DEVELOPMENT AND EXPLORATION OF END-USER HEALTHCARE TECHNOLOGY ACCEPTANCE MODELS

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This dissertation consists of three studies that collectively investigate the factors influencing the consumer adoption intention towards emerging healthcare technologies. Essay 1 systematically reviews the extent literature on healthcare technology adoption and serves as the theoretical foundation of the dissertation. It investigates different models that have been previously applied to study healthcare technology acceptance. Meta-analysis method is used to quantitatively synthesize the findings from prior empirical studies. Essay 2 posits, develops, and tests a comprehensive biotechnology acceptance model from the end-user's perspective. Two new constructs, namely, perceived risk and trust in technology, are integrated into the unified theory of acceptance and use of technology. Research hypotheses are tested using survey data and partial least square – structural equation modeling (PLS-SEM). Essay 3 extends the findings from the Essay 2 and further investigates the consumer's trust initiation and its effect on behavioral adoption intention. To achieve this purpose, Essay 3 posits and develops a trust model. Survey data allows testing the model using PLS-SEM. The models developed in this dissertation reflect significant modifications specific to the healthcare context. The findings provide value for academia, practitioners, and policymakers.

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INTRODUCTION

Background

Over the past decade, many new technologies have emerged in the healthcare field. Among those emerging technologies, genetic testing products and services are one that is rapidly growing. Currently, two practical models exist, which are clinical testing initiated by healthcare providers and direct-to-consumer (DTC) product that can be conveniently purchased online or in store (Borry, Howard, Sénécal, & Avard, 2010). The cumulative number of new testing products available on the market from 2014 to 2017 grew from a few hundred to almost 14,000 (Phillips, Deverka, Hooker, & Douglas, 2018). However, despite the growth in testing options, a paucity of research addresses the consumer's acceptance of this technology.

The study of technology acceptance focuses on identifying the factors that influence user behavioral intention (BI) regarding new technology use. Different theoretical models in the Information System (IS) area are relevant to such behavioral intention, such as the technology acceptance model (TAM) (Davis, 1989), the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003), and the UTAUT 2 model that measures the new technology acceptance and usage in a consumer context by incorporating the constructs of hedonic motivation, price value and habit (Venkatesh et al., 2012). Building upon the literature, this research consists of three studies that investigate the significant factors influencing the end-user behavioral adoption intention of emerging healthcare technologies. The first study systematically reviews the existing literature on the healthcare technology acceptance. The second study investigates the consumer's behavioral intention to use gene repair technology as it becomes available in the future. Finally, the third study further explores consumer's initial trust formation in the gene testing technology and the role of trust in the adopting process.

Problem Statement

Despite the rapid growth of gene testing services and quick advances in gene repair technology, little research examines the likely acceptance of such emerging healthcare technologies from a consumer perspective. There is a need to address this deficiency so that the scholars and healthcare professionals comprehend the antecedents of end-user perception and behavioral intention related to the use of such technologies. The addressing of this gap is an extension of the current technology acceptance models. Contextualizing and extending the model to emerging healthcare technologies are particularly important because it is not a given that established technology acceptance models are relevant to this new context. The models developed by this research reflect significant modifications for this unique application and the findings provide value for academia, practitioners and policymakers.

Research Questions

This research intends to answer the following questions through three essays: (1) What are the variables positively correlated with user's behavioral adoption intention for a healthcare technology? (2) What are the constructs affecting consumer behavioral intention to adopt gene repair technology that is not currently available? (3) What is the role of trust in the end-user behavioral adopting process?

Purpose and Contribution

The purpose of this research is to understand the consumer adoption intention of a new technology in the healthcare field. The first study conducts a systematic literature review of the existing studies on the healthcare technology acceptance. The meta-analysis method is employed to analyze the results. The second study empirically investigates the consumer's behavioral intention to use a specific emerging healthcare technology, namely, the gene repair technology, as it becomes available in the future. Finally, the third study further explores the role of trust in the adopting process and the trust initiation. The contribution of this research falls into both academia and industry.

This study contributes to theory in three aspects. Firstly, the results from meta-analysis in this research indicate the different significant level each predetermined construct has towards the end-user behavioral adoption intention of a technology in the healthcare field. Secondly, this research posits and develops a comprehensive technology acceptance model specifically to the biotechnology in the healthcare field by integrating perceived risk and trust factors. Finally, this research posits and develops a trust model that reflects the factors influencing how end-users trust a healthcare biotechnology.

In addition to academic contributions, this research also contributes to practice by providing evidence and insights for practitioners and policymakers in the relevant industry to better market the emerging healthcare technologies and make consistent policies that benefit the end-user.

Research Design

This research consists of three studies that investigate the significant factors influencing the end-user behavioral adoption intention of a healthcare technology.

Essay 1 systematically reviews the existing literatures on the healthcare technology adoption and serves as the theoretical foundation of the current research. It investigates different models that have been previously applied to study the healthcare technology acceptance. Meta-analysis method allows to quantitatively synthesize the findings from prior empirical studies.

Essay 2 posits, develops, and tests a comprehensive biotechnology acceptance model from the end-user's perspective. Two new constructs, namely, perceived risk and trust in technology, are integrated to the UTAUT model. A research survey is designed and distributed to undergraduate students from a major research school in the U.S. southwest region. Research hypotheses are tested using partial least square – structural equation modeling (PLS-SEM).

Essay 3 extends the findings from the previous essay and further investigates consumer's trust initiation and its effect on behavioral adoption intention. To achieve this purpose, Essay 3 posits and develops a trust model. Survey data from undergraduate students from a major research school in the U.S. southwest region allows to test the model using PLS-SEM.

ESSAY 1

A META-ANALYSIS OF TECHNOLOGY ACCEPTANCE IN HEALTHCARE

1.1 Introduction

Healthcare innovation offers indubitable benefits in a wide spectrum from specialized disease treatment to large-scale public health. In near two decades, tremendous efforts are put into developing and realizing a quality healthcare delivery system, which is safe, effective, patient-centered, timely, efficient, and equitable (Institute of Medicine (US) Committee on Quality of Health Care in America, 2001). Because of the advancement in health technology and data science, more recently, various consumer-oriented and patient-centered healthcare applications, such as health information administrative and communicating technologies, smart health applications, and direct-to-consumer (DTC) services like genetic testing, are emerging in the consumer market. Nevertheless, there still exist enormous opportunities for scientific advancement and according commercialization (Shen, Wang, & Yang, 2020). Technology firms and healthcare organizations are actively embracing the trend that transforms medicine and healthcare in various aspects, including AI and machine learning, robotics, computer and machine vision, wearable technology, 3D printing, extended reality, digital twins, and 5G (Marr, 2019). As a result, the global digital health market had a value of $95.8 billion in 2018 and is project for a 27.7% annual growth rate from 2019 to 2025, at the time the revenue is forecasted to reach $509.2 billion (Grand View Research, 2019).

Aligning with the rapid healthcare technology advancement and commercialization, designing and promoting a healthcare ecosystem and person-centric healthcare becomes contemporary topics. In the healthcare ecosystem developed by (Dai & Tayur, 2019), patient is an integral part that directly interacts with delivery and financing entities, which are empowered by innovations and regulated by policymaking entities. In contrast to patient-centered healthcare, a person-centric healthcare places the person, rather than the patient, as a central key because it aims to improve the person's health quality in a life-long term (Tsekleves & Cooper, 2017). Despite the increasing number of emerging healthcare applications in the market, many researchers in medical institutes highlight the importance of verification and validation of end-user adoption intention and how an emerging technology can meet the consumer needs (Mathews et al., 2019). Numerous studies posited and tested technology acceptance models in various contexts in order to empirically investigate the consumer behavioral adoption intention. However, there exist inconsistencies in the extant literature in terms of what factors influences the consumers adoption intention, how significant the correlations are, and whether moderating effects exist between the exogenous variables and behavioral intention. Varying conceptualizations of major constructs from technology acceptance models are also observed from the systematic literature review conducted in this study. For instance, social influence is a construct in the unified theory of acceptance and use of technology (UTAUT). It refers to the users believe that their important friends and family members support the adoption of a specific technology (Venkatesh, Morris, Davis, & Davis, 2003). (Tavares & Oliveira, 2016) investigated the patient adoption of electronic health record portal and found that social influence insignificantly correlates with behavioral intention. Whereas in another similar context of adopting personal health record apps to promote workplace health, the social influence is found to be a significant predictor of behavioral intention (Park et al., 2020). Therefore, the inconsistent results and conceptualization variation necessitate a systematic examination on consumer adoption intention towards emerging healthcare technologies.

A few studies have made attempts to provide a comprehensive view. For example, (Or & Karsh, 2009) conducted a systematic literature review to identify factors influencing consumer acceptance of health information technology. That study examined 52 articles and presented results in a descriptive format. Similarly, (Holden & Karsh, 2010) qualitatively analyzed 16 datasets in 22 studies that are technology acceptance model (TAM) based and consider healthcare professionals as end-users. Only two studies used quantitative approach to study the user adoption intention of e-health applications (Chauhan & Jaiswal, 2017) and health information technology (Tao et al., 2020). Meta-analysis was employed to estimate the effect sizes of construct relationships and investigate potential moderating effects. However, both studies primarily focused on the studies that adopt technology acceptance model (TAM) as theoretical framework. In addition, (Chauhan & Jaiswal, 2017) did not distinguish the medical professionals from general consumer. There is a need to synthesize the findings in the extent literature that adopt different technology acceptance models and investigate the emerging healthcare technology adoption intention from the consumer perspective.

This study aims to address the research gap by conducting a systematic literature review on the empirical studies of consumer adoption intention towards various emerging healthcare technologies and quantitatively synthesizing the findings with a meta-analysis of correlations approach implemented in the studies such as Nair (2006). The objective of the current research is to examine the correlations between various exogenous constructs existed in different technology acceptance models and the consumer behavioral adoption intention, as well as the potential existence of moderating effects. In particular, this study aims to answers the following research questions:

- How aggregate exogenous variables affect consumer adoption intention?
- Which individual variable is positively correlated with consumer adoption intention?
- Are there moderating factors influencing the relationship between exogenous variables and consumers adoption intention?

This study contributes to the technology acceptance literature by synthesizing the prior empirical findings and presenting a comprehensive view of the consumers adoption intention in the healthcare context. Practical implications are also discussed to provide insights to the technology designers, providers, and regulatory authorities.

The rest of the paper is organized as follows. The next section reviews the conceptual framework that guides meta-analysis on emerging healthcare technology acceptance and discuss additional potential influencing factors. Section 3 presents the data collection and meta-analysis procedures. The results are presented in Section 4. Section 5 discusses the findings, research contributions, and limitation. In Section 6, the paper is ended with concluding remarks.

1.2 Literature Review

The study of technology acceptance focuses on identifying the factors that influence user behavioral intention regarding new technology use. Different theoretical models in the Information System (IS) area are relevant to such behavioral intention. The technology acceptance model (TAM) is a widely used model that conceptualizes how perceived usefulness, perceived ease of use, and user acceptance of information technology influence behavioral intention (Davis, 1989). A large body of TAM literature indicates the popularity of the theoretical framework (Chauhan & Jaiswal, 2017; King & He, 2006; Tao et al., 2020). Till now, many researchers studying the topic of healthcare technology acceptance remain interest in TAM and contextualize its core constructs in the studies (Kumar & Natarajan, 2019; Werber et al., 2018; Zhang et al., 2017). Venkatesh et al. (2003) extended TAM by comparing eight technology acceptance models and integrating across those to develop a unified theory of acceptance and use of technology (UTAUT). The UTAUT has four core determinants including performance expectancy, effort expectancy, social influence, and facilitating conditions, which directly affect user behavioral intention and the usage of new technology, and up to four moderators. These moderators, namely, gender, age, experience, and voluntariness of use, moderate the relationships between determinants and behavioral intention (Venkatesh et al., 2003). Performance expectancy refers to the degree to which an individual believes that using information technology can help them increase job performance. Effort expectancy refers to the degree of ease of using technology. Social influence measures how an individual perceives that others' opinion influences their use of the technology. Facilitating conditions refer to the degree to which an individual believes that resources and technical support are available to support the adoption of technology. In the healthcare context, the UTAUT model was adapted in studying the consumer adoption intention of various emerging technologies, such as electronic health record applications (Park et al., 2020), hospital report cards (Emmert & Wiener, 2017), and telehealth services (Cimperman et al., 2016; Diño & de Guzman, 2015).

The UTAUT model was initially presented to measure the adoption intention and usage of an information system in the organizational context. To extend the UTAUT to measure the new technology acceptance and usage in a consumer context, (Venkatesh et al., 2012) developed the UTAUT2 model, which conceptualized the original constructs to a consumer setting and incorporated three additional constructs including hedonic motivation, price value, and habit. The UTAUT2 model are becoming increasingly popular in studying emerging healthcare technology adoption intention. Researchers adapted this model in order to explain additional variation of the consumers adoption intention in different contexts. For instance, (Dwivedi et al., 2016) investigated the consumer adoption of mobile health using data sample obtained from U.S., Canada, and Bangladesh. The authors found an inconsistent significance of the correlation between hedonic motivation and behavioral intention across the three countries, whereas the positive correlations between price value and behavioral intention are supported in all demographics.

This study includes all the constructs in the UTAUT2 model and additional three constructs, namely, perceived risks, trust in technology, and self-efficacy because of the following reasons. First, consumer's acceptance behavior is regarded as a risk-taking process because of the potentially unfavorable outcomes (Bauer, 1960). Perceived risks psychologically measure the consumer's perception of uncertainty (Cox & Rich, 1964). As a construct originated from the marketing field, perceived risk appears to be one of the critical factors influencing consumer adoption intention particularly in the healthcare context because behavioral intention is shown to be significantly correlated with the consumer's security and privacy confidence about a healthcare technology (Gao et al., 2015; Kumar & Natarajan, 2019; Shareef et al., 2014; Whetstone & Goldsmith, 2009). Second, specific to healthcare, the role of trust is well studied and is regarded as an imperative that influences the consumer's experience of receiving healthcare services (Thorne & Robinson, 1988). The extant IS literature reveals that there is a significant correlation between trust and consumer adoption intention, for example, in the context of e-commerce (Oliveira et al., 2017). The same correlation is also posited and validated in various empirical studies about emerging healthcare technologies such as Internet-based patient-physician communication application (Klein, 2007a), RFID technology (Werber et al., 2018), and e-health services (Kumar & Natarajan, 2019). The current research also considers a number of relevant constructs, including attitude (Borges Jr & Kubiak, 2016; Park et al., 2016; Yun & Park, 2010), perceived reliability (Shareef et al., 2014), and reassurance (Lee et al., 2017), that have similar operationalization to the trust and are found in prior researches. Third, self-efficacy is defined as the degree of consumer's confidence at his or her ability to use a technology or enact recommended response (Johnston & Warkentin, 2010; Sun et al., 2013). Prior studies investigating the correlation between self-efficacy and behavioral intention in the healthcare context show mixed findings (Gao et al., 2015; Klein, 2007; Koivumäki et al., 2017; Ma & Liu, 2005). Therefore, this construct, together with other similar constructs, such as personal innovativeness (Park et al., 2016; Whetstone & Goldsmith, 2009; Zhang et al., 2017) and self-concept (Dwivedi et al., 2016), are included in the current meta-analytic study.

The research methodology used to test the hypotheses between the forementioned variables and behavioral intention varies in the extent literature. These methodologies include covariance-based structural equations modeling (CB-SEM) (Borges Jr & Kubiak, 2016; Cimperman et al., 2016; Dwivedi et al., 2016; Jeon & Park, 2015; Koivumäki et al., 2017; Lazard et al., 2016; Lee et al., 2017; Noblin et al., 2013; Park et al., 2016; Shareef et al., 2014; Werber et al., 2018; Wilson & Lankton, 2004; Yun & Park, 2010), partial least square-based structural equations modeling (PLS-SEM) (Diño & de Guzman, 2015; Emmert & Wiener, 2017; Gao et al., 2015; Klein, 2007a; Klein, 2007b; Kumar & Natarajan, 2019; Tavares & Oliveira, 2016; Tavares et al., 2018; Wang et al., 2020; Zhang et al., 2017), linear regression (Krishnan et al., 2015; Park et al., 2020; Whetstone & Goldsmith, 2009), and hierarchical regression (Liang et al., 2011; Ma & Liu, 2005).

The current research uses a meta-analysis method to test the validity of the relationships between a series of exogenous variables and consumer adoption intention in healthcare context. The meta-analytic procedure also investigates the potential existence of moderating factors on such relationships. Based on the UTAUT2 model and relevant empirical studies, this research presents the following hypotheses:

H1. Aggregate exogenous variables are positively correlated with consumer adoption intention.

H2. The correlation between aggregate exogenous variables and behavioral intention is influenced by moderating factors.

H3. Individual exogenous variable is positively correlated with consumer adoption intention.

H4. The correlation between Individual exogenous variable and behavioral intention is influenced by moderating factors.

1.3 Meta-Analysis of Correlations

1.3.1 Validity of Construct Operationalization

The exogenous variables in this meta-analytic study are selected from the extant literature after a systematic literature review. In these empirical studies, all the relevant constructs retain a content validity, convergent validity, and discriminant validity. However, the construct operationalization in the prior studies varies due to the specific research context. The following summarizes and validates the 11 construct operationalizations with definitions.

- *Effort expectancy* measures the degree of ease associated with using a technology. Perceived ease of use in TAM is also included as well as the convenience construct operationalized by (Lee et al., 2017).

- *Facilitating conditions* measure the consumers' perceptions of the availability of resources and assistance to the technology usage. A consistency appears in all the articles that adopted this construct.

