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3D Printing in the Era of the Prosumer: The Role of Technology Readiness, Gender, and Age in User Acceptance of Desktop 3D Printing in American Households

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3D PRINTING IN THE ERA OF THE PROSUMER: THE ROLE OF TECHNOLOGY READINESS, GENDER AND AGE IN USER ACCEPTANCE OF DESKTOP 3D PRINTING IN AMERICAN HOUSEHOLDS

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Abstract

Technology acceptance of Desktop 3D printing for fabrication at home is an emerging field of research in Asia and Europe. The proposal explains how Desktop 3D printing provides an innovative manufacturing alternative to the traditional manufacturing processes and as such facilitates innovation among prosumers. The link of how such innovations have the potential to sustain economic growth is also explained thus substantiating the need to understand the Technology acceptance of Desktop 3D printing for fabrication at home. The unified theory of acceptance and use of technology (UTAUT) model (Williams et al., 2015) was the most commonly used model in previous research to study the adoption of Desktop 3D printing for fabrication at home. The current research proposes an extension to the UTAUT model that accounts for the Technology Readiness of the individual. The extended UTAUT model is applied to study the acceptance of Desktop 3D printing for fabrication in American households which will be a new contribution to the literature. Partial Least Squares Structural Equation Modeling (PLS-SEM) is proposed to analyze the extended UTAUT model to determine the key factors that influence the acceptance of Desktop 3D printing. A multi-group analysis based on Gender is also proposed to identify how significant the differences are in the key factors. This research contributes theoretically to the emerging stream of research that focuses on integrating technology acceptance theories with the Technology readiness concept. Practically, this research contributes to the techno-marketing literature of 3D printer manufactures that seek to increase the adoption rate of Desktop 3D printers by women in American households.

Keywords: 3D printing, UTAUT, Technology Readiness, American households

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CHAPTER 1 – INTRODUCTION

Introduction to Research Area

The Digital revolution, which began in the second half of the 20th century, was stimulated by the development of semiconductors, mainframe computing, personal computing and the internet (Schwab, 2016). This revolution led to the expansion of the information economy and electronic networks (Westerman et al., 2014). Along with this expansion, the typical lines between goods and services in the economy were blurring and firms had to adjust their operation strategy to include what is called the “Value Package” prism (Correa et al., 2007): goods and services are bundled by the firm to provide a solution to the customer that is customized to their needs. The “Value package” prism concept has its roots in the service-dominant logic espoused by Vargo and Lusch (2004) in which customers co-create their own value. The “service-dominant” logic challenged the established view of buyers as passive consumers and promoted the idea that consumers should be included in the value creation process leading to the co-creation of value. The realization of that idea in which consumers can be actively involved in creating value and extracting benefits through their consumption from the co-created value is aligned with the notion of prosumption (Xie et al., 2008, Ritzer et al., 2012). Xie et al. (2008, p.110) define prosumption as “value creation activities undertaken by the consumer that result in the production of products they eventually consume and become their consumption experience.”

In essence the consumer becomes a prosumer. A prosumer is an individual that produces value for self-consumption (Xie et al., 2008). As the authors elaborate, the increasing availability of advanced household tools and the outsourcing of certain aspects of production and delivery to customers are some of the factors that lay the foundations for consumer value creation. Lang et al. (2020) did a study on the prosumer literature during a time of crisis such as the Covid-19 pandemic. The authors suggested new categories for prosumers and show the growth of the “economic” prosumer during the crisis. An “economic” prosumer secures financial incentives when creating value for others to remain resilient in a time of crisis (Lang et al., 2020). The “economic” prosumer is an individual that produces value for self-consumption or consumption by others (Lang et al., 2020). The authors elaborate that the circumstances of the crisis have driven prosumers toward freelance work. An example cited by the authors is the making and selling of homemade protective equipment by some of the “economic” prosumers.

The confluence of the digital revolution and the service-dominant economy led to the concept of self-service technologies (SST). Self-service technologies can be defined as “technological interfaces that enable customers to produce a service independent of any direct service employee involvement (Meuter et al., 2000; Hughes et al., 2015). SSTs include services like automated teller machines (ATM), telephone banking, e-services (provision of services over the internet) and self-service kiosks in retail, restaurants, airlines, and hotels (Blut et al., 2016). More recently, the concept of self-service kiosks has even extended to the 3D printing industry. 3D printing is the process of producing a physical solid object from a digital file (Gibson et al., 2015). As an example, Piecemaker Technologies introduced 3D printing kiosks to toy stores (Krassenstein, 2015). The Kiosks allowed children and parents to create and print their customized toys in the store using a simple and engaging touch screen. Another example is the

"MyProAction" 3D printing vending machine developed by a group of students in Italy (Neal, 2018). This 3D printing machine can give the customer a new printed smartphone case from the plastic bottles the customer wants to recycle.

Irrespective of the application, the key question of "why do certain individuals adopt new technologies whereas others don't" in a consumer or prosumer context has become of importance to companies providing such technology-based products and services (Blut et al., 2016; Considine & Cormican, 2017). The extant literature on the general topic of "technology acceptance" has three main streams of research. The first stream of research focuses on extending the application of technology acceptance theories previously applied at the employee level, at the consumer level or prosumer level (Hilton et al.,2013;Blut et al., 2016). These theories were founded on Psychology, Organizational Behavior or Sociology research and focused on identifying the factors that influenced an individual's behavioral intention to accept or use a specific technology and the individual's use behavior. A prominent theory in this stream of research is the Unified Theory of Acceptance and Use of Technology (UTAUT) (Williams et al., 2015). Hartmann and Vanpoucke (2017) and Halassi et al. (2018) are examples of research work that used the UTAUT model to study the factors that influence user acceptance of 3D printing technology for fabrication at home in European markets. The second stream focuses on understanding the technology readiness of the consumer (Parasuraman, 2000; Colby, 2002; Parasuraman & Colby, 2015). The technology readiness concept focuses on understanding the overall mindset of the consumer. Does the overall mindset of the consumer enable the consumer to adopt new technologies in general or does it inhibit the consumer from adopting new technologies? The emerging third stream focuses on integrating technology acceptance theories (stream 1) with the technology readiness concept (stream 2). As an example, Perry (2017) used the integrated approach to study the factors that influence consumer acceptance of 3D printed apparel. This proposed study focuses on the use of the integrated approach to study the factors that influence user acceptance of 3D printing technology for fabrication at home in the US market.

Rationale for the Current Study

The Internet started with the "read-only" web, Web 1.0, where users could only search for information and read it with little room for interaction or content generation (Getting, 2007). However, with the advent of Web 2.0 technologies (i.e. technologies that use the internet such as Facebook, Twitter, Flicker, Youtube, Instagram, etc) came the "democratization" of innovation and production of digital content using digital media (Rayna & Striukova, 2015). Consumers were no longer just "consuming" digital content they also became involved in "producing" digital content which realized the concept of digital "prosumers" (Ritzer & Juergenson, 2010; Rayna & Strikov, 2015). In effect, Web. 2.0 technologies gave users the empowerment to innovate and produce their own digital content (the "democratization" effect). Another key aspect of Web 2.0 is the power of the "network effect": when people are connected with ideas effectively, they both tend to grow (Rayna & Sriukova, 2015). That is, more people combine to create value through more ideas and the cycle is perpetual (the "decentralized" effect). Getting people together through the "network effect" to design a product is referred to as design crowdsourcing (Rayna & Sriukova, 2015).

Similar to the impact of the internet on information technology, 3D printing is decentralizing and democratizing manufacturing (Rayna et al., 2015; Rayna & Striukova, 2015, 2016). 3D printing is the bridge between the digital and physical domains (Schwab, 2016). As Anderson (2015) elaborates, it is now possible to make a digital design on an individual's desktop and send the file to a commercial manufacturing service for manufacturing or simply manufacture it on the individual's desktop 3D printing machine. Anderson (2015) argues that this capability has transformed the "maker" movement. He called it "Digital DIY". The bridge between the digital and physical domains also led to the growth of online 3D printing platforms in the consumer and prosumer community (Rayna et al., 2015; Yoo et al., 2016; Chaudhuri et al., 2019). Just like the Web 2.0 technologies, 3D printing platforms provide an interface for firms and users to engage in co-creation activities around physical objects. The study of Rayna et al. (2015) led to the conclusion that the existing online 3D platforms will evolve to online 3D crowdsourcing platforms offering "design crowdsourcing" (the crowd co-designing a product with the user for 3D printing) and "printing crowdsourcing" (users owning 3D printers and willing to print 3D objects from digital files for a fee). An example of such a platform in the USA is Kraftwurx (www.kraftwurx.com). However, the authors emphasize the sweet spot for innovation is to co-design on 3D crowdsourcing platforms and 3D print the product at home. Following the study of Rayna et al. (2015), a research stream on the viability of business models for 3D printing at home emerged touting the expansion of the innovation sphere and contribution to economic growth (Piller et al., 2015; Rayna & Striukova,2016; Holzmann et al., 2017; Hanbal & Knight, 2018). Steenhius and Pretorious (2017) did an exploratory study on consumer adoption of 3D printing using multiple 3D printing forums and concluded that the adoption rate for home 3D printing is still low given the viability of home fabrication business models using desktop 3D printing. Concurrently, a research stream on factors influencing user acceptance of 3D printing for home fabrication emerged in Asia and Europe (Wang, et al., 2016; Hartmann & Vanpoucke, 2017; Halassi et al., 2018; Lotjonen, 2019). To date, a comprehensive literature review, as discussed in chapter 2, has not yielded any published academic research on user acceptance of 3D printing for home fabrication in the US market. This is an opportunity for this study to fill such a gap in the published literature. Addressing this gap will inform both academics and practitioners on the key variables that impact the behavioral intention to use and purchase 3D printers for home fabrication in the US market

With women leaving the US workforce in large numbers due to the Covid-19 pandemic (Vesoulis, 2020), there is need to find alternate job solutions such as Freelance work. In 2019, 35% of the US workforce freelanced (http://freelancerunion.org) with 58% of employees who worked remotely considering a future in freelancing. Freelancers are self-employed and have the potential to be micro-entrepreneurs (Eveland & Maclennan, 2019). A micro-entrepreneur is defined as "a person who sets up or runs a small business" which differs from the definition of the entrepreneur as "a person who organizes and operates a business or businesses, taking on greater than normal financial risks in order to do so" (Evelan & Maclennn, 2019, p.2). Prior to the pandemic, 62% of businesses in the US were small businesses with less than 5 employees (Perilli, 2018). The current study will also contribute to understanding the factors which drive women (compared to men) to accept 3D printing technology for fabrication at home. Using desk top 3D printing for fabrication at home could provide a possible freelance work opportunity. Finally, this study will also contribute to the ongoing research on business models for 3D printer manufacturers (Holzmann et al., 2019). The results will aid 3D printer manufacturers to adapt the appropriate "techno-marketing strategy". As Colby (2002, p.37) points out a techno-ready marketer "recognizes the unique consumer behavior for cutting-edge products and services and applies this knowledge in the marketing mix and in servicing customers"

Research Aim and Objectives

The research aim of this study is to enhance the knowledge and understanding of an American's propensity to accept desktop 3D printing for fabrication at home. To this end, a theoretical extension of the UTAUT (Williams et al., 2015) model that incorporates the

Technology Readiness concept is proposed. In more specific terms, the main objectives of this research are:

- Investigate the key factors, in the UTAUT model, that influence an American's behavioral intention to purchase and use Desktop 3D printing for fabrication at home. The emphasis will be on individuals that do not currently own a desktop 3D printer at home.
- Clearly identify the key factors that are more salient for females in accepting desktop 3D printing for fabrication at home compared to males.
- Examine how Technology Readiness, and Age influence the key factors for male and female behavioral intentions to purchase and use Desktop 3D printing.

The research objectives contribute at the theoretical, practical and academic perspectives.

From a theoretical perspective, the research examines the viability of the proposed extended UTAUT model in predicting an individual's behavioral intention to purchase and use a "cutting-edge" technology, such as 3D printing. In doing so, it contributes to the emerging third stream of research (see discussion earlier in this chapter) that focuses on integrating technology acceptance theories and the technology readiness concept. As will be discussed in chapter 2, the proposed extend UTAUT model has not been used before in the context of 3D printing.

From a practical perspective, this study contributes to the understanding of the factors that impact the adoption of Desktop 3D printing by American households. This understanding is very important for 3D printer manufactures to implement the appropriate techno-marketing strategies that address the needs of potential prosumers in the US market. The literature review, discussed in chapter 2, shows that to date no similar study has been done for the US market. A better understanding of the role of technology readiness, age and gender will increase the probability of successfully implementing the appropriate techno-marketing strategies. There is a need to focus on the female prosumer population to encourage the transition toward freelancing. That will help to alleviate the impact of the female job loss in the US due to the pandemic situation.

Recently, the European Journal of Marketing called for research papers, for a special issue of the journal forthcoming in 2021, focusing on the "Understanding of prosumer behavior in the platform ecosystem". (www.emraldgrouppublishing/journal/ejm, accessed on November 4th, 2020). The editors argue that despite the fast-growing trend of "prosumption" there is a clear research gap in the academic literature when it comes to prosumption behavior. From the academic perspective, this research thus contributes to the literature on prosumption behavior. Desktop 3D printing at home is part of the online 3D printing platform ecosystem. There is an opportunity for this study to contribute to the research area identified by the editors that deals with theories and techniques that can be applied to Prosumer research with emphasis on technology adoption. Furthermore, the extended model proposed in this research can be applied in other countries and serve as a basis for comparing the intention to adopt Desktop 3D printing technology in different countries.

Research Structure

Chapter 2 starts with a discussion of the foundations of 3D printing and the evolution of the 3D printing "ecosystem" that contributed to the transformation of the user from a "consumer" to a "prosumer". Following this discussion, the next sections in Chapter 2 discuss the foundations of the UTAUT model, the foundations of the technology readiness concept, the current existing theoretical models on the acceptance of desktop 3D printing for home fabrication, the proposed research questions, and the proposed research model with relevant hypotheses to be tested.

Chapter 3 focuses on the research methodology applied in this study. Justification for using an online survey is provided. Following that, the sample size calculation, data collection procedure and statistical analysis are discussed.

CHAPTER 2 – LITERATURE REVIEW

A Primer on 3D Printing

Today most of us participate in the process of 2D printing at home. By a click of a button a word document (2D digital file) is sent to a desktop laser printer or inkjet printer (see Figure 1). In a matter of minutes, we have a printed document on our desk. Thus, for most people the definition of "printing" involves the idea of putting ink on a sheet of paper. Similar to laser or ink jet printers (2D printers), it has been suggested by many researchers that 3D printers will eventually become more common in homes as they become more affordable (Kietzmann et al., 2015; Peterson & Pearce, 2017). Manufacturers of desktop 3D printing systems are focused on offering cheaper machines to make 3D printing a viable option for individual customers (at home), self-employed engineers and designers and small businesses (Steenhuis & Pretorius, 2016).

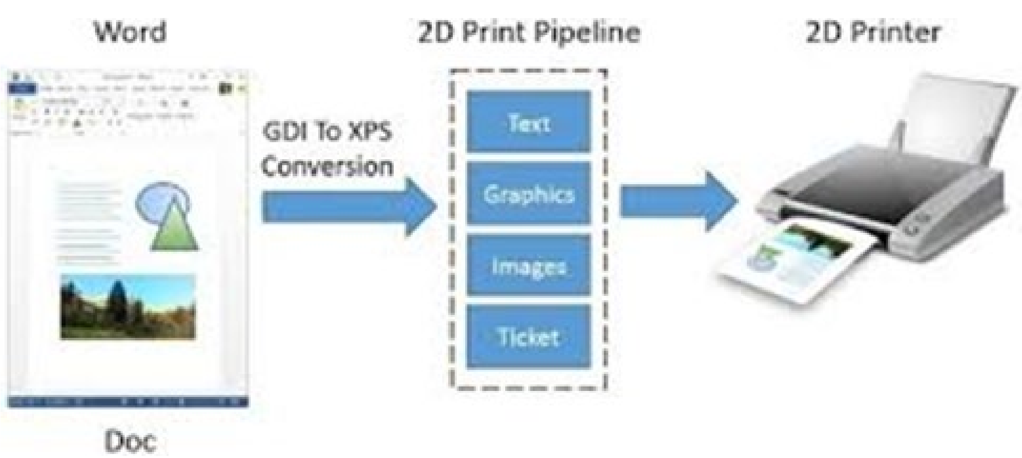

Figure 1. 2D printing process (Source: www.blog.windows.com)

But what is 3D printing? 3D printing is the process of printing a solid, physical 3D object, from a 3D model (3D digital file). The 3D model is first sliced into "paper-thin" cross-sections or layers using a computer software. These layers are printed one at a time stacked upon each other (hence the name "additive manufacturing" being also used) until the entire solid object is printed (see Figure 2). Vance (2012) referenced desktop 3D printing as a "factory on your desk" given the fact that with 3D printing it is feasible to translate any design idea that has a 3D model into a physical prototype or production part thus circumventing the traditional manufacturing processes that we associate with "factories". The materials available for 3D printing are plastic, metal alloys, ceramics, wood particles, sand particles, sugar particles and even chocolate (Gibson et al., 2015).

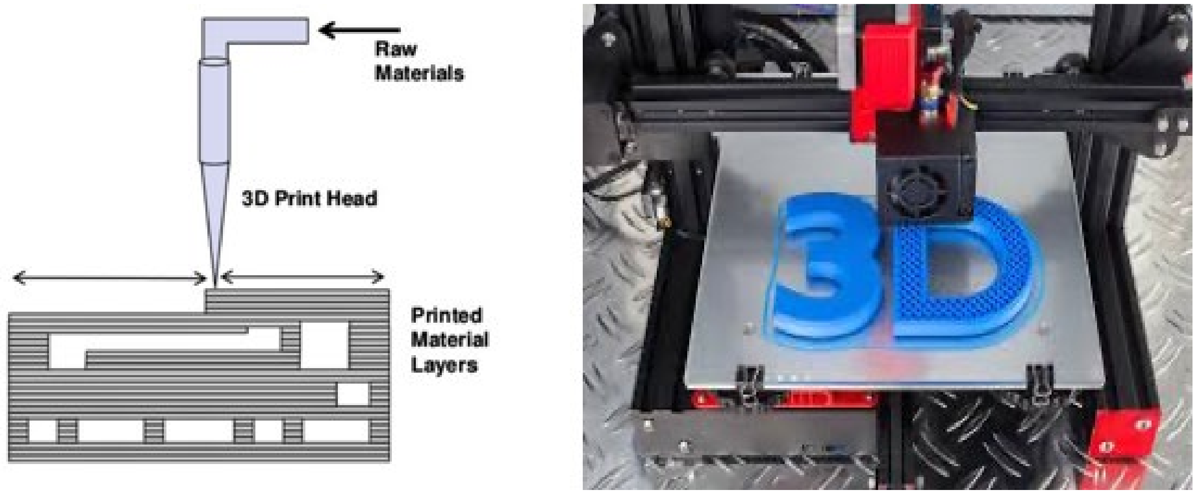

Figure 2. 3D printing process (Source: www.essentracomponents.com)

The conventional business model most manufacturers use is built around the "design-manufacture- distribute" model (Grichnik et al., 2008). The "design" phase focuses on translating a captured solution for a customer need into a product. The "manufacture" phase focuses on production at a certain scale or volume at centralized locations to reduce the per-unit cost of the product (through achieving the so called "economies of scale"). The conventional approach to manufacturing is to start with a solid physical form out of which material is removed using lathe, milling or drilling machines to make the final shape of a certain component or part of the final product (e.g., shaft, gear sprocket, etc.). Such an approach is known as “subtractive manufacturing” or “subtractive machining” (De Garmo, 1988). Subtractive manufacturing methods gave birth to the field of “Design for Manufacturing” (DFM) which emphasized designing parts that could be manufactured cost effectively using such processes (Ulrich & Eppinger, 2004). The goal of DFM is to increase efficiency and reduce variation to enable efficient repetitive production which is the key to high volume production. Efficient high-volume production combined with efficient material handling methods are among the key drivers to reduce the per-unit cost and maintain the competitiveness of the traditional manufacturing firm (Grichnik et al., 2008). As digital technologies facilitated the communication among companies, distributed supply chains became the norm (Simchi-Levi, 2003). Low-wage countries dominated the manufacturing field and the “China price” was born (Hout & Ghemawat, 2011). That trend was only feasible as the costs of transportation of the involved parts were offset by the labor cost savings. Nevertheless, DFM had a major drawback: it changed the mindset of design from “creative expression” to “creative circumnavigating” of manufacturing constraints (de Jong & de Bruijn, 2013). Even when lead users are involved with the firm as part of co-creation to the next novel product concept (von Hippel, 1986; Frank et al., 2006), DFM still limited the scope of product innovation (de Jong & de Bruijn, 2013) and design optimization.

