NextDoor Crocker Highlands, social media, email, and word-of-mouth to obtain the requisite respondent minimum.

Survey responses were screened for missing data and outliers. The analysis revealed missing values. To explain the incomplete cases, a missing value analysis procedure was conducted using SmartPLS 3.2.6. The original sample size of the dataset was 135. The sample size fell to 126 after removing the cases with missing values, which still met the criteria for PLS-SEM analysis.

Partial Least Squares is a structured equation modeling method that was used for data analysis and is extensively used in MIS research (Gefen & Straub, 2000; Urbach et al., 2010). Results from the internal consistency and reliability test of the measurement model showed that all the scores were above suggested thresholds. Discriminant validity was assessed by: (1) examining the AVE of the latent constructs to see if they were greater than the square of the correlations among the latent constructs; (2) examining the Fornell–Larcker (1981) criterion confirming discriminant validity; and (3) examining the loadings and cross-loadings between the individual indicators and the constructs to ensure that each indicator loads more highly with its own construct than with other constructs. The above tests of indicator item reliability, convergent validity, and discriminant validity validated the measurement model.

The structural model was evaluated for multicollinearity. Results indicated that both the tolerance level and the VIF values were within the acceptable guidelines recommended by Hair et al. (2014). The explanatory power of the structural model was evaluated by examining the coefficient of determination (R^2) value in the final dependent (endogenous) construct (net benefits). The R^2 for the overall model moderately explained 50.1% of the variance in net benefits. Path estimation was performed using Bootstrapping to examine the significance of the path values (β value) in the structural model.

Each path effect size in the structural equation model was evaluated by measuring if an independent construct had a substantial impact (effect) on a dependent construct. The latent constructs use and user satisfaction were each eliminated from the structural model and the PLS algorithm run in SmartPLS 3.2.6. This process confirmed that use had a large effect on net benefits, though not as large as user satisfaction. The path coefficients and the path significance (t-values) were used for hypotheses testing. During hypotheses testing, three non-significant relations were not supported. EMIS system quality did not positively affect user satisfaction; information quality did not positively affect use, and information quality did not positively affect user satisfaction. All other hypotheses were supported.

From the academic perspective, the study extends the applicability of the IS success model to the utility industry environment. Utility service providers can evaluate their EMIS web portals by using the success constructs identified in this study to measure and thus improve both their website and the back-end EMIS system. The results of this research are significant because the results can be used to help utility service providers implement methods that could enhance utility customer's EMIS use and satisfaction. Understanding the relative importance of system use and user satisfaction can help utility providers put more emphasis on the quality factors perceived by utility customers to aid them in managing their energy consumption.

The study provided a solid theoretical foundation from which future studies can build upon. As previously mentioned, a limitation of this study is that data was not gathered from different utility service provider regions in the United States in order to develop a comparative analysis. Such comparisons could provide significant insights into the effect of regional differences on the model. This study encourages researchers to consider all major regions of the United States as potential locations to test the model. Future research may collect primary data from different utility service provider regions to understand better the relationships and impacts of those factors on EMIS success.

The empirical results of this study indicated that information quality had no significant direct effect on EMIS use or user satisfaction. This was a surprising finding and is a compelling research opportunity to investigate possible causality. Furthermore, this study included a predictive investigation. The results of the predictive investigation were statistically significant, as the model accounted for 50% of the variance in net benefits. It is recommended that this predictive study be expanded to evaluate other IS success variables that would increase the explanatory strength of the model.

Appendix A

IRB Approval Letter

NOVA SOUTHEASTERN UNIVERSITY
Institutional Review Board

MEMORANDUM

To:	**Gwendolyn D Stripling, (PhD - Dissertation phase)** **College of Engineering and Computing**
From:	**Ling Wang, Ph.D.,** **Center Representative, Institutional Review Board**
Date:	**March 9, 2017**
Re:	**IRB #: 2017-186; Title, "Determinants of Energy Management IS Success: An Empirical Validation of The DeLone & McLean Information Systems Success Model"**

I have reviewed the above-referenced research protocol at the center level. Based on the information provided, I have determined that this study is exempt from further IRB review under **45 CFR 46.101(b) (Exempt Category 2)**. You may proceed with your study as described to the IRB. As principal investigator, you must adhere to the following requirements:

1) CONSENT: If recruitment procedures include consent forms, they must be obtained in such a manner that they are clearly understood by the subjects and the process affords subjects the opportunity to ask questions, obtain detailed answers from those directly involved in the research, and have sufficient time to consider their participation after they have been provided this information. The subjects must be given a copy of the signed consent document, and a copy must be placed in a secure file separate from de-identified participant information. Record of informed consent must be retained for a minimum of three years from the conclusion of the study.