- *Habit* reflects the consumers' prior experience about a technology. A similar construct of resistance to change operationalized by (Krishnan et al., 2015) is also considered in this category. The negative correlation coefficient is converted to a positive value in data analysis.

- *Hedonic motivation* is defined as the joyfulness and pleasure of using a technology. The similar construct of enjoyment operationalized by (Lee et al., 2017) is also included.

- *Perceived risk* is defined as the minimal risk perception of using a technology. It consists of perceived privacy risk, perceived security risk, and perceived barriers.

- *Performance expectancy* measures the degree to which customers believe that using the target technology will provide beneficial results (Venkatesh et al., 2012). Perceived usefulness in TAM captures similar definition and therefore is included with performance expectancy.

- *Price value* refers to the consumers' perception of trade-off value between cost and benefic as a result of using a technology. The current study considers functional congruence (Gao et al., 2015), perceived cost (Park et al., 2016), and perceived financial risk (Krishnan et al., 2015) as similar operationalizations to price value. It is notable that the negative correlation coefficients from prior studies, such as perceived cost and perceived financial risk, were transferred to a positive value to fit the meta-analysis in this study.

- *Self-efficacy* refers to the consumers' beliefs that they are capable of performing a certain task. It also involves personal innovativeness and self-concept found in the prior studies.

- *Social influence* represents that the consumers' family and friends believe that they should use the specific technology. All the studies adopted this construct and included in the current research used the same definition.

1.3.2 Sample

The sample used for meta-analysis in this research was collected from the ABI/INFORM Global, Academic Search Complete, Business Source Complete, and Scopus databases. We had three searching combinations, which are

1. AB healthcare AND AB technology acceptance model AND AB consumer
2. AB healthcare AND AB technology acceptance model AND AB end user
3. AB healthcare technology acceptance AND AB bio*

A total of 218 articles were returned and thus screened. Out of these articles, we retained 28 articles for the meta-analysis because they have complete information that is needed for the analysis. A summary of selected articles is presented in appendix A.

1.3.3 Meta-Analytic Procedures and Heuristics to Guide Hypothesis Testing

The current study adopted a two-stage meta-analytic procedure recommended by (Nair, 2006) and (Xu et al., 2020). To test H1 and H2, we compute the compound attenuation factor (A) by

$$A_i = \sqrt{\alpha_{xxi}\alpha_{yyi}} \quad \text{(Eq. 1.1)}$$

where α_{xx} and α_{yy} are reliability of variables. Then, we compute the following:

$$\text{Corrected correlations } r_i' = r_i/A_i \quad \text{(Eq. 1.2)}$$

$$\text{Individual study weight } W_i = N_i A_i^2 \quad \text{(Eq. 1.3)}$$

where r is study correlations and N is sample size for each study. This allows us to compute weighted sample mean correlations ($\bar{r}$) and weighted mean corrected correlations ($\overline{r'}$) using the following formulas:

$$\bar{r} = \sum N_i r_i / \sum N_i \quad \text{(Eq. 1.4)}$$

$$\overline{r'} = \sum W_i r_i' / \sum W_i \quad \text{(Eq. 1.5)}$$

Then, we compute corrected study sampling error (e_i) and weighted mean sampling error variance ($\bar{e}$) by:

$$e_i = (1 - \bar{r}^2)^2 / (N_i - 1)A_i^2 \quad \text{(Eq. 1.6)}$$

$$\bar{e} = \sum W_i e_i / \sum W_i \quad \text{(Eq. 1.7)}$$

Next, weighted mean variance of the corrected correlations ($S_{r'}^2$) and estimated population correlation variance (S_ρ^2) are computed by:

$$S_{r'}^2 = \sum W_i r_i' / \sum W_i \quad \text{(Eq. 1.8)}$$

$$S_\rho^2 = S_{r'}^2 - \bar{e} \quad \text{(Eq. 1.9)}$$

In the end, two ratios, namely, Ratio 1 and Ratio 2, can be computed by:

$$RATIO1 = \overline{r'}/S_{\rho} \qquad \text{(Eq. 1.10)}$$

$$RATIO2 = \bar{e}/S_{r'}^{2} \qquad \text{(Eq. 1.11)}$$

Table 1.1 shows the data for the Stage 1 analysis.

The testing procedures for the H3 and H4 are similar to the procedures illustrated above. A result of $RATIO1 \geq 2$ indicates that positive correlation exists between the individual exogenous construct and behavioral intention. A result of $RATIO2 \leq 0.75$ indicates that moderating factor exists (Hunter & Schmidt, 1990; Gerwin & Barrowman, 2002; Mackelprang et al., 2010; Nair, 2006). Table 1.2 shows the data for the Stage 2 analysis.

1.4 Results

We tested the correlation between aggregate exogenous variables and behavioral intention based on the data shown in Table 1.1 and calculated RATIO1 and RATIO2. The RATIO1 for the aggregate model is 3.81, which is greater than 2, indicating a significant correlation. The RATIO2 is 0.45, which is less than 0.75. It suggests that moderating factors exist in the aggregate model. Therefore, both H1 and H2 are supported. In Stage 2, we tested the correlation between each individual exogenous variable and behavioral intention using the data shown in Table 1.2. The value of RATIO1 for habit (3.90), perceived risks (13.03), trust (2.61), and performance expectancy (2.13) are greater than the 2 threshold, which suggest these three constructs are significantly correlated with behavioral intention. The value of RATIO2 for performance expectancy (0.11), effort expectancy (0.15), social influence (0.17), facilitating conditions (0.23), hedonic motivation (0.30), price value (0.34), habit (0.42), trust (0.15), and self-efficacy (0.18) are smaller than 0.75 suggesting the existence of moderating factors. However, the RATIO2 for perceived risks is 0.93, which is great than the cut-off value of 0.75.

Table 1.1: Stage 1 data

Study	N	Eα	Bα	r	r'	W	e
Wilson and Lankton (2004)	163	0.9350	0.9600	0.4270	0.4507	146.3088	0.0063
Ma and Liu (2005)	86	0.9267	0.8900	0.3122	0.3437	70.9271	0.0131
Klein (2007a)	143	0.8000	0.9100	0.2341	0.2743	104.1040	0.0089
Klein (2007b)	294	0.8267	0.8950	0.1762	0.2048	217.5208	0.0042
Whetstone and Goldsmith (2009)	542	0.8590	0.9400	0.2338	0.2602	437.6433	0.0021
Yun and Park (2010)	212	0.8950	0.8800	0.4247	0.4786	166.9712	0.0055
Liang et al. (2011)	330	0.8233	0.9300	0.1951	0.2230	252.6810	0.0036
Noblin et al. (2013)	562	0.8835	0.7000	0.3296	0.4192	347.5689	0.0026
Shareef et al. (2014)	326	0.8120	0.8120	0.2436	0.3000	214.9461	0.0043
Gao et al. (2015)	341	0.8350	0.8250	0.1296	0.1562	234.9064	0.0039
Gao et al. (2015)	297	0.8561	0.8380	0.1325	0.1565	213.0820	0.0043
Krishnan et al. (2015)	128	0.9838	0.9870	0.2063	0.2094	124.2936	0.0074
Lazard et al. (2015)	333	0.9350	0.9800	0.1919	0.2005	305.1279	0.0030
Diño and de Guzman (2015)	82	0.8617	0.8910	0.2099	0.2395	62.9551	0.0147
Jeon and Park (2015)	94	0.8600	0.9100	0.3264	0.3690	73.5644	0.0126
Park et al. (2016)	877	0.9028	0.9220	0.2273	0.2492	729.9582	0.0013
Tavares and Oliveira (2016)	360	0.8843	0.9000	0.1064	0.1193	286.5086	0.0032
Borges and Kubiak (2016)	111	0.8500	0.9200	0.3825	0.4325	86.8020	0.0106
Dwivedi et al. (2016)	387	0.8190	0.8190	0.1509	0.1843	259.5845	0.0035
Dwivedi et al. (2016)	359	0.8190	0.8190	0.1357	0.1657	240.8032	0.0038
Dwivedi et al. (2016)	375	0.8190	0.8190	0.1264	0.1543	251.5354	0.0036

(table continues)

Study	N	Eα	Bα	r	r'	W	e
Cimperman et al. (2016)	400	0.9500	0.9200	0.2492	0.2665	349.6000	0.0026
Koivumäki et al. (2017)	855	0.7712	0.8850	0.2138	0.2587	583.5478	0.0016
Zhang et al. (2017)	436	0.8298	0.8821	0.2708	0.3165	319.1278	0.0029
Lee et al. (2017)	313	0.8675	0.8230	0.2204	0.2609	223.4671	0.0041
Emmert and Wiener (2017)	780	0.8600	1.0000	0.1343	0.1449	670.8000	0.0014
Werber et al. (2018)	531	0.9147	0.9200	0.2711	0.2956	446.8330	0.0021
Tavares et al. (2018)	386	0.8843	0.9100	0.1057	0.1178	310.6142	0.0030
Kumar and Natarajan (2019)	253	0.9235	0.8930	0.2598	0.2861	208.6454	0.0044
Park et al. (2020)	687	0.8460	0.9500	0.1682	0.1876	552.1419	0.0017
Wang et al. (2020)	406	0.7985	0.7770	0.1550	0.1967	251.8964	0.0036

Table 1.2: Stage 2 data

Study	N	Eα	Bα	r	r'	W	e
Performance Expectancy							
Wilson and Lankton (2004)	163	0.9600	0.9600	0.6720	0.7000	150.2208	0.0056
Ma and Liu (2005)	86	0.9400	0.8900	0.4145	0.4532	71.9476	0.0117
Klein (2007a)	143	0.8700	0.9100	0.3480	0.3911	113.2131	0.0074
Klein (2007b)	294	0.8400	0.8950	0.3360	0.3875	221.0292	0.0038
Whetstone and Goldsmith (2009)	542	0.8430	0.9400	0.4299	0.4830	429.4916	0.0019
Yun and Park (2010)	212	0.8800	0.8800	0.1760	0.2000	164.1728	0.0051
Liang et al. (2011)	330	0.8500	0.9300	0.4106	0.4618	260.8650	0.0032
Noblin et al. (2013)	562	0.8690	0.7000	0.5874	0.7532	341.8646	0.0024

(table continues)

Study	N	Eα	Bα	r	r'	W	e
Shareef et al. (2014)	326	0.8120	0.8120	0.3167	0.3900	214.9461	0.0039
Gao et al. (2015)	341	0.8290	0.8250	0.0713	0.0862	233.2184	0.0036
Gao et al. (2015)	297	0.8600	0.8380	0.1428	0.1682	214.0420	0.0039
Krishnan et al. (2015)	128	0.9870	0.9870	0.1895	0.1920	124.6936	0.0067
Lazard et al. (2015)	333	0.9500	0.9800	0.3829	0.3968	310.0230	0.0027
Diño and de Guzman (2015)	82	0.8370	0.8910	0.1707	0.1977	61.1529	0.0138
Jeon and Park (2015)	94	0.8000	0.9100	0.4320	0.5063	68.4320	0.0123
Park et al. (2016)	877	0.9300	0.9220	0.3999	0.4319	751.9924	0.0011
Tavares and Oliveira (2016)	360	0.9000	0.9000	0.1800	0.2000	291.6000	0.0029
Borges and Kubiak (2016)	111	0.8500	0.9200	0.2975	0.3364	86.8020	0.0097
Dwivedi et al. (2016)	387	0.8190	0.8190	0.1147	0.1400	259.5845	0.0032
Dwivedi et al. (2016)	359	0.8190	0.8190	0.1310	0.1600	240.8032	0.0035
Dwivedi et al. (2016)	375	0.8190	0.8190	0.0737	0.0900	251.5354	0.0033
Cimperman et al. (2016)	400	0.9400	0.9200	0.2350	0.2527	345.9200	0.0024
Zhang et al. (2017)	436	0.9308	0.8821	0.3798	0.4192	357.9624	0.0023
Lee et al. (2017)	313	0.8660	0.8230	0.3291	0.3898	223.0807	0.0037
Emmert and Wiener (2017)	780	0.8850	1.0000	0.3460	0.3678	690.3000	0.0012
Werber et al. (2018)	531	0.9320	0.9200	0.3551	0.3835	455.3006	0.0018
Tavares et al. (2018)	386	0.9000	0.9100	0.1530	0.1691	316.1340	0.0026
Kumar and Natarajan (2019)	253	0.9180	0.8930	0.4535	0.5009	207.4028	0.0040
Park et al. (2020)	687	0.7900	0.9500	0.0553	0.0638	515.5935	0.0016
Wang et al. (2020)	406	0.7960	0.7770	0.3104	0.3947	251.1078	0.0033

(table continues)

Study	N	Eα	Bα	r	r'	W	e
Effort Expectancy							
Wilson and Lankton (2004)	163	0.9100	0.9600	0.1820	0.1947	142.3968	0.0067
Ma and Liu (2005)	86	0.9100	0.8900	0.3713	0.4126	69.6514	0.0138
Park et al. (2016)	143	0.8300	0.9100	0.1162	0.1337	108.0079	0.0089
Klein (2007b)	294	0.8500	0.8950	0.0978	0.1121	223.6605	0.0043
Liang et al. (2011)	330	0.8000	0.9300	0.0944	0.1094	245.5200	0.0039
Noblin et al. (2013)	562	0.8980	0.7000	0.0718	0.0906	353.2732	0.0027
Shareef et al. (2014)	326	0.8120	0.8120	0.2192	0.2700	214.9461	0.0044
Gao et al. (2015)	341	0.8520	0.8250	0.0613	0.0732	239.6889	0.0040
Gao et al. (2015)	297	0.8520	0.8380	0.1440	0.1704	212.0509	0.0045
Krishnan et al. (2015)	128	0.9900	0.9870	0.4673	0.4727	125.0726	0.0077
Lazard et al. (2015)	333	0.9200	0.9800	0.0009	0.0010	300.2328	0.0032
Diño and de Guzman (2015)	82	0.9040	0.8910	0.2884	0.3213	66.0480	0.0146
Jeon and Park (2015)	94	0.9200	0.9100	0.2208	0.2413	78.6968	0.0122
Tavares and Oliveira (2016)	360	0.9100	0.9000	0.1684	0.1860	294.8400	0.0032
Dwivedi et al. (2016)	387	0.8190	0.8190	0.2948	0.3600	259.5845	0.0037
Dwivedi et al. (2016)	359	0.8190	0.8190	0.3194	0.3900	240.8032	0.0040
Dwivedi et al. (2016)	375	0.8190	0.8190	0.3112	0.3800	251.5354	0.0038
Cimperman et al. (2016)	400	0.9500	0.9200	0.4940	0.5284	349.6000	0.0027
Koivumäki et al. (2017)	855	0.8330	0.8850	0.1591	0.1853	630.3103	0.0015
Lee et al. (2017)	313	0.8580	0.8230	0.3432	0.4084	221.0199	0.0043
Emmert and Wiener (2017)	780	0.8820	1.0000	-0.0397	-0.0423	687.9600	0.0014

(table continues)

Study	N	Eα	Bα	r	r'	W	e
Werber et al. (2018)	531	0.8840	0.9200	0.1149	0.1274	431.8517	0.0022
Tavares et al. (2018)	386	0.9100	0.9100	0.1547	0.1700	319.6466	0.0030
Kumar and Natarajan (2019)	253	0.8890	0.8930	0.1760	0.1976	200.8509	0.0047
Park et al. (2020)	687	0.9600	0.9500	0.0768	0.0804	626.5440	0.0015
Wang et al. (2020)	406	0.8090	0.7770	0.0785	0.0990	255.2088	0.0037
Social Influence							
Gao et al. (2015)	341	0.8140	0.8250	0.1530	0.1867	228.9986	0.0036
Gao et al. (2015)	297	0.8580	0.8380	0.1184	0.1396	213.5442	0.0039
Diño and de Guzman (2015)	82	0.8440	0.8910	0.1705	0.1966	61.6643	0.0137
Tavares and Oliveira (2016)	360	0.9800	0.9000	0.0794	0.0845	317.5200	0.0026
Dwivedi et al. (2016)	387	0.8190	0.8190	0.1065	0.1300	259.5845	0.0032
Dwivedi et al. (2016)	359	0.8190	0.8190	0.0901	0.1100	240.8032	0.0035
Dwivedi et al. (2016)	375	0.8190	0.8190	0.1310	0.1600	251.5354	0.0033
Emmert and Wiener (2017)	780	0.8640	1.0000	0.0458	0.0493	673.9200	0.0012
Tavares et al. (2018)	386	0.9700	0.9100	0.0970	0.1032	340.7222	0.0025
Park et al. (2020)	687	0.9200	0.9500	0.3956	0.4232	600.4380	0.0014
Wang et al. (2020)	406	0.8480	0.7770	0.0975	0.1201	267.5118	0.0031
Facilitating Conditions							
Tavares and Oliveira (2016)	360	0.8000	0.9000	0.0040	0.0047	259.2000	0.0032
Dwivedi et al. (2016)	387	0.8190	0.8190	0.2621	0.3200	259.5845	0.0032
Dwivedi et al. (2016)	359	0.8190	0.8190	0.2457	0.3000	240.8032	0.0035
Dwivedi et al. (2016)	375	0.8190	0.8190	0.2539	0.3100	251.5354	0.0033

(table continues)