With firms competing to lead in a digital environment (an outcome of the digital revolution- Westerman et al., 2014; Rayna & Striukova, 2015)) and the digitalization of manufacturing (Wolfgang & Al Khawali, 2015; Schwab, 2016; Ustundag,A. & Cevikcan, E., 2018)), Direct Digital Manufacturing (DDM) is becoming the new norm in many manufacturing industries (Holmstrom & Partanen, 2014;Ustundag& Cevikcan, 2018). DDM is the fabrication of a component in a seamless manner from a computer model (3D digital file to an actual end-use part in hand (Chen et al.,2015). DDM was a key enabler for additive manufacturing (3D printing) to return to manufacturing the ability to produce anything than can be imagined rather than being limited by the constraints of subtractive manufacturing (Poprawe et al., 2015). Based on this new freedom, some authors argue that DDM flips DFM (design for manufacturing) to MFD (manufacturing for design) (Petrick & Simpson, 2013). Candi and Beltagui (2019) surveyed 177 US Firms to evaluate the impact of adopting DDM and 3D printing on the Firms' innovation performance and the corresponding business impact. The authors found that the greatest benefit came to firms that considered the human factors in their processes. These results are consistent with earlier research by Brauner & Ziefle (2015) in which the authors posited the integration of human factor knowledge in the development of technologies such as 3D printing was key to successful adoption. Candi & Beltagui (2015) also found that firms with the most turbulent market conditions benefited the most out of adopting DDM and 3D printing technologies

Instrumental to the rise of direct digital manufacturing was the digital revolution which sparked the rise of Web 2.0 technologies: Social media sites (e.g. FaceBook), Video Sharing Sites (e.g. Youtube), image sharing site (e.g. Flicker, Instagram), etc. The key aspect of Web 2.0 technologies is the ability to provide all users the freedom to create, share, collaborate, and communicate digital content. In effect Web 2.0 technologies offered users empowerment and lowered the barriers to user creation (Rayna & Striukova, 2015) of digital content. Web 2.0 "democratized" the necessary tools that inspire invention and the tools to produce these inventions (Anderson, 2012). The role of the user changed slowly from being a passive consumer to becoming part of the production process (example: users not only consume Youtube videos, they can also produce and post their videos.). The increasingly blurred line between the roles of the user as a consumer and a producer, gave rise to a new brand of “prosumer”. While Anderson (2012) used the term “makers”, Ritzer (2012, 2015) argues that “makers” are better seen as “prosumers”. In that context, users are not simply recipients of finished digital products but are also integral part of the co-creation process (Rayna & Striukova, 2015). With the advent of DDM, taking the co-creation process further to include physical goods became feasible. Following the “prosumer” trend of Web 2.0, the popularity of online 3D printing platforms started to rise, where the user could sell or buy 3D models, 3D printed products or 3D printing services (Rayna et al., 2015). Examples of such platforms in the USA are Thingiverse, MAKEXYZ, White Clouds, 3Dagogo, 3DLT, Cubify Cloud, FastProtos, and KraftWurx. The growth of online 3D printing platforms was highly disruptive to the existing industrial model (based on economies-of-scale) because the “economies-of-one” became feasible (Petrick & Simpson, 2013; Rogers et al., 2016). With accessibility to 3D printing systems, the user could now participate at any stage of the “design-manufacture-distribute” model starting with the idea and finishing with a fully manufactured part that is eventually distributed (Kietzmann et al., 2015). Now design has moved beyond the expert domain to also include hobbyists and prosumers.

The level of user involvement in the manufacturing process was the key outcome of a qualitative study involving 22 online 3D printing platforms is shown in Figure 3 (Rayna et al., 2015). What this figure shows is that the online 3D platforms created an ecosystem in which the degree of user involvement/ participation in the “design-manufacture-distribute” varied based on interest. The degree of user involvement flows from the lowest degree of participation (user buys the design and it is printed and delivered by the Platform) to the highest degree (user co-designs the product on the platform and prints it at home for consumption or future distribution). The highest degree of involvement also offered the greatest opportunity for innovation (Rayna et al., 2015). Interestingly, Rayna et al. (2015) found that very few of these platforms offered a high degree of user participation thus the majority of the 3D printing platforms did not really leverage user innovation adequately. Users still needed more opportunities to co-design and 3D print at home. An analysis of 79 3D printer manufacturers startups found that startups which focused on delivering affordable commercial desktop 3D printers (for home use) had the highest investment levels and ranked high on their value proposition (Hahn et al., 2014). This result is consistent with the industrial trend to downsize manufacturing equipment toward desktop manufacturing (Lipson & Kurman, 2010; Devore et al., 2012). Manufacturers of desktop 3D printers are constantly improving their quality to blur the difference between industrial 3D printing systems and personal desktop 3D printing systems (Kleer & Piller,2019; Holzmann et al., 2020).

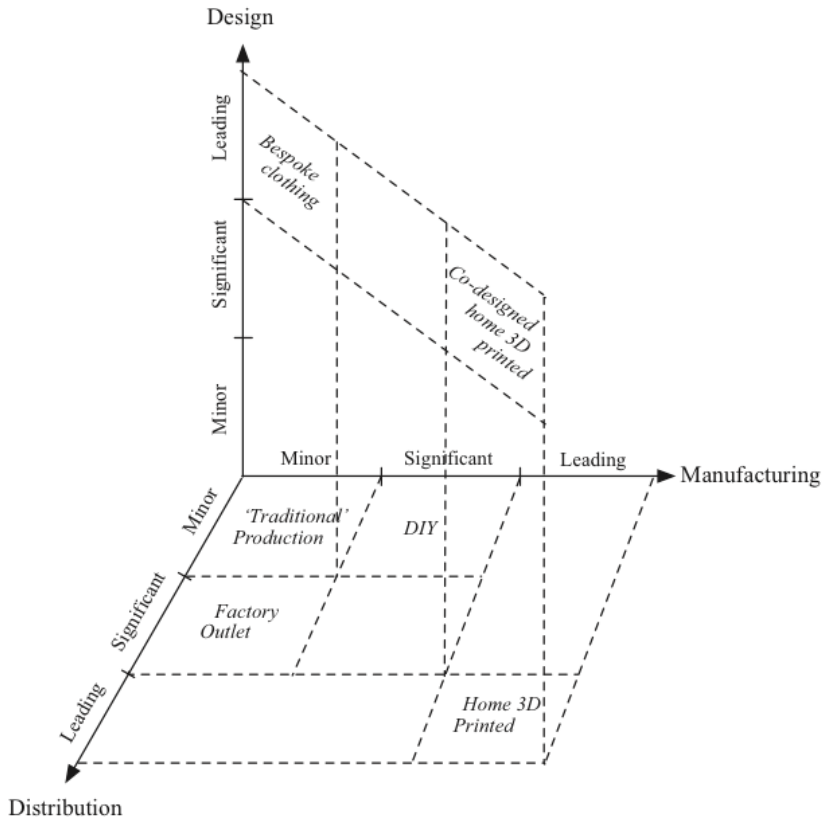

Figure 3. Level of user involvement in the manufacturing process (Rayna et al.,2015)

Based on their previous work on 3D printing platforms, Rayna and Striukova (2016) argue that DDM has paved the way to home fabrication. Given the economies-of-one, DDM enables user innovation to serve any niche market regardless of how small the market segment might be. The authors espouse that home fabrication will be an avenue to "monetize" the "long tail". Anderson (2006) proposes that it is possible to have a viable business model that is not based on the high-volume head (high volume, low variety) of a traditional demand curve but rather based on what can be regarded as misses on the "long tail" (high variety and low volume) of the curve. With DDM, entrepreneurs and inventors can break free from the reliance on large companies to manufacture their ideas (Anderson,2012). Based on this concept, Rayna and Striukova (2016) argued that the value capture is best when 3D printing is done at home rather than using an online 3D printing platform. The authors give examples in which the online 3D platform retained 30-50% of the revenue if users attempted to use those platforms for manufacturing and distribution. Along the same lines, Holzmann et al. (2017) argued that as the 3D printing ecosystem keeps evolving there will be more widespread entrepreneurial activities on the part of the user. The authors use the term “user entrepreneur” which was first proposed by Shah and Tripsas (2007). According to Shah and Tripsas (2007, p.24), user entrepreneurship is defined as the “commercialization of a new product and/or service by an individual or group of individuals who are also users of the product/or service”. The authors outlined the four key characteristics that promoted user entrepreneurship: combining enjoyment with financial benefits, low opportunity costs, markets with high niche demand and innovative products characterized by high level of demand uncertainty. Holzmann et al. (2017) argue that DDM provides user entrepreneurs the opportunity to apply manufacturing technologies with which they are familiar and with low investment costs given the declining costs of 3D printers. Furthermore, using the 3D printing technology, users can adapt quickly to high demand uncertainty. The argument of Holzmann et al. (2017) is not new but rather a confirmation of Schumpeter’s theory of entrepreneurship. Schumpeter (Frank, 1998) proposed that for entrepreneurs to implement their innovations, they must first be in command of the means of production. According to Schumpeter’s theory it is the creative response of entrepreneurs and entrepreneurship innovation that fuels the engines of economic growth (Frank, 1998). As an example, in their supporting arguments for direct digital manufacturing, Holzmann et al. (2017) cited the work of Fox (2013) which focused on DIY local inventions and production of physical goods for use or sale, such as self-assembled furniture, self-assembled boat kits, or self-assembled micro-electronics. On the topic of DIY local inventions, Fox (2013) argues that countries that have off-shored their manufacturing may have a new source of wealth creation via DIY local inventions, production and sale of physical goods. Building upon Fox's (2013) argument on DIY local inventions, Peterson et al. (2017) discuss the potential application of 3D home fabrication to the toy industry which they estimate to be worth billions of dollars and could be another source of wealth creation

Kleer and Piller (2019) argued that a large body of empirical research has shown that locally innovating lead users have become the originators of many consumer products. The authors substantiate these findings through the use of the User Innovation Theory (von Hippel, 1986) which proposes that users have a higher tendency to innovate when they have the ability to understand and apply technologies needed to turn their needs into a fitting situation on their own. This theory fits like a glove with the Schumpeter's theory of entrepreneurship. Kleer and Piller (2019), argued that 3D printing is an important element of a set of technologies (such as 3D scanning, cognitive computing, internet of things, augmented reality, big data, cloud computing, robotics) that has lowered the cost for users to innovate thus giving rise to the "low-cost innovative niches". The authors further elaborate that "low-cost innovative niches" are fields where the users have local information not available to the bigger centralized manufactures thus the users innovate more efficiently. Once again, the user innovation concept is linked to the "long tail" concept by Anderson (2006, 2012). Overall, Lipson and Kurman (2010), Weller et al. (2015), Piller et al. (2015), Borger et al. (2016), Rayna and Striukova (2016), Holzmann et al. (2017) and Hanibal and Knight (2018) argue that there is a viable business model for 3D home fabrication (3D printing at home) driven by the trend of localization in manufacturing and going after the "long tail". Eyers and Potter (2015) discuss the potential of consumer-to-consumer (C2C) e-commerce in the era of 3D printing.

A Delphi study by Jiang et al. (2017) on the projected economic and societal implications of 3D printing by 2030 showed that 3D printing is still a subject of controversial discussion. With 65 3D printing experts from academia and industry included in the study, it was found that academics believe that 3D home fabrication is the logical future while industrial experts believe that de-globalization of production (de-globalization of supply chains) is the future and 3D printing will be done at local industrial facilities. Nevertheless, both sides agree that the topic of 3D home fabrication needs further research. Grichnik et al. (2008) and Buckley and Strange (2015) elucidate that globalization is all about product cost and manufacturing efficiency regardless of place. However, this globalization concept has clearly been challenged by recent tariff wars and the Covid-19 pandemic. For example, Broune (2020) argued, in his article "How the Coronavirus is accelerating Deglobalization", that deglobalization was mainly driven by the unsettling realization that the entire supply chain system now has a single point of failure- China. Keintop (2020) argued that while the Covid-19 pandemic might have shed some more light on the ongoing deglobalization phenomenon, the deglobalization phenomenon had already started back as early as 2008. Part of Keintop's (2020) argument was based on the fact that labor costs no longer played a key role in manufactured products due to advances in robotics and other manufacturing technologies. He also argued that the miniaturization and localization of manufacturing allowed for the development of multiple supply chains and local customization of products sold around the world. Prior work by Strange and Zucchella (2017) showed that the impact of new digital technologies, such as the internet of things, big data and analytics, robotic systems and 3D printing is disruptive to the existing global value chains in such a way to affect the location and organization of activities withing the chain. Building upon that, Rehnberg and Ponte (2018) gave examples from the automotive and aerospace industries showing how 3D printing stimulated the shift toward the localization of production. These findings are consistent with the point of view espoused by Porter and Kramer (2011) on "Creating Shared Value". The authors argue that firms that focus mainly on outsourcing and off-shoring to be competitive have weakened their connection to local communities. As such the authors espoused that future gains in productivity and innovation will be based on how firms build supportive local industry "clusters" at the firm's location: That would be the new way of strategic thinking for competitiveness. Ben-Ner and Siemsen (2017) argue that 3D printing is the key to the development of local supply chains in the era of de-globalized production. Chaudhuri et al. (2019) studied the role of local 3D printing service providers on the adoption of 3D printing by firms and found that the local service providers played a key role in the future adoption by manufacturing firms. From the user perspective, Pauceanu and Dempere (2018) argued that users would use nearby "fablabs" (a fablab is a small workshop offering personal digital fabrication facilities for individuals and small businesses) or local service providers rather than buy private 3D printers. The authors noted that the number of fablabs are increasing (they estimate that there were 1,300 fablabs worldwide in 2018). Rayna and Striukova (2016) and Kleer and Piller (2019) emphasize that the role of these fablabs or local service providers is a transition phase in moving from centralized manufacturing by firms to customer home fabrication.

Per the study of Hahn et al. (2014), a key focus of investment in startups of 3D printer manufacturers is to make consumer 3D printing affordable and easy to use for everyone. While Hudson et al. (2016) and Wade et al. (2017) argue that a key hurdle for the adoption of 3D desktop printers is the 3D modeling required, the modeling and scanning technologies have progressed at a fast pace due to the level of investment in startups operating in that space. For example, 3D scanning apps can be used to generate models of an existing object from images obtained by a smartphone or tablet (Ayshu, 2020). 3D modelling can also be done using free on-line software such as TinkerCad (www.tinkercad.com). In an experimental study, Kamel et al. (2018) found that new users were able to learn how to use a modelling software in less than one hour and were subsequently able to produce 3D models of their designs. Formlab (www.Formlab.com) offers a free software to review 3D models for any errors before printing. CloudF3D offers a service to users to start an online retail business based on 3D printed products or a 3D printing service. ETSY is an example of an online marketplace that facilitates for users the sale of their 3D printed products. Another example is the DIY 3D printer kits sold on Amazon.com. These DIY kits address a wide range of needs from beginners to experts (Smith, 2019) making the use of 3D printers cheaper and more popular. The first commercial 3D desktop printers were introduced in 2009 and by 2015 about 278,000 units (all costing less than $5000) were sold worldwide (Flynt, 2019). With the introduction of metallic materials for 3D printing, the number of printers sold jumped to 528,000 units by 2018 (Flynt, 2019). By 2018, desktop 3D printers were considered to have improved substantially over initial models, to become more user friendly, more reliable, easier to use and producing higher quality parts (Winnan,2018). Sjostedt and Miller (2016) studied consumer 3D printing in the setting of a peer-to-peer platform (3D Hubs) where individuals can sell access to their personal 3D printers. The authors found that the industry trend of easier to use desktop 3D printers had a negative effect on the benefit of offering 3D printing as a service through 3D Hubs. That is, more individuals would prefer to get their own 3D printers rather than to use the services of 3D Hubs.

According to Poltorak &Lenner (2011), an innovation is an “idea” that has been commercialized. As de Jong and de Bruijn (2013) point out, it is possible that the increasing rate of user innovations (enabled by 3D printing technology) will address the needs of users that have not been served or not served adequately by the existing industry thus displacing many future innovations by these industries at least in the foreseeable future. That observation by the authors provides a link to economic growth based on "ideas". Indeed, Jones and Romer (2009) propose an economic growth model in which "ideas" is a key tenet. The authors postulate that in the long run, the increase in productivity of any country will be determined by the stream of "ideas" generated. The interaction between people to realize production will be of key importance to keep the country on a path of economic growth. As Rayna et al. (2015) propose (see Figure 3), the sweet spot for innovation in the design-manufacture-distribute model is Co-design/3D printing at home. In essence the 3D printing ecosystem provides the opportunity for people to jointly come up with ideas and quickly transform these ideas into a viable product. A study by Woodson et al. (2019) shows that 3D printing has the potential to be an inclusive innovation enabler. Marginalized communities will eventually be able to afford home 3D printers and participate in the 3D printing ecosystem. Thus, there is the potential that all communities across a country can contribute to the innovation cycle. In summary, the 3D printing ecosystem (particularly co-design/ 3D print at home) is an enabler of user innovation (Rayna et al.,2015) which leads to more ideas for economic growth (Jones-Romer Model) which in turn drive the potential for user entrepreneurship (Frank, 1998; Shah, S.K. & Tripsas,M. (2007)). As Anderson (2012, p.15) states "a generation of 'makers' using the Web's innovation model will help drive the next big wave in the global economy as the new digital design and rapid prototyping gives everyone the power to invent- creating the "long tail of things".

Despite the declining cost of desktop 3D printers, the improvement of user friendliness and the improvement in technological capabilities, the consumer adoption rate of 3D printers is still low (Steenhius & Pretorius, 2016). The global 3D printing market is projected to be worth US$35.4 billion by 2027 with firms still buying the largest share of 3D printers (Businesswire, 2020) During the same period, the desktop 3D printer market size is expected to increase to a worth of US$5.13 billion which is fueled by growing demand for personalized and customized products (Global Newswire, 2020). The emergence of a new field of research focused on the adoption of desktop 3D printers for home fabrication began in 2016. As the field is still in its infancy there is a limited number of publications available in the extant literature. To date, one study came from China (Wang et al., 2016) and 3 studies from Europe (Hartmann &Vanpoucke, 2017; Halassi et al., 2018; Lotjonen, 2019). Based on the current literature, no such studies have been done in the USA which is a key motive for this proposed study. As previously discussed in Chapter 1, the research objectives of this study contribute at the theoretical, practical and academic perspectives. From a practical perspective, the results of this study will contribute to the techno-marketing strategies of 3D printer manufactures in the US market. From the theoretical and academic perspectives, this study contributes to the emerging third stream of research (as discussed in chapter 1) that focuses on integrating technology acceptance theories and the technology readiness concept. The next section will introduce the current state of research in individual technology acceptance in general.

Fundamentals of the Unified Theory of Acceptance and Use of Technology

With the advent of the digital revolution, organizations invested substantial resources in information technology (IT) and computer technology to automate industrial processes (Hayes et al., 2005; Crandall, 2017). These investments were aimed at increasing individual productivity and hence overall organizational productivity (Hayes et al., 2005). With time it became clear that for a new technology to improve productivity, the technology had to be accepted and used by employees in the organization. System failures were not the result of poor technology performance but rather the result of poor user acceptance (Davis, 1993).

Over the last three decades, a great amount of research went into the understanding of individual acceptance and use of technology (Venkatesh et al., 2007; Williams et al., 2013). Most of the technology acceptance theoretical perspectives used or further developed by research were founded in Psychology, Organizational behavior or Sociology research. With a multitude of theoretical models available in the literature, researchers were confronted with the fact that they must select constructs across models or work with their favorite model. In doing so, there was always the risk of losing important constructs which are relevant to the research at hand but absent in the "favorite" model. Thus, there was a need to integrate the apparently fragmented theories of technology acceptance into a unified theoretical model that would capture key constructs. With that objective, Venkatesh et al. (2003) developed the Unified theory of Acceptance and Use of Technology (UTAUT). UTAUT is based on conceptual and empirical similarities across eight prominent previous models used in information technology acceptance research. The eight models were: the technology of reasoned action (TRA); the technology acceptance model (TAM), the motivational model (MM), the theory of planned behavior (TPB), the combined model of TAM and TPB (c-TAM-TPB), the model of PC utilization (MPCU), the diffusion of innovation theory (DOI), and the social cognitive theory (SCT). Each of these models is briefly explained in Appendix A with the respective literature references.

These theoretical models employ "behavioral intention" and/or "usage behavior" of information technology as their key dependent variable(s). The role of "behavioral intentions" as a predictor of "usage behavior" is of key importance and has been well established in the literature (Sheppard et al., 1988; Ajzen, 1991; Taylor & Todd, 1995b). Out of 32 constructs and four moderators, Ventkatesh et al. (2003) formulated the UTAUT model with three direct determinants of behavioral intention and, two direct determinants of usage behavior and four moderators of key relationships as shown in Figure 4. The definitions of the direct determinants in the UTAUT model are given in Table 1. This table also defines the direct determinants of the UTAUT2 model which will be discussed in subsequent paragraphs. In the UTAUT and UTAUT2 model the definition of behavioral intention (BI) is the same. Behavioral intention is a measure of the individual's propensity to use a given technology (Venkatesh et al., 2003)

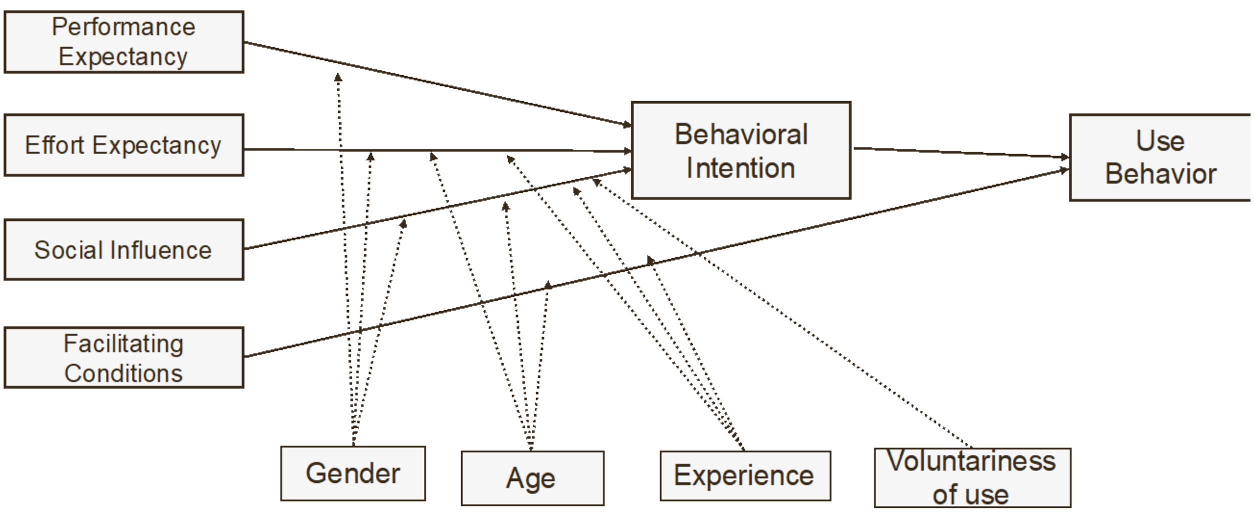

Figure 4. UTAUT Model (Venkatesh et al.,2003)

Table 1

Definition of UTAUT and UTAUT2 Constructs

Construct	Definition
Performance Expectancy (PE) UTAUT and UTAUT2 models	Refers to the degree an individual believes using the technology will provide gains in job performance.. The constructs from the different models contributing to this construct are: ***perceived usefulness*** (TAM & c-TAM-TPB), ***extrinsic motivation*** (MM), ***job-fit*** (MPCU), ***relative advantage*** (IDT) and ***outcome expectations*** (SCT)
Effort Expectancy (EE) UTAUT and UTAUT2 models	Refers to the degree of ease of use of the technology. The constructs from the different models contributing to this construct are: ***perceived ease of use*** (TAM), ***complexity*** (MPCU), ***ease of use*** (IDT)
Social Influence (SI) UTAUT and UTAUT2 models	Refers to the extent to which a consumer behavior is influenced by how other people (social environment, friends, family) will view them as a result of their use of the new technology. The constructs from the different models contributing to this construct are: ***subjective norm*** (TRA,TAM,c-TAM-TPB), ***social factors*** (MPCU), ***image*** (IDT)
Facilitating conditions (FC) UTAUT and UTAUT2 models	Refers to consumer's perceptions of the resources and support available to perform some behavior. The constructs from the different models contributing to this construct are: ***perceived behavioral control*** (TPB, c-TAM-TPB), ***facilitating conditions*** (MPCU), and ***compatibility*** (IDT)
Hedonic motivation (HM) UTAUT2 model	Refers to the fun or pleasure derived from using a technology. Innovativeness and Novelty seeking add to the derived fun or pleasure. This construct was first used in MATH model (Brown & Venkatesh, 2005).
Price value (PV) UTAUT2 model	From marketing research, the trade-off between the perceived price and perceived quality of the product determines the perceived value. The perceived value has powerful influence on the purchase intention (Zeithaml,1988)
Habbit (HT) UTAUT2 model	Refers to the extent to which people tend to perform behaviors automatically because of learning (Limayem et al,2007)
Adopted from Venkatesh et al (2003, 2012)	

Using a longitudinal study, which covered a six-month period with 3 distinct temporal points of measurement, data from four organizations (which were introducing a new technology) were analyzed using the eight models. The three temporal points of measurement were used to capture user perception after 1 week, 1 month and 3 months of the training on the new IT systems. Similarly, usage behavior was measured 1 month, 3 months and 6 months after training on the new IT systems. The analysis showed that the eight models could account for 36%-53% in the behavioral intention variance and 35%-39% in use behavior variance. Using the same data set, the UTAUT model could account for 69% (with moderation) in the behavioral intention variance and 47 % in the use behavior variance. In the same study, the UTUAT model was further tested on two additional organizations and the analysis showed that the UTAUT model could account for 70% (with moderation) in the behavioral intention variance and 48% for usage behavior. A summary of the UTAUT findings is given in Table 2.