2) ADVERSE EVENTS/UNANTICIPATED PROBLEMS: The principal investigator is required to notify the IRB chair and me (954-262-5369 and Ling Wang, Ph.D., respectively) of any adverse reactions or unanticipated events that may develop as a result of this study. Reactions or events may include, but are not limited to, injury, depression as a result of participation in the study, life-threatening situation, death, or loss of confidentiality/anonymity of subject. Approval may be withdrawn if the problem is serious.

3) AMENDMENTS: Any changes in the study (e.g., procedures, number or types of subjects, consent forms, investigators, etc.) must be approved by the IRB prior to implementation. Please be advised that changes in a study may require further review depending on the nature of the change. Please contact me with any questions regarding amendments or changes to your study.

The NSU IRB is in compliance with the requirements for the protection of human subjects prescribed in Part 46 of Title 45 of the Code of Federal Regulations (45 CFR 46) revised June 18, 1991.

Cc: Maxine Cohen, Ph.D.
Ling Wang, Ph.D.

Appendix B

Approval to use the DAS Survey Instrument

RE: Seeking Permission to Use Survey/Questionnaire Tool
Peter Seddon <p.seddon@unimelb.edu.au>
Sun 4/10/2016, 9:14 PMGwendolyn Stripling
HI Gwendolyn,
Yes, permission granted.
Cheers, peter

Peter B Seddon
Honorary Professorial Fellow, Department of Computing and Information Systems
The University of Melbourne, Australia (the land of the black swan!)
e-mail: p.seddon@unimelb.edu.au; peterbseddon@gmail.com
Phone: (Australia +61) 0407 984453

From: Gwendolyn Stripling [gstripli@nova.edu]
Sent: Monday, 11 April 2016 1:14 PM
To: Peter Seddon
Subject: Seeking Permission to Use Survey/Questionnaire Tool

Seeking Permission to Use Survey/Questionnaire Tool

April 10, 2016

Name: Gwendolyn D. Stripling
Institution: Nova Southeastern University
Department: College of Engineering and Computing
Address: 3301 College Avenue – Carl DeSantis Building
City/State/Zip: Fort Lauderdale-Davie, Florida 33314-7796

Dear Sir:

I am a doctoral student from Nova Southeastern University writing my dissertation titled *Determinants of Energy Management IS Success:*

An Empirical Validation of The DeLone and McLean Information Systems Success Model, under the direction of my dissertation committee chaired by

Dr. Maxine S. Cohen, who can be reached at 954 262-2072 (phone) or [redir.aspx?REF=o4-ek3VkLpDBNtvZJpVfd2vOmLlBkpvhcxC1YuOM5bqJFPWIv2HTCAFtYWlsdG86Y29oZW5tQG5vdmEuZWR1]cohenm@nova.edu (email).

I would like your permission to use portions of the Departmental Accounting System (DAS) Evaluation questionnaire/survey instrument in my research study. I would like to use and print your survey under the following conditions:

- I will use the surveys only for my research study and will not sell or use it with any compensated or curriculum development activities.
- I will include the copyright statement on all copies of the instrument.
- I will send a copy of my completed research study to your attention upon completion of the study.

If these are acceptable terms and conditions, please indicate so by replying to me through e-mail: gstripli@nova.edu

Sincerely,

Gwendolyn D. Stripling

Appendix C

Approval to use the EUCS Survey Instrument

Re: Seeking Permission to Use Survey/Questionnaire Tool
Reza Torkzadeh <reza.torkzadeh@unlv.edu>
Sun 4/10/2016, 9:14 PMGwendolyn Stripling
Hi Gwendolyn,

You are welcome to our EUCS instrument.