Study	N	Eα	Bα	r	r'	W	e
Cimperman et al. (2016)	400	0.9400	0.9200	0.1222	0.1314	345.9200	0.0024
Emmert and Wiener (2017)	780	0.8090	1.0000	0.1853	0.2060	631.0200	0.0013
Tavares et al. (2018)	386	0.8100	0.9100	0.0000	0.0000	284.5206	0.0029
Park et al. (2020)	687	0.8700	0.9500	0.1131	0.1244	567.8055	0.0015
Wang et al. (2020)	406	0.7410	0.7770	0.1334	0.1758	233.7573	0.0036
Hedonic Motivation							
Gao et al. (2015)	341	0.8550	0.8250	0.2043	0.2433	240.5329	0.0035
Gao et al. (2015)	297	0.8500	0.8380	0.0833	0.0987	211.5531	0.0039
Krishnan et al. (2015)	128	0.9910	0.9870	0.3974	0.4018	125.1990	0.0067
Tavares and Oliveira (2016)	360	0.9300	0.9000	0.0353	0.0386	301.3200	0.0028
Dwivedi et al. (2016)	387	0.8190	0.8190	0.0082	0.0100	259.5845	0.0032
Dwivedi et al. (2016)	359	0.8190	0.8190	-0.0410	-0.0500	240.8032	0.0035
Dwivedi et al. (2016)	375	0.8190	0.8190	0.0819	0.1000	251.5354	0.0033
Lee et al. (2017)	313	0.8750	0.8230	0.0700	0.0825	225.3991	0.0037
Tavares et al. (2018)	386	0.9300	0.9100	0.0651	0.0708	326.6718	0.0026
Price Value							
Gao et al. (2015)	341	0.8200	0.8250	0.2575	0.3130	230.6865	0.0036
Gao et al. (2015)	297	0.8500	0.8380	0.0272	0.0322	211.5531	0.0039
Krishnan et al. (2015)	128	0.9630	0.9870	0.0289	0.0296	121.6616	0.0069
Park et al. (2016)	877	0.8620	0.9220	0.0155	0.0174	697.0080	0.0012
Tavares and Oliveira (2016)	360	0.9300	0.9000	-0.0093	-0.0102	301.3200	0.0028
Dwivedi et al. (2016)	387	0.8190	0.8190	0.1229	0.1500	259.5845	0.0032

(table continues)

Study	N	Eα	Bα	r	r'	W	e
Dwivedi et al. (2016)	359	0.8190	0.8190	0.0983	0.1200	240.8032	0.0035
Dwivedi et al. (2016)	375	0.8190	0.8190	0.0819	0.1000	251.5354	0.0033
Tavares et al. (2018)	386	0.9400	0.9100	0.0000	0.0000	330.1844	0.0025
Habit							
Krishnan et al. (2015)	128	0.9850	0.9870	0.0955	0.0969	124.4410	0.0067
Tavares and Oliveira (2016)	360	0.7400	0.9000	0.2871	0.3518	239.7600	0.0035
Tavares et al. (2018)	386	0.7300	0.9100	0.2701	0.3314	256.4198	0.0033
Perceived Risks							
Whetstone and Goldsmith (2009)	542	0.9580	0.9400	0.1629	0.1716	488.0818	0.0017
Liang et al. (2011)	330	0.8200	0.9300	0.0804	0.0920	251.6580	0.0033
Shareef et al. (2014)	326	0.8120	0.8120	0.1868	0.2300	214.9461	0.0039
Gao et al. (2015)	341	0.8170	0.8250	0.1332	0.1622	229.8425	0.0036
Gao et al. (2015)	297	0.8510	0.8380	0.1923	0.2277	211.8020	0.0039
Krishnan et al. (2015)	128	0.9870	0.9870	0.0592	0.0600	124.6936	0.0067
Cimperman et al. (2016)	400	0.9700	0.9200	0.1455	0.1540	356.9600	0.0023
Koivumäki et al. (2017)	855	0.7706	0.8850	0.1634	0.1978	583.0938	0.0014
Kumar and Natarajan (2019)	253	0.9910	0.8930	0.2567	0.2728	223.8956	0.0037
Park et al. (2020)	687	0.6900	0.9500	0.2001	0.2472	450.3285	0.0019
Trust							
Klein (2007a)	143	0.7000	0.9100	0.2380	0.2982	91.0910	0.0092
Yun and Park (2010)	212	0.9100	0.8800	0.6734	0.7525	169.7696	0.0049
Shareef et al. (2014)	326	0.8120	0.8120	0.2517	0.3100	214.9461	0.0039

(table continues)

Study	N	Eα	Bα	r	r'	W	e
Park et al. (2016)	877	0.8920	0.9220	0.3113	0.3433	721.2658	0.0012
Borges and Kubiak (2016)	111	0.8500	0.9200	0.4675	0.5287	86.8020	0.0097
Lee et al. (2017)	313	0.8710	0.8230	0.1394	0.1646	224.3687	0.0037
Werber et al. (2018)	531	0.9280	0.9200	0.3434	0.3716	453.3466	0.0018
Kumar and Natarajan (2019)	253	0.8960	0.8930	0.1532	0.1713	202.4324	0.0041
Self-Efficacy							
Ma and Liu (2005)	86	0.9300	0.8900	0.1507	0.1656	71.1822	0.0118
Klein (2007b)	294	0.7900	0.8950	0.0948	0.1127	207.8727	0.0040
Whetstone and Goldsmith (2009)	542	0.7760	0.9400	0.1086	0.1272	395.3565	0.0021
Gao et al. (2015)	341	0.8580	0.8250	0.0266	0.0316	241.3769	0.0035
Gao et al. (2015)	297	0.8720	0.8380	0.2197	0.2571	217.0286	0.0039
Park et al. (2016)	877	0.9270	0.9220	0.1826	0.1975	749.5666	0.0011
Dwivedi et al. (2016)	387	0.8190	0.8190	0.1474	0.1800	259.5845	0.0032
Dwivedi et al. (2016)	359	0.8190	0.8190	0.1065	0.1300	240.8032	0.0035
Dwivedi et al. (2016)	375	0.8190	0.8190	-0.0491	-0.0600	251.5354	0.0033
Koivumäki et al. (2017)	855	0.7100	0.8850	0.3188	0.4022	537.2393	0.0016
Zhang et al. (2017)	436	0.7288	0.8821	0.1618	0.2018	280.2933	0.0030

It suggests there is no moderating effect between the correlation of perceived risks and behavioral intention. Therefore, both H3 and H4 are partially supported. Table 1.3 summarizes the overall results.

Table 1.3: Overall results on meta-analysis of correlation

Exogenous variables	n	N	$\overline{r'}$	$\bar{e}$	RATIO1	RATIO2
Aggregate model	28	11449	0.0072	0.0033	3.81	0.45
Performance expectancy	27	10594	0.0282	0.0031	2.13	0.11
Effort expectancy	23	9271	0.0226	0.0035	1.30	0.15
Social influence	8	4460	0.0157	0.0027	1.44	0.17
Facilitating conditions	7	4140	0.0106	0.0024	1.88	0.23
Hedonic motivation	6	2946	0.0115	0.0034	1.01	0.30
Price value	6	3510	0.0084	0.0028	0.94	0.34
Habit	3	874	0.0097	0.0040	3.90	0.42
Perceived risks	9	4159	0.0029	0.0027	13.03	0.93
Trust	8	2766	0.0209	0.0031	2.61	0.15
Self-efficacy	8	4849	0.0147	0.0027	1.67	0.18

Note: n = number of studies; N = total sample size

1.5 Discussion

The current research conducts a systematic literature review and quantitatively analyzes the prior empirical studies with meta-analysis. The findings indicate that the adoption of technology acceptance models that are originated from traditional IS research, such as TAM and UTAUT, is prevalent in investigating the emerging healthcare technologies in a consumer setting. Because of the higher value of RATIO1, 3.81 comparing with 2, it is conceivable that the aggregate technology acceptance model is both transferable and valid in this new healthcare context to explain the consumer behavioral adoption intention.

Among the constructs selected from the extant literature, perceived risk has the significant effect on behavioral intention because it has a high value of RATIO1 (13.03) in the Stage 2 analysis.

The higher RATIO2 value of 0.93 also indicates that perceived risk directly correlates with behavioral intention without moderating factors. It reveals that consumers have strong risk averse preference while evaluating a healthcare technology for potential adoption. In studying traditional IS technologies, such as mobile payment, the consumers' perceived performance risk, financial risk, and privacy risk imposes s strong negative effect on their adoption intention (Yang et al., 2015). The current research validates the same effect in the healthcare context. For example, (Gao et al., 2015) studied the wearable technology of both fitness and medical devices adoption in China and found that perceived privacy risk is negatively correlated with consumers' intention to adopt both devices. In another study of e-health services adoption in India, having confidence about the privacy and security on the service significantly influences the consumers' continuance intention (Kumar & Natarajan, 2019). Relevant legislations are also in effect since 2018 in both U.S. and Europe aiming to granting consumers more control over their personal information thus enhance data privacy and data sharing transparency. The California Consumer Privacy Act of 2018 (CCPA) (2018) endows California consumers the rights to:

- Know about the personal information a business collects about them and how it is used and shared
- Delete personal information collected from them (with some exceptions)
- Opt-out of the sale of their personal information
- Non-discrimination for exercising their CCPA rights

Similarly, in May 25, 2018, one of the toughest security and privacy laws, General Data Protection Regulation (2018), became applicable to all European members. This law protects consumers' data security and privacy and impose tremendous penalties to violations. From the practitioner's view, obtaining consent form about data collection and sharing, providing information about data security and privacy, and emphasizing data usage transparency are critical parts that could improve the adoption rate while promoting an emerging healthcare technology.

Habit positively correlates with consumers behavioral adoption intention (RATIO1 = 3.90). Studies investigating electric health record adoption shows that the consumers' prior learning experience positively influences their adoption intention (Tavares & Oliveira, 2016; Tavares et al., 2018). While there exists a significant correlation between this individual construct and behavioral intention, the findings from the current research show that a few studies adapted the habit construct into the acceptance models. This could be explained by the nature of emerging technology and lack of the consumers' prior experience. However, a lower value of RATIO2 (0.42) indicates the existence of moderating factors. Healthcare technology could be classified to different categories, such as biotechnology, administrative technology, and recreational technology, based on its nature and intended purpose. Therefore, this classification could be one of the moderating factors and is worth considered in the future research.

Trust is another core construct significantly correlated with behavioral intention. The trust effect has been studied for many years. In primary care, patient trust in healthcare provider is one of the factors strongly associated with adherence and satisfaction (Safran et al., 1998). Regarding to a more contemporary topic of patient-centered healthcare, the ability of practitioners demonstrating professionalism and conveying trust are proven to tightly associate with the quality of care and consumers' satisfaction (Perera & Dabney, 2020). This significant correlation is consistent across various health related context including wearable technology (Park et al., 2016), online communication technology (Klein, 2007), RFID adoption (Werber et al., 2018), vital sign monitor (Borges Jr & Kubiak, 2016), and mobile health applications (Shareef et al., 2014). The lower RATIO2 value of 0.15 indicates the existence of potential moderating factors. Consumers' attention to news and specific events, their sensemaking, and threshold of trust change could affect their trusting beliefs on an information technology (McKnight et al., 2020).

Performance expectancy, social influence, facilitating conditions, and self-efficacy are not significantly correlated with behavioral intention according to the meta-analysis on the sampled studies. But each individual relationship could be moderated by other factors. These findings align with evolution of healthcare technologies and expert's vision of emerging technology. For example, genetic testing as a biotechnology was applied to clinical diagnosis in early 2000, when *BRCA* genes analysis for hereditary breast and ovarian cancer was commercialized and offered to costumers. Various factors including the legislation of Patient Protection and Affordable Care Act, increased education of potential consumers, robust scientific evidence, comprehensive clinical guidance, and celebrity endorsements could individually or together influence the relationship between each construct and consumers adoption intention (Chen et al., 2018). With a forward looking perspective, according to Eric Topol, the executive vice president and professor in Scripps Research Institute, some healthcare technologies that are emerging now, such as telemedicine, are likely to become more patient autonomy where consumers can use the technology to generate and interpret own data of their choice (Michaud & Cousens, 2020).

Hedonic motivation and price value have no significant influence on behavioral intention with relatively low values of RATIO1, which are 1.01 and 0.94 respectively. These findings are expected because of the uniqueness of healthcare. First, the primary purpose of many health-related technologies is for the diagnosis, disease prevention, and improved health outcome. Hedonic effect is not the practitioners or end-users major concern. For example, (Lee et al., 2017) studied the consumers' intention to use mobile health application and found that the consumers' enjoyment is not significantly correlated with their adoption intention. Second, we could interpret the insignificance regarding price value with three reasons. One reason lies on the comprehensive insurance coverage and increased government funding. According to the World Health Organization Global Health Expenditure Database (https://apps.who.int/nha/database), the average out-of-pocket expenditure worldwide accounts for 18.12% of total current health expenditure. In the U.S., this percentage decreased from 15.47% in 2000 to 10.81% in 2018. For biotechnology, such as genetic testing, many major insurance companies consider the services are necessary for clinical diagnosis and include the relevant cost in the policy. Second reason is the technology advancement itself because it will drive down the price. In general, the direct-to-consumer (DTC) technologies in retail setting are considerably cheaper. For example, a wearable device like Fitbit costs around $100. A genetic testing kit manufactured by 23andMe for health and ancestry testing costs $199 and can be conveniently bought from Walmart. Third reason is that certain emerging healthcare technologies like telehealth and electronic health record system act an administrative function and are an integral part of the whole healthcare process. Therefore, the cost associated such technologies are often negligible or integrated into other areas.

1.6 Limitations and Opportunity for Future Research

The current research has several limitations. First, while the data for the meta-analysis coming from a systematic literature review, the target keyword search in a number of selected databases may result in some missing articles that are not included in this study. Second, because of the limited number of articles involved in the meta-analytic procedure, it is hard to determine the moderating factors for both the aggregated model and the correlation between each individual construct and behavioral intention. Future research is encouraged to investigate further the moderating effects to the consumers adoption intention on healthcare technology. Third, because of the rapid technology advancement and increasing number of emerging healthcare technologies available in the market, future empirical study in the context specific setting brings value in understanding consumers behavior, technology commercialization and promotion, and guidance to relevant legislation.

1.7 Conclusion

This study quantitatively investigates the consumers adoption intention towards emerging healthcare technologies through a structured literature review and meta-analysis. It contributes to the technology acceptance literature because the meta-analytic procedure synthesizes the findings from prior empirical studies and validates the relationship between each individual exogenous variable and behavioral intention. A comprehensive view of consumers adoption intention in the healthcare context is presented. Among a group of selected exogenous variables, perceived risks, habit, and trust have a significant positive correlation with behavioral intention. The results also strongly suggest that there exist moderating factors in both the aggregated model and several individual relationships. In addition, this study discusses practical implications for service designers, providers, and regulatory authorities.

ESSAY 2

CONSUMER BEHAVIORAL INTENTION OF ADOPTING EMERGING HEALTHCARE TECHNOLOGY

2.1 Introduction

Over the past decade, several new healthcare technologies have emerged. Along with the precision medicine initiated by the Obama administration in 2015 (The White House), technologies related to molecular medicine have rapidly advanced. Among those emerging technologies, gene test and repair technologies garner dramatic attention from researchers, practitioners, and consumers. Since 2007, direct-to-consumer (DTC) gene test products were promoted (Borry et al., 2010). The cumulative number of new testing products available on the market from 2014 to 2017 grew from a few hundred to almost 14,000 (Phillips et al., 2018). Gene repair technology is also emerging. Many researchers and clinical professionals are spending significant efforts in its advancement. One of the landmarks is the work led by Ma et al. (2017). Their team successfully corrected a pathogenic gene mutation in human embryos and published results in Nature. Recent advancement of genome editing technology empowers researchers to assess various gene functions and develop potential targeted therapy of inheritable diseases (Li et al., 2020). In business, gene therapy-based treatment, such as ZOLGENSMA for spinal muscular atrophy (SMA), was approved by the U.S. Food and Drug Administration (FDA) (2019) and commercialized. Similarly, a medicine named Nusinersen for treatment of SMA has a list price of $118,000 per 5ml injection, which makes it among one of the most expensive drugs (Canadian Agency for Drugs and Technologies in Health, 2018). At the same time, the good news is that many insurance companies like Blue Cross Blue Shield, Aetna, and Cigna now consider this drug in their policies because the treatment is judged as medically necessary for the patients.

Despite the rapid emergence of gene repair, in academia, most of the researchers studying emerging biotechnology usually focus on the technical mechanism for a specific human disease and publish their works in clinical journals. Little research examines the likely acceptance of such technology from a consumer perspective. The study of this topic is both timely and necessary. There is a strong need to address this deficiency so that the scholars and healthcare professionals comprehend the antecedents of end-user perception and behavioral intention related to the use of emerging healthcare technology. This study addresses two research questions: (1) what are the factors affecting consumer behavioral intention to adopt gene repair technology, and (2) what are the relationships among these factors and consumer behavioral intention?

In this research, we aim to develop a gene repair contextualized technology acceptance model built upon the literature and empirically test that model using survey data. Contextualizing and extending the model to gene repair technology is particularly important because it is not a given that established technology acceptance models are applicable in this new context. First, we posit a theoretical model that is specific to a biotechnology context by integrating perceived risk and trust in technology constructs within the unified theory of acceptance and use of technology (UTAUT), which has been increasingly applied and validated with several technology acceptance studies in the healthcare field, such as healthcare wearable device (Wang et al., 2020).

Second, we empirically test the derived research hypotheses and validate the relationships between the predetermined antecedents and end-user behavioral intention to use gene repair technology. The proposition and validation of the research model fill the gap of emerging healthcare technology acceptance from a consumer's perspective. The findings also reveal the transferability of prior information system acceptance research to new and emerging venues.

Third, we discuss the importance of practical implications because gene repair technology is not generally available today and better understanding of technology acceptance is likely to influence its development and delivery. Serving as a forward-looking study, this study generates impactful implications for policy makers and legislations to guide the development and commercialization of gene repairing technology and similar emerging healthcare technology.