Table 2

Summary of Results : Application of UTAUT in Organizational Setting

Independent Variable	Dependent Variable	Moderators	Findings
Performance Expectancy (PE)	Behavioral Intention (BI)	Gender, Age	The effect of PE on BI was moderated by gender and age such that it was stronger for men and particularly young men.
Effort Expectancy (EE)	Behavioral Intention (BI)	Gender, Age, Experience	The effect of EE on BI was moderated by gender, age and experience such that it was stronger for women, particularly older women at the early stages of experience with a technology
Social Influence (SI)	Behavioral Intention (BI)	Gender, Age, Voluntariness, Experience	The effect of SI on BI was moderated by Gender, Age, Voluntariness and experience such that it was stronger for women particularly older women in mandatory settings in the early stages of experience with a technology.
Facilitating conditions (FC)	Behavioral Intention (BI)	None	Nonsignificant effect of FC on BI was found as hypothesized. However there was a significant effect on use behavior, with the effect being stronger for older workers with increased experience.

Adopted from Venkatesh et al (2003). User Acceptance of Information Technology: Toward a Unified Theory, MIS Quarterly, 27 (3), 425-478.

The findings of the study provided a refined view of how the predictors of behavioral intention and usage behavior are dynamic in nature. As Venkatesh et al. (2003) emphasized, this time evolution is the key to having a complete picture of an individual's perception of a new technology. The dynamic nature of the predictors can only be captured when the complex range of potential moderating variables are considered. Furthermore, Venkatesh et al. (2003) posited that the interplay of these key demographic variable adds richness to the understanding of the technology adoption context. The results of the UTAUT model encompassed a lot of the previous results scattered in the literature: Davis et al. (1989), Levy (1988), Morris and Venkatesh (2000), Plude and Hoyer (1985), Venkatesh et al.(2000), Venkatesh and Morris (2000), Sun and Zhang (2006) proposed expanding the moderator variables from four to ten variables which can be categorized into three groups: Organizational factors (voluntariness/mandatory, routine/non-routine tasks), technology factors (simple/ complex, work-oriented/entertainment-oriented, individual/group technology) and individual factors (gender, age, absorptive capacity, experience, and cultural background). Venkatesh et al. (2016) built upon Suns and Zhang's (2006) work and proposed to add extra variables that could possibly be antecedents that directly impact the key UTAUT constructs (PE, EE, SI, FC) or variables that could be direct predictors of behavioral intention.

Taiwo and Downe (2013) focused on 37 studies, involving the adoption of information systems, to conduct a meta-analytic review of empirical findings using the UTAUT model. Their conclusion is that only the effect of performance expectancy (PE) on behavioral intention (BI) had strong significance and the effects of effort expectancy (EE), social influence (SI), and facilitating conditions (FC) were weak. In a follow up meta-analysis of the UTAUT model, Khechine et al. (2016) pointed out that Taiwo and Downe (2013) only considered studies that only had direct effects without moderation and only considering 37 studies was limited. Using a larger sample size of 74 studies involving the adoption of information systems, the authors validated the UTAUT model and confirmed the PE, EE, SI and FC are the main predictors of BI (intention to use). In a literature review of 174 articles on the UTAUT model, Williams et al. (2015) showed that UTAUT research was developing quickly with no clear areas of maturity. The use of the UTAUT model had extended to other new technologies (e.g. collaborative technologies and health information systems), new user populations (e.g. health care professionals) and new cultural settings (e.g. China and India). The majority of the authors worked in business schools or information management departments. The most popular source of primary data was the US followed by China, Taiwan and Malaysia. The majority of the studies used a cross-sectional approach and employed a survey methodology for data collection. The commonly employed survey instruments were questionnaire survey (e.g. telephone survey online or web-based survey). Most of the data analysis involved covariant-based structural equation modeling (CB-SEM) or partial least square structural equation modeling (PLS-SEM). A total of 102 out of 174 studies were quantitative in nature and very few studies used the original UTAUT model in its entirety.

After the successful application of the UTUAT model in several organizational settings, Venkatesh (2006) and Venkatesh et al. (2007) spent some effort to propose a trajectory for the future development of the UTAUT model. With the increased use of self-service technologies, the trajectory led to extending the use of the UTAUT model to a consumer context leading to the UTAUT2 model shown in Figure. 5 (Venkatesh et al., 2012).

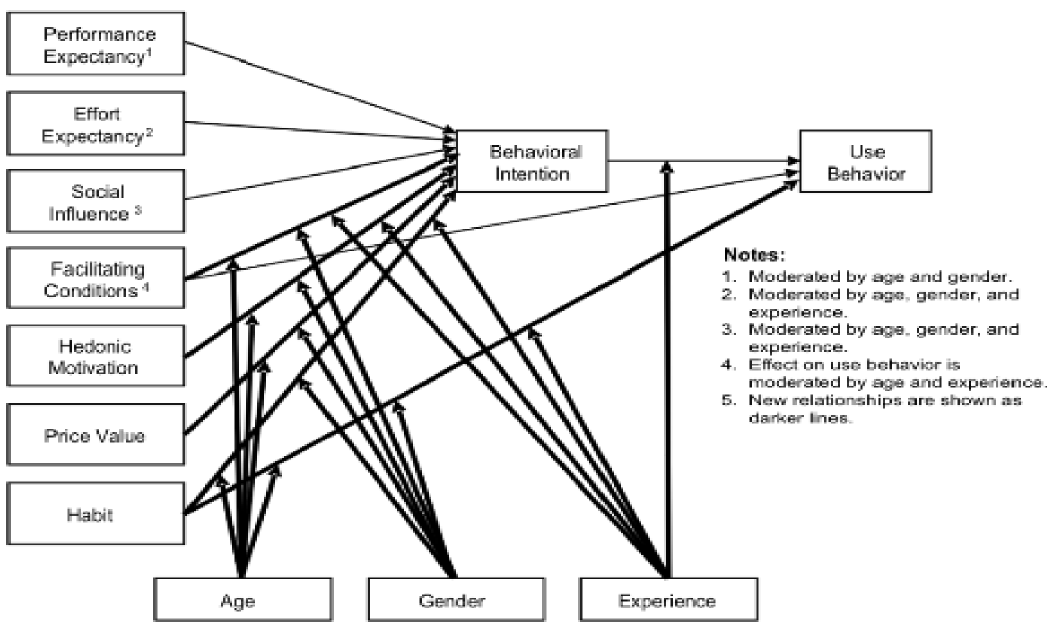

Figure 5. UTAUT2 model (Venkatesh et al.,2012)

In this model, voluntariness was dropped as a moderator, FC was assumed to be a predictor of BI and usage behavior, and three new predictors of BI were added. The definitions of new constructs are given in Table 1 along with the definition of the constructs in the UTAUT model. A longitudinal study was conducted on consumers using mobile internet technology to validate the UTAUT2 model. The UTAUT2 model was able to account for 74% (with moderation) of variation in BI and 52% (with moderation) of variation in usage behavior. Using the same data set, the original UTAUT model could only account for 56% (with moderation) of variation in BI and 40% (with moderation) of variation in usage behavior. Without moderation, there were significant direct effects for PE, EE, SI, HM, HT, and FC on consumer BI. Similar to the UTAUT model, higher-order interaction terms due to moderation have a significant effect on the relationships as shown in the previous results in Table 2. The results for the new constructs in the UTAUT2 model are given in Table 3. Overall, individual differences (age, gender, experience) have been empirically shown to moderate the direct effect on the BI and Usage behavior constructs. The findings once again validate the dynamic nature of the technology adoption context. Within the consumer technology adoption context, hedonic motivation has been found to be a more critical determinant of BI than PE in the early stages of the technology(Venkatesh et al., 2012). This is in line with the previous work of Brown and Venkatesh (2005). As explained by Brown and Venkatesh (2005), hedonic motivation encompasses elements of innovativeness and novelty seeking. As experience increases with the technology, the novelty seeking diminishes and consumers will end up using the technology for purposes of gains in efficiency or effectiveness (i.e. performance expectancy (PE) becomes dominant). The authors also point out that hedonic motivation play an important role in younger men's technology adoption and use.

Table 3

Summary of Results : Application of UTAUT2 in a Consumer Setting

Independent Variable	Dependent Variable	Moderators	Findings
Hedonic Motivation (HM)	Behavioral Intention (BI)	Gender, Age, Experience	Without moderation, HM had a significant effect on BI. Age, Gender and Experience moderated the effect of HM on BI such that the effect was stronger for younger men in the early stages of experience with a technology (HM X Gender X Age X Experience)
Price Value (PV)	Behavioral Intention (BI)	Gender, Age	Without moderation, PV had a significant effect on BI. Age and gender moderated the effect of PV on BI such that the effect was stronger among women particularly older women (PV X Gender x AGE)
Habit (HT)	Behavioral Intention (BI)	Gender, Age, Experience	Without moderation, HT had a significant effect on BI. Age, Gender and Experience moderated the effect of HT on BI such that the effect was stronger for older men with high levels of experience with the technology. (HT X Gender X Age X Experience)
Facilitating conditions (FC)	Behavioral Intention (BI)	Gender, Age, Experience	Without moderation, FC had a significant effect on BI. Age and Gender moderated the influence of FC on BI such that it was stronger for older women (FC X Gender X AGE). Experience had no moderating effect.

Adopted from Venkatesh et al (2012). Consumer Acceptance And Use of Information Technology: Extending The Unified Theory of Acceptance and Use of Technology, MIS Quarterly, 36 (1), 157-181.

Since the UTAUT2 model was developed it has been used in many consumer technology acceptance studies (Venkatesh et al., 2016; Blut et al., 2016)). It has also been used in the user acceptance of 3D printing technology (Hartmann & Vanpoucke, 2017; Halassi et al., 2018; Lotjonen, 2019). The UTAUT2 model will also be used in the present study but with a new moderating variable – the technology readiness index, discussed below. The next section will discuss the stream of research which deals with consumer technology acceptance: the one that deals with the consumer technology readiness.

Technology Readiness Concept

The work of Kraus (1995) shed light on the significant role of attitude toward a technology in guiding, influencing, directing, shaping or predicting the adoption and use of technology. Kraus' (1995) research made it clear that there was a need for more research in understanding attitudes toward technology in general rather than attitudes toward specific technologies. Based on an extensive qualitative research on peoples' reaction to technology, Mick and Fournier (1998) identified eight technology triggers which shape the attitude of individuals: Control/Chaos, Freedom / Enslavement, New / Obsolete, Competence /

Incompetence, Efficiency / Inefficiency, Fulfills / Create needs, Assimilation / Isolation and Engaging / Disengaging. The findings suggest that these triggers may act simultaneously thus creating positive and negative feeling that coexist within an individual. The relative dominance of positive or negative feelings is likely to vary across individuals. As such, each individual can be located on a technology attitude continuum ranging from "resistant" (strongly dominant negative feelings) to "receptive" (strongly dominant positive feelings). Based on this seminal qualitive research, Parasuraman (2000) developed a psychographic construct that can be quantitatively measured for techno-marketing purposes. Psychographics is the "study and classification of people according to the attitudes, aspirations and other psychological criteria" as defined in marketing research (Birkett, 2020).

Parasuraman (2000) introduced the Technology Readiness (TR) construct to measure an individual's propensity to embrace and use new technologies at home and at work to accomplish defined goals. The author emphasized that the construct taps into the individual's "overall state of mind" resulting from a "gestalt" of mental "enablers" and "inhibitors" that collectively determine the individual's attitude to use new technology. Here it must be emphasized that it is the "attitude" in general toward technology and not a specific technology that is being evaluated (as originally intended in the work of Kraus (1995)). The general definition of "attitude" is: "a settled way of thinking or feeling about someone or something that is reflected in a person's behavior" (Kraus, 1995). Parasuraman (2000) espoused that TR is an individual-level characteristic that is stable over a period of time and not subject to sudden fluctuations in response to a stimulus. He defined TR as a higher-order construct that is composed of four lower-order constructs (also referred to as four dimensions) as shown in Figure 6. The definitions of the four dimensions are given in Table 4. Using these construct definitions, Parasuraman (2000) developed and validated a technology readiness scale (also referred to as technology readiness index) based on a study of 1200 individuals (college and Young professionals) in the USA. The results of the study showed that high levels of TR were correlated with high adoption rates of technology-based services.

Colby (2002) argued that the TR concept and scale is valid for both the business and consumer context. He elaborates that understanding an employee's attitude toward "cutting-edge" technology is as critical as understanding a consumer's attitude. In this case the context of "cutting-edge" was self-service technologies and in particular e-service. As TR is an individual trait, Colby (2002) argued that it is expected to vary like other traits in the population and it is expected to be normally distributed. Based on that argument, Colby (2002) proposed to divide individuals into segments as shown in Table 5. These segments would be the market segments

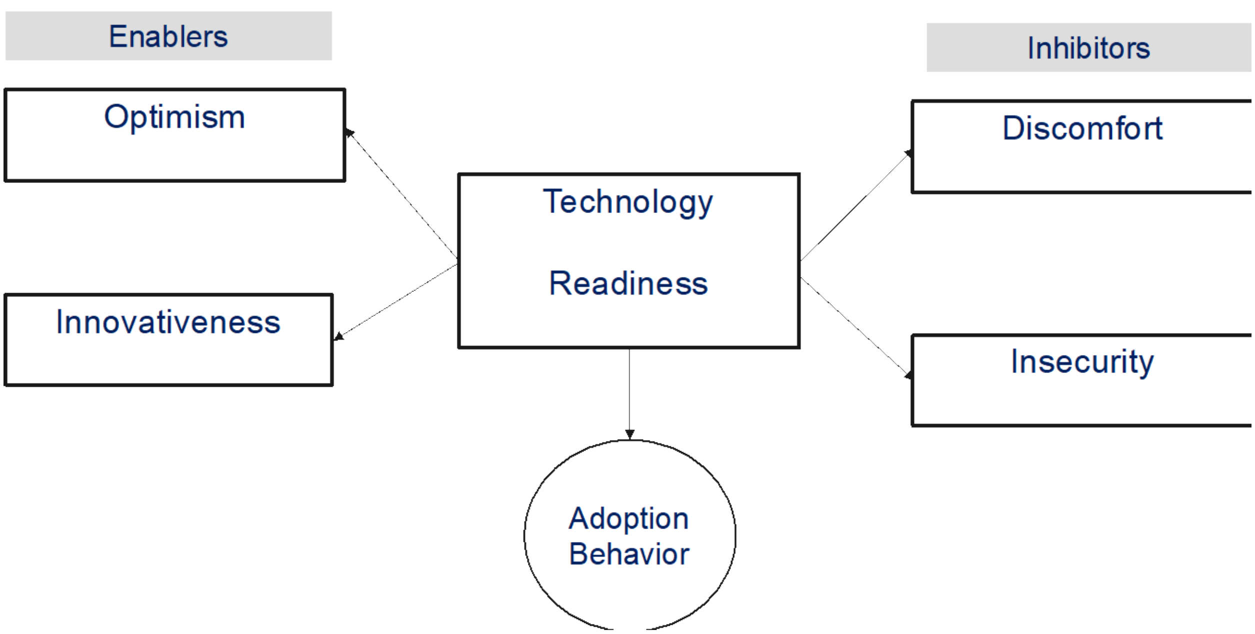

Figure 6. Dimensions of Technology Readiness (Parasuraman,2000)

Table 4

Four Dimension of Technology Readiness

Dimension	Definition
Optimism	"A positive view of technology and a belief it offers people increased control, flexibility and efficiency in their lives" . It is an overall dimension that captures the feeling that in general " technology is a good thing"
Innovativeness	" A tendency to be a technology pioneer and thought leader". It is a general measure of the extent an individual thinks he/she is at the forefront of trying new technology and can be considered by others as an opinion leader
Discomfort	" A perceived lack of control over technology and a feeling of being overwhelmed by it" It is a general measure of the extent an individual has paranoia about technology with the belief that technology is "exclusionary" rather than "inclusive of people.
Insecurity	" distrust of technology and skepticism about its ability to work properly and potential harmful consequences" .

Adopted from Parasuraman (2000)

that are of importance from the techno-marketing point of view. It is important to emphasize that this segmentation is based on the premise that the four dimensions (optimism, innovativeness, discomfort, insecurity) are relatively independent and therefore an individual could harbor both "enablers" and "inhibitors" feelings toward technology in general. Using the Parasuraman's (2000) dataset, Colby (2002) was able to verify the existence of these segments in

Table 5

Four dimensions defining Market Segments

Segments	Optimism	Innovativeness	Discomfort	Insecurity
Explorers	High	High	Low	Low
Pioneers	High	High	High	High
Skeptics	Low	Low	Low	Low
Paranoids	High	Low	High	High
Laggards	Low	Low	High	High

Adopted from Colby (2002).

the US market. Explorers are the group of consumers that have a low degree of resistance and a high degree of motivation to use a "cutting-edge" technology. They are the highest techno-ready group and are the first to adopt a new technology. Pioneers hold both positive and negative feelings about technology. They desire the benefits of new technology but are more practical about difficulties of new technologies. They tend to need help in adopting new technologies as they must overcome their inherent negative feelings. This set of consumers are the second most techno-ready group. Skeptics do not involve technology much in their lives thus they have a detached view of technology with no strong or negative feelings. They need to be convinced of the benefits of a new technology before making a decision to adopt. Paranoids are below average in technology readiness and are highly concerned with risk. They are held back by their low innovativeness and high level of "inhibitors". Laggards are the last group to adopt "cutting edge" technology. They have a high level of "inhibitors" thus a high level of resistance to use new technologies. Tsikriktsis (2004) attempted to replicate Colby's (2000) work in the UK. He was only able to detect 4 segments: The "Paranoid" segment was not detected.

The idea of segmenting the population is not new. In Rogers's work on diffusion of innovation (Valente & Rogers,1995), Rogers also segmented the population in to five segments based on a normal distribution: innovators (2.5%). Early adopters (13.5%), early majority (34%), late majority (34%) and laggards (16%). Based on a study in the USA, Parasuraman and Colby (2015) demonstrated that "explorers" are equivalent to" early adopters" and "laggards" are equivalent in both definitions. Pioneers, Skeptics and Paranoids fell between "early majority" and "late majority".

In addition to being an individual trait, Westjohn et al. (2009) argued that TR is a "situational" trait that represents attitude and is culturally influenced, based on the previous work of Srite and Karhanna (2006). Srite and Karhanna (2006) argued that "espoused national cultural values" are an important set of individual characteristics that moderate technology acceptance.

These “espoused national cultural values” are categorized in the four dimensions defined by Hofstede (1983): masculinity / femininity, individualism / collectivism, power distance and uncertainty avoidance. The authors clearly pointed out that these “espoused cultural values” cannot predict any single individual’s behavior as the effect of these values is not uniform across all individuals in a specific culture. However, these values have a strong moderating role. The argument set forth by Westjohn et al. (2009) is that the variation of technology readiness in the population inherently includes the cultural value variation thereby leading the authors to suggest the idea of treating TR as a “situational” trait. Meng et al. (2010) assessed the cross-cultural validity of the Technology Readiness Index developed by Parasuraman (2000) in a comparative study between the US and China. The results showed that in general the American consumer was more ready and willing to adopt new technologies compared to the Chinese consumer. While the US and Chinese cultures are relative similar in the dimensions of uncertainty avoidance dimension and the masculinity / femininity, they differed in the dimensions of individualism/collectivism and power distance. Their analysis showed that the differences had a discernable influence on the “enablers” and “inhibitors”. The individualism and low power distance dimensions in the US resulted in higher “enablers” compared to China. In another cross-cultural study comparing the US and Chile, Rojas-Mendes et al. (2017) showed the impact of the dimensions of individualism / collectivism and uncertainty avoidance on technology readiness. Developing countries such as Chile score high on the uncertainty avoidance dimensions leading to higher levels of “inhibitors” for technology adoption. This work of Rojas-Mendez et al. (2017) showed that it is important to consider both demographics and TR. (a Psychographic construct) in studying technology adoption and use. The key conclusions of this research are shown in Table 6.