Good luck.

Torkzadeh

Sent from my iPad

On Apr 10, 2016, at 7:19 PM, Gwendolyn Stripling <gstripli@nova.edu> wrote:

Seeking Permission to Use Survey/Questionnaire Tool

April 10, 2016

Name: Gwendolyn D. Stripling
Institution: Nova Southeastern University
Department: College of Engineering and Computing
Address: 3301 College Avenue – Carl DeSantis Building
City/State/Zip: Fort Lauderdale-Davie, Florida 33314-7796

Dear Sir:

I am a doctoral student from Nova Southeastern University writing my dissertation titled *Determinants of Energy Management IS Success:*

An Empirical Validation of The DeLone and McLean Information Systems Success Model, under the direction of my dissertation committee chaired by

Dr. Maxine S. Cohen, who can be reached at 954 262-2072 (phone) or cohenm@nova.edu (email).

I would like your permission to use the End-User Computing Satisfaction (EUCS) survey/questionnaire instrument in my research study.

I would like to use and print your survey under the following conditions:

- I will use the surveys only for my research study and will not sell or use it with any compensated or curriculum development activities.
- I will include the copyright statement on all copies of the instrument.
- I will send a copy of my completed research study to your attention upon completion of the study.

If these are acceptable terms and conditions, please indicate so by replying to me through e-mail: gstripli@nova.edu

Sincerely,

Gwendolyn D. Stripling

Appendix D

Approval to use the SERVQUAL Survey Instrument

Re: Seeking Permission to Use Survey/Questionnaire Tool
leyland pitt <lpitt@sfu.ca>
Sun 4/10/2016, 9:10 PMGwendolyn Stripling;Richard Watson
<rwatson@terry.uga.edu>;bkavan@unf.edu
Hi Gwendolyn
The SERVQUAL instrument isn't our - it comes from the original developers, and was published in a peer reviewed journal which means its in the public domain and you don't need anyone's permission to use it

Best regards
Leyland Pitt
On Apr 10, 2016, at 11:53 PM, Gwendolyn Stripling <gstripli@nova.edu> wrote:

Seeking Permission to Use Survey/Questionnaire Tool

April 10, 2016

Name: Gwendolyn D. Stripling
Institution: Nova Southeastern University
Department: College of Engineering and Computing
Address: 3301 College Avenue – Carl DeSantis Building
City/State/Zip: Fort Lauderdale-Davie, Florida 33314-7796

Dear Sir:

I am a doctoral student from Nova Southeastern University writing my dissertation titled *Determinants of Energy Management IS Success: An Empirical Validation of The DeLone and McLean Information Systems Success Model*, under the direction of my dissertation committee chaired by Dr. Maxine S. Cohen, who can be reached at 954 262-2072 (phone) or cohenm@nova.edu (email).

I would like your permission to use portions of the Service Quality Perceptions questionnaire/survey instrument in my research study. I would like to use and print your survey under the following conditions:

- I will use the surveys only for my research study and will not sell or use it with any compensated or curriculum development activities.
- I will include the copyright statement on all copies of the instrument.
- I will send a copy of my completed research study to your attention upon completion of the study.

If these are acceptable terms and conditions, please indicate so by replying to me through e-mail: gstripli@nova.edu

Sincerely,

Gwendolyn D. Stripling

Appendix E

Participation Letter

Title of Study: An Empirical Assessment of Energy Management Information System Success Using Structural Equation Modeling

Principal investigator(s)
Gwendolyn D. Stripling, M.A.
627 Santa Ray Avenue
Oakland, CA 94610
510-830-7778

Co-investigator(s)
Maxine S. Cohen, Ph.D.
College of Engineering and Computing
Nova Southeastern University
3301 College Avenue
Ft. Lauderdale-Davie, Florida
33314-7796
954-262-2072

Institutional Review Board
Nova Southeastern University
Office of Grants and Contracts
(954) 262-5369/Toll Free: 866-499-0790
IRB@nsu.nova.edu

Description of Study: Gwendolyn D. Stripling is a doctoral student at Nova Southeastern University engaged in research for the purpose of satisfying a requirement for a Doctor of Philosophy degree. The purpose of this study is to evaluate the effectiveness of utility smart meter web portals in helping utility customers better manage their energy consumption through improved decision-making. Improved energy management decision-making may achieve both economic and social benefits for the utility customer and for the environment.