To realize these goals, the rest of the research is organized as follows. Section 2 reviews the relevant literature and derives research hypotheses. Next, methodology and data collection are discussed in Section 3, followed by hypothesis testing with structural equation modeling in Section 4. Section 5 discusses theoretical contribution and practical relevance of this study. We discuss limitations and directs future research in Section 6 followed by a conclusion in Section 7.

2.2 Literature Review and Hypotheses Development

Performance expectancy (PE) is the degree to which an individual believes that using a proposed technology will assist in their job performance (Venkatesh et al., 2003). Previous studies indicate that performance expectancy could be one of the most important variables predicting the potential adoption of innovative technologies, for example, in the context of text-based smoking cessation intervention (Andrews et al., 2013). In this study, performance expectancy is defined as the degree of usefulness, which refers to how much a potential end-user expects gene repair technology to improve their quality of life when the technology becomes available. This research sets aside the potential ethical issues and focuses on the targeted gene repair research that started decades ago.

Researchers expect promising results that include permanent and stable correction of disease-causing gene mutations. These corrections are anticipated to completely cure the related disease (Parekh-Olmedo et al., 2005). Along with the development of such technology, continuous improvement of safety and efficacy is essential to extend the clinical research to the clinical treatment of inherited diseases (Cavazzana-Calvo & Fischer, 2007). Recent successful preclinical studies and rapidly advanced genome editing tools also provide significant optimism for the likelihood of the technology's future application (Maeder & Gersbach, 2016). Thus, we posit the following alternative hypothesis:

> *Ha1: Performance expectancy of gene repair technology is positively correlated with the end-user behavioral intention.*

Social influence (SI) refers to a user's belief that their important others think they should use the new technology (Venkatesh et al., 2003). Thus, the surrounding people of the potential technology users could significantly influence the user's awareness and behavioral intention toward the use of the new technology (Alalwan et al., 2016). In the organizational setting, interpersonal communication and help from co-workers are important factors that break barriers and positively influence the adoption of a system. The social network construct effectively captures those informal communications and predicts the individual adoption of technology in the organization (Sykes et al., 2009). In the consumer setting, social norms, consumer's significant others, and peer groups will influence an individual's willingness to learn about a product with a positive inclination (Sheth & Parvatlyar, 1995). This finding represents the relational market behavior, which helps the consumer simplify their buying task and information processing, reduce perceived risks, and maintain psychological comfort.

In the current study, with the context of emerging technology acceptance in healthcare, it is expected that interpersonal influence plays a crucial role in influencing the consumer adoption intention of gene repair technology as it becomes available. The sources of such social influence are an individual's significant others, friends, neighbors, and celebrities like Angelina Jolie's announcement of her medical choice (2013). Social influence is related to the potential user's surroundings, which influence acceptance. The relevant hypothesis is:

Ha2: Social influence is positively correlated with the end-user behavioral intention.

Facilitating conditions (FC) refer to user beliefs that resources and technical support are available to assist in their adoption of the new technology (Venkatesh et al., 2003; Venkatesh et al., 2012). Users who have access to a favorable set of facilitating conditions tend to have a higher behavioral intention to adopt a new technology (Venkatesh et al., 2012). In this study, the construct of facilitating conditions is defined as the professional counseling service that is available to the potential users of gene repair technology when it becomes available. Practically, the construct of facilitating conditions has two dimensions in the current study. First, it measures the potential consumer's access to relevant resources. Various studies operationalized facilitating conditions in their technology acceptance models and found it to be a significant factor directly or indirectly associated with the behavioral adoption intention (Kohnke et al., 2014). Second, it represents the degree of training and education of the gene repair technology a consumer will receive prior to the decision-making. Mathieson et al. (2001) integrated user's perceived resources to TAM and found that user's access to adequate resources positively influences the technology adoption intention.

We anticipate that the implementation of gene repair technology will evolve in conjunction with the current practice of gene test, where genetic consultation is an integral part of the process. This consultation includes order recommendation, education on the clinical procedure, result interpretation, and follow-ups as needed (U.S. National Library of Medicine, 2019). Primary care providers or genetic specialists are often the ones who order gene test to patients based on their disease symptoms and family history. The operating model is likely to stay the same regarding gene repair. Therefore, we hypothesize:

Ha3: Facilitating conditions of gene repair technology is positively correlated with the end-user behavioral intention.

Making a decision involves a degree of risk-taking due to the potential of unfavorable consequences (Bauer, 1960). This decision-making process has long been interest in marketing, where the consumer's perception of uncertainty is measured by perceived risks (Cox & Rich, 1964). Martins et al. (2014) integrated perceived risks in the UTAUT to explain user adoption of mobile banking and found a significant relationship. In the context of mobile payment acceptance, Yang et al. (2015) defined perceived risks as a multi-dimensional construct, which consists of performance risk, financial risk, privacy risk, time risk, and psychological risk. In that context, perceived risk was found to have a strong negative effect on behavioral adoption intention. Another example related to biotechnology is the influencing effect of perceived risks on the acceptance of genetically modified plants, goods, and drugs (Siegrist, 2000). However, these contexts are not specific to the unique application of gene repair technology, and, as a result, contextualization of the terminology is required, along with testing to determine the transference of the construct to the new UTAUT model. The current study integrates the construct of perceived risks to explain the end-user behavioral intention of using gene repair technology. The items in the construct asked about the minimum risk perception towards gene repair technology. Therefore, we hypothesize:

> *Ha4: Minimum perceived risks of gene repair technology is positively correlated with the end-user behavioral intention.*

The trust construct has evolved over time in technology adoption models (Wu et al., 2011). In this research, we focus on a recent definition of trust as applied to technology acceptance. Trust is a fundamental relationship between patients and healthcare providers. Trust involves economic and social interactions that include uncertainty and is measured by the feeling that an individual or technology will meet perceived expectations (Montague et al., 2010; Pearson & Raeke, 2000).

Trust also appears to correlate positively with performance expectancy and negatively with perceived risks. Pavlou (2003) argued that consumers' trust in e-commerce is positively correlated with perceived usefulness. In the UTAUT model, the construct of perceived usefulness pertains to performance expectancy (Venkatesh et al., 2003). Practically speaking, negative emotion arises from perceived risk and positive emotion arises from performance expectancy. Both emotions affect users' adoption intention of technology in their appraisal stage. Platt et al. (2019) found that users' belief in medical deception negatively contributes to their trust in healthcare information sharing whereas the belief of improved health outcome has a positive effect. Furthermore, empirical evidence of both relationships exists beyond the U.S. and western culture. For example, in the context of connected health technologies in western countries like French and Switzerland, the trust from elderly significantly impacts the service quality of the new service delivery model (Etemad-Sajadi and Dos Santos, 2020). With the similar application, Pal et al. (2018) studied healthcare-related Internet of Things adoption among the elderly in Asian countries and found a significant correlation between perceived trust and performance expectancy.

In the current study, trust in technology is defined as the degree the consumer believes that relevant policy exists to regulate gene repair technology as it develops the potential to improve healthcare conditions. We hypothesize:

> *Ha5.1: Trust in the gene repair technology is positively correlated with the end-user behavioral intention.*
>
> *Ha5.2: Trust in the gene repair technology is positively correlated with the end-user performance expectancy.*
>
> *Ha5.3: Trust in the gene repair technology is positively correlated with the minimum end-user perceived risks.*

The original UTAUT model incorporates effort expectancy, which measures the ease of using information technology (Venkatesh et al., 2003). In the current study, we excluded this construct from the model because the consumer of gene repair technology should expect a high degree of ease of use. The actual repairing procedure is not the scope of this study. Healthcare professionals are highly likely to be engaged in selecting appropriate gene repair service for the potential consumer. The actual business model of gene repair is expected to follow the current clinical practice of gene test. The latter discussion section will expand on this point for practical implications. Therefore, the effort expectancy is not applicable and excluded from our model. Figure 2.1 shows the structural form of the newly developed research model.

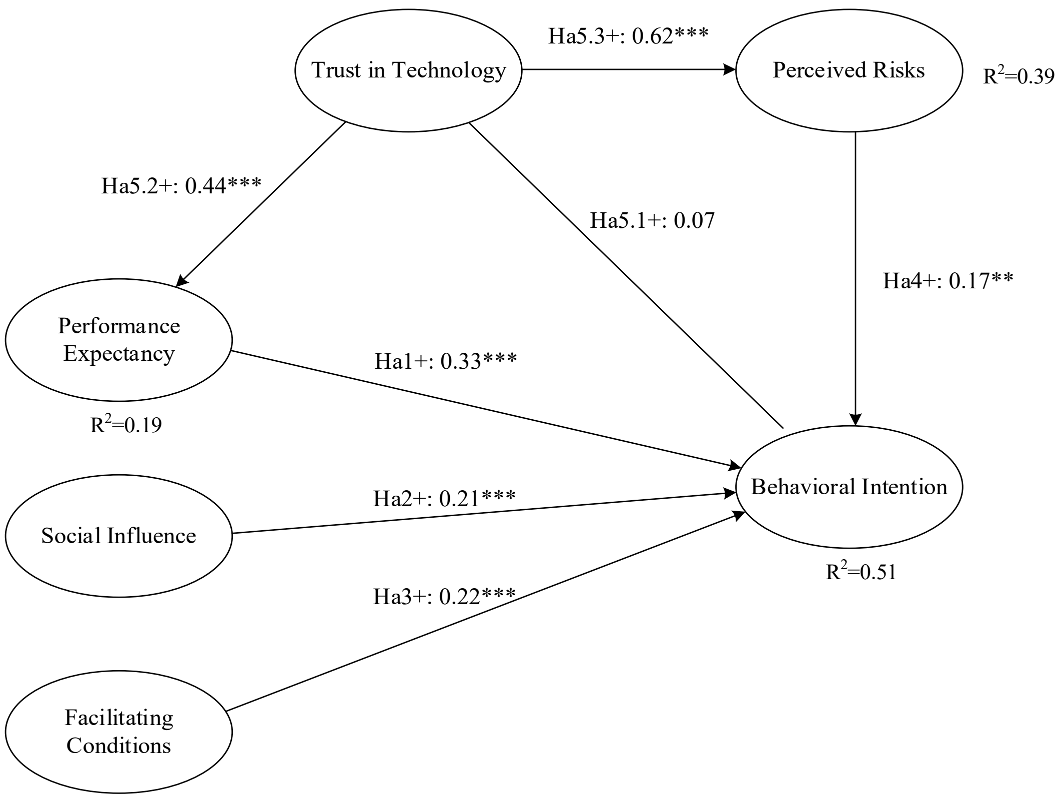

Figure 2.1: Results of PLS analysis

Notes: 1. $^{**}p < 0.01$, $^{***}p < 0.001$. 2. Perceived risks is reverse coded in the survey to measure the minimum perceived risks on gene repair technology.

2.3 Methodology: Instrument Development and Data Collection

We contextualized the survey questions from the prior studies with modifications to fit our research. All the items were validated in both the original UTAUT model and other studies with topics transferable to or within the healthcare context. Items within the same construct were grouped in the manner they were administered in the sources cited. In the questionnaire, all the questions used a 5-point Likert scale from strongly disagree to strongly agree. For consistency in question style, the construct of perceived risks had measurement items that asked about the minimum perceived risks towards gene repair technology. At the beginning of the survey, a brief background of gene repair technology was provided. Survey participants were asked to indicate the level of agreement or disagreement for each survey item assuming that gene repair technology has passed the clinical trial and related products are available on the market.

Table 2.1: Sample characteristics (n = 300)

Characteristics		Respondents
Age	Under 18	7 (2%)
	18-21	187 (62%)
	22-25	65 (22%)
	26-29	14 (5%)
	30 or older	27 (9%)
Gender	Male	133 (44%)
	Female	167 (56%)
Education Level	First-year undergraduate student	74 (25%)
	Sophomore	64 (21%)
	Junior	105 (35%)
	Senior	49 (16%)
	Graduate student	4 (1%)
	Other	4 (1%)
Household Income Level	Less than $20,000	58 (19%)
	$20,000 to $34,999	56 (19%)
	$35,000 to $49,999	32 (11%)
	$50,000 to $ 74,999	58 (19%)
	$75,000 to $99,999	32 (11%)
	Over $100,000	64 (21%)

Note: Numbers represent frequency, followed by the percentage (rounded) among the sample in each category.

We collected survey data using Qualtrics, which is an online self-administered survey tool, and analyzed data using WarpPLS 6. The participants were undergraduate students from a major public university in the U.S. southwest region. Participation in the survey was voluntary, and extra course credit was provided as an incentive. During the data collection period, multiple reminders were announced either on the course website or in the class to increase the response rate. The survey was distributed to five courses with 1339 students. A total of 574 responses were received. After cleaning the data, 300 valid responses were retained for data analysis and represented a 22.4% valid response rate. Table 2.1 shows the sample demographics. Most of the students (84%) were aging from 18 to 25 years old. The student sample and clustered age group may represent a potential limitation in conducting a study of technology adoption. However, for the topic of this study, the sampled students are a valid group of respondents and an ideal population in terms of being a potential user of gene repair technology. The validity of this group is predicated on the likelihood that the subjects will have their first child when such technology becomes available and will compose a significant portion of potential consumers. In the technology acceptance study, younger people are found to have the most efficiency beliefs and attitudes towards a healthcare innovation even though they may lack of professional knowledge and working experience (Taiminen et al., 2019).

2.4 Results

In this study, common method bias and non-response bias were assessed. We performed Harman's one-factor test to check whether all items load on a single factor (Harman, 1976). The factor analysis extracted four factors with an eigenvalue greater than one. They explained 64.53% of the total variance with the first factor not accounting for the majority of the variance. Therefore, the evidence suggested that common method bias is not an issue. To assess non-response bias, we grouped the responses into the early 90% received and the late 10% received and compared the demographics of both groups using independent sample t-test, as suggested by Karahanna et al. (1999). The results showed no significant difference between the two groups, indicating that non-response bias does not present in this study.

2.4.1 Measurement Reliability and Validity

The first step of the construct validation is to identify a group of measurement items that both theoretically and logically connect to the constructs to achieve content validity (O'Leary-Kelly & Vokurka, 1998). In the current study, we assured the content validity of measurement by a thorough literature review of the relevant research. All of the measurement items were adapted from previous studies and were empirically validated. Convergent validity was examined through the factor loadings of each item. All of the items have indicator loadings greater than the recommended value of 0.7 suggested by Hair et al. (2011) except for one item (PR2) that has a loading of 0.69. However, the factor loading is only slightly below the recommended value. Therefore, we retained this item in the instrument because we modified the item to fit our topic in the healthcare context, and it is important to preserve the construct content validity.

Construct reliability was examined using composite reliability, which is known as Dillon–Goldstein rho (Dillon & Goldstein, 1984). The values of each latent variables range from 0.83 to 0.94, as in Table 2.2, suggesting good construct reliability. Discriminant validity was established by comparing the square root of AVE with the correlations between each construct (Fornell & Larcker, 1981). Examination of the correlation matrix, as in Table 2.2, showed the square roots of AVE in the diagonal are higher than the correlations between other constructs, which supports the discriminant validity of the measurement.

2.4.2 Structural Model Results

The R-square values show that our model explains 51.1% of the variance in behavioral intention to use gene repair technology in the future, 19.0% of the variance in the performance expectancy, and 38.8% of the variance in the perceived risk. We conducted a post-hoc power analysis at 0.05 α level, the statistical powers ($1-\beta$) to predict all three R2 are at the maximum 1.00.

Table 2.2: Variable summary and correlation matrix

Construct	Mean	St.Dev.	CR	AVE	PE	SI	FC	TR	PR	BI
Performance expectancy (PE)	3.65	0.85	0.89	0.67	**0.82**					
Social influence (SI)	2.97	0.98	0.91	0.83	0.41	**0.91**				
Facilitating conditions (FC)	2.30	0.98	0.93	0.86	0.18	0.34	**0.93**			
Trust in technology (TR)	3.44	0.97	0.86	0.69	0.43	0.42	0.25	**0.83**		
Perceived risks (PR)	2.98	0.88	0.83	0.61	0.38	0.49	0.41	0.62	**0.78**	
Behavioral intention (BI)	3.01	1.05	0.94	0.83	0.55	0.54	0.44	0.45	0.53	**0.91**

Note: The bolded numbers in the diagonal row are square roots of the average variance extracted.

Hypothesis 1 tests the relationship between performance expectancy and behavioral intention. The supported Hypothesis 1 ($\beta = 0.33$, $p < 0.001$) indicates a positive direct effect of performance expectancy on behavioral intention. Hypothesis 2 is supported ($\beta = 0.21$, $p < 0.001$), which indicates a positive direct effect of social influence on behavioral intention. Facilitating conditions ($\beta = 0.22$, $p < 0.001$) has a significant positive effect on behavioral intention. This supports Hypothesis 3. Hypothesis 4 tests the relationship between perceived risks and behavioral intention and is supported ($\beta = 0.17$, $p = 0.002$), indicating a positive direct effect of perceived risks on behavioral intention. Among the three constructs correlated with trust in technology, we found that trust has a significant positive effect on performance expectancy ($\beta = 0.44$, $p < 0.001$). It also has a significant positive effect on perceived risks ($\beta = 0.62$, $p < 0.001$), which in our model is inversely coded. Surprisingly, the relationship between trust in technology and behavioral intention is not significant ($\beta = 0.07$, $p = 0.124$). To this end, the Hypothesis 5.2 and 5.3 are supported, whereas the Hypothesis 5.1 is not supported. We further analyzed the mediating effect. The results show that performance expectancy and perceived risks fully mediates the effect between trust in technology and behavioral intention. Figure 2.1 shows the PLS path modeling results.

2.5 Discussion

The pace of investigating technology acceptance in healthcare from the consumer perspective presents a gap in the literature because many innovative technologies like gene repair are rapidly advancing. This is the first study exploring the salient antecedents of gene repair technology adoption and their interrelationships with consumer behavioral intention. The development of the theoretical model and results presented in this research provide important contributions to both academics and practitioners.