Table 6

Summary of Demographics, attitudes and technology readiness

Construct / Variable	Conclusions
Gender	1- Males are more technology ready than females 2- Males score higher than females on innovativeness and lower on discomfort and insecurity
Age	1- Younger individuals are expected to be more technology ready than their older counterparts 2- Younger individuals are expected to to score higher on optimism and innovativeness and lower on discomfort and insecurity
Education	1- More educated individuals are expected to be more technology ready than less educated individuals 2- Educated individuals score higher on optimism and innovativeness and lower on discomfort and insecurity
Education	Education is positively related to contributors and negatively related to inhibitors
Country	1- Individuals in developed countries are expected to be more technology ready than counterparts in developing countries 2- individuals in developed countries are expected to show higher adoption of specifics technologies when compared to counter parts in developing countries 3- Above a certain income level, culture becomes more dominant than income in contributing to Technology readiness for both developed and developing countries.
Technology	1- No difference was observed for technologies used at work versus at home 2- Contributors have stronger effects on the intention and use behaviors of hedonic technologies 3- Inhibitors have stronger effects on the intention and use behaviors of utilitarian technologies.
Demographic variables versus TRI	1- For developing countries, demographic variables have a stronger impact on technology adoption than TRI. 2- Among demographic variables, Education has the strongest contribution to technology adoption for developing countries.

Adopted from Rojas-Mendez, J.I., Parasuraman, A. & Papadopoulous, N. (2017). Demographics, attitudes and technology readiness : A cross-cultural analysis and model validation. Marketing intelligence & planning, 36 (1), 18-39.

In general the authors argue that as a country develops and demographic differences are normalized in the society (i.e. gender equality, more higher education graduates, etc.), TR will be a stronger predictor of technology adoption. In countries that are far from this normalized condition, demographics will be the key predictor of technology adoption and use. The authors further comment that while the US is a developed country, the demographics differences are not fully normalized thus it is important to consider both demographics and TR effects in the analysis. This comment is consistent with the previous UTAUT model analysis that showed the importance of the moderating role of Gender and Age. The work of Parasuraman and Colby (2015), which was focused in the US, showed that the segment with the highest TR score (i.e explorers) tend to be younger, higher educated, owned the largest number to technology gadgets and more likely worked in a technology profession. Interestingly, this segment also had a high degree of ethnic diversity. The pioneer segment turned out to be the most ethnically diverse. The laggard segment were the mirror opposite of the explorer segment. To support their work, the authors cited the work of Colby and Albert (2003), which studied TR variation across ethnic groups (i.e. Whites, African Americans and Latinos) within the USA. That research found a higher portion of pioneers among African Americans than Whites. Latinos had the highest percentage of skeptics compared to Whites and African Americans.

The conclusion of the meta-analysis done by Blut and Wang (2020) are shown in Table 7. A key takeaway from this meta-analysis is that TR can best be used with other technology acceptance models (e.g. TAM) when used as a moderator or considered as an antecedent to the other key constructs. The authors point out that TR, conceptually, can be considered as an antecedent to self-efficacy, risk, and attitude because it is a technology related individual trait while the other constructs are specific beliefs toward a specific technology. Another key takeaway is when considering how to best include the TR construct in existing models (four dimensions, two dimensions – enablers /Inhibitors, or one dimensional – overall composite), many studies have shown that the two-dimension approach is the most parsimonious

Table 7

Summary of Meta-analysis Results

Construct / Variable	Conclusions
Enablers	1- Enablers have a direct positive relation to usage intention 2-Enablers have an indirect positive relation to actual usage behavior
Inhibitors	1- Inhibitors have a direct negative relation to usage intention 2- Inhibitors have an indirect negative relation to actual usage behavior
Age	Age is negatively related to contributors and positively related to inhibitors (i.e as age increases , the inhibitors increase and the contributors decrease)
Education	Education is positively related to enablers and negatively related to inhibitors
Customer Experience	Customer technology related experiences is positively related to enablers and negatively related to inhibitors.
Technology	1- No difference was observed for technologies used at work versus at home 2- enablers have stronger effects on the intention and use behaviors of hedonic technologies 3- Inhibitors have stronger effects on the intention and use behaviors of utilitarian technologies.
Country	1- Enablers have stronger effect on technology intention and use behavior in high GDP countries 2- Inhibitors have stronger effect on technology intention and use behavior in low GDP countries. 3- Enablers have a weaker effect on technology intention and use behavior in low-HDI countries (emerging countries) 4- Inhibitors have a stronger effect in technology intention and use behavior in high- HDI countries (developed countries)

Adopted from Blut,M., &Wang, C. (2020). Technology readiness: a meta-analysis of conceptualizations of the construct and its impact on technology usage. Journal of the Academy of Marketing Science, 48, 649-669.

as demonstrated in the TRAM models. The results of the two-dimensional approach still gave a comprehensive way to measure TR. As the authors point out, most of the technology adoptions studies using the available technology acceptance models in the literature have focused on one perspective at a time: consumer attitude, demographics or culture. Thus, when TR is included with demographics in a technology acceptance model, a more holistic view is obtained as consumer attitude and culture are inherent in the TR concept. Following the trend toward more holistic modeling, the model proposed in this research will add TR as a moderator in the UTAUT2 model along with the existing demographic variables (Age, Gender). The use of TR as a moderator is based on the recommendations of Parasuraman and Colby (2015) and the conclusions of the meta-analysis by Blut and Wang (2020). The next section will shed light on the existing models in the literature dealing with the user acceptance of 3D printing in a home setting. That will be a gateway to proposed research model in this study

User acceptance of Desktop 3D printing for Home Fabrication

User acceptance of 3D printing for home fabrication is an emerging field of study with scant literature on the topic at the time of this writing. To date there are three key models that have been discussed in the literature. The first model published in this field was based on integrating TAM and DOI and adding the DIY construct as a moderator (Wang et al., 2016). That study was done in China and examined the behavior of Chinese consumers. The second published model was based on adding DIY as a moderator (in addition to the demographic moderators of Age and Gender) and also a predictor of BI in the UTAUT2 model (Hartmann and Vanpoucke, 2017). That study was done in Germany and studied the behavior of German consumers. The third model published was based on using DIY as a predictor only of BI in the UTAUT2 model, controlling for all demographic variables. (Halassi et al., 2018). That study was done in the Netherlands and examined the behavior of Dutch consumers. The second and third models are the most relevant for this proposed study as they utilize the UTAUT2 model. While both studies examined populations in Europe, further analysis of their results in this section will show the inherent effect of culture on the key predictors of the behavioral intention to use 3D printing for home fabrication.

In Europe, part-time work has been on the rise. In 2019, almost 27% of employees in Germany were working part-time while in the Netherlands 47% employees were working part-time (Michaels, 2019). Hartmann and Vanpoucke (2017) noted, based on a review of the literature, that there are many signs that 3D printing will be used in households in the near future creating opportunities for future business models. However, they also noted that knowledge about home Users adoption of 3D printing is limited and perhaps the field is understudied. Against this backdrop and a with a desire to respond to Venkatesh et al. (2012) call to use the UTAUT2 model in new applications, Hartmann and Vanpucke (2017) proposed the modified model shown in Figure 7 to study the User acceptance of 3D printing for home fabrication in the German market. The authors considered 3D printing for home fabrication to be in its infancy and dropped the Habit construct as they assumed there was no prior experience with 3D printing at home to form a Habit. Instead of Habit, the authors added the DIY construct as an independent variable. DIY was both a predictor of BI and a moderator variable for some of the other constructs (see Figure 7). The authors referred to the work of Wolf and Mcquitty (2011;2013) to justify that 3D printing will fulfill the needs of the DIY individual: sense of empowerment, a craftsman identity, a need for uniqueness and the feeling of being part of a community. It offers the individual the “make or buy” decision. Self-servicing has been described as a DIY behavior (Dabholkar, 1996), however Wolf & Mcquitty (2013) argues that DIY can be differentiated from self-servicing by the greater involvement associated with DIY behavior: DIY behavior typically requires more labor and expertise from individuals.

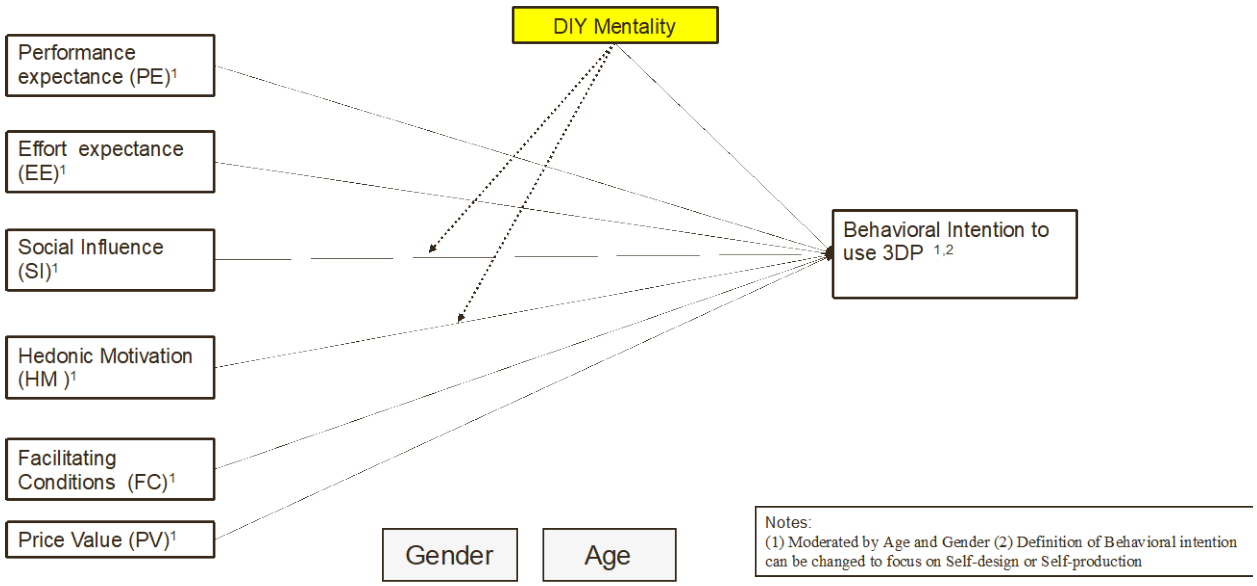

Figure 7. Modified UTAUT2 model used by Hartmann & Vanpoucke (2017)

Hartmann & Vanpoucke (2017) used PLS-SEM to validate their model and test their hypotheses. The results of a survey of 150 individuals within Germany (53% male, 47% female, 60% between ages of 18-35) are shown in Table 8. Overall the authors found that the modified UTAUT2 model (without Habit construct and Experience moderator) was able to account for 62 % in variance of BI. When DIY was added to the modified UTAUT2 model, as a moderator and predictor, the explained variance increased to 66% .

Table 8

Summary of results: Application of UTAUT in German Households.

Independent Variable	Dependent Variable	Moderators	Findings
Performance Expectancy (PE)	Behavioral Intention (BI)	Gender, Age	Without moderation, PE had significant effect on BI in all models except Self-design model. With moderation, only the high order interaction term was significant (PE X AGE X Gender). Post Hoc analysis showed that PE X DIY was significant.
Effort Expectancy (EE)	Behavioral Intention (BI)	Gender, Age	Without moderation EE had significant effect on BI in all models but opposite to the hypothesis. With moderation EE X AGE was significant. Post Hoc Analysis showed that EE X DIY was significant.
Social Influence (SI)	Behavioral Intention (BI)	Gender, Age, DIY	Without moderation, SI had significant effect on BI in all models. With Moderation only SI X GEN and SI X DIY were significant.
Facilitating conditions (FC)	Behavioral Intention (BI)	Gender, Age	Without moderation, FC had significant effect on BI in all models. With Moderation only the high order interaction term was significant (FC X AGE X Gender).
Hedonic Motivation (HM)	Behavioral Intention (BI)	Gender, Age, DIY	Without moderation, HM had significant effect on BI in UTAUT2 model and Self-Design model. The effect of HM on BI was significant with the moderation of Age and DIY. Gender had no effect.
Price Value (PV)	Behavioral Intention (BI)	Gender, Age	No significant effect without moderation. The effect of PV on BI was significant with the moderation of (PV X GEN) and (PV X Gender X AGE)- 3 way interaction.
Do-it-Yourself (DIY)	Behavioral Intention (BI)	None	DIY had a direct significant effect on BI
Do-it-Yourself (DIY)	Behavioral intention (BI) Self-design focus	None	DIY had a direct significant effect on Self-design.
Do-it-Yourself (DIY)	Behavioral intention (BI) Self-production focus	None	No significant effect.

Adopted from Hartmann and Vanpoucke (2017). User Acceptance of Technologies in Their Infancy: The case of 3D printing Business Model. Journal of Organizational and End User Computing, 29, 1-24.

The authors used SMARTPLS to analyze the role of the interaction effects; however, they lacked in explaining what the results meant or the significance of the study. It was left for the reader to go through the results tables to extract meaningful results. The authors suggested further research to fully understand the role of the interaction effects. The authors were more concerned to show that their proposed model could be applied to a technology in its infancy and would have adequate explanation of variance in BI. In the modified UTAUT2 model, the moderating interaction effects (AGE x GENDER) was confirmed for PE, FC and PV which was consistent with the original UTAUT2 model. It was expected that the interaction (AGE x GENDER) would have an effect on EE, SI and HM as proposed in the UTAUT2 model. However, it was found that only AGE had an effect on EE and HM, while Gender had an effect on SI. Unlike the original UTAUT2 model, HM in the modified UTAUT2 model was found to be more significant on BI for older individuals. The authors were unable to offer a clear or convincing explanation for this outcome. They suggested the possibility that older individuals were not familiar with the limitations of the technology compared to the younger individuals who could be considered digital natives. That explanation did not seem to be adequate as the authors claimed that their sample was focused on early adopters and all participants were given the same training to ensure the same level of understanding of 3D printing. The authors admitted that more research is required to understand that result further. The authors did not indicate if they had any questions the survey asking for previous experience with 3D printing. There is the possibility that older individuals could have been exposed to the technology via their work and know more about the benefits of the technology. Also, the authors did not examine the effect of AGE on DIY behavior in their models. Previous research on DIY behavior showed that Hedonic motivation is an outcome of DIY behaviors (Wolf & Mcquitty, 2011; Collier & Wayment, 2018). Therefore, if the outcome of DIY behavior for older individuals is more significant on HM, then it is prudent to expect that fact to be reflected in the results of the model. However, the more important issue to consider is: should DIY be a direct predictor of BI or should the relation be mediated through HM. As the current literature seems to suggest the HM is an outcome of DIY, then conceptually it is prudent to think of mediation analysis.

The results show that the Facilitating Conditions (FC) have a significant positive relation to the intention to use 3D Printing. That meant the individuals with limited knowledge of the new technology would be willing to acquire the knowledge and resource to use the technology. On the other hand, Effort expectancy had a significant negative relation to the intention to use (opposite to the original hypothesis). That meant the individuals perceived more effort to learn and use 3D printing. The authors did not have a clear explanation for this result nor did they discuss the impact of age on this result. Post hoc analysis showed that this negative effect was stronger for individuals low in DIY. There is clearly an interaction that the authors proposed to be a subject of further research.

Hartmann & Vanpoucke (2017) also attempted to differentiate between Behavioral intention to self-design for 3D printing and Behavioral intention to self-produce using 3D printing. The results showed that explained variance in the Behavioral intention to self-design was higher than self-produce. The authors rushed to conclude that individuals would prefer to self-design at home and do the 3D printing using online platforms. While that conclusion might be correct at the instant when the research was done, the authors failed to consider that this might be a transition point. The sweet spot per the research of Rayna et al. (2015) is to co-design and print at home. What the results show is that there is a strong tendency to co-design at that point of time of research. Beside mentioning that women tended to be more interested in "Self-production", the authors failed to show in details of the multi-group analysis they performed. Interestingly, Wolf & Mcquitty (2011) refer to a study of German DIYers which found that 60% of respondents perceived that their "self-production" quality is superior to the available commercial products. That fact serves as a basis to question the validity of the conclusions of Hartmann and Vanpoucke (2017). How would the results have differed if the sample were to include more German DIYers? In conclusion, Hartmann and Vanpoucke (2017) did the analysis in line with the recommendations for PLS-SEM (Hair et al., 2017). However, the authors had a hard time explaining the meaning of their results (especially high-order interaction terms) which resulted in many open questions. In many cases, the authors concluded that more research is required on the topic and willfully admitted that their results cannot be generalized. While the authors do not mention any issues with the selected sample, the question still remains what would have been the conclusions if more German DIYers were in the selected sample, which raises the question if the DIY construct can be generally applied to the rest of the population? Also, from the conceptual point of view (based on the existing research), should DIY be an antecedent to HM and not a moderator or a direct predictor of BI?

Following the work of Hartmann and Vanpoucke (2017), Halassi et al. (2018) did a similar study in the Netherlands and proposed the modified UTAUT2 model shown in Figure 8.

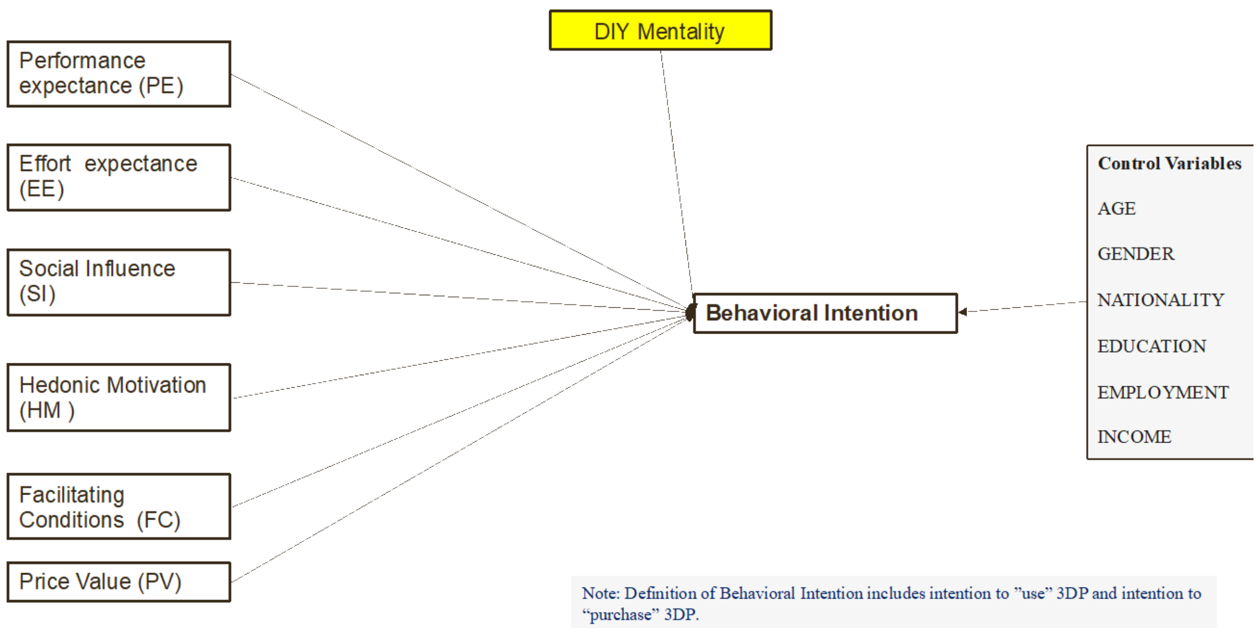

Figure 8. Modified UTAUT2 model used by Halassi et al. (2018)

The moderating variables were all considered as control variables and categorial. While the proposed model looks more parsimonious and the modeling technique will allow for multi-group analysis (e.g. male vs. female, etc.), it will not capture the interaction effects readily (Hair et al., 2017). For example, It will be difficult to discern if the behavior of old females differs from the behavior of old males thus the interaction effect of age and gender is not reflected accurately. It is not clear why the authors decided to pursue this approach. While Hartmann and Vanpoucke

(2017) defined DIY in terms of economic benefit and lack of product availability, Halassi et al. (2018) defined DIY in terms of benefit of self-well-being and lack of product availability. Nevertheless, both papers fail to consider that conceptually DIY might be an antecedent to HM. Halassi et al. (2018) also expanded the behavioral intention (intention to use 3D printing) to also include purchase intention.

Halassi et al. (2018) also used PLS-SEM and SMARTPLS software to validate their model and test the hypothesis. The results of a survey of 196 individuals within the Netherlands (51% male, 49% female, 67% < 34 yrs, 41 % university degree) showed that their model was able to account for 67 % variance in BI (this result cannot be compared directly to the previous results due to the change done to the DIY and BI constructs). Using multi-group analysis, the female model had a predictive power of 68% compared to 70% for the male model. The modified UTAUT2 model (neglecting any heterogeneity in the data – Gender, Age, Income, etc) showed that facilitating conditions (FC), Hedonic Motivation (HM) and DIY behavior were the best predictors of BI (in decreasing order of significance) while PE, EE, SI, PV had no significant effect. When multi-group analysis was used to compare the gender groups, it was found that, for women, social influence (SI) was a significant contributor after facilitating conditions (FC). For men, hedonic motivation (HM) was a significant contributor after FC. The other control variables did not show any significant differences.

In the modified UTAUT2 model by Hartmann and Vanpoucke (2017), the key predictors (without moderation) in descending order of significance were FC, EE, PE, DIY, SI. Hedonic moderation only had significant effect with the moderation of AGE and interaction term (HM x AGE) had a more significant effect on BI than DIY as a predictor. The interaction term (HM x DIY) had a more significant impact on BI than DIY as a predictor. The interaction terms (HM x

DIY and HM x AGE) diminished the significant direct effect of HM on BI. In contrast, the results of Halassi et al. (2018) showed that when HM is a key predictor, DIY also became key predictor. The key thing to recall is that Halassi et al. (2018) changed the construct of DIY to include subjective well-being. Per the literature (Wolf & Mcquitty, 2011; Collier & Wayment, 2018), Hedonic motivation (HM) is an outcome of DIY, therefore it makes sense that higher DIY behavior would lead to higher HM. Halassi et al. (2018) did not offer an explanation as to why PE, EE, SI and PV did not show any significant effects. Given that 67% of the sample were less than 34 years, the authors were not inclined to generalize their results and suggested further research.

Using the model suggested by Halassi et al. (2018), Lotjonen (2019) investigated user acceptance of 3D printing in Finland. The sample was primarily focused on students. The author found that FC, PV and PE were the significant predictors with a combined explained variance of 50.8 % in BI. PV was the only construct that showed a difference in Gender. It was more important for women, particularly non-Finnish nationality. PE was more significant for individuals without a degree particularly non-Finnish nationality. Neither Hedonic Motivation nor DIY were in the top 3 predictors thus once again establishing a strong correlation. The overall explained variance in BI in the Finnish sample was 62%. Again, the results were not generalizable due to the sample bias toward students. Nevertheless, if is worthwhile to compare how the models perform in different cultural settings especially when comparing two countries in Europe using the same modified UTAUT model: Finland versus the Netherlands. In the Netherlands, there was no significant impact from the control variables of nationality, income or education. In Finland, the HM and DIY constructs were not key predictors. The difference in the results shed some light on the inherent impact of culture.