If you agree to participate, you will be asked to complete the attached questionnaire. This questionnaire will help the writer identify the factors that contribute to smart meter web portal effectiveness. The data from the questionnaire will be used to identify relevant factors that can be used to design effective smart meter web portals. This data will also be used to establish guidelines for smart meter web portal design and implementation. The questionnaire will take approximately fifteen minutes to complete.

Risks/Benefits to the Participant: There may be minimal risk involved in participating in this study. There are no direct benefits to for agreeing to be in this study. Please understand that although you may not benefit directly from participation in this study, you have the opportunity to enhance knowledge necessary to help contribute to how smart meter web portals can be made more effective. If you have any concerns about the risks/benefits of participating in this study, you can contact the investigators and/or the university’s human research oversight board (the Institutional Review Board or IRB) at the numbers listed above.

Cost and Payments to the Participant: There is no cost for participation in this study. Participation is completely voluntary and no payment will be provided.

Confidentiality: Information obtained in this study is strictly confidential unless disclosure is required by law. All data will be secured in a locked filing cabinet. Your name will not be used in the reporting of information in publications or conference presentations.

Participant's Right to Withdraw from the Study: You have the right to refuse to participate in this study and the right to withdraw from the study at any time without penalty.

I have read this letter and I fully understand the contents of this document and voluntarily consent to participate. All of my questions concerning this research have been answered. If I have any questions in the future about this study they will be answered by the investigator listed above or his/her staff.

I understand that the completion of this questionnaire implies my consent to participate in this study.

Appendix F

EMIS Survey

Part A. Pacific Gas & Electric Utility

Pacific Gas & Electric offers the California Alternate Rates for Energy Program (CARE) and the Family Electric Rate Assistance Program (FERA). Both the CARE and FERA programs give qualified households discounts on their energy bills.

1. Pacific Gas & Electric is my utility service provider.

Yes	No	Don't Know
1	2	3

2. I am enrolled in the CARE Program.

Yes	No	Don't Know
1	2	3

3. I am enrolled in the FERA Program.

Yes	No	Don't Know
1	2	3

4. Have you ever logged into the PG&E Smart Meter website to make an online payment?

Yes	No	Don't Know
1	2	3

5. Have you ever logged into the PG&E Smart Meter website to view your energy data?

Yes	No	Don't Know
1	2	3

Part B. Demographics Profile Questions

1. I am over 18?

    - o Yes
    - o No

2. What is your gender?

    - o Female
    - o Male
    - o Decline to answer

3. How frequently do you use the Internet?
    - o Almost every day
    - o At least once a week
    - o At least once a month
    - o Less than once a month

Part C. System Quality

1. The smart meter website is easy to use.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

2. The smart meter website is very responsive.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

3. The smart meter website keeps my home energy data private.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

4. The smart meter website provides a Green Button for downloading data.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

Part D. Information Quality

1. The charts and graphs provided by the smart meter website are in a useful format.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

2. The charts and graphs provided by the smart meter website are accurate.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

3. The charts and graphs provided by the smart meter website are easy to understand.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

4. The charts and graphs provided by the smart meter website are relevant.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

Part E. Service Quality

1. The smart meter website offers online help when needed.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

2. The smart meter website provides energy information to help me understand my utility bill.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

3. The smart meter website allows me to download my home energy data.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

Part F. Use

1. I use the smart meter website to get energy information about my residence.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

2. I use the smart meter website to better understand what the energy terms mean.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

Part G. User Satisfaction

1. I will continue to use the smart meter website.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

2. Overall, I am satisfied with the smart meter website.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

Part H.   Net Benefits

1. The smart meter website helps reduce my energy bills.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

2. The smart meter website increases my understanding of my energy usage.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

3. The smart meter website helps me make better decisions about energy usage.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

4. The smart meter website helps me to compare my energy usage to neighbors.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

References

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