2.5.1 Insights for Academics

The main contribution of the current study to academia is positing and testing the new theoretical model in the context of this new healthcare technology. Specifically, this research provides the following implications. First, we integrated perceived risks and trust in the UTAUT model because they are particularly relevant to the healthcare technology studied. Building upon existing literature, we developed a unique model by integrating both constructs into the UTAUT model and modified the measurement items to fit the context of emerging healthcare technology. Different from many other consumer technologies, such as video games or social media related technologies, emerging medical innovation like gene repair technology will provide substantial benefits of diagnosis and treatment for life-threatening diseases as it becomes available. The traditional exogenous factors in the UTAUT and UTAUT2 model impose different weights on the adopting decision of potential consumers in this context. For example, in this study, we also tested the correlation between the price value and adoption intention and found the results to be insignificant as perceived in the literature review. On the other hand, our findings show that the performance expectancy is one of the most important factor positively correlated with the adoption intention whereas the study of the patient adoption of electronic health record portal shows that the habit, an exogenous factor in the UTAUT2 model, imposes heavier effect on the behavioral adoption intention (Tavares & Oliveira, 2016). In addition, when studying the consumers' behavioral intention to adopt gene repair technology, evaluating their perceived risk and trust in such technology is crucial. Our findings confirmed the proposed hypotheses and clearly revealed their relationships to the adoption intention.

Second, we successfully extended the UTAUT model to the healthcare context in studying the gene repair technology adoption from the consumer's perspective. Although the UTAUT model was proposed and applied to study the organizational information system acceptance, it was then modified and extended to study some applications in healthcare, such as wearable devices (Gao et al., 2015). It is likely that IT practice will continue to expand into new venues as the consumer's intention of adopting an emerging healthcare innovation is different from the adoption of many other consumer technologies. The current research will help set an understanding about how to contextualize and transfer existing research and knowledge. The findings have shown that the original constructs of performance expectancy, social influence, and facilitating conditions from the UTAUT model, along with the minimum perceived risks and trust, are all positively correlated with consumer's behavioral adoption intention. Comparing with the TAM model, which is still a dominating framework in the healthcare context nowadays (Chauhan & Jaiswal, 2017), the integrated theoretical model in this study has compelling advantages in offering comprehensiveness and practical implications.

Third, in the context of the current study with a unique application of gene repair technology, we found that the correlation between the trust in technology and the consumer behavioral intention is fully mediated by the performance expectancy and the perceived risk. This finding reveals the mechanism of how trust in technology transfers to behavioral adoption intention. Rather than acting as a direct antecedent, trust is positively correlated with the performance expectancy and minimum perceived risk, which positively influences consumer behavioral intention. Studying the influence of trust in the absence of the mediators has the risk of not identifying the significance of trust and, as a result, providing incomplete understanding about the mechanism of the transformation from the trust to behavioral intention. Furthermore, the results of our model indicate that trust explains 19% of the variation in the performance expectancy and 39% in the perceived risk, meaning trust imposes a heavier effect on the perceived risk than on the performance expectancy. This finding also aligns with the priority of safety in healthcare (Flin, 2007). Thus, not only does the current study have the potentials to bridge the gaps in emerging healthcare technology adoption research, but it also emphasizes the assurance needed by consumers and helps improve future development and delivery of the service. The practical implications of this research are discussed in the next section.

2.5.2 Insights for Practitioners

When a healthcare innovation successfully translates to clinical application, it often indicates the substantial benefit of improving healthcare outcomes. In the current study, gene repair technology is assumed to be proposed and initiated by healthcare professionals as such technology becomes available. It is also likely that professional genetic testing laboratories are not well understood by patients because many of whom may know little about genetic testing and how it is conducted. The situation is likely to stay the same with gene repair technology in the future. The full mediation towards trust in this study emphasizes the importance of the efforts that healthcare professionals spend on educating potential consumers. Providing more education about scientific procedures is likely a plus because it will reduce the negative emotions that arise from perceived risks (Wakefield, 2015). This statement is supported by the value of trust in the model, which suggests that proper introduction to the technology, and elaboration of the technology efficacy and minimum risk associated with such technology are significantly correlated with consumer behavioral intention. As a result, the findings in this work should draw attention from healthcare professionals.

In addition, the findings of this study reveal the importance of social influence and facilitating conditions. When healthcare professionals started promoting genetic testing services several years ago, the celebrities in social media significantly contributed to the awareness, public education, and popularization of such services. Examples include Angelina Jolie (2013)'s medical decision regarding breast and ovarian cancer and sudden cardiac death of Olympic athletes due to hypertrophic cardiomyopathy (HCM), which is an inheritable genetic heart disease (Wasfy et al., 2016). Because of such high-profile cases, the public is increasingly aware that those severe threats can be detected using genetic tests and prevented via clinical surgery or early actions. When consumers adopt genetic testing services, genetics expert, such as a certified genetic counselor, is often involved before and after the diagnosis. These professionals help guide their patients in testing decisions, understanding results, and how best to use the results (American Board of Genetic Counseling, 2019). Our findings confirm the same effect from social influence and facilitating condition to the application of gene repair technology when it becomes available. When healthcare professionals promote gene repair technology in the future, it is critical to establish a reliable counseling system to aid consumer's comprehension and behavioral intention.

Our findings also provide insights to policy makers. To effectively manage an emerging healthcare product, it is necessary to have institutional functions including legitimation, regulation, and technology standards in place (Rusinko and Sesok-Pizzini, 2003). In the previously mentioned example of gene therapy-based treatment, ZOLGENSMA, a dilemma arises between the FDA approval and healthcare insurance companies paying for the $2.1 million treatment cost (Roland, 2019). The family of the young patient often has to appeal for the insurance payment. The findings of this study call attention to legislating authorities and policymakers for evaluation of the performance expectancy and perceived risk associated with gene repair technology because, first, both are significantly correlated with consumer behavioral intention; and second, trust in governmental institutions will influence the likelihood of a physician ordering such product just as they do with biopharmaceutical (Nonis and Hudson, 2009). Therefore, both the potential consumers and healthcare professionals are unneglectable parties and should be involved in the policymaking process. A well-established policy needs to obtain compliance from stakeholders, protect the consumer's interest and safety, facilitate a helping environment, and stimulate trust while such technology is commercialized.

2.6 Limitations and Future Research

While this study contributes to the technology acceptance research in healthcare, we need to acknowledge some limitations. First, the samples collected and used to test the proposed model came from a major research university in the U.S. southwest region. Although the group of undergraduate students is valid for addressing the concerns relevant to this research because they are potential users of gene repair technology, they are expected to have limited knowledge about it and less immediate needs for the technology at the time of answering the survey. The group who has immediate needs and are actively looking for the clinical trial of such technology are unrepresented in the current study, and they may weigh the endogenous variables differently. A future study exploring the behavioral intention of this group will require the involvement of government authorities and healthcare organizations.

In addition, as we developed the model based on the information technology acceptance and trust literature, a number of exogenous factors remain unexplored. While medical innovation often relays on abundant resources and is ingrained in regulations, the large size of the potential market and consumer demands will motivate continuous medical technology development (Ijzerman & Steuten, 2011). Future studies exploring the feedback mechanisms among stakeholders, policymakers, and consumers will help us understand better the underlying relationships among exogenous and endogenous factors and provide fruitful insights for practitioners and policymakers.

2.7 Conclusion

This research draws on the consumer's perspective to study end-user behavioral adoption intention of gene repair technology as it becomes available. This research posits a comprehensive model by integrating trust and perceived risk in a contextualized UTAUT model and validates the model using survey data. The findings show significant correlations between social influence and facilitation conditions with consumer behavioral intention. The findings also demonstrate the full mediating effects of performance expectancy and perceived risk to the relationship between trust and behavioral intention. Therefore, this research contributes to the emerging topic of technology acceptance in healthcare and provides fruitful insights for practitioners and policymakers. Educating consumers on the technology, establishing a reliable counseling system, and reinforcing a clear regulation are critical for the successful realization of potential benefits of such technology.

ESSAY 3

AN INVESTIGATION OF THE CONSUMER'S TRUSTING MECHANISM IN EMERGING HEALTHCARE TECHNOLOGY*

3.1 Introduction

Precision medicine aims to provide personalized disease treatment and prevention by taking into account an individual's genetic variability and differences in environment and lifestyle (Collins & Varmus, 2015). Since the Precision Medicine Initiative was announced by the Obama administration in 2015, numerous scientific breakthroughs on the healthcare technology aligning with the same scope have resulted. As one of the prominent biotechnology innovations that have become available to consumers and physicians, genetic testing gradually draws industrial and academic attention because of the significant advances of genetic sequencing technologies, its promising capability, and cost reduction. The utilization of genetic testing products and services has demonstrated great competence that assists from personal health risk assessment to clinical diagnosis, prevention, and treatment. As of August 2017, approximately 75,000 genetic testing products were available on the market (Phillips et al., 2018) and the forecasted market size by 2026 is worth around $18 billion (Acumen Research and Consulting, 2019).

Despite the unprecedented growth of both genetic testing market and relevant products available in this market, a paucity of research exists to investigate how consumers are willing to adopt such emerging biotechnologies in healthcare. The review of literature conducted for this study shows a few papers examining adoption of the biotechnology in a related context. One example is the study investigating adoption intention of genetic testing in Malaysia (Mustapa et

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al., 2019). In that study, the factor of trust in key players is found to significantly correlate with adoption intention. Many other papers largely focus on the acceptance of specific genetic testing technology, such as breast cancer screening (Rainey et al., 2018), or technology awareness (Hann et al., 2017). There remains a strong need to study how end-users trust such emerging healthcare technology and the influential factors of forming end-user's trust on adopting this type of healthcare technology. The objective of this research is to study the initial trust formation towards emerging healthcare technology using the context of genetic testing and the influence of trust on the behavioral adoption intention from the consumer's perspective. Specifically, the current research aims to address the following questions: (1) how is a consumer's trust initiated towards an emerging healthcare technology; and (2) what are the relationships between consumer's trusting belief and willingness to adopt such technology?

To answer both questions, we conducted an extensive literature review and a quantitative investigation. First, we reviewed existing literature on the technology acceptance models, including the technology acceptance model (TAM) (Davis, 1989), the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003), and the extension of the original UTAUT model (UTAUT2) (Venkatesh et al., 2012) as well as the operationalization of their constructs in the healthcare field. For example, Gao et al. (2015) studied the adoption of wearable devices in healthcare and proposed an integrated acceptance model incorporating the UTAUT2 model. Pan et al. (2019) operationalized constructs from the TAM to study the adoption intention of the smart healthcare powered by the medical Internet-of-Things in both clinical and non-clinical environment.

We also reviewed the relevant literature about the trust and its effect on the consumer's adoption intention (Li et al., 2008; Pavlou, 2003; Siegrist, 2000). Because decision-making involves uncertainty, and the unfavorable outcome could be especially severer in healthcare, trust becomes a fundamental and critical component in the consumer's decision-making process. Literature suggests various trusting bases that can potentially influence the consumer's trusting beliefs, such as personality, cognitive reputation, calculative cost and benefit, technology institutional normality, and technology structural assurance. In addition, trusting beliefs positively correlate with trusting attitude, which also significantly influences trusting intention (Li et al., 2008).

Next, we developed a genetic testing contextualized technology acceptance model as suggested by Ketokivi and Mantere (2010). Drawing from the technology acceptance theory and trust formation theory, our model integrates the trust-related constructs to investigate the consumer's trusting mechanism in the context of healthcare. Finally, we used the structural equation modeling (SEM) approach with survey data to test the model.

This study contributes to the literature and provides practical implications. In the realm of technology acceptance, the mainstream of information technology acceptance includes the adaption of TAM, TAM2, UTAUT, TUAUT2, and other models. In the healthcare setting, some TAM and TAM-derived constructs, such as perceived usefulness or performance expectance, are consistently found significant in explaining the consumer's behavioral adoption intention (Holden and Karsh, 2010). Trust is not a primary construct in those traditional technology acceptance models; however, trust is often a significant factor affecting the consumer's intention to adopt an emerging technology (Li et al., 2008; Pavlou, 2003). The current research extends this research stream by examining the relevant UTAUT constructs in conjunction with trust, as well as the technology institutional trust base, user's cognitive trust base, and social influence toward trusting beliefs of biotechnology. The tested model provides better understanding of the consumer's trusting mechanism in healthcare. From a practical standpoint, this paper provides critical insights to regulatory authorities on the policy-making and healthcare institutes and professionals on how to better utilize genetic testing to meet the users' best interest.

The paper is structured as followings. We conduct a thorough literature review in Section 2. Section 3 develops the research model and research hypotheses. Further, we present the research methodology in Section 4 and data analysis and results in Section 5. Subsequently, in Section 6, the results are discussed and academic and practical implications are presented. Section 7 presents the limitations in this study. In the end, the conclusion is presented in Section 8.

3.2 Literature Review

3.2.1 Genetic Testing Services

The Human Genome Project mapping the human genome was completed for the first time in 2003 and provided the foundation for the development of genetic testing ("The Human Genome Project," 2019). This work was collectively done by an international team of researchers from six countries including China, France, Germany, Great Britain, Japan, and the United States, took 13 years, and cost $3 billion (Collins et al., 2003). Since the first mapping of the human genome in 2003, genetic testing technologies have undergone groundbreaking and rapid advancement. With Next Generation Sequencing (NGS) technologies and their wide applications, the impact of genetic testing on medical research is accelerating. An increasing number of relevant studies in the top science journals are making a profound impact (Cristiano et al., 2019; Zhou et al., 2019).

Besides the continuous scientific breakthrough based on genetic sequencing, consumers have gained access to this increasingly sophisticated biotechnology ranging from clinical testing services to the direct-to-consumer (DTC) products. Once DTC became available in the market, the commercialized product grew in value from a niche specialty of rare hereditary disease diagnosis to include broad applications of disease and trait assessments. Clinical usage is classified into different types including diagnostic testing, carrier testing, predictive testing, pre-symptomatic testing, pharmaco-genetics and newborn screening (Katsanis & Katsanis, 2013). For example, noninvasive prenatal testing (NIPT) is a DNA-based technology that allows early detection of fetal inherited disorders by testing maternal blood. One of the applications is the testing for trisomy syndromes. This method is advantageous over traditional testing protocols because of the improved safety along with its better outcomes, which result from the less invasive nature of a test that also has advantages of sensitivity and specificity (Allyse et al., 2015). Comparing with the clinical testing that is initiated by physicians and often involves extensive genetic counseling, DTC genetic testing emerged in 2007 and is available to consumers directly from the shelf or via online orders (Swan, 2010). For example, 23andMe (https://www.23andme.com/) is one of the major companies in this market and provides ancestry test and health risk assessment that includes the FDA approved Parkinson's disease and Late-Onset Alzheimer's disease tests ("FDA News Release," 2017). The 23andMe testing kit collects saliva samples for DNA sequencing and the kits can be conveniently obtained at retailers such as Walmart and CVS Pharmacies. This paper focuses on the consumer's behavioral intention of adopting the genetic testing technology that is utilized in the context of emerging healthcare technology because a better understanding of such emerging technology acceptance will influence its delivery and social implications in the healthcare context.

3.2.2 Technology Adoption Models

The technology acceptance and adoption theory in the Information System (IS) field is one of the core theoretical foundations of this paper. A number of models exist to study user's behavioral intention to use an emerging technology (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012) and have been empirically validated in broad contexts. The TAM model is the one that founded a research stream and gained the most popularity because it satisfies the key characteristics of generalizability, verifiability, as well as parsimony (Lee et al., 2003). The model conceptualizes the perceived usefulness and perceived ease of use as determinants of user's behavioral acceptance intention (Davis, 1989). Further, the acceptance intention leads to the actual adoption of the relevant technology or provides sufficient proxy of such correlation (Chau & Hu, 2002; Moon & Kim, 2001). It is also better to use behavioral intention comparing with actual usage as a dependent variable when the technology implementation is at an early stage (Egea & González, 2011). However, some researchers oppose the studies that are solely TAM-based because the model is too simple to contribute to practice, narrows the selection of other possible determinants, and maybe overly applied (Lee et al., 2003).

The unified theory of acceptance and use of technology (UTAUT) was proposed by Venkatesh et al. (2003) through reviewing and consolidating eight technology acceptance models including the TAM. It has four core determinants, which are performance expectancy, effort expectancy, facilitating conditions and social influence, and up to four moderators of age, gender, experience and voluntariness (Venkatesh et al., 2003). Initially, the UTAUT was applied to study the user's adoption intention of IS in an organizational context. In 2012, Venkatesh et al. (2012) extended the original UTAUT model to the UTAUT2 model by incorporating three additional variables of price value, hedonic motivation and habit, which enables the later model to study an emerging technology acceptance from the consumer's perspective. However, it is notable that the current study excludes these variables from the UTAUT2 because they are not suited to the context of emerging genetic testing technology in healthcare. First, the hedonic motivation is excluded because the major purpose of genetic testing service is to aid clinical diagnostics. The recreational use of genetic testing does not fit the scope of the current study. Second, the price value measures a consumer's cognitive tradeoff between the perceived benefit and cost. The cost of a necessary genetic testing in a clinical setting is often covered by insurance (Graf et al., 2013). In addition, the Genetic Information Nondiscrimination Act of 2008 (GINA) protects insurance payers from policy coverage discrimination such as denying coverage or increasing premium due to the payers' genetic information. Therefore, the price value is excluded from the proposed model. Third, the habit measures the degree of consumer's automatic behavior caused by their previous interaction with the similar technology. Regarding an emerging healthcare technology, like genetic testing in this research, a consumer is unlikely to have prior experience with it. Therefore, the proposed model also excludes the habit construct from the UTAUT2.