Hartmann and Vanpoucke (2017) and Halassi et al. (2018) responded to the call of Vankatesh et al. (2012; 2016) to extend the application of the UAUAT2 model to other applications and investigate other predictors of BI. The authors decided to investigate the DIY variable which had not been investigated earlier in the UTAUT literature (Williams et al., 2015). However, these authors used different definitions of DIY and different modeling techniques which led to different conclusions. Furthermore, the DIY literature clearly indicates there is a relationship between DIY and Hedonic motivation. This fact brought to light the question if DIY is really an independent predictor of BI or should that relation be mediated by Hedonic motivation or perhaps it is just sufficient to have Hedonic motivation knowing that it is driven by many factors including DIY. From the results of Hartmann and Vanpoucke (2017), Halassi et al. (2018) and Lotjonen (2019), the impact of the DIY construct was very sensitive to the sample selected. All authors concluded that their results cannot be generalized based on their samples and suggested further research. None of the authors attempted to argue that adding the DIY construct to the UTAUT model gives a more holistic view (i.e effect of general attitude toward technology or cultural impact). With the third stream of research focused on integrating the technology acceptance models with technology readiness, there is an opportunity to take a different perspective to the 3D printing at home concept. The next sections will focus on the research questions and the proposed modified UTAUT2 model in this study.

Research Questions

As discussed previously, the research on the acceptance of 3D printing for home fabrication, using the modified UTAUT2 model, showed that the factors that impact the intention to adopt the technology differs for each country. The literature review has shown that no similar research has been done on the US market. The research questions are aligned with the research aims and objectives outlined in Chapter 1. The answers to these questions will contribute to the theoretical, practical and academic perspectives discussed in Chapter 1.

1) What are the key variables (PE, EE,SI, HM, FC, PV) that predict the behavioral intention to adopt Desktop 3D printing by male and female adults in US households?
2) How different are the impacts of the key variables between males and females?
3) How do the interactions of enablers, inhibitors and age affect the impact of the key variables on behavioral intention for males and females?

Research Model and Hypotheses

The goal of this research is to examine the factors that influence individuals in US households to adopt desktop 3D printing for home fabrication. Similar to the work of Hartmann & Vanpoucke (2017) and Halassi et al. (2018), the UTAUT2 model is used as the baseline model for technology acceptance and adoption. In contrast to the previous research, this research will use the Psychographic variable TR instead of DIY. The TR construct measures the general overall mindset ("gestalt") of the individual toward technology. It is a construct that will be applicable to a general population, unlike DIY which could be more prevalent in a DIY community or as Lang et al. (2020) classifies them the "DIY prosumers". Also, TR is considered as a "situational trait" that is inherently influenced by cultural differences, thus it will also add the cultural aspect to the model. This is a step toward the holistic view of modeling technology acceptance as discussed in the previous sections. As such this research will fall in the third stream of research that focuses on the merging of technology acceptance models with technology readiness. Based on previous research (Wolf & Mcquitty, 2011,2013; Wolf et al., 2015; Collier & Wayment, 2018) it will be sufficient to represent DIY mentality through hedonic motivation. TR has also been shown to be independent of whether the technology is used at home or at work.

Adding the TR construct to the UTAUT model will also serve well in future studies for the cross-cultural validation of the proposed modified UTAUT2 model.

Previous research by Tsourela & Roumeliotis (2015) and Qasem (2020) have taken a similar approach to merge the UTAUT model with TR to study technology-based services. This will be the first time such a research approach is attempted in the context of 3D printing. In this context, desktop 3D printing is considered as a self-service technology. The proposed research model is shown in Figure 9. Similar to Hartmann & Vanpoucke (2017) and Helassi et al. (2018), desktop 3D printing for home fabrication in the USA market will be considered to be in its infancy. Thereby the Habit construct and the experience moderator will be dropped from the UTAUT2 model. Technology Readiness (TR) will be added as a moderator. As pervious research has shown, it is best to use TR as a moderator or mediator in the integrated models (Blut & Wang, 2020). Parasuraman & Colby (2015) recommended using TR as a moderator. Tsourela & Roumeliotis (2015) used a composite definition of TR (one dimensional variable) as a moderator. Qasem (2020) defined TR as two dimensional in terms of "enablers" and "Inhibitors". Both approaches have been used in the literature with preference to use the two-dimensional approach (Blut & Wang, 2020). In this research a two-dimensional approach will be used following the work of Jin (2013) on the TRAM model. TR will be measured in terms of Enablers (Optimism and Innovativeness) and Inhibitors (Discomfort and Insecurity). Gender has been kept as a control variable because part of the research will also seek to understand how significantly different the acceptance factors are between females and males in the USA.

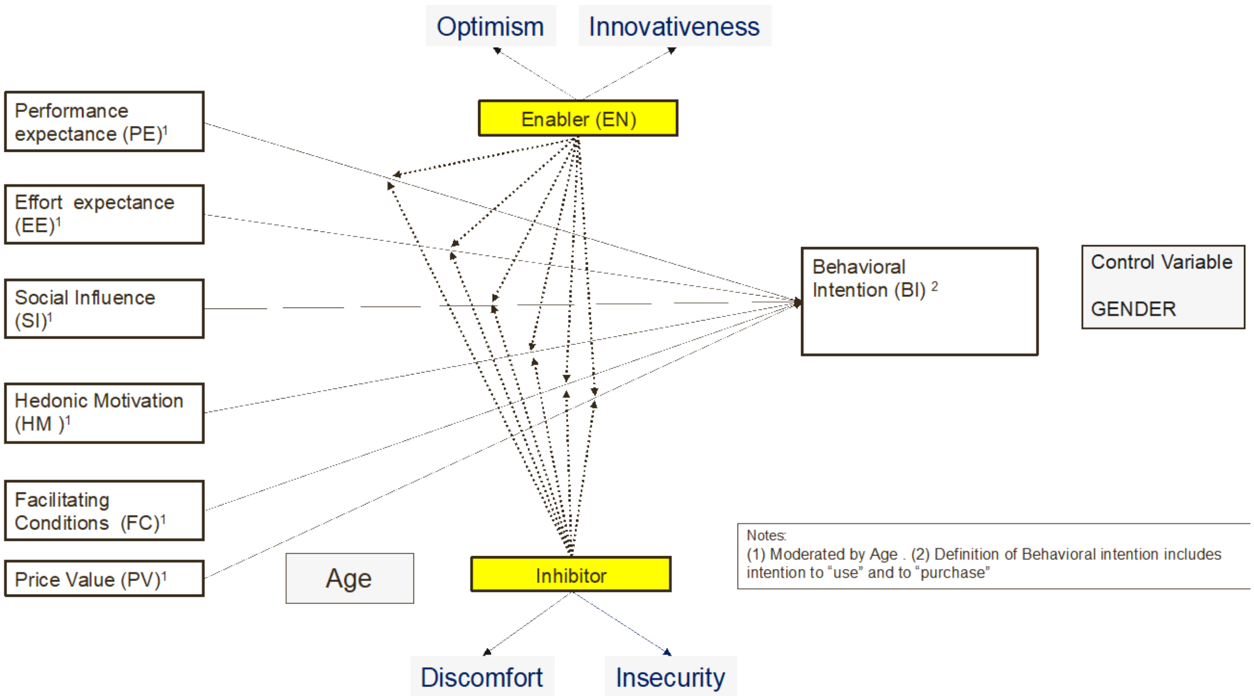

Figure 9. Proposed research model

The hypotheses set forth in this study are grounded in the previous seminal work of Venkatesh et al., 2003, Venkatesh et al., 2012, Rojas-Mendez et al. 2017 and Blut et al., 2020. A summary of their research results was given in Table 2, Table 3, Table 6 and Table 7. The hypotheses are given in Table 9. Within the 3D printing context, it will be the first time that such an approach will be used. As such, it will be a strong contribution to the emerging field of research.

Table 9

List of Hypotheses based on model shown in Figure 9.

Independent Variable	Dependent Variable	Moderators	Control Variable	Hypothesis
Performance Expectancy (PE)	Behavioral Intention (BI)	Enablers, Inhibitors, Age	Gender	**H1(a)** : PE is positive related to the intention to adopt desktop 3D printing for home fabrication such that the effect is stronger for men. **H1(b)** : Enablers will positively moderate the effect of PE on BI such that the effect will be stronger for men particularly young men **H1(c):** Inhibitors will negatively moderate the effect of PE on BI such that the effect will be stronger for women particularly old women.
Effort Expectancy (EE)	Behavioral Intention (BI)	Enablers, Inhibitors, Age		**H2(a)** : EE is positive related to the intention to adopt desktop 3D printing for home fabrication such that the effect is stronger for women. **H2(b)** : Enablers will positively moderate the effect of EE on BI such that the effect will be stronger for women particularly young women **H2(c):** Inhibitors will negatively moderate the effect of EE on BI such that the effect will be stronger for women particularly old women.
Social Influence (SI)	Behavioral Intention (BI)	Enablers, Inhibitors, Age		**H3(a)** : SI is positive related to the intention to adopt desktop 3D printing for home fabrication such that the effect is stronger for women. **H3(b)** : Enablers will positively moderate the effect of SI on BI such that the effect will be stronger for women particularly young women **H3(c):** Inhibitors will negatively moderate the effect of SI on BI such that the effect will be stronger for women particularly old women.
Facilitating conditions (FC)	Behavioral Intention (BI)	Enablers, Inhibitors, Age		**H4(a)** : FC is positive related to the intention to adopt desktop 3D printing for home fabrication such that the effect is stronger for women. **H4(b)** : Enablers will positively moderate the effect of FC on BI such that the effect will be stronger for women particularly young women **H4(c):** Inhibitors will negatively moderate the effect of FC on BI such that the effect will be stronger for women particularly old women.
Hedonic Motivation (HM)	Behavioral Intention (BI)	Enablers, Inhibitors, Age		**H5(a)** : HM is positive related to the intention to adopt desktop 3D printing for home fabrication such that the effect is stronger for men. **H5(b)** : Enablers will positively moderate the effect of HM on BI such that the effect will be stronger for men particularly young men **H5(c):** Inhibitors will negatively moderate the effect of HM on BI such that the effect will be stronger for women particularly old women.
Price Value (PV)	Behavioral Intention (BI)	Enablers, Inhibitors, Age		**H6(a)** : Enablers will positively moderate the effect of PV on BI such that the effect will be stronger for women particularly young women **H6(b):** Inhibitors will negatively moderate the effect of PV on BI such that the effect will be stronger for women particularly old women.

Summary

This chapter started by developing the foundations of why 3D printing for home fabrication has a viable business model and provides the opportunity for user entrepreneurship. From the literature, it was shown how the digital revolution eventually led to the emergence of Direct Digital manufacturing (DDM) which enabled the use of 3D printing via online 3D printing platforms and at home. User innovation is now more feasible as the line between design and manufacturing is blurred with DDM. With this opportunity for innovation, multiple researchers worked on developing viable business models 3D printing at home. Despite this potential, the literature indicates that the adoption of 3D printing for home use is still low. That fact encouraged the emergence of a research field to look at the factors that influence individuals to adopt a new technology such as 3D printing for home use. The technology acceptance models used in the scant literature on the adoption of 3D printing for home fabrication mainly used the UTAUT2 model with the DIY variable added as a predictor and moderator. An analysis of that literature showed that the DIY variable was not consistent in its performance as a predictor variable because it was sensitive to the definitions of the sub-constructs. That is seen in the comparison of the results from Germany, Netherlands and Finland. Furthermore, the DIY literature suggests that conceptually Hedonic motivation is an outcome of DIY behavior thus DIY could be considered an antecedent to HM. That fact is not clearly considered in the existing modified UTAUT2 models. Therefore, there is an opportunity to consider other stable variables to add to the UTAUT2 model. There is an emerging stream of work that is focused on integrating the technology acceptance models (such as UTAUT) with the Technology Readiness concept. A review of the Technology Readiness was given before formulating the research model proposed in this research. The proposed model integrates TR into the UTUAT2 model as a moderator to investigate the factors that influence the adoption of 3D printing for home use in the US. This will be the first time such an integrated approach will be used in the 3D printing context. As such the results of this study certainly contribute to the emerging stream of work.

CHAPTER 3 – RESEARCH METHODOLOGY

Research Philosophy

In business and management research, the Positivism research philosophy is considered as a dominant form of research (Meyers,2013; Ravitch & Riggan,2017). Positivist researchers focus on the predictive understanding of the phenomena at hand by breaking down the subject matter in terms of independent variables, dependent variables and the corresponding relationships. The role of the researcher within this philosophy is limited to data collection and interpretation in an objective manner. Thus, any determined variation will stem from the individual characteristics of the participants in the sample. Following what has been established in the literature survey in the previous chapter, the current study adopted a Positivism research philosophy approach. A nonexperimental quantitative methodology to study the phenomena of technology acceptance in American households was utilized. Specifically, a cross-sectional study was done to study the acceptance of desktop 3D printing in American households. The identified independent variables, dependent variables and the corresponding relationships are consistent with the UTAUT2 Model and Technology Readiness concept discussed in Chapter 2.

Population and Sample

The sampling frame for this study was the population of the United States of America. The minimum sample size calculation was based on the "minimum R-squared method" developed by Hair et al. (2017) and commonly used in partial least square structural equation modeling (PLS-SEM). This method builds upon Cohen's (1992) power tables for least square regression. Hair et al. (2017) provide a summary table listing the minimum required sample size based on three steps: 1- maximum number of arrows pointing at the dependent variable (9 in this study), 2-Significance level to be detected (5% in this study following the work of Venkatesh et al., 2003; Hartmann & Vanpucke, 2017), 3- Minimum R^2 required for the model (0.1 in this study following the work of Hartmann & Vanpucke,2017; Halassi et al., 2018). Assuming a statistical power of 80% (as used the previous research of Hartmann and Vanpoucke, 2017; Halassi et al., 2018; Litjonen,2019), the table provides the recommended a minimum sample size of 150 participants. As gender is a grouping variable for multiple group analysis, the overall sample size used in this study is 300 (150 male and 150 female).

Data Collection Procedure

In the proposed study, an online-survey instrument via Qualtrics was employed to measure 8 independent variables (PE, SE, SI, HM, FC, PV, Enabler (EN), Inhibitor (IN)) and one dependent variable (BI). Data was also collected on the following sociodemographic data: Gender, Age, and Race. To avoid repeated participation, Qualtrics placed a preventing cookie on the participant's browser. To be eligible to participate in the study, the participant must have not owned a 3D printer at home.

Independent variables. The independent variables (PE, SE, SI, HM, FC, PV,EN, IN) were measured using validated scales from prior literature. The measurement model, measurement scale and component order of each variable are shown in Table.10

Each construct was measured using multiple items (indicators) as shown in Appendix B. All questions were rated on a five-point Likert scale with the anchors "Strongly disagree" and "Strongly agree". As the context in the questionnaire had not changed and all items were already validated successfully in prior studies (Hartmann and Vanpoucke, 2017;

Hallassi et al., 2018; Jin,2013) and these studies established Content validity was not an area of concern, it was not considered further in this study. Furthermore, common-method variation, due to self-reporting, was found not to be of major concern (Venkatesh et al., 2003,2012; Hartmann and Vanpoucke, 2017; Halassi et al., 2018), thus it was not analyzed further in this study.

Dependent variables. The dependent variable in this study was Behavioral intention. It was measured using a multiple item Likert scale as previously validated in the Literature. (see Appendix B). A five point Likert scale with anchors "strongly disagree" and "strongly agree" was used.

Sociodemographic information. Age, Gender and Race information was also collected as shown in Appendix B. Age was coded as continuous variable consistent with prior research (Venkatesh et al., 2003). Prior research measured Gender using a dummy variable (Male = 0, Female = 1 (Venkatesh et al., 2003,2012; Hartmann and Vanpoucke, 2017; Halassi et al., 2018). Given that gender is now considered to be a spectrum, and in contrast to previous research, individuals were asked in the questionnaire to pick "he/him" or "she/her" pronouns depending on which end of the spectrum they identified with most closely (Mclaren, 2019). Each selection was then converted to a male or female input for the dummy variable. Race was coded as categorical variables consistent with previous research (Perry, 2017; Halassi et al., 2018).

Data Gathering Plan

A Qualtrics online survey was used for this study. All instructions and questionnaire were in English. At the outset of the survey, the participants were asked a question (Do you have a 3D printer at home?) to determine the eligibility for the study. The eligible participants were given a written explanation of 3D printing as shown in Appendix C.

That was to ensure that all participants had the same minimum knowledge. That training material was reviewed for ease of understanding and completeness by two Rollins MBA graduates, a Professor of communications at Rollins, an undergraduate in psychology at Rollins and a 3D printing engineer at Siemens.

The first set of questions in the questionnaires gathered sociodemographic data. The second set of questions in the questionnaires rated the participants agreement with various items on a five point Likert scale (1= “Strongly disagree” to 5= “Strongly agree”). A pilot study with at least 30 participants was carried out to refine the data gathering plan as required. Also, the Pilot Study was required to determine the time needed to fill out the survey. Once the pilot study and any required modifications were completed, the survey was released to the remaining participants. Double registration was prevented by Qualtrics via a prevention cookie on the participant’s browser. Furthermore, a timing mechanism by Qualtrics was used to detect participants that have rushed through the questionnaire and the responses of these participants were eliminated. That measure was to minimize straight lining. The study ran for a period of 7-10 days.

Ethical Consideration

- Adult participants in this study were recruited by Qualtrics. The definition of an adult in this study is 18 years or older.
- No names, date of birth or Social security numbers were collected for this study
- Renumeration for participants was through Qualtrics.
- All participants signed a consent from that stated the purpose of the study clearly) see Appendix D)
- Participants could terminate their participation at anytime

- No debriefing of the participants was required as no deception to the goals of this study were intended.
- This study did not involve any vulnerable population (under age of 18, incarcerated or mentally ill)
- All participants were made aware that their responses are confidential
- An appropriate evaluation of IRB form was done prior to initiating the study.

Statistical Data Analysis

As the purpose of this study was focused on identifying the key “driver” constructs that maximize the explained variance in Behavioral intention to use and buy 3D printing for home fabrication, partial least squares structural equation modeling technique (PLS-SEM) was recommended per the current trends in the literature. PLS-SEM is one of the emerging second-generation multivariate analysis techniques used in business research (Hensler et al., 2009; Hair et al., 2011; Richter et al., 2014; Hensler et al., 2015; Hair et al., 2017; Hair et al., 2018a). This study utilized the partial least squares structural equation modeling technique (PLS-SEM) to test significance of the path coefficients in the model shown in Figure 9. PLS-SEM is based on a series of ordinary least square regression analysis. Multiple studies in the literature have shown that the method is not sensitive to small sample size given the complex model setup given in this study- several interaction terms and higher-order constructs (Hair et al., 2017; Hair et al., 2018a). SMARTPLS 3.0 (Hair et al., 2017) which is based on PLS-SEM was used in this study for modeling, computing the path coefficients and testing the hypotheses.

There were two key models evaluated. The first model (Model 1) was the UTAUT2 model shown in figure 5. The model was evaluated without the Habit construct and the experience moderator. Model 1 served as a baseline to compare the results of the Model 2 (Figure 9) with respect to the variance explained in the Behavioral intention. Initially the models were evaluated separately for males and females then a multigroup analysis was performed. Following the systematic procedure outlined by Hair et al. (2017, 2018a, 2018b), the analysis took 5 stages:

1) Data Examination (missing data, suspicious response patterns, outliers, data distribution). The criteria for evaluation are shown in Figure.10 (Schafer & Graham, 2002; Hair et al., 2015). Confirmed suspicious responses were deleted from the dataset. Identified outliers without a clear explanation were retained in the dataset. If the outlier was the result of an entry error it was deleted. While PLS-SEM allows for nonnormality in the data, extremely nonnormal data can prove problematic in the assessment of the model (Hair et al., 2017). The skewness and kurtosis was used to evaluate the degree of non-normality.

Data Examination

- **Missing Data**
  - Observations with >15% missing data will be deleted from data sets
  - Less than 5% of values per indicator missing, mean value replacement will be used
- **Suspicious response patterns**
- **Outliers (use SPSS or R)**
- **Data distribution**
  - $-1<\text{Skewness}<1$
  - $-1<\text{Kurtosis}<1$

Figure 10. Data Examination Criteria

2) Assessment of the Measurement model (convergent validity, Internal consistency reliability, Discriminant validity). A glossary of the statistical terms is given in Appendix E. Table 10 shows that the constructs were measured reflectively per the proposed model

in Figure. 9. These constructs have also been measured reflectively in previous research (Venkatesh et al., 2003, 2012; Hartmann and Vanpoucke, 2017; Halassi et al., 2018). In reflective measurement, the direction of the arrows is from the construct to the indicators (Figure 11.), indicating the assumption that the construct causes the covariation of the indicator variables. The indicator variables are given in Appendix B with the questionnaires. The evaluation criteria are shown in Figure 12 (Hair et al., 2011, 2017). The results were reported in the format shown in the example of Table 11.

Table 10

List of Independent Variables

Variable	Measurement Model	Measurement Scale	Coding	Higher-order Component ?
Performance Expectancy (PE)	Reflective	Interval	Likert scale	No
Effort Expectancy (EE)	Reflective	Interval	Likert scale	No
Facilitating Conditions (FC)	Reflective	Interval	Likert scale	No
Hedonic Motivation (HM)	Reflective	Interval	Likert scale	No
Price Value (PV)	Reflective	Interval	Likert scale	No
Social Influence (SI)	Reflective	Interval	Likert scale	No
Enabler (EN)	Reflective-Reflective	Interval	Likert scale	Yes
Inhibitor (IN)	Reflective-Reflective	Interval	Likert scale	Yes
AGE	N/A	Ratio	Ratio	No
GENDER	N/A	Nominal	Dummy Variable (Male=0, Female=1)	No

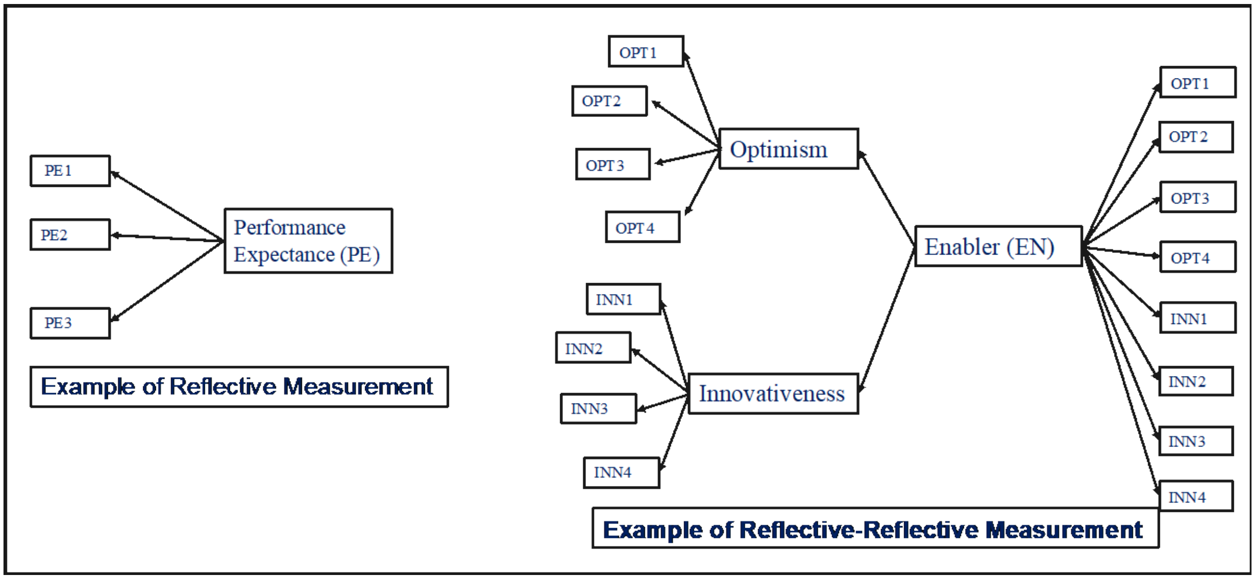

Figure 11. Examples of Reflective measurement

Evaluation of Reflective measurement Models

- **Convergent Validity**
  - Outer Loading >0.70
  - Indicator Reliability > 0.50
  - AVE > 0.50
- **Internal Consistency Reliability**
  - Cronbach α : 0.60 – 0.90 (lower limit)
  - Composite Reliability : 0.60- 0.90 (upper limit)
- **Discriminant Validity**
  - HTMT confidence interval does not include 1
- **Confirmatory Tetrad Analysis (extra non-mandatory analysis)**
  - Empirically evaluate whether the measurement model specification chosen based on theoretical grounds is supported by the data

* Key point : reliability is a necessary condition for validity

Figure 12. Measurement model evaluation criteria

Table 11

Results Summary for Reflective Measurement

Latent Variable (Independent Variable)	Indicators	Convergent Validity			Internal Consistency Reliability		Discriminant Validity
		Loading	Indicator Reliability $(\text{loading})^2$	AVE	Composite Reliability	Cronbach's Alpha	
		>0.70	>0.50	>0.50	0.60-0.90	0.60-0.90	HTMT confidence interval does not include 1?
PE	PE1						
	PE2						
	PE3						

3) Assessment of the structural model (collinearity, Path coefficient significance, R^2 Value, effect size f^2, predictive relevance Q^2). A glossary of the statistical terms is given in Appendix E. Once the construct measures were confirmed to be reliable and valid, the next step was to assess the structural model which included the proposed relations between the independent variables and the dependent variable. At that stage the predictive power (ability to maximize the explained variance in the dependent variable) of the proposed model was determined. In PLS-SEM, the structural model is assessed on the basis of heuristic criteria not goodness-of-fit measurement (Hair et al., 2017, 2018b) as shown in Figure 13. Most researchers report the p values to assess the significance level (Hair et al., 2011, 2017). For a significance level of 5 % , as used in the previous literature (Venkatesh et al., 2003, Hartmann & Vanpoucke, 2017), the p value must be less than 0.05 to conclude that the relationship under consideration was significant at the 5 % level. That was the criteria used to test the proposed hypotheses. In addition, SMARTPLS 3.0 calculates a bootstrap confidence interval to test whether a path coefficient is significantly different from zero. As the possibility of non-normality in the

data is assumed in PLS-SEM, the parametric significance tests typically used in regression analysis cannot be readily used to test the significance of the path coefficients (Hair et al., 2017). Rather PLS-SEM relies on a non-parametric technique that uses bootstrapping. The concept of bootstrapping relies on drawing a large number of random samples from the original sample with replacement. With replacement implies that each drawn sample is returned to the population before the next random sample is drawn. Once drawn, the bootstrap samples are used to estimate the PLS path model. It is recommended to use 5,000 bootstrap samples (Hair et al., 2017). That means 5,000 PLS path models are estimated. The estimates of the coefficients from these models form a bootstrap distribution of path coefficients. It is this bootstrap distribution that is used to calculate the confidence interval for testing the significance of the path coefficient. The confidence interval provides information on the stability of the estimated path coefficient. If the confidence interval for an estimated path coefficient does not include zero, then a significant effect can be assumed. The results will be reported in a table format as shown in the example of Table 12. This approach was used in previous relevant research using the UTAUT2 model (Venkatesh et al., 2012; Hartmann et al., 2017; Halassi et al., 2018).

Evaluation of Structural measurement Model

- **Collinearity Assessment**
  - Variance inflation factor < 5
- **Structural path coefficients significance**
  - *P < 0.05*
  - Bootstrapping confidence interval for path coefficient does not include zero
- **R^2 Value**
  - 0.25 Weak
  - 0.50 moderate
  - 0.75 significant
- **Effect size f^2 of each independent variable on R^2**
  - No effect if value less than 0.02
- **Predictive relevance : Stone-Geisser Q^2**
  - Applicable to reflective measurement models
  - Value > 0 suggest that the model has predictive relevance for intention to use 3D printing
- **Effect size q^2 of each independent variable on Q^2**
  - 0.02 small predictive relevance
  - 0.15 medium predictive relevance
  - 0.35 large predictive relevance

* Key point : PLS-SEM depends on heuristic criteria to evaluate structural model not goodness- of-fit criteria

Figure 13. Structural model evaluation criteria

Table 12

Significance Testing Results of the Structural Model Path Coefficients

Path	Path Coefficients	P Values	95 % Confidence Intervals	Significance (p<0.05)?
PE -> BI				

4) Multi-group analysis (males versus females). As Gender was a categorical variable (male or female) and was an observable heterogeneity, multi-group analysis was required (i.e. Model 2A(males) and Model 2B(females)). Prior to performing the multi group analysis (MGA), it was important to establish measurement invariance (Hair et al., 2018b). Measurement invariance gives the confidence that the differences in the male and female models are not the results of distinctive content and / or meaning of the independent / dependent variables across groups and / or difference in measurement scale. For this purpose, SMARTPLS 3.0 aides in determining the Configural invariance (exists when the

constructs are equally parameterized and estimated across groups) and the compositional invariance (exists when the composite scores in the measurement model are the same across groups despite possible differences in group specific weights used to calculate the scores.) When both configurational and compositional invariance were established then measurement invariance was established and the multi-group analysis was feasible. The path coefficients of Model 2A and Model 2B were different but the question was how large was the difference and how meaningful was the difference? Technically, MGA tests the null hypothesis (H_0) that the path coefficients between the male and female groups are not significantly different. In SMARTPLS 3.0, a one-tailed test can be performed involving a non-parametric technique that builds upon bootstrapping results from each of the two groups (Hensler et al., 2009; Hair el al, 2018). This approach has been used in prior research by Hartmann and Vanpoucke (2017) and Halassi et al. (2018). The approach allows for testing only one sided hypotheses such that the path coefficients for group 1 (males), $p^{(1)}$, are larger than the path coefficients for group 2 (females), $p^{(2)}$ .The resulting p value indicated whether the path coefficient is significantly larger in the first group (male) than the second group (female) thus allowing to test the hypotheses in Table 9. To illustrate the working principle of this non-parametric technique, a simple model with two constructs and two groups giving the estimated path coefficients of $p^{(1)}$ =0.336 and $p^{(2)}$=0.501 (Hair et al., 2018) could be considered. The interest is to test the hypothesis $p^{(1)} > p^{(2)}$. To test this hypothesis 10 bootstrap samples are drawn for $p^{(1)}$ and $p^{(2)}$ and compared as shown in Table 13. Now each bootstrap sample estimate of $p^{(1)}$ (e.g. 0.357) is compared with each bootstrap sample estimate of $p^{(2)}$ ((i.e. 0.494, 0.423….,0.538). The number of cases where $p^{(1)}> p^{(2)}$ are indicated by an X as shown in

Table 13. In this example there are 11 cases which meet the criteria. Dividing this number by 100 (which is the total number of comparisons, 10x10) yields the p value of 0.11 which is greater than the 0.05 limit. Therefore, it cannot be concluded that the path coefficient in group 1 is significantly larger than the path coefficient in group 2.

Table 13

Data Matrix for Multi-Group analysis using Non-parametric technique.

		Bootstrap Path coefficients Samples, $p^{(1)}$									
		0.357	0.226	0.318	0.281	0.372	0.318	0.296	0.308	0.415	0.272
Bootstrap Path coefficients Samples, $p^{(1)}$	0.494										
	0.423										
	0.324	X				X				X	
	0.591										
	0.698										
	0.291	X		X		X	X	X	X	X	
	0.509										
	0.400									X	
	0.526										
	0.538										

Note : X denotes situations when $p^{(1)} > p^{(2)}$.
Example adopted from Hair et al (2018)

5) Interpretation of results and drawing conclusions. The results from stages 3 and 4 were instrumental in testing the hypothesis in Table 9. The final results are discussed further in the next chapter .

CHAPTER 4 – DATA ANALYSIS AND FINDINGS

Data collection

An online survey via Qualtrics was employed in the USA to collect data on the eight independent variables (PE,SE,SI,HM,FC,PV, Enabler, Inhibitor) and one dependent variable (Behavioral intention, BI). The questionnaires were thoroughly reviewed with the Qualtrics team prior to the launching of the pilot study. Two pilot studies of 30 participants each were performed to determine the "speed check" time limit. In the first pilot study, the speed check limit was set to 3.5 minutes. The results showed individuals that spent 3.5 minutes or less on the survey had lots of missing data and in most cases used straight lining. Between 3.5 minutes and 7 minutes, the straight lining decreased but there was still some missing data. In the second pilot study, the speed check time limit was set to 7.5 minutes and forced response option was enabled. This approach eliminated the missing data problem and substantially reduced the straight lining. It was also recommended by the Qualtrics team to keep the overall survey time to 15 minutes to ensure more participants finish the survey, especially those taking the survey on their cell phones. The average response time was 14.5 minutes which was acceptable according to the Qualtrics team. In both studies, the "Prevent Ballot-Box stuffing" option was enabled to avoid double entry. The IP addresses in the pilot studies were reviewed to ensure that the option worked efficiently. The official questionnaire was launched successfully after the pilot studies for a period of 2 weeks. It was specifically requested to collect responses for 150 male participants and 150 female participants. Over this period, Qualtrics was able to collect 313 responses from participants that did not own a 3D printer at home.

Data analysis

Within the 313 records collected, 155 were males and 158 were females. Also, out of these 313 records, 96 participants (54 male and 42 female) had heard about 3D printing prior to the survey but do not own a 3D printer at home. With respect to ethnicity, 195 classified themselves as white and the balance classified themselves in the non-white categories (Asian, Black, Hispanic, Other). The data were examined using the evaluation criteria outlined in Figure 10 and no evidence of missing data or outliers was found. However, there was evidence of straight lining in a few records leading to the elimination of 5 records from the 158 female records and 4 records from the 155 male records. The data distribution of the variables in the records was then evaluated per the requirements in Figure 10. It was found that Age was the only variable that had a slight skewness beyond the recommended limits. However, this was not surprising as it was also highlighted in previous studies by Hartmann and Vanpoucke (2017) and Halassi et al. (2018). The non-normality was not extreme to the point of invalidating he use of PLS-SEM. For the male sample, the median age was 34 years (minimum 18 years and maximum 65 years) while for the female sample the median age was 30 years (minimum 18 years and maximum 65 years). The average age for the entire sample was 33.8 years which was very close to average age of 33.6 in the German study (Hartmann & Vanpoucke, 2017). At the end of all the reviews, the final male sample size was 151 while the female sample size was 153. Both sample sizes were above the required minimum sample size of 150.

SMARTPLS Modeling

SmartPLS 3.3.3 (Ringle et al., 2015) was used to compute the path models. Model 1 was the UTAUT2 model with Age moderation (Figure 5). Shown in figure 14 is the path model on SmartPLS. The blue circles are the independent variables (PE,EE,SI,FC,HM,PV) , dependent variable (BI) and the moderator variable (Age). The yellow boxes are the indicator variables (measured variables) as outlined in appendix B. All the indicator variables are reflectively measured as demonstrated in Figure 11. The green circles are the two-way interaction terms due to the Age moderation (e.g. PE x AAGE also written as PE * AGE, etc.). For example, the interaction term PE*AGE moderates the path PE - > BI.

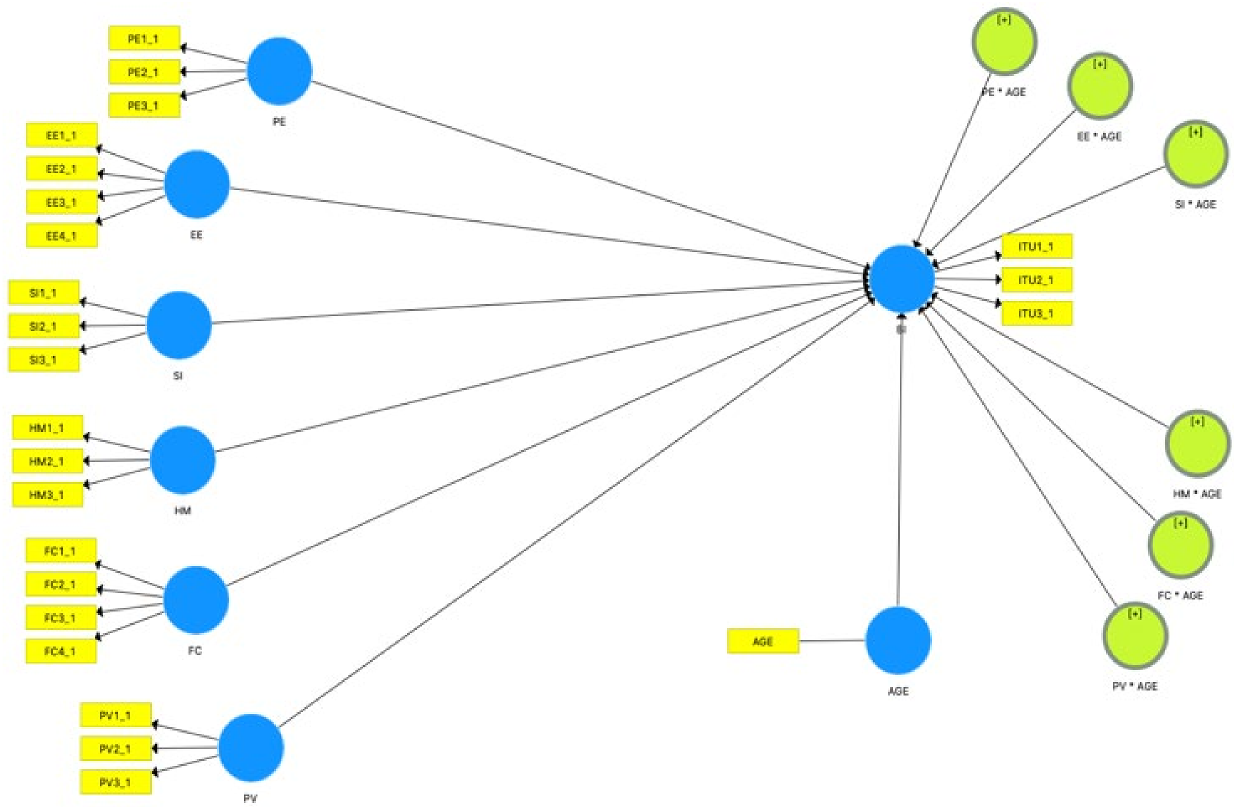

Figure 14. SMARTPLS path model – Model 1 (UTAUT2)

Model 2 is the proposed research model (Figure 9). Shown in Figure15 (Model 2-a) is the path model in SMARTPLS without any moderation. Model 2-a clearly shows the reflectively measured indicators and the higher order constructs (Enabler (EN) and Inhibitor (IN)). The higher order constructs are modeled as reflective-reflective measurements as previously demonstrated in Figure 11. In model 2-b (Figure 16), the higher order constructs (EN and IN) moderate the other relationships (PE->BI, EE->BI, etc.). The green circles are the two-interaction terms (i.e. PE *EN, PE* IN, EE*EN, EE*IN, etc.). For clarity purposes, all indicator variables are hidden and not shown in Figure 16. When Age is added as moderator to the Enabler and Inhibitor constructs, the three-way interaction terms are shown in Model 2-c (Figure 17). The dark green circles in Figure 17 are the three-way interaction terms (i.e. PE*EN*AGE, PE*IN*AGE, EE*EN*AGE, EE*IN*AGE, etc.) . Model 2-c is the final research model.