The UTAUT model has been increasingly applied to and validated in healthcare technology acceptance studies, such as healthcare wearable device (Wang et al., 2020), mobile health service (Hoque and Sorwar, 2017), and health IT system (Kijsanayotin et al., 2008). However, despite the quick advances in gene repair technology, there is fewer studies on the acceptance of such emerging healthcare technology. With this unique context, contextualizing the terminology and validating the transference of the UTAUT constructs to the new model is required. In addition, using the UTAUT model alone to study a technology adoption may result a narrow perspective and limited findings because of the direct causal influence of exogenous constructs on behavioral intention (Shachak et al., 2019). To better investigate the consumer's acceptance intention and trusting mechanism, this study also accounts theories about trust formation.

3.2.3 Initial Trust Formation Models

Many studies have shown the importance of trust in influencing human behavior during the decision-making process. In the realm of IS research regarding technology acceptance, trust is identified as a critical factor that significantly affects the user's behavioral intention to adopt an application, primarily an information system, within an organization or at a broader context (Li et al., 2008; Pavlou, 2003). However, trust is not a primary construct in traditional technology acceptance models like TAM and UTAUT. Adding it to the tested research model enhances the ability to explain the dependent variable, which is often behavioral intention (Tao et al., 2020), but many studies either focus on the trusting factors or integrate a comprehensive trust construct into a traditional technology acceptance models (such as Dhaggara et al., 2020, Kamal et al., 2020, and Pal et al., 2018). In those studies, the trust construct is a single exogenous variable that directly correlates with adoption intention. To specifically study the consumer's trusting intention, McKnight et al. (2002) investigated the influence of trust factors on consumer's intention to transact with web-based vendors and developed two endogenous constructs of trusting beliefs and trusting intentions. The former measures the consumer's perception of a vendor's attributes where this perception consists of competence, benevolence, and integrity beliefs. The later construct, trusting intentions, measures the consumer's intention to conduct trust-related actions, which, therefore, results in actual behavior. To further investigate the initial trust formation towards an emerging technology, Li et al. (2008) proposed and tested a trusting model within the context of national identity system. The authors used eight external determinates that were conceptually grouped as five trusting bases. These are personality, cognitive, calculative, and organizational and technological institutional trusting bases. The results show that cognitive reputation, calculative cost, and organizational situational normality are significantly correlated with trusting beliefs. However, in that study's context using the national identity system, the technology related institutional trust bases were not significantly correlated with trusting beliefs. While it is different from the results in the current study, the change in context to a medical application might potentially explain that difference.

The current study investigates the consumer's trusting mechanism in the context of genetic testing. Because of the unique circumstances that exhibit in the healthcare industry and the features of such biotechnologies as discussed above, we primarily focus on the cognitive trust base and technology institutional trust base as external determinants as they are particularly relevant to the application and context of the current research. The cognitive trust base substitutes for the consumers' cognitive familiarity when they have no prior experience with an emerging technology and represents their cognitive reputation to such technology. The technology institutional trust base represents the consumers' expectations for the technology in general. The mediating effects of the consumer's perceived usefulness and risks from genetic testing on the relationship between trusting beliefs and trusting intention are also investigated in the current study. The perceived usefulness refers to the consumer's performance expectancy towards the genetic testing technology (Venkatesh et al., 2012), while the perceived risks refers to the potential adverse results associated with this technology (Annes et al., 2010).

Grounded upon the literature of trust in technology, initial trust formation model, and the variables from the UTAUT framework that are in conjunction with the trust, we develop and posit a conceptual model to investigate the antecedents of consumer's trusting beliefs and the influence of such beliefs to behavioral adoption intention of emerging technology in healthcare in Section 3. Specifically, we operationalize the relevant constructs in the context with a genetic testing application as suggested by McKnight & Chervany (2006). We posit a conceptual model with a number of hypotheses.

3.3 Research Model and Hypotheses Development

The purpose of this research is to investigate the trusting mechanism that influences the end-user's intention to adopt emerging healthcare technology within the context of genetic testing.

In the technology acceptance research, Gefen (2000) claims that the familiarity with the technology is both a precondition and primary source of user's trust formation towards the trustee in e-commerce. When people have no prior interaction with the trustee, the cognitive trust base substitutes the knowledge trust base (Li et al., 2008). Also, the user, as a trustor, will categorize an unfamiliar trustee as trustworthy if the trustee exhibits good reputation (McKnight et al., 1998). In the IS studies investigating a system adoption intention, where the end-users have no prior experience with the studied system, cognitive reputation is defined as a substitute of familiarity that is based on the system reputation and reported experience by other users (Li et al., 2008). In that study, the empirical results also support the significant correlation between cognitive reputation and user's trust beliefs. In the healthcare context, there also exists the same relationship (Xie, et al, 2020). Therefore, the current research posits that the end-user's cognitive reputation on genetic testing technology positively affects individual trusting beliefs and it is hypothesized that:

H1: Cognitive reputation is positively correlated with trusting beliefs.

Literature of trust studies also suggests that institutional structures and proper social environment are likely to enhance the users' trust toward an unfamiliar trustee (Li et al., 2008; McKnight et al., 1998). This institutional-base trust can be further classified into two subcomponents, which are situational normality and structural assurance (Li et al., 2008; McKnight et al., 2002). Situational normality represents the users' perception that a typical state of the environment and proper order exist, and such beliefs consist of the attributes of benevolence, competence, and integrity (McKnight et al., 2002). Structural assurance represents the users' beliefs that result from legal structures, such as regulations and laws, and guarantees from the technology. Many IS researches on technology acceptance have empirically validated that better technology assurance in place positively influences the user's initial trusting beliefs toward the technology (Xie et al., 2020). In the organizational context, both technology and organizational structures affect users' initial trust formation towards a new technology. However, the current research only operationalizes the technology situational normality and technology structural assurance rather than the organizational operationalization because the application of this paper is genetic testing in the consumer's context. When consumers anticipate a normal or favorable environment and there exists proper structural assurance including laws, regulations, and the robust of genetic testing technology itself, they are likely to have a higher degree of trusting beliefs on this emerging biotechnology. Both technology situational normality and structural assurance constructs together reflectively form a secondary construct of institutional trust base. Therefore, it is hypothesized that:

H2: Institutional trust base is positively correlated with trusting beliefs.

The study of trusting beliefs has evolved and the relevant construct was adapted to marketing (Schlosser et al., 2006), IS (Li et al., 2008), healthcare (Pal et al., 2018), and other areas with the aim to study the user's intention and decision-making process. The current research focuses on the recent definition of trusting beliefs that apply to the user's decision-making process of adopting an emerging biotechnology. The extant literature indicates that a significant correlation exists between trust and consumer adoption intention. For example, various studies have shown that trust is a significant influence on the consumer's behavior in the context of e-commerce (Pavlou, 2003) and mobile banking (Kim et al., 2009). In the latter context, consumer's trusting beliefs positively correlates with trusting intention, which then affects adoption behavior (Dimitriadis and Kyrezis, 2010). In the healthcare context, the construct of trusting beliefs was found to positively affect the consumer's intention to adopt applications such as home healthcare robots (Alaiad & Zhou, 2014), Radio Frequency Identification (RFID) personal medical technology (Katz & Rice, 2009), and electronic logistics information system (Tung et al., 2008). Trusting beliefs form consumer attitudes toward a new technology, where the attitude is a personal determinant of intention to trust (Li et al., 2008). The rationale gleaned from the literature is that consumers do not adopt in the absence of trust. As a result, it is important to understand better consumer trusting intention and the relationship with trusting beliefs. Consistent with this need for better understanding, the expanded understanding provided from the current research helps advance both literature and practice related to consumer adoption intention and other related actions. In the context of genetic testing, the attitude of consumer behaviors, for example, advocating for such emerging biotechnology, providing personal and medical information, and ordering specific testing, relates to their intention to trust the genetic testing technology. Therefore, it is hypothesized that:

H3: Trusting beliefs are positively correlated with trusting intention.

When customers evaluate their intention to adopt an emerging biotechnology, there is uncertainty involved in this decision-making process measured by the feeling that the technology will perform as expected in meeting the consumer's needs (Montague et al., 2010). In this appraisal stage, positive feelings arise from performance expectancy while negative feelings arising from perceived risk. Both positive and negative feelings are positively and negatively correlated with the users' adoption intention, respectively (Wakefield, 2015).

Performance expectancy is a construct adapted from the UTAUT2 and measures the degree that consumers benefit from using a technology (Venkatesh et al., 2012). In the literature of e-commerce adoption (Pavlou, 2003), consumer's trust positively affects the perceived usefulness, which is the construct pertaining to performance expectancy in UTAUT2. Similarly, the significance of the performance expectancy construct was supported in health information technology (Miao et al., 2017). The current study defines the performance expectancy as the degree of the consumer's belief to which using genetic testing will result in positive outcomes regarding personal and family health. Many studies about employing genetic testing as a tool to provide evidence-based diagnosis and treatment, for example, breast cancer screening and prevention (Rainey et al., 2018), were published in medical journals. The findings of those publications consistently support better resource utilization. Therefore, in the current research, we posit that performance expectancy mediates the correlation between trusting beliefs and trusting intention and hypothesize:

H4a: Trusting beliefs are positively correlated with performance expectancy;

H4b: Performance expectancy is positively correlated with trusting intention.

In contrast to performance expectancy, the perceived risks of adopting genetic testing services can result in negative feelings and, as a result, undermine the end-user's intention to adopt this technology. In technology acceptance research, the construct of perceived risks was contextualized in various contexts and found to have a significant negative effect on the consumer's behavioral intention (Siegrist, 2000; Yang et al., 2015). However, few efforts conceptualize and measure the end-user's behavioral intention to adopt emerging biotechnology in the healthcare context and the role of trust in the related decision-making process. There is a need to contextualize the terminology and test the transference of the existing constructs to the newly developed model in the current study. In practice, potential risks of DTC genetic testing include the loss of patient protection, inaccurate clinical results, and genetic screening without appropriate result interpretation and follow-up (Annes et al., 2010). We believe the clinical genetic testing also shares similar attributes and posit that perceived risks mediate the correlation between trusting beliefs and trusting intention. To maintain consistency in the survey item design, the construct of perceived risks is measured as the perceived minimum risk of genetic testing. So, it is hypothesized that:

H5a: Trusting beliefs are positively correlated with perceived risks;

H5b: Perceived risks are positively correlated with trusting intention.

Social influence is a construct adapted from the UTAUT2 model and refers to the degree that users believe their important referents support the technology adoption (Venkatesh et al., 2012). Broadly speaking, the opinion of others could influence the users' awareness of the technology and their behavioral adoption intention (Alalwan et al., 2016; Talukder et al., 2019). In the technology acceptance research, a direct relationship between social influence and adoption intention exists and is supported in the U.S. and internationally, such as in the context of home healthcare robots adoption in the U.S. (Alaiad and Zhou, 2014) and mobile health service adoption in Bangladesh (Hoque and Sorwar, 2017). Intuitively, in the context of the current study, the potential users of genetic testing could incorporate the beliefs from their surrounding social network to own belief systems. The social influence is defined as the degree the individual's family and friends think that the induvial should adopt genetic testing technology. A variety of empirical studies demonstrates evidence in supporting the significant relationship between social influence and trusting beliefs (Li et al., 2008; Xie et al., 2020). Therefore, we posit that social influence has a direct relationship with trusting intention and indirectly influences trusting intention through trusting beliefs. It is hypothesized that:

H6a: Social influence is positively correlated with trusting beliefs;

H6b: Social influence is positively correlated with trusting intention.

3.4 Research Methodology

3.4.1 Instrument Development

To test the hypotheses, we designed a survey following the procedures suggested by Dillman (2011) and administered the survey with an online survey tool of Qualtrics. All of the measurement items were collected from prior literature with topics within or transferable to the healthcare context (see Table 3.1). Adapting from prior research, we contextualized the measurement items to fit the current research context. To achieve instrument style consistency, the questions for perceived risks were reversely coded to measure the minimal perceived risk towards genetic testing technology. To improve the testability of the research model, we utilized institutional trust base as a second-order reflective construct consisting of situational normality and structural assurance. We explained the rationale for doing this and its assessment in detail in Section 5.1. A complete list of the measurement items with each construct is presented in Appendix C. In the questionnaire, all items were measured by 5-point Likert scale from strongly disagree to strongly agree and the items within the same construct were grouped together in aligning with the ways they were administered in the sources cited, as listed in Table 3.1.

Table 3.1: Construct summary

Construct	# of Questions	Sources
Trusting Beliefs	11	Li et al. (2008)
Trusting Intention	6	Li et al. (2008) & McKnight et al. (2002)
Social Influence	3	Cimperman et al. (2016)
Tech. Situational Normality	12	Xie et al. (2020)
Tech. Structural assurance	3	Hoffmann et al. (2014)
Cognitive Reputation	3	Hsu et al. (2014)
Perceived Risk	3	Venkatesh, et al. (2003) & Kohnke, et al. (2014)
Performance Expectancy	4	Venkatesh, et al. (2003) & Pavlou (2003)

3.4.2 Data Collection

With Institutional Review Board (IRB) approval, we invited college students from a large public university in the U.S. southwest region to participate in the current study. A total of 926 complete survey responses were returned. After cleaning the data to discard incomplete and invalid ones, a final of 525 responses were retained for analysis. Table 3.2 summarizes the sample demographics. Non-response bias is assessed by grouping the responses into early 90% and late 10% received and comparing the demographics of both groups with independent sample t-test as suggested by Karahanna et al. (1999). The results indicate no significant difference between the two groups, thus, suggesting non-response bias is not a problem in the current study.

Table 3.2: Sample characteristics (n = 525)

Characteristics		Respondents
Age	18-21	347 (66%)
	22-25	121 (23%)
	26-29	25 (5%)
	30 or older	32 (6%)
Gender	Male	244 (46%)
	Female	281 (54%)
Education Level	First-year undergraduate student	101 (19%)
	Sophomore	131 (25%)
	Junior	213 (41%)
	Senior	76 (14%)
	Graduate student	4 (1%)
Household Income Level	Less than $20,000	49 (9%)
	$20,000 to $34,999	68 (13%)
	$35,000 to $49,999	84 (16%)
	$50,000 to $ 74,999	110 (21%)
	$75,000 to $99,999	59 (11%)
	Over $100,000	155 (30%)

Note: Numbers represent frequency, followed by the percentage (rounded) among the sample in each category.

In some empirical studies of technology acceptance in an organization, limitation exists because of student sample. However, the current study focuses on the decision-making process to adopt genetic testing services and the trusting mechanism from the consumer's perspective. The respondents in this sample are a relevant and valid group that represents an ideal population with an age range from 18 to 25. Because the genetic testing technology is not widely available, the college students in this age group are likely to be the potential users and beneficiaries of this technology in the future. Individuals in this group are likely to get married and subsequently have children. Their thoughts about the willingness to adopt this technology in the future is relevant to understanding behavioral adoption intention. In the questionnaire, only 20 respondents reported that they actually engaged in genetic testing for clinical reasons. In addition to the data analysis in the results section, we also tested the proposed hypotheses with the groups consisting of the respondents that identified themselves as familiar with the technology (sample size is 211) as well as those that stated they were not familiar with the technology (sample size is 314) in order to gain better understanding about the sample and how the respondents' prior familiarity with the technology might influence the results. The results are consistent across the two subsamples and the comprehensive sample with only H6a being insignificant with the subsample familiar with the technology ($p = 0.14$) and also not significant at the 5% level with the subsample not familiar with the technology ($p = 0.09$). The findings suggest that the groups were not significantly different in terms of this model and support that the educational paragraph provided at the front of the survey helped mitigate potential differences in the two groups. As such, we do not consider the student sample a significant limitation.

3.5 Data Analysis and Results

This research tests both the measurement model and the structural model by conducting structural equation modeling (SEM). Partial least squares (PLS) technique is used, and the analyzing procedures are implemented in SmartPLS3. The current study employs PLS-SEM instead of covariance-based structural equation modeling (CB-SEM) for two reasons. First, because of the exploratory nature of this study, using PLS technique has a unique advantage in this situation (Hair et al., 2017; Torres et al., 2018) as it avoids the factor indeterminacy issue that may exhibits in CB-SEM (Lowry & Gaskin, 2014) while producing similar estimates (Reinartz et al., 2009). Second, PLS is preferred in a broad spectrum of research situations where the models are complex and contain second-order latent variables (Hair et al., 2017).

3.5.1 Creating the Second-Order Reflective Constructs: Institutional Trust Base

This study classifies institutional trust base into two subcomponents of situational normality and structural assurance. The model suggests institutional trust base as a second-order reflective construct that aggregates the two first-order constructs: technology situational normality and technology structural assurance. Based on the extant literature and the aforementioned hypothesis development, we believe that adding a second-order construct as reflective-reflective construct can enhance the testability of the research model (Li et al., 2008; McKnight et al., 2002; Peng et al., 2020).

For the higher-order construct of institutional trust base, prior study suggests the following methods to calculate measurement statistics of a second-order construct (Hair et al., 2017). The AVE of second-order construct can be calculated as the mean of the first-order constructs' squared loadings. The composite reliability is a measure of internal consistency. Equation 3.1 represents the formula of calculating the composite reliability for the second-order construct:

$$\rho_c = \frac{(\sum_{i=1}^{M} l_i)^2}{(\sum_{i=1}^{M} l_i)^2 + \sum_{i=1}^{M} var(e_i)} \qquad \text{(Eq. 3.1)}$$

Loading (l_i) measures the loading of the first-order construct *i* of the second-order construct measured with *M* first-order constructs (i = 1,…, M). The measurement error (e_i) represents the error of first-order construct i. The $var(e_i)$ denotes the variance of the measurement error, which is defined as $1 - l_i{}^2$. Cronbach's alpha is another measure of internal consistency. Equation 3.2 represents the formula to calculate Cronbach's alpha for the second-order construct:

$$Cronbach's\ alpha = \frac{M \cdot \bar{r}}{(1 + (M-1) \cdot \bar{r}} \qquad \text{(Eq. 3.2)}$$

The mean correlation ($\bar{r}$) is calculated as the average correlations of all first-order constructs for the second-order construct. There are a total of *M* first-order constructs. The related results are presented in Table 3.3.