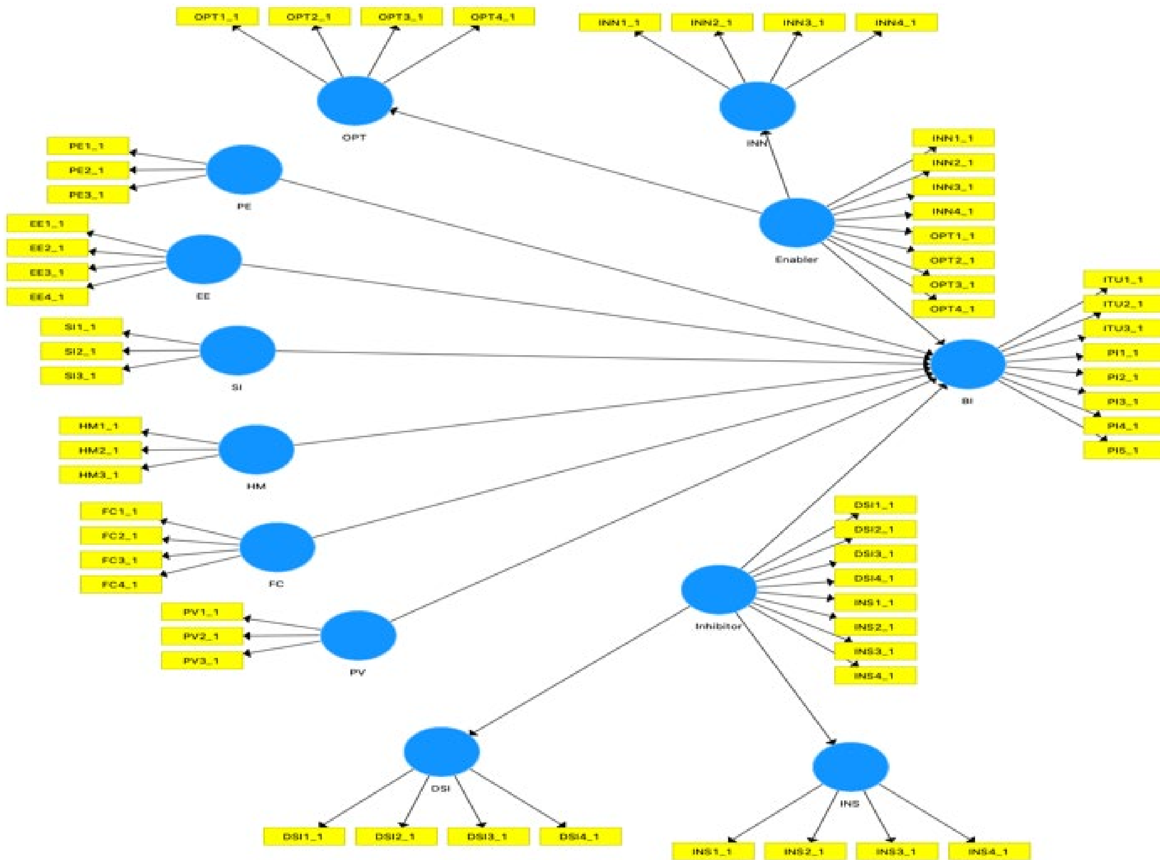

Figure 15. SMARTPLS path model - Model 2-a

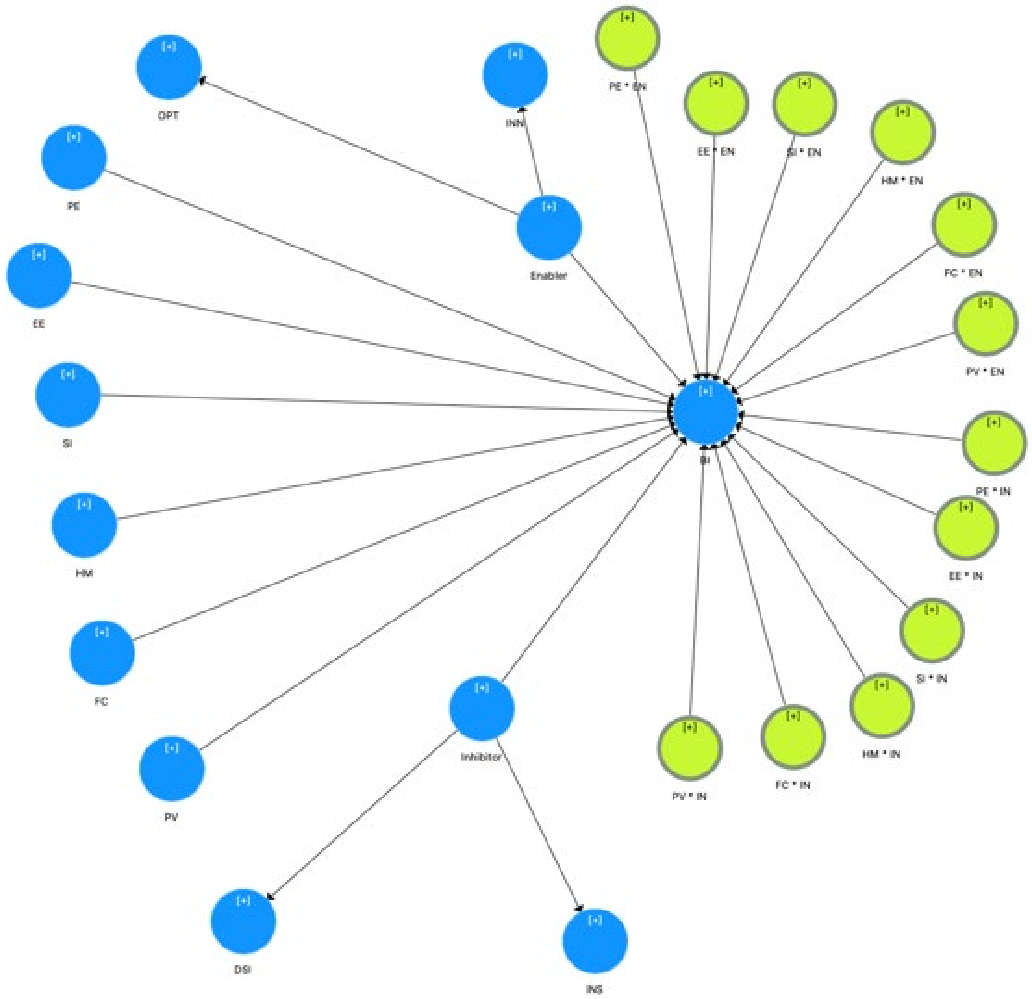

Figure 16. SMARTPLS path model - Model 2-b

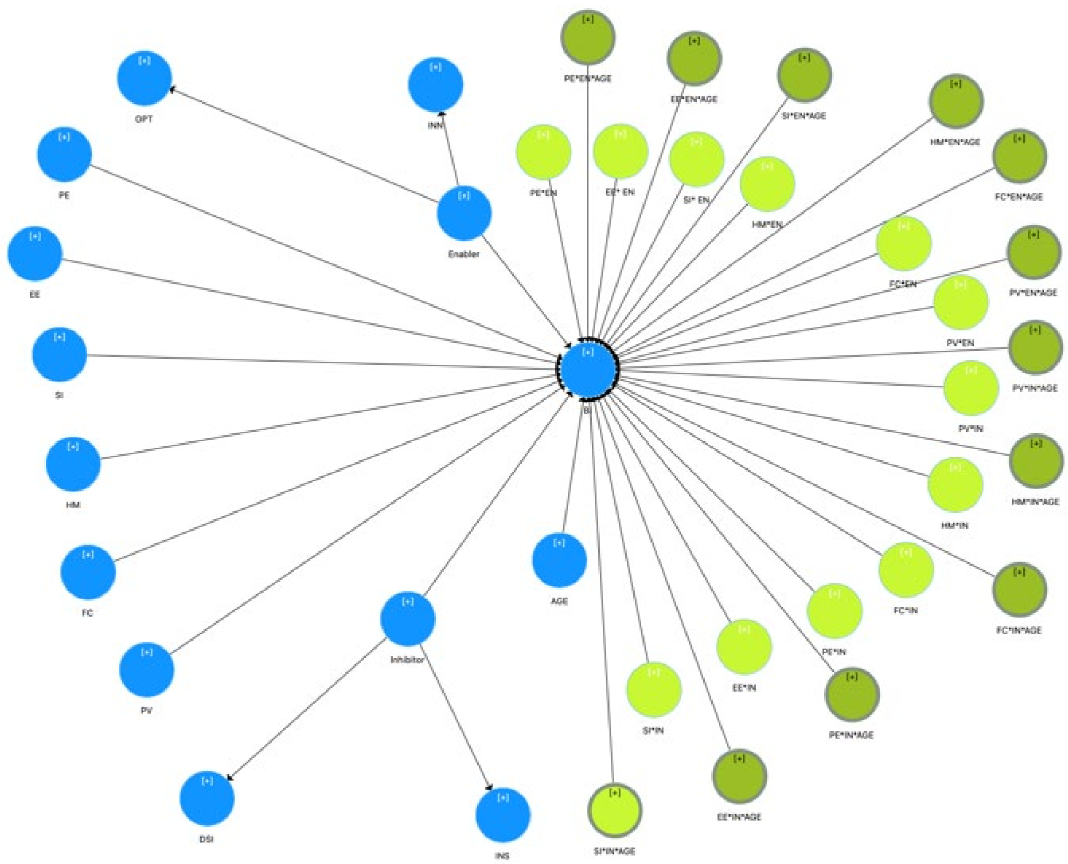

Figure 17. SMARTPLS path model – Model 2-c

Measurement model evaluation

Model 1 and Model 2-a were used to assess the reflective measurement models per the criteria outlines in figure 12. For both models the maximum number of iterations defined in SMARTPLS was 300 and the convergence criteria limit (Stop criteria) was given as 10^{-7}. These values were recommended by Hair et al. (2017). For Model 1, the standard path weighting scheme option was used for the PLS Algorithm. For Model 2-a, the factor weighting scheme was used per the recommendation of Hair et al. (2018b) when higher order constructs are included in the path model. Model 1 converged in 3 iterations for both the male and female data sets. Model 2-a converged in 7 iterations for both the male and female data sets. The models were evaluated separately for the male and female data sets. The reflective measurement model evaluations for Model 2-a are shown in Table 14 for the male data set and Table 15 for the female data set.

Table 14

Measurement Model Results : Model 2 (Male)

Latent Variable (Independent Variable)	Indicators	Convergent Validty			Internal Consistency Reliability		Discriminant Validity
		Loadings	Indicator Reliability	AVE	Composite Reliability	Cronbach's Alpha	
		> 0.70	>0.50	>0.5	0.60-0.90	0.60-0.90	HTMT confidence interval does not include 1
Performance expectancy (PE)	PE1	0.71	0.51	0.72	0.88	0.80	Yes
	PE2	0.90	0.80				
	PE3	0.92	0.84				
Effort expectancy (EE)	EE1	0.73	0.53	0.68	0.89	0.84	Yes
	EE2	0.79	0.63				
	EE3	0.89	0.79				
	EE4	0.88	0.77				
Social Influence (SI)	SI1	0.87	0.76	0.81	0.93	0.88	Yes
	SI2	0.92	0.85				
	SI3	0.90	0.80				
Hedonic Motivation (HM)	HM1	0.91	0.83	0.81	0.93	0.89	Yes
	HM2	0.92	0.85				
	HM3	0.87	0.76				
Facilitating Conditions (FC)	FC1	0.90	0.80	0.74	0.87	0.71	Yes
	FC2	0.90	0.80				
	FC3	0.89	0.79				
	FC4	0.87	0.76				
Price Value (PV)	PV1	0.89	0.79	0.81	0.93	0.89	Yes
	PV2	0.92	0.84				
	PV3	0.90	0.81				
Optimism	OPT1	0.85	0.72	0.75	0.92	0.89	Yes
	OPT2	0.88	0.77				
	OPT3	0.88	0.77				
	OPT4	0.86	0.74				
Innovativeness	INN1	0.81	0.65	0.70	0.90	0.86	Yes
	INN2	0.86	0.74				
	INN3	0.83	0.69				
	INN4	0.85	0.72				
Discomfort	DSI1	0.69	0.48	0.57	0.84	0.75	Yes
	DSI2	0.73	0.54				
	DSI3	0.80	0.64				
	DSI4	0.80	0.64				
Insecurity	INS1	0.80	0.65	0.63	0.87	0.80	Yes
	INS2	0.81	0.65				
	INS3	0.80	0.64				
	INS4	0.76	0.57				
Behvaioral Intention	ITU1	0.88	0.77	0.79	0.92	0.89	Yes
	ITU2	0.88	0.77				
	ITU3	0.92	0.85				
	PI1	0.90	0.80				
	PI2	0.89	0.80				
	PI4	0.85	0.73				
	PI5	0.87	0.75				

Table 15

Measurement Model Results : Model 2 (Female)

Latent Variable (Independent Variable)	Indicators	Convergent Validty			Internal Consistency Reliability		Discriminant Validity
		Loadings	Indicator Reliability	AVE	Composite Reliability	Cronbach's Alpha	
		> 0.70	>0.50	>0.5	0.60-0.90	0.60-0.90	HTMT confidence interval does not include 1
Performance expectancy (PE)	PE1	0.69	0.48	0.65	0.85	0.74	YES
	PE2	0.90	0.80				
	PE3	0.87	0.76				
Effort expectancy (EE)	EE1	0.76	0.58	0.66	0.89	0.83	YES
	EE2	0.76	0.58				
	EE3	0.86	0.74				
	EE4	0.86	0.74				
Social Influence (SI)	SI1	0.83	0.69	0.78	0.92	0.86	YES
	SI2	0.91	0.82				
	SI3	0.91	0.83				
Hedonic Motivation (HM)	HM1	0.83	0.69	0.80	0.92	0.87	YES
	HM2	0.92	0.85				
	HM3	0.93	0.86				
Facilitating Conditions (FC)	FC1	0.85	0.71	0.67	0.89	0.84	YES
	FC2	0.87	0.75				
	FC3	0.80	0.63				
	FC4	0.76	0.57				
Price Value (PV)	PV1	0.85	0.73	0.77	0.91	0.85	YES
	PV2	0.91	0.82				
	PV3	0.87	0.76				
Optimism	OPT1	0.81	0.65	0.67	0.89	0.83	YES
	OPT2	0.87	0.75				
	OPT3	0.79	0.62				
	OPT4	0.81	0.65				
Innovativeness	INN1	0.81	0.65	0.68	0.89	0.84	YES
	INN2	0.88	0.77				
	INN3	0.74	0.55				
	INN4	0.86	0.74				
Discomfort	DSI1	0.67	0.45	0.53	0.82	0.70	YES
	DSI2	0.72	0.51				
	DSI3	0.75	0.57				
	DSI4	0.77	0.59				
Insecurity	INS1	0.75	0.57	0.57	0.84	0.75	YES
	INS2	0.77	0.59				
	INS3	0.77	0.59				
	INS4	0.72	0.52				
Behavioral Intention	ITU1	0.89	0.80	0.77	0.94	0.90	YES
	ITU2	0.89	0.79				
	ITU3	0.90	0.82				
	PI1	0.86	0.74				
	PI2	0.89	0.80				
	PI4	0.86	0.74				
	PI5	0.85	0.73				

It is noticed that the indicator PI3 under Behavioral intention (BI) has been eliminated. In the first evaluation of Model 2-a, there was a strong collinearity between PI3 and ITU3 (Appendix B). PI3 was a measurement for the question “The likelihood that I would buy a 3D printer is high”. ITU3 was a measurement for the question “The probability is high the I plan to start using 3D printing in the future”. ITU3 could be perceived as having a 3D printer at home to start using it in the future. As such PI3 would be redundant especially that in the sequence of questionnaire, ITU3 came first. Such collinearity was not previously reported in the literature especially in works of Halassi et al. (2018) from which the proposed Behavioral intention measurement was adopted. Following the procedure outlined in Hair et al. (2017), the impact of deleting PI3 was evaluated. It was decided to retain ITU3 as it was used in the original UTAUT2 model. Removal of the PI3 indicator did not significantly impact the loading of the other indicators for Behavioral intention but the convergent validity was satisfied. In Table 15, there were two incidents (PE1 and DSI1) where the loadings were slightly lower than the set limits. The impact of the indicator deletion (i.e. PE1 and DSI1) on the internal consistency reliability was analyzed per the recommendations of Hair et al. (2017). The deletion of the indicators did not significantly increase the overall internal consistency reliability of PE and DSI above the set limits thus it was decided to keep the indicators per the recommendations of Hair et al. (2017). The results in Table 14 and Table 15 show that the Model2-a has met the convergent validity, internal consistency reliability and discriminant validity criteria. Similar results were obtained for Model 1 for both the male and female samples. There wasn’t a significant change in the loading factors for the common independent variables (PE,EE,SI,FC,HM,PV). Based on these findings, the structural model was evaluated next with a focus on the hypothesized relationships between the defined constructs.

Structural model evaluation

Model 2-c (Figure 17) has both the two-way interaction terms (shown in light green) and the three-way interaction terms (shown in dark green). As the three-way interaction terms are dependent on the two-way interaction terms, it was first necessary to determine the two-way interaction terms. This is where Model 2-b is of importance. Through Model 2-b, the two-way interaction terms were calculated. Model 2-b was evaluated separately for the male and female data sets. For both models the maximum number of iterations defined in SMARTPLS was 300 and the convergence criteria limit (Stop criteria) was given as 10^{-7}. There was no impact on the measurement results discussed earlier. Convergence occurred in less than 10 iterations. The moderation analysis was done using a two-step calculation method (Hensler & Fassot, 2010; Hair et al., 2017; Becker et al., 2018). A factor weight scheme option for the PLS algorithm was selected because of the higher order constructs. The result showed that there were no collinearity concerns between the constructs (Table 16). The results of the two-way interaction terms for the male and female models were exported in non-standardized format to be added to the original male and female data sets. The updated data sets are then imported to generate Model 2-c. This technique has been discussed in the works of Hensler and Fassot (2010) and Becker et al. (2018).

Table 16
Collinearity Assessment of key constructs

Constuct	Model 2 (Male) VIF	Model 2 (Female) VIF
PE -> BI	2.78	2.39
EE -> BI	2.55	2.86
SI -> BI	2.19	1.87
HM -> BI	2.28	1.94
FC -> BI	3.04	2.65
PV -> BI	2.81	2.55
EN -. BI	2.47	2.63
IN -> BI	2.38	2.44

Model 2-c was then analyzed using the factor weight scheme option for the PLS algorithm with a maximum of 300 iterations and a Stop criteria of 10^{-7} . The model converged in less than 10 iterations for the male and female data sets. Initially the moderation analysis was done using the two-step calculation method as previously used in Model 2-b. The SmartPLS output for the male data set is shown in Figure 18 and the output for the female data set in Figure 19. Both the male and female models had a Stone-Geisser Q^2 value greater than zero indicating high predictive relevance for the intention to use 3D printing for home fabrication. The numerical output is tabulated in Table 17 for the male data set and Table 18 for the female data set under “Simple effect + interaction”. It should be noted that in SmartPLS, the simple effect represents the relationship between the independent variable and dependent variable when the moderator variable is equal to its mean value (as the data is standardized) especially when the two-step calculation method is used. Thus, to calculate the main effects (i.e. effects when the moderator is not present) it was necessary to change the moderation calculation method to the orthogonal method.

Table 17

Structural model results : Model 2 (Male).

Stone-Geisser Q^2 : 0.665

Main Effect	Path Coefficients	p Values	95% Confidence interval	Significance (p <0.05) ?
PE -> BI	0.298	0.001	[0.129,0.473]	YES
EE -> BI	0.116	0.075	[-0.024,0.35]	NO
SI -> BI	0.288	0.030	[0.123,0.506]	YES
HM -> BI	0.12	0.068	[-0.029,0.331]	NO
FC -> BI	0.229	0.012	[0.20,0.507]	YES
PV -> BI	-0.005	0.326	[-0.158,0.173]	NO
EN -> BI	0.303	0.003	[0.160,0.438]	YES
IN - > BI	-0.109	0.071	[-0.146,0.043]	NO
Simple Effect + Interaction	Path Coefficients	p Values	95% Confidence interval	Significance (p <0.05) ?
PE -> BI	0.126	0.035	[0.020,0.288]	YES
EE -> BI	0.074	0.377	[-0.10,0.132]	NO
SI -> BI	0.135	0.028	[0.072,0.385]	YES
HM -> BI	0.098	0.172	[-0.018,0.314]	NO
FC -> BI	0.112	0.031	[0.070,0.378]	YES
PV -> BI	0.03	0.6	[-0.035,0.057]	NO
EN -> BI	0.121	0.037	[0.107,0.332]	YES
IN - > BI	-0.093	0.205	[-0.131,0.041]	NO
Age - > BI	0.014	0.48	[-0.050,0.082]	NO
PE * EN - > BI	0.131	0.031	[0.065,0.335]	YES
EE * EN - > BI	0.093	0.443	[-0.089,0.120]	NO
SI * EN - > BI	0.143	0.029	[0.070,0.450]	YES
HM * EN - > BI	0.095	0.26	[-0.024,0.245]	NO
FC * EN -> BI	0.124	0.039	[0.107,0.356]	YES
PV * EN -> BI	-0.035	0.304	[-0.251,0.129]	NO
PE * IN - > BI	-0.057	0.209	[-0.110,0.095]	NO
EE * IN -> BI	-0.073	0.533	[-0.119.0.100]	NO
SI * IN - > BI	-0.108	0.079	[-0.219,0.077]	NO
HM * IN - > BI	-0.016	0.31	[-0.044,0.135]	NO
FC * IN - > BI	-0.103	0.065	[-0.212.0.016]	NO
PV * IN - > BI	0.014	0.54	[-0.021,0.120]	NO
PE*EN*AGE ->BI	-0.219	0.029	[-0.417,-0.077]	YES
EE * EN * AGE- > BI	0.027	0.306	[-0.089,0.102]	NO
SI * EN *AGE- > BI	-0.121	0.031	[-0.258,-0.054]	YES
HM * EN*AGE - > BI	0.035	0.54	[-0.027,0.105]	NO
FC * EN *AGE-> BI	-0.113	0.043	[-0.31,-0.046]	YES
PV * EN *AGE-> BI	0.043	0.431	[-0.029,0.105]	NO
PE * IN*AGE - > BI	0.069	0.291	[-0.077,0.119]	NO
EE * IN*AGE -> BI	0.087	0.317	[-0.083,0.113]	NO
SI * IN *AGE- > BI	0.11	0.076	[-0.045,0.208]	NO
HM * IN *AGE- > BI	-0.025	0.26	[-0.125, 0.054]	NO
FC * IN *AGE- > BI	0.109	0.323	[-0.043,0.120]	NO
PV * IN *AGE- > BI	-0.018	0.267	[-0.095,0.019]	NO

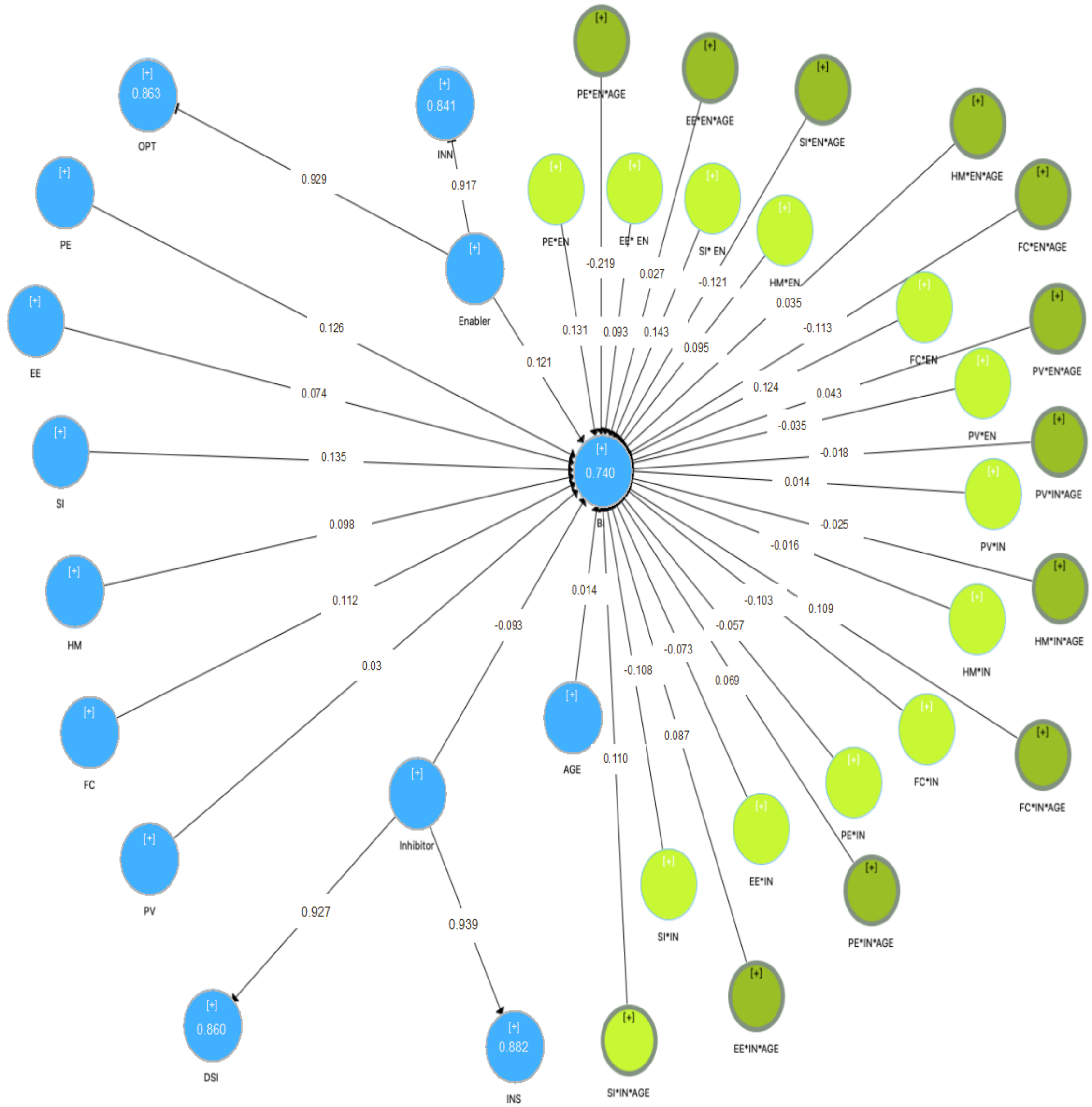

Figure 18. Model 2-c (male) – Simple effect and interaction terms

Table 18

Structural model results : Model 2 (Female).