3.5.2 Assessment of the Measurement Model

The normality of construct is examined with skewness and kurtosis. The results support the contention that the constructs used in the model do not differ from a normal distribution. The reliability of the measurement items is assessed by the outer loadings of the items with the relevant latent variables. All of the standardized loadings are greater than the recommended value of 0.7 (Hair et al., 2011) with two items for the technology situational normality having a loading of 0.69. As shown in Appendix A, both items are modified to fit the healthcare context and are retained to preserve content validity. Construct reliability is evaluated by Cronbach's alpha and composite reliability (CR) that should exceed 0.7. As shown in Table 3.4, all reliabilities exceed the criteria indicating sufficient internal consistency.

Construct validity is assessed in both convergent validity and discriminant validity. To assess convergent validity, the average variance extracted (AVE) for each construct is calculated, and, as shown in Table 3.4, is 0.54 or higher. Therefore, convergent validity is supported. The discriminant validity is also supported by the evidence of the square root of the AVE for each construct being above 0.7 and greater than the correlations with other constructs.

Table 3.3: Variable summary and correlation matrix

Const	Cr Alpha	Comp Rel	AVE	CR	TSN	TSA	TB	PE	PR	SI	TI	ITB
CR	0.81	0.89	0.72	0.85[1]	0.49[3]	0.59	0.65	0.57	0.67	0.48	0.61	
TSN	0.86	0.89	0.59	0.40[2]	0.77	0.41	0.51	0.38	0.49	0.32	0.53	
TSA	0.86	0.91	0.78	0.47	0.36	0.88	0.41	0.47	0.67	0.52	0.69	
TB	0.88	0.90	0.54	0.56	0.46	0.36	0.73	0.56	0.55	0.42	0.62	
PE	0.80	0.87	0.63	0.46	0.33	0.36	0.48	0.79	0.59	0.50	0.81	
PR	0.74	0.85	0.65	0.52	0.41	0.54	0.47	0.49	0.81	0.52	0.74	
SI	0.83	0.90	0.75	0.39	0.28	0.44	0.36	0.40	0.41	0.86	0.60	
TI	0.84	0.88	0.55	0.50	0.47	0.36	0.54	0.68	0.61	0.51	0.74	
ITB	0.90	0.80	0.67	0.51	0.91	0.71	0.51	0.42	0.55	0.40	0.61	0.82

Note: CR (Cognitive Reputation)， TSN (Tech. Situational Normality), TSA (Tech. Structural Assurance), TB (Trusting Beliefs), PE (Performance Expectancy), PR (Perceived Risks), SI (Social Influence), TI (Trusting Intention), ITB (Institutional Trust Base). [1] The bolded numbers on the diagonal are the square roots of the AVE. [2] Correlation coefficients are below the main diagonal. [3] HTMT ratios are above the main diagonal.

Table 3.4: Hypothesis testing summary

Hypothesis	Path Coeff	t-Value	Supported
H1: Cognitive Reputation -> Trusting Beliefs	0.38	8.90	Yes
H2: Institutional Trust Base -> Trusting Beliefs	0.27	5.67	Yes
H3: Trusting Beliefs -> Trusting Intention	0.16	4.15	Yes
(Total Effect)	0.48	13.05	N/A
(Indirect Effect Through Performance Expectancy and Perceived Risk)	0.32	11.87	N/A
H4a: Trusting Beliefs -> Performance Expectancy	0.48	12.23	Yes
H4b: Performance Expectancy -> Trusting Intention	0.40	10.87	Yes
H5a: Trusting Beliefs -> Perceived Risk	0.47	14.37	Yes
H5b: Perceived Risk -> Trusting Intention	0.27	7.80	Yes
H6a: Social Influence -> Trusting Beliefs	0.11	2.33	Yes
H6b: Social Influence -> Trusting Intention	0.18	5.06	Yes

In addition, Heterotrait-Monotrait Ratio (HTMT) is calculated based on the multitrait-multimethod matrix as another criterion considered more reliable (Henseler et al., 2015). All HTMT values shown in Table 3.3 are smaller than the suggested threshold of 0.85 confirming discriminant validity is met.

In addition, we also checked for common method bias with Harman's test and marker test. Harman's single-factor test was conducted to examine whether one general factor accounts for the majority of variance. The results show that the first factor explains 31% of the variance, which is below 50% and not accounting for the majority of variance (Fuller et al., 2016). Therefore, the current study does not consider common method bias an issue. Another technique is the partial correlation marker test suggested by Lindell and Whitney (2001). We selected age as a suitable marker variable because it is seemingly unrelated to any other variables in the proposed model (Visinescu et al., 2015). The marker test results indicate the absence of common method bias because the marker variable does not significantly correlate with other latent variables and the correlation coefficient is sufficiently small.

3.5.3 Test of the Structural Model

Bootstrapping technique with iterations of 5000 subsamples is used to estimate the significance level. The model testing results with PLS-SEM are summarized in Table 3.4. Figure 3.1 depicts the results. Looking at the exogenous variables to trusting beliefs, both cognitive reputation and institutional trust base are significantly correlated with trusting beliefs with path coefficients of 0.38 and 0.27, respectively. Therefore, Hypotheses 1 and 2 are supported. Then, the direct and indirect relationships between trusting beliefs and trusting intention are examined following the procedure suggested by (Zhao et al., 2010). Hypothesis 3 deals with the direct effect and is supported with a path coefficient of 0.16. Hypotheses 4(a,b) and 5(a,b) deal with the indirect effects and are supported at $p < 0.001$. The total and indirect effects of trusting beliefs to trusting intention are also reported in Table 3.4. Together, the results show that performance expectancy and perceived risks partially mediate the relationship between trusting beliefs and trusting intention. Finally, social influence is significantly correlated with trusting beliefs ($p < 0.05$) and trusting intention ($p < 0.001$) with path coefficients of 0.11 and 0.18, respectively, supporting H6a and H6b. R^2 was calculated to analyze explanatory power of the proposed model (Shmueli and Koppius, 2011) and in-sample predictive power (Rigdon, 2012). Overall, the model explains about 31% of the variance in trusting beliefs and 61% of the variance in trusting intention. Q^2 was also calculated considering its characteristics of combining the aspects of in-sample explanatory power and out-of-sample prediction (Shmueli et al., 2016). The Q^2 value of 0.20 on trusting beliefs and 0.33 on trusting intention support the predictive relevance of the proposed model (Hair et al. 2019).

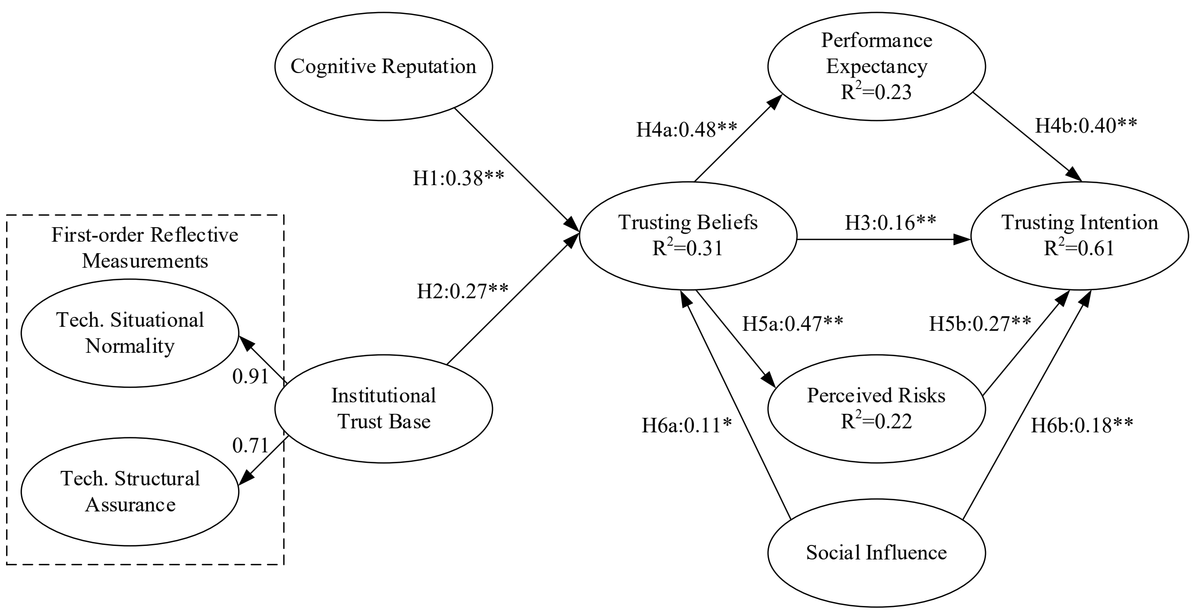

Figure 3.1: **Results of PLS analysis**

Notes: 1. *p < 0.05, **p < 0.001. 2. The measurement items for perceived risks are inversely coded in the survey to measure the perceived minimum risk.

3.6 Discussion

In recent years, genetic testing technology has emerged in the healthcare industry and is expected to seize an increasing share of the related consumer market. However, technology acceptance research generally focuses on traditional technologies with little investigation into the consumer's decision-making process and behavioral intention toward adopting emerging biotechnology. The current research studies the consumer's trusting mechanism towards such technology and how trusting beliefs influence adopting behavior. The newly developed trust model in this research and the results provide important theoretical and practical implications.

3.6.1 Theoretical Implications

The contribution of the current research to academics is multifold. The first objective is to investigate how the consumer's trust is initiated towards genetic testing as an emerging healthcare technology that directly serves the end-user. The trust model developed in this study uses a technology institutional trust base that is reflectively measured by technology situational normality and structural assurance. The technology situational normality measures the influence of the consumer's perception of the healthcare technologies to their trusting beliefs, whereas the technology structural assurance measures the trusting beliefs resulted from legal structures. The results show there is significant positive relationship between the institutional trust base and the consumer's trusting beliefs. Comparing with the prior study conducted in the context of national identify system (Li et al., 2008), where the technology institutional trust base insignificantly correlates with trusting beliefs, the findings of this paper reveal that the influence of such trust base is significant in the healthcare context. These results also align with other technology acceptance studies in healthcare (Mustapa et al., 2019; Xie et al., 2020). The possible reason for this contradictory finding could be that in contrast to a national-level e-government information system, consumers are more interested in understanding the providers of the consumer-centered healthcare products and the relevant legal structures.

Another objective of this paper is to evaluate the relationship between the consumer's trusting beliefs and behavioral adoption intention. Previous researches show that the consumers' behavioral adoption intention align with their trusting beliefs and trusting intention (Li et al., 2008). Trust is considered a critical factor that are consistently found to affect users' behavioral intention in adopting an emerging technology (Alaiad & Zhou, 2014; Katz & Rice, 2009; Tao et al., 2020; Tung et al., 2008). If an organization can make a profound impression of genetic testing technology and foster the development of trust, consumers are likely to show the intention to adopt. Building upon existing literature, the current research integrates the constructs of performance expectancy and social influence from the UTAUT2 model and the unique construct of perceived risks. All of these variables in this study are relevant to the consumer's trust formation in the context of genetic testing, and the results show they significantly correlate with trusting beliefs and trusting intention. Specifically, this research posits and tests the mediation effects of both performance expectancy and perceived risks in terms of the correlation between trusting beliefs and trusting intention. The results indicate the partial mediation exists between their relationship. Therefore, with the technology institutional determinants of trust, end-user's cognitive trust base, social influence, as well as mediating factors, the consumer's trusting mechanism in the healthcare context is explained and further understood.

3.6.2 Practical Implications

Successful translation of emerging biotechnology to healthcare practice often brings a profound impact on healthcare outcomes. This study investigates the consumer's behavioral intention to adopt genetic testing, how their initial trust is formed towards this biotechnology, and how the trust-related factors influence the consumer's decision-making process. The results provide critical answers to these questions and valuable insights for practitioners and regulating authorities. First, it is essential to establish technology situational normality and structural insurance as they together form into an institutional trust base. These institutional structures and the proper social environment contribute to the consumer's initial trusting beliefs. Since 2014, the U.S. Food and Drug Administration (FDA) started exercising restrictive regulatory controls on the commercialized genetic testing products and services (Curnutte, 2017). From the scholarly and marketing standpoint, the increased and more restrictive regulations reduce innovations and raise financial burdens that are especially burdensome for small and mid-size clinical laboratories, thus may create a monopoly market (Evans & Watson, 2015). However, from the consumer's perspective, regulatory controls help people form initial trusting beliefs that the biotechnology is well designed and competently administrated. Such believes also suggest the technology provides accurate and reliable results, and laws, regulations, and other legal structures exist to protect the consumer's best interests. Also, for emerging biotechnology that most consumers do not have prior experience with, their cognitive trust represents the cognitive reputation of the whole system in general, which in turn emphasizes the importance of the technology robustness during market introduction. In other words, a case of technology failure, especially biotechnology in the healthcare context, will jeopardize consumer's trusting beliefs and negatively affect their adoption intention.

Furthermore, the findings show the partial mediation effects of performance expectancy and perceived risks to the relationship between trusting beliefs and trusting intention. The mediation effects practically capture the consumer's concern about genetic testing and healthcare biotechnology in general. In healthcare, adopting an innovation like genetic testing requires attention to the improvement of the expected performance and reduction of perceived risks. Due to the uniqueness of healthcare, performance expectancy of genetic testing is not only evaluated by the accuracy of the results, but the test administration, whether a genetic counselor is available to interpret the results, and what are the follow-up recommendations. However, many healthcare providers who do not specialize in genetics lack of relevant background, education, interest, and ability to thoroughly interpret the results (Ramos & Weissman, 2018). The authority of those healthcare providers is a significant factor influencing the consumer's decision-making process and loyalty, especially in the circumstance where genetic testing is accessible in a variety of market channels beyond major hospitals (Miao et al., 2019). Our results reveal the critical role of genetic counseling because a certified counselor often interacts with consumers before and after the test to guide their testing decisions, interpret results, and provide professional advice on follow-up actions (American Board of Genetic Counseling, 2020). Besides, several potential risks can arise, such as failure to diagnose or assess a genetic condition, inappropriate diagnoses, and emotional distress resulted from misdiagnoses or misunderstanding of the results (Schleit et al., 2019). Based on our findings, appropriate risk mitigation strategies and communicating these strategies to potential consumers will help them build trusting intention. If an onsite practice is a financial burden to implement, centralized expertise could serve consumers adequately by providing remote counseling.

Lastly, the social influence factor is non-negligible because the findings show it positively correlates with both trusting beliefs and trusting intention. In past years, celebrities in social media largely contributed to the public's awareness of genetic testing and educated people about the technology. For example, Angelina Jolie (2013) adopted the test of breast and ovarian cancer because of her family medical history. Then based on the results she took preventive measures to reduce the risk of developing such a disease in the future. She then published an article on the New York Times discussing her medical choice and encouraging people to explore and consider adopting genetic testing as needed. When it comes to a specific hereditary disease assessment, it is also likely that opinions from the consumers' family and friends will significantly influence their decision-making process in terms of trust. To better help an individual make an adoption decision, presenting similar cases and initiating family communication certainly adds value.

3.7 Limitations and Future Work

The current research develops and tests a theoretical model that investigates the consumer's trusting mechanism in emerging healthcare technology. However, it includes some limitations that may serve as future research directions. First, although the sample remains valid in the current research context, the group who has immediate needs of genetic testing or has already adopted such technology is underrepresented in this study. Survey data from genetic testing users could provide additional insight into the issue. However, with the high-level concern of privacy, it could be very challenging to obtain the relevant sample data and self-selection bias is more likely with such a sample. Second, the sample collected in this research came from the U.S. southwest region. Verification in other countries and regions is desirable. Testing of potential moderating effect of demographics could also generate insightful findings. Future research can build upon the current framework, adjust it to another context, and test the proposed alternative hypotheses to increase the generalizability of the findings.

3.8 Conclusion

This research addresses a gap in the existing literature and provides insides into the aforementioned challenges that industrial practitioners are currently facing toward the consumer's acceptance of emerging healthcare technology. Specifically, the current research investigates the consumer's trusting mechanism and how that influences their behavioral adoption intention in the context of genetic testing. Based on technology acceptance theory and trust formation theory, the authors establish a theoretical framework by integrating trust-related factors that correlate to the consumer’s trusting beliefs and trusting intention. Using a survey approach, the authors identify technology institutional trust base, end-user’s cognitive trust base, and social influence as the significant determinants of trusting beliefs. The findings also reveal that mediation effects of performance expectancy and perceived risks exist in the relationship between trusting beliefs and trusting intention. This research extends the existing technology acceptance literature to the healthcare context, provides an improved generalized understanding of the consumer’s trusting mechanism in emerging biotechnology, and discusses practical insights for regulatory authorities, healthcare institutes, and medical professionals.

CONCLUSION

This dissertation consists of three essays. Essay 1 quantitatively investigates the consumers adoption intention towards emerging healthcare technologies through a structured literature review and meta-analysis. It contributes to the technology acceptance literature because the meta-analytic procedure synthesizes the findings from prior empirical studies and validates the relationship between each individual exogenous variable and behavioral intention. A comprehensive view of consumers adoption intention in the healthcare context is presented. Among a group of selected exogenous variables, perceived risks, habit, and trust have a significant positive correlation with behavioral intention. The results also strongly suggest that there exist moderating factors in both the aggregated model and several individual relationships. In addition, this study discusses practical implications for service designers, providers, and regulatory authorities.

Essay 2 draws on the consumer's perspective to study end-user behavioral adoption intention of gene repair technology as it becomes available. This research posits a comprehensive model by integrating trust and perceived risk in a contextualized UTAUT model and validates the model using survey data. The findings show significant correlations between social influence and facilitation conditions with consumer behavioral intention. The findings also demonstrate the full mediating effects of performance expectancy and perceived risk to the relationship between trust and behavioral intention. Therefore, this research contributes to the emerging topic of technology acceptance in healthcare and provides fruitful insights for practitioners and policymakers. Educating consumers on the technology, establishing a reliable counseling system, and reinforcing a clear regulation are critical for the successful realization of potential benefits of such technology.

Essay 3 addresses a gap in the existing literature and provides insides into the aforementioned challenges that industrial practitioners are currently facing toward the consumer's acceptance of emerging healthcare technology. Specifically, essay 3 investigates the consumer's trusting mechanism and how that influences their behavioral adoption intention in the context of genetic testing. Based on technology acceptance theory and trust formation theory, the authors establish a theoretical framework by integrating trust-related factors that correlate to the consumer's trusting beliefs and trusting intention. Using a survey approach, this essay identifies technology institutional trust base, end-user's cognitive trust base, and social influence as the significant determinants of trusting beliefs. The findings also reveal that mediation effects of performance expectancy and perceived risks exist in the relationship between trusting beliefs and trusting intention. This research extends the existing technology acceptance literature to the healthcare context, provides an improved generalized understanding of the consumer's trusting mechanism in emerging biotechnology, and discusses practical insights for regulatory authorities, healthcare institutes, and medical professionals.

Collectively, the three essays address the research questions about consumer adoption intention towards emerging healthcare technology and consumer trusting mechanism. Both academic and practical contributions are discussed in each essay.

APPENDIX A

SUMMARY OF THE SAMPLE ARTICLES FOR ESSAY 1

Article	Technology	Sample and Unit of Analysis	Theory	Method	Findings
Wilson and Lankton (2004)	eHealth Services	163 patients who recently registered for access to e-health service	TAM, motivational model, integrated model	CB-SEM	All tested IT acceptance models performed well in predicting patients' behavioral intention to use e-health. Antecedent factors of satisfaction with provider, information-seeking preference, and Internet dependence uniquely predicted constructs in the models.
Ma and Liu (2005)	Web-based electronic medical records	75 senior health care trainees and 11 staff workers	TAM	Hierarchical multiple regression	Internet self-efficacy (ISE) explained 48% of the variation in PEOU. ISE and PEOU together explained 50% of the variation in PU, and the full model explained 80% of the variance in BI
Klein (2007a)	Internet-based patient-physician communication application	143 patients who are first-time users of the application	TAM, Theory of Reasoned Action (TRA)	PLS-SEM	Results suggest that behavioral intentions shape use behaviors, perceived usefulness (PU) influences behavioral intentions, and perceived ease of use (PEOU) impacts PU. Additionally, the analysis reveals that patient trust beliefs in both their provider and the Web site vendor shape behavioral intentions, with perceived vendor reputation and PEOU influencing user trust beliefs in the vendor.
Klein (2007b)	Patient-physician portal	294 patients majority from primary care providers	TAM	PLS-SEM	Usefulness and innovativeness have a positive direct effect on BI with respect to both functions, namely communications and information access. Additionally, patients with greater healthcare needs foresee increased use of portals to access their personal medical information. Finally, patients in primary care, as opposed to specialist, provider settings intend to engage in electronic communications.
Whetstone and Goldsmith (2009)	Personal health records (PHRs)	542 college students	TAM	Correlation, Multiple linear regression, AMOS	The results showed that being innovative with regard to healthcare, confidence in the privacy and security of the records, and especially perceived usefulness of PHRs were positively associated with intent to create a PHR. Gender, age, presence of a chronic illness, and awareness of PHRs were largely unassociated.
Yun and Park (2010)	Disease information on the Internet	212 Internet users of two health information websites	TAM	CB-SEM, variance–covariance matrix analysis	Consumers' health consciousness, perceived health risk and Internet health information use efficacy were found to influence consumers' beliefs, attitude and intention of use disease information on the Internet. But Internet health

Article	Technology	Sample and Unit of Analysis	Theory	Method	Findings
					information use efficacy did not significantly influence perceived usefulness. It was also identified that consumers' perceived credibility of the information in the websites was the main determinant in forming of attitude towards disease information on the Internet.
Liang et al. (2011)	Online health information	330 participants from social networking websites	TAM	Hierarchical regression	a person's intention to continue online health information seeking (OHIS) increases as perceived usefulness (PU) and ease of use (PEOU) and disability level increase. The OHIS intention is also predicted by a negative inter- action between PU and disability, a positive interaction between PEOU and disability, and a negative interaction between PU and PEOU.
Noblin et al. (2013)	Electronic health record (EHR)	562 patients	TAM	CB-SEM	Although the perceived usefulness of a personal health record was a significant determining factor related to intention to adopt, technology barriers were indirectly related to intention to adopt as well. Technology barriers can be addressed by providing office staff for hands-on training as well as assistance with interpretation of medical information.
Shareef et al. (2014)	Mobile health	326 diabetic patients	TAM	CB-SEM	Perceived usefulness, perceived ease of use, perceived reliability, and perceived security and privacy are the independent constructs that can act as the driving influences of attitude towards adopting an M-health system for diabetic patients.
Gao et al. (2015)	Wearable device	462 participants from three social network groups (341 fitness device users and 297 medical device users)	UTAUT2, protection motivation theory (PMT), privacy calculus theory	PLS-SEM	Consumer's decision to adopt healthcare wearable technology is affected by factors from technology, health, and privacy perspectives. Specially, fitness device users care more about hedonic motivation, functional congruence, social influence, perceived privacy risk, and perceived vulnerability, but medical device users pay more attention to perceived expectancy, self-efficacy, effort expectancy, and perceived severity.

Article	Technology	Sample and Unit of Analysis	Theory	Method	Findings
Krishnan et al. (2015)	Consumer health informatics (CHI) applications	People from hospitals, clinics, and online	TRA, TAM, UTAUT2	Regression	The findings indicate that the factors Hedonic Motivation, Perceived Ease of Use and Performance Expectancy have a positive linear relationship with the intention to adopt CHI applications.
Lazard et al. (2015)	Patient portal	333 patient portal users	TAM	CB-SEM with Mplus	The hypothesized model accounted for 29% of the variance in BIs to use the portal, 46% of the variance in the PU of the portal, and 29% of the variance in the portal's PEU. Additionally, one dimension of the aesthetic evaluations functions as a predictor in the model – simplicity evaluations had a significant positive effect on PEU.
Diño and de Guzman (2015)	Telehealth	82 technology-trained older adults	UTAUT, Health Behavior Model (HBM)	PLS-SEM	The study revealed that the UTAUT constructs, particularly effort expectancy, have yielded a significant influence on the behavioral intention of elderly to participate in Telehealth. Further, gender showed no moderating effect on these variables. Results of the study supported the espousal of UTAUT Model as an indispensable framework in empowering older adults using Telehealth.
Jeon and Park (2015)	Mobile obesity-management applications	94 adult Android smartphone users	TAM	CB-SEM	The results indicate that compatibility, perceived usefulness, and perceived ease of use significantly affected the behavioral intention to use the mobile obesity-management app. Technical support and training also significantly affected the perceived ease of use; however, the hypotheses that self-efficacy affects perceived use- fulness and perceived ease of use were not supported in this study.
Park et al. (2016)	Wearable device	877 smartphone users who purchased wearable devices	TAM	CB-SEM	Perceived control and interactivity of wearable healthcare devices as well as users' innovative tendencies are positively associated with usage intention, while perceived cost has no significant effects on user intention to use the devices. The results also supported the explanatory strength and predictability of TAM.
Tavares and Oliveira (2016)	Electronic health record (EHR)	360 participants from three educational institutions	UTAUT2	PLS-SEM	The statistically significant drivers of behavioral intention are performance expectancy, effort expectancy, habit, and self-perception. The predictors of use behavior are habit and behavioral intention. The model explained 49.7% of the

Article	Technology	Sample and Unit of Analysis	Theory	Method	Findings
					variance in behavioral intention and 26.8% of the variance in use behavior.
Borges and Kubiak (2016)	Continuous glucose monitoring (CGM) patient system	111 participants with diabetes from online groups	TAM	CB-SEM	In general, participants evaluated CGM positively; however, the feeling of information overload represented a major barrier to the sustained use of CGM, while perceptions of usefulness and ease of use constituted incentives for using this technology. Moreover, patients without CGM experience imagined more information overload than current users reported. Current users showed more intention to use CGM than former users.
Dwivedi et al. (2016)	Mobile health	1121 diabetic patients	UTAUT2	CB-SEM	The findings suggest that the UTAUT model could partially shape technology artefact behaviour and the extended UTAUT must consider specific determinants relevant to cognitive, affective, and conative or behavioural aspects of citizens. The finding also suggests that this mobile service system should reflect a country's cultural traits.
Cimperman et al. (2016)	Home telehealth services (HTS)	400 participants aged 50 years and above	UTAUT	CB-SEM	The level at which HTS are perceived as easy to use and manage is the leading acceptance pre- dictor in older users' HTS acceptance. Together with Perceived Usefulness and Perceived Security, these three factors represent the key influence on older people's HTS acceptance behavior.
Koivumäki et al. (2017)	MyData-based preventive eHealth services	855 faculty and staff from the University of Oulu	UTAUT2	CB-SEM with Mplus	The statistically significant drivers for behavioral intention were effort expectancy, self-efficacy, threat appraisals, and perceived barriers.
Zhang et al. (2017)	Wearable device	436 participants from online communities of relevent device and field research interviews	TAM, UTAUT	PLS-SEM	Results show that the adoption intention of healthcare wearable technology is influenced by technical attributes, health attribute and consumer attributes simultaneously. For technical attributes, perceived con- venience and perceived credibility both positively affect perceived usefulness, and perceived usefulness influ- ences adoption intention. The relation between perceived irreplaceability and perceived usefulness is only supported by males. For health attribute, health belief affects perceived usefulness for females. For consumer attributes, conspicuous consumption and

Article	Technology	Sample and Unit of Analysis	Theory	Method	Findings
					informational reference group influence can significantly moderate the relation between perceived usefulness and adoption intention and the relation between consumer innovativeness and adoption intention respectively. What's more, consumer innovativeness significantly affects adoption in- tention for males.
Lee et al. (2017)	Mobile health	313 participants aged 40 years and above	Personal values, context values, content values	CB-SEM	Context values (health stress, epistemic) produce an effect on contents values and contents values (convenience, usefulness), excepting reassurance and enjoyment, positively affect the intention to use mHealth Applications.
Emmert and Wiener (2017)	Hospitals report cards (HRC)	780 potential users	UTAUT	PLS-SEM	Performance expectancy, facilitating conditions, and attitude were found to be significantly related to HRC use intention, with notable differences between users and non-users. Effort expectancy and social influence did not show any significant effects in both subsamples.
Werber et al. (2018)	RFID subcutaneous microchip (RFID-SM)	531 participants from social network, web pages, a primary school, and a retirement home	TAM	CB-SEM	Perceived usefulness has a significant impact on behavioural intentions to adopt RFID-SM in the future, while the influence of perceived ease of use is not significant. The most influential external variable is perceived rrust, indicating the lack of confidence in personal data security ensured by the state and other institutions. Health concerns factor has a negative effect on the perceived rrust and perceived usefulness of RFID-SM.
Tavares et al. (2018)	Electronic health record (EHR) portal	386 students	UTAUT2	PLS-SEM	The statistically significant drivers of behavioral intention are performance expectancy, effort expectancy, social influence, and habit. Habit and behavioral intention are the statistically significant drivers of technology use. The model explains 52% of the variance in behavioral intention and 31% of the variance in technology use.
Kumar and Natarajan (2019)	eHealth	253 patients and care-givers	expectation-confirmation model (ECM), TAM	PLS-SEM	The main finding from the path analysis indicates that along with perceptual (confirmation, perceived ease-of-use, perceived usefulness), and emotional factor (satisfaction), post adoption expectation beliefs (perceived trust, perceived

Article	Technology	Sample and Unit of Analysis	Theory	Method	Findings
					privacy and security) – also shown a significant association towards continuance intention of e-Health services.
Park et al. (2020)	Electronic health record (EHR) apps	687 workers	UTAUT	Pearson correlation analysis, multiple linear regression, CB-SEM	Effort expectancy, social influence, performance expectancy, and facilitating conditions exerted significant positive effects on behavioral intention, whereas perceived risk exerted a significant negative effect on behavioral intention. Performance expectancy had a significant effect on path differences depending on gender and age. Workers' mean scores for the main variables were higher relative to those of health experts for all remaining variables except perceived risk, and significant differences were observed for all remaining variables except facilitating condition.
Wang et al. (2020)	Wearable device	406 adult smartphone users	Task-Technology Fit (TTF), UTAUT	PLS-SEM	The results indicated that performance expectancy, effort expectancy, facilitating conditions, social influence, and task-technology fit positively affected consumers' behavioral intention to use HWDs, and together accounted for 68.0 % of its variance. Both task and technology characteristics were significant determinants of task-technology fit and exerted impacts on behavioral intention through the mediating roles of task-technology fit and effort expectancy.

APPENDIX B

MEASUREMENT ITEMS FOR ESSAY 2

Performance Expectancy (PE)	
PE1	I would find gene repair technology useful for my health if it is available.
PE2	Using gene repair technology enables me to improve my life quality.
PE3	Using gene repair technology allows me to control inherited diseases.
PE4	Using gene repair technology will increase my chances of improving my family's happiness.
Social Influence (SI)	
SI1	People who influence my behavior are likely to think that I should use gene repair technology when it becomes available.
SI2	People who are important to me are likely to think that I should use gene repair technology when it becomes available.
Facilitating Conditions (FC)	
FC1	I have the resources necessary to use gene repair technology.
FC2	I have the knowledge necessary to use gene repair technology.
Trust (TR)	
TR1	I would trust gene repair technology if strict government regulations exist.
TR2	I would trust gene repair technology if it is provided by a reputable medical facility.
TR3	In general, I anticipate that gene repair technology is accurate and harmless.
Perceived Risk (PR)	
PR1	I would characterize the decision to use gene repair technology as an insignificant risk when it becomes available.
PR2	I would characterize the decision to use gene repair technology as high potential for gain when it becomes available.
PR3	In general, I believe using gene repair technology is not risky.
Behavioral Intention (BI)	
BI1	I predict I would use gene repair technology if it is available in the future.
BI2	I have seriously thought of using gene repair technology in the future if it is available.
BI3	In general, I intend to use gene repair technology when it becomes available.

APPENDIX C

MEASUREMENT ITEMS WITH FACTOR LOADINGS FOR ESSAY 3

Cognitive Reputation (CR)	
Gene testing technology is known for working in the users' best interest.	0.70
Gene testing technology has a reputation for being accurate.	0.93
Gene testing technology is recognized for being reliable.	0.91
Technology Situational Normality (TSN)	
Most healthcare technologies are employed for user well-being.	0.69
In general, healthcare technologies are competently administered.	0.70
I feel that most healthcare technologies can meet the requirements for which they were designed.	0.69
I am comfortable relying on results from healthcare technologies.	0.82
I feel fine using healthcare technologies since they are generally reliable and accurate.	0.86
I always feel confident that I can rely on healthcare technologies to do their part when I interact with them.	0.82
Technology Structural Assurance (TSA)	
I feel assured that legal structures adequately protect me from any problem with gene testing technology.	0.89
I feel confident that regulations, laws, and social norms make it safe for me to use gene testing technology.	0.92
In general, gene testing technology is robust and safe.	0.84
Trusting Beliefs (TB)	
Gene testing technology is effective and provides a useful aid to diagnosis.	0.73
Gene testing technology would be an accurate tool in assisting diagnosis.	0.73
Gene testing technology would be a reliable tool in assisting diagnosis.	0.71
In general, gene testing technology is efficient in assisting diagnosis.	0.72
Gene testing technology would be accurate in providing information about me.	0.71
I would characterize the gene testing technology as trustworthy.	0.73
Gene testing technology would provide the results it claims to provide.	0.78
Gene testing technology would generate an accurate report.	0.75
Performance Expectancy (PE)	
I would find gene testing technology useful for my health.	0.80
Using gene testing technology enables me to improve my life quality.	0.78
Using gene testing technology allows me to diagnose inherited diseases.	0.75
Using gene testing technology will increase my chances of improving my family's happiness.	0.85
Perceived Risks (PR)	
I would characterize the decision to use gene testing technology as an insignificant risk.	0.75
I would characterize the decision to use gene testing technology as high potential for gain.	0.82
In general, I believe using gene testing technology is not risky.	0.85
Social Influence (SI)	
People who influence my behavior are likely to support my use of gene testing technology.	0.85
People who are important to me are likely to support my use of gene testing technology.	0.90

People who are important to me are likely to recommend the use of gene testing technology.	0.84
Trusting Intention (TI)	
I feel that relying on gene testing technology would be beneficial.	0.78
I would feel safe using gene testing technology.	0.77
I would feel comfortable supporting the adoption of gene testing technology in the U.S. healthcare system.	0.77
I would be willing to provide general personal information like my name, address, and phone number when using gene testing technology.	0.70
Faced with a serious illness that required me to see the doctor, I would consider using gene testing technology as a diagnostic aid.	0.71
If I were ill, I would want to use gene testing technology.	0.72

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