Stone-Geisser Q^2 : 0.616

Main Effect	Path Coefficients	p Values	95% Confidence interval	Significance (p <0.05) ?
PE -> BI	0.125	0.068	[-0.070,0.220]	NO
EE -> BI	0.274	0.035	[0.150,0.525]	YES
SI -> BI	0.3	0.029	[0.119,0.433]	YES
HM -> BI	0.223	0.042	[0.085,0.437]	YES
FC -> BI	0.389	0.001	[0.148,0.623]	YES
PV -> BI	-0.104	0.073	[-0.158,0.173]	NO
EN -> BI	0.141	0.033	[0.060,0.338]	YES
IN - > BI	-0.263	0.007	[-0.436,-0.043]	YES
Simple Effect + Interaction	Path Coefficients	p Values	95% Confidence interval	Significance (p <0.05) ?
PE -> BI	0.098	0.342	[-0.020,0.138]	NO
EE -> BI	0.133	0.041	[0.065,0.332]	YES
SI -> BI	0.125	0.028	[0.072,0.325]	YES
HM -> BI	0.102	0.073	[-0.018,0.304]	NO
FC -> BI	0.129	0.031	[0.070,0.328]	YES
PV -> BI	0.037	0.46	[-0.035,0.09]	NO
EN -> BI	0.109	0.058	[0.057,0.335]	YES
IN - > BI	-0.139	0.034	[-0.337,-0.023]	YES
Age - > BI	0.025	0.53	[-0.059,0.067]	NO
PE * EN - > BI	0.028	0.341	[-0.036,0.102]	NO
EE * EN - > BI	0.143	0.026	[0.077,0.322]	YES
SI * EN - > BI	0.119	0.021	[0.060,0.320]	YES
HM * EN - > BI	0.117	0.044	[0.044,0.317]	YES
FC * EN -> BI	0.139	0.041	[0.101,0.361]	YES
PV * EN -> BI	0.106	0.063	[-0.067,0.229]	NO
PE * IN - > BI	-0.127	0.033	[0.055,0.315]	YES
EE * IN -> BI	-0.157	0.036	[-0.317.-0.078]	YES
SI * IN - > BI	-0.163	0.001	[-0.319,-0.067]	YES
HM * IN - > BI	-0.025	0.43	[-0.095,0.049]	NO
FC * IN - > BI	-0.13	0.029	[-0.232.-0.020]	YES
PV * IN - > BI	-0.102	0.061	[-0.212,0.017]	NO
PE*EN*AGE ->BI	-0.093	0.313	[-0.117,0.077]	NO
EE * EN * AGE- > BI	-0.144	0.031	[-0.280,-0.089]	YES
SI * EN *AGE- > BI	-0.216	0.039	[-0.391,-0.073]	YES
HM * EN*AGE - > BI	-0.12	0.029	[-0.220,-0.065]	YES
FC * EN *AGE-> BI	-0.243	0.042	[-0.387,-0.043]	YES
PV * EN *AGE-> BI	0.067	0.315	[-0.031,0.119]	NO
PE * IN*AGE - > BI	0.171	0.038	[-0.029,0.331]	YES
EE * IN*AGE -> BI	0.203	0.029	[0.097,0.373]	YES
SI * IN *AGE- > BI	0.218	0.031	[-0.065,0.387]	YES
HM * IN *AGE- > BI	-0.097	0.178	[-0.119,0.03]	NO
FC * IN *AGE- > BI	0.213	0.037	[-0.041,0.310]	YES
PV * IN *AGE- > BI	0.108	0.045	[-0.067,0.235]	YES

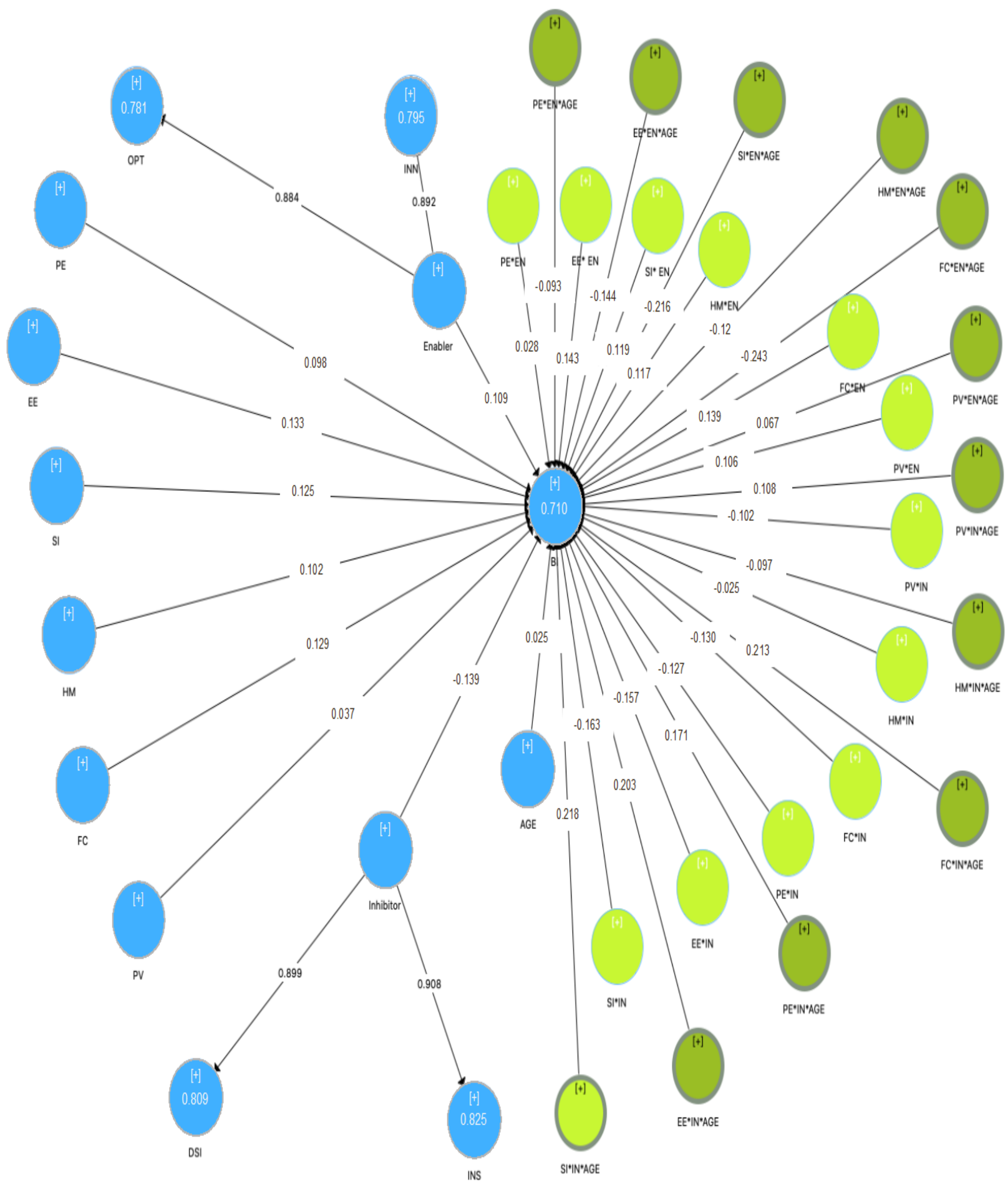

Figure 19. Model 2-c (female) – Simple effect and interaction terms

The details of the orthogonal method are discussed in details in Hair et al. (2017) and Hair et al. (2018b). Using Model 2-c, it is easy to switch between the two-step method and the orthogonal method. The main effect results are also given in Table 17 and Table 18 under the “Main effect” title. To calculate the significance of the path coefficients (at the 5% level), it was necessary to run a bootstrap analysis with 5000 subsamples. The p-values and the confidence interval are also given in Table 17 and Table 18. Once again, both the two-step method and orthogonal method had to be used for the bootstrap analysis.

Thus far, the structural model evaluation showed there is no collinearity concerns (Table 16). A comparison of the R^2 values for Model 1 and Model 2-c is shown in Table 19. From the adjusted R^2 values, it can be concluded that the proposed research model has a higher predictive power compared to the original UTAUT2 model. Based on the criterion shown in Figure 13, the R^2 values for the male and female models are between moderate and substantial. The effect sizes f^2 and q^2 (refer to Figure 13) for the key constructs used in the hypotheses are given in Table 20. From these results the predictive relevance for Model 2-c is of between medium and high predictive relevance. The evaluation of the hypotheses required multigroup analysis and that is discussed next.

Table 19
Explained Variance in Behavioral intention

	Model 1		Model 2	
	male	female	male	female
R^2	0.65	0.63	0.74	0.71
Adjusted R^2	0.63	0.61	0.72	0.69

Table 20
Effect sizes of key structural paths

Constuct	Model 2 (Male) : effect size f^2	Model 2 (Female) : effect size f^2	Model 2 (Male) : effect size q^2	Model 2 (Female) : effect size q^2
PE -> BI	0.229	0.023	0.213	0.011
EE -> BI	0.027	0.145	0.011	0.119
SI -> BI	0.161	0.157	0.133	0.126
HM -> BI	0.034	0.109	0.015	0.078
FC -> BI	0.152	0.211	0.121	0.201
PV - > BI	< 0.02	< 0.02	< 0.02	<0.02
EN -> BI	0.131	0.087	0.119	0.063
IN -> BI	0.079	0.139	0.056	0.121
AGE -> BI	0.06	0.08	0.013	0.017

Evaluation of research hypotheses

Prior to performing multigroup analysis to investigate the differences between the male and female samples, it was necessary to establish measurement invariance via configurational and compositional invariance. Configurational and compositional invariance were established following the procedure outlined in Hair et al. (2018b). Configurational invariance was established by ensuring the male and female models had identical indicators for all constructs, there was identical data treatment and identical algorithm settings were used. The compositional invariance was established using a five-step approach clearly outlined in Hair et al. (2018b). The final outcome showed that compositional invariance was established.

Given that measurement invariance was established, it was possible to proceed to the multigroup analysis. The male dataset was defined as group 1 and the female dataset was defined as group 2. The path coefficients for group 1 and group 2 may be different but the question is how large the difference is and how meaningful the difference is. The multigroup analysis in SmartPLS tests the null hypothesis (H_0) that the path coefficients between the male and female groups are not significantly different. Technically, this approach allows for testing only one-sided hypotheses such that the path coefficients for group 1 (males), $p^{(1)}$, are larger than the path coefficients for group 2 (females), $p^{(2)}$ .The resulting p value will indicate whether the path coefficient is significantly larger in the first group (male) than the second group (female) . The multigroup analysis in SmartPLS uses the bootstrapping algorithm. For the analysis, 5000 subsamples were used. The factor weighting scheme was selected for the PLS algorithm. The results for the key constructs and interaction terms needed for the evaluation are given in Table 21.

Table 21

Multigroup analysis using Model 2-c. Group 1 (male) and Group 2 (female)

Hypothesis	Construct / interaction term	Difference (Group 1 - Group 2)	p- value	1- p	Significant (p<0.05)?	Hypothesis Supported
H1 (a)	PE	0.170	0.029	0.971	YES	YES
H1 (b)	PE* EN* AGE	-0.125	0.031	0.969	YES	YES
H1 (c)	PE* IN* AGE	-0.104	0.961	0.039	NO	YES
H2 (a)	EE	-0.153	0.965	0.035	NO	YES
H2 (b)	EE* EN* AGE	0.115	0.963	0.037	NO	YES
H2 (c)	EE* IN* AGE	-0.117	0.973	0.027	NO	YES
H3 (a)	SI	-0.011	0.481	0.519	NO	NO
H3 (b)	SI* EN* AGE	0.103	0.959	0.041	NO	YES
H3 (c)	SI* IN* AGE	-0.107	0.962	0.038	NO	YES
H4 (a)	FC	-0.159	0.955	0.045	NO	YES
H4 (b)	FC* EN* AGE	0.130	0.962	0.038	N0	YES
H4 (c)	FC* IN* AGE	-0.105	0.969	0.031	NO	YES
H5 (a)	HM	-0.103	0.960	0.040	NO	NO
H5 (b)	HM* EN* AGE	0.153	0.974	0.026	NO	NO
H5 (c)	HM* IN* AGE	0.074	0.437	0.563	NO	NO
H6 (a)	PV* EN* AGE	-0.021	0.561	0.439	NO	NO
H6 (b)	PV* IN* AGE	-0.128	0.967	0.033	NO	YES

H1(a): *PE is positively related to the intention to adopt 3D printing for home fabrication such that the effect is stronger for men*

Referring to Table 17 and Table 18, the path coefficient PE -> BI (main effect) is significant at the 1% level for the male group compared to the 10% level for the female group. The difference in the path coefficients between the male group (group 1) and female group (group 2) is significant at the 5% level, as indicated in Table 21, with the effect being stronger for the male group. Thus, the hypothesis is supported.

H1(b): *Enablers will positively moderate the effect of PE on BI such that the effect will be stronger for men particularly young men.*

Referring to Table 17 and Table 18, the two-way interaction term PE*EN positively moderates PE-> BI for the male group at the 5% significant level. It is statistically non-significant for the female group. The three-way interaction term, PE*EN*AGE negatively moderates PE*EN -> BI for the male group at the 5% significant level. It is statistically non-significant for the female group. The negative moderation of PE*EN*AGE indicates that the positive moderation effect of PE*EN decreases as Age increases. Referring to Table 21, PE*EN*AGE is more significant for the male group thus leading to the conclusion that the hypothesis is supported.

H1(c): *Inhibitors will negatively moderate the effect of PE on BI such that the effect will be stronger for women particularly old women.*

Referring to Table 17 and Table 18, interaction terms PE*IN and PE*IN*AGE are insignificant for the male group. For the female group PE*IN negatively moderate PE -> BI at the 5% significant level. The interaction term PE*IN*AGE positively moderates PE*IN ->BI at the 5% significant level thus indicating the negative moderating effect of PE*IN increases with AGE. Referring to Table 21, PE*IN*AGE is more significant for the female group thus leading to the conclusion that the hypothesis is supported.

H2(a): *EE is positively related to the intention to adopt 3D printing for home fabrication such that the effect is stronger for women*

Referring to Table 17 and Table 18, the path coefficient EE -> BI (main effect) is significant for the female group at the 5% level at 10% for the male group. The difference in the path coefficients between the male group (group 1) and female group (group 2) is statistically non-significant at the 5% level, as indicated in Table 21, with the effect being stronger for the female group. Thus, the hypothesis is supported.

H2(b): *Enablers will positively moderate the effect of EE on BI such that the effect will be stronger for women particularly young women.*

Referring to Table 17 and Table 18, the two-way interaction term EE*EN positively moderates EE-> BI for the female group at the 5% significant level. It is statistically non-significant for the male group. The three-way interaction term, EE*EN*AGE negatively moderates EE*EN -> BI for the female group at the 5% significant level. It is statistically non-significant for the male group. The negative moderation of EE*EN*AGE indicates that the positive moderation effect of

EE*EN decreases as Age increases. Referring to Table 21, EE*EN*AGE is more significant for the female group thus leading to the conclusion that the hypothesis is supported.

H2(c): *Inhibitors will negatively moderate the effect of EE on BI such that the effect will be stronger for women particularly old women.*

Referring to Table 17 and Table 18, the two-way interaction term EE*IN negatively moderates EE-> BI for the female group at the 5% significant level. It is statistically non-significant for the male group. The three-way interaction term, EE*IN*AGE positively moderates EE*EN -> BI for the female group at the 5% significant level. It is statistically non-significant for the male group. The positive moderation of EE*EN*AGE indicates that the negative moderation effect of EE*EN increases as Age increases. Referring to Table 21, EE*EN*AGE is more significant for the female group thus leading to the conclusion that the hypothesis is supported.

H3(a): *SI is positively related to the intention to adopt 3D printing for home fabrication such that the effect is stronger for women*

Referring to Table 17 and Table 18, the path coefficient SI -> BI (main effect) is significant for the female group and male group at the 5% level. The difference in the path coefficients between the male group (group 1) and female group (group 2) is not significant at the 5% level as indicated in Table 21. Thus, the hypothesis is not supported.

H3(b): *Enablers will positively moderate the effect of SI on BI such that the effect will be stronger for women particularly young women.*

Referring to Table 17 and Table 18, the two-way interaction term SI*EN positively moderates SI-> BI for the female group and male group at the 5% significant level. The three-way interaction term, SI*EN*AGE negatively moderates SI*EN -> BI for the female group and male group at the 5% significant level. The negative moderation of SI*EN*AGE indicates that the positive moderation effect of SI*EN decreases as Age increases. Referring to Table 21, SI*EN*AGE is more significant for the female group thus leading to the conclusion that the hypothesis is supported.

H3(c): *Inhibitors will negatively moderate the effect of SI on BI such that the effect will be stronger for women particularly old women.*

Referring to Table 17 and Table 18, the two-way interaction term SI*IN negatively moderates SI-> BI for the female group at the 1% significant level and at the 10 % level for the male group. The three-way interaction term, SI*IN*AGE positively moderates SI*IN -> BI for the female group at the 5% significant level and at the 10% level for the male group. The positive moderation of SI*IN*AGE indicates that the negative moderation effect of SI*EN increases as Age increases. Referring to Table 21, SI*IN*AGE is more significant for the female group thus leading to the conclusion that the hypothesis is supported.

H4(a): *FC is positively related to the intention to adopt 3D printing for home fabrication such that the effect is stronger for women*

Referring to Table 17 and Table 18, the path coefficient FC -> BI (main effect) is significant for the female group at the 1% level and for the male group at the 5% level. The difference in the path coefficients between the male group (group 1) and female group (group 2) is not significant at the 5% level, as indicated in Table 21, with the effect being stronger for the female group. Thus, the hypothesis is supported.

H4(b): *Enablers will positively moderate the effect of FC on BI such that the effect will be stronger for women particularly young women.*

Referring to Table 17 and Table 18, the two-way interaction term FC*EN positively moderates FC-> BI for the female group and male group at the 5% significant level. The three-way interaction term, FC*EN*AGE negatively moderates SI*EN -> BI for the female group and male group at the 5% significant level. The negative moderation of SI*EN*AGE indicates that the positive moderation effect of SI*EN decreases as Age increases. Referring to Table 21, SI*EN*AGE is more significant for the female group thus leading to the conclusion that the hypothesis is supported.

H4(c): *Inhibitors will negatively moderate the effect of FC on BI such that the effect will be stronger for women particularly older women.*

Referring to Table 17 and Table 18, the two-way interaction term FC*IN negatively moderates FC-> BI for the female group at the 5% significant level and at the 10 % level for the male group. The three-way interaction term, FC*IN*AGE positively moderates SI*IN -> BI for the female group at the 5% significant level. It is statistically non-significant for the male group. The positive moderation of FI*IN*AGE indicates that the negative moderation effect of FC*IN increases as AGE increases. Referring to Table 21, FC*IN*AGE is more significant for the female group thus leading to the conclusion that the hypothesis is supported.

H5(a): *HM is positively related to the intention to adopt 3D printing for home fabrication such that the effect is stronger for men*

Referring to Table 17 and Table 18, the path coefficient HM -> BI (main effect) is significant for the female group at the 5% level and for the male group at the 10 % level. The difference in the path coefficients between the male group (group 1) and female group (group 2) is not significant at the 5% level as indicated in Table 21. Thus, the hypothesis is not supported.

H5(b): *Enablers will positively moderate the effect of HM on BI such that the effect will be stronger for men particularly younger men.*

Referring to Table 17 and Table 18, the two-way interaction term HM*EN positively moderates HM-> BI for the female group at the 5% significant level. It is statistically non-significant for the male group. The three-way interaction term, HM*EN*AGE negatively moderates HM*EN -> BI for the female group at the 5% significant level. It is statistically non-significant for the male group. The negative moderation of HM*EN*AGE indicates that the positive moderation effect of HM*EN decreases as Age increases. Referring to Table 21, HM*EN*AGE is more significant for the female group thus leading to the conclusion that the hypothesis is not supported.

H5(c) :*Inhibitors will negatively moderate the effect of HM on BI such that the effect will be stronger for women particularly older women.*

Referring to Table 17 and Table 18, the two-way interaction term HM*IN negatively moderates HM ->BI and is statistically non-significant for the male group and female group. The three-way interaction term, HM*IN*AGE is statistically non-significant for the male group and for the female group. Referring to Table 21, HM*IN*AGE is not significant for the male group or female group thus leading to the conclusion that the hypothesis is not supported.

H6(a): *Enablers will positively moderate the effect of PV on BI such that the effect will be stronger for women particularly younger women.*

Referring to Table 17 and Table 18, the two-way interaction term PV*EN positively moderates PV-> BI for the female group at the 10% significant level. It is statistically non-significant for the male group. The three-way interaction term, PV*EN*AGE is statistically non-significant for the male group and female group. Referring to Table 21, PV*EN*AGE is not more significant for the female group thus leading to the conclusion that the hypothesis is not supported.

H6(b): *Inhibitors will negatively moderate the effect of PV on BI such that the effect will be stronger for women particularly old women.*

Referring to Table 17 and Table 18, the two-way interaction term PV*IN negatively moderates PV-> BI for the female group at the 10% significant level. It is i statistically non-significant for the male group. The three-way interaction term, PV*IN*AGE is statistically non-significant for the male group and significant for the female group at the 5% level. The positive moderation of PV*IN*AGE indicates that the negative moderation effect of PV*IN increases as

Age increases. Referring to Table 21,   PV *IN*AGE is significant for the female group thus leading to the conclusion that the hypothesis is supported.

Summary

The evaluation of the measurement models and the structural models for Model 1 (original UTAUT2 model) and Model 2 (proposed research model) were discussed in this chapter. Following the structured procedures outlined in Hair et al. (2017) and Hair el al. (2018b), it was shown that the measurement models and the structural models passed the evaluation criteria. The next step was to evaluate the significance of the path coefficients. For the male dataset, the evaluation of the main effects in Model 2-c showed that Performance expectancy (PE) and Enabler (EN) were significant at the 1% level. Social influence (SI) and Facilitating conditions (FC) follow at the 5% significant level. Hedonic motivation (HM), Effort expectancy (EE) and Inhibitor (IN) were significant at the 10% level. For the female dataset, the evaluation of the main effect in Model 2-c showed that Facilitating conditions (FC) and Inhibitor (IN) are significant at the 1% level. Social influence (SI), Effort Expectancy (EE), Hedonic Motivation (HM) and Enabler (EN) were significant at the 5% level. Price value was not significant for both groups. A multigroup analysis was preformed to determine any significance in the path coefficient differences. Out of the initially 17 proposed hypotheses, 12 hypotheses were supported by the multigroup analysis.

CHAPTER 5 – CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH

Conclusions

The focus of this research was on the acceptance of 3D printing for home fabrication in US households. Unlike the previous research models in the literature that used DIY as a moderator in the UTAUT2 model to study the acceptance of 3D printing for home fabrication, the proposed research model used the Technology readiness constructs (Enablers and Inhibitors) as moderators in the UTAUT2 model. The final results showed that there was an improvement in the predictive power of the proposed research model compared to the original UTAUT2 model and the previous research models that used DIY as a moderator. For the female sample, the predictive power of the proposed research model was at 69 % compared to 61 % for the original UTAUT2 model which only had Age as the moderator. Similarly, for the male group, the predictive power of the proposed research model was at 72% compared to 63% for the original UTAUT2 model which only had Age as moderator. The results of this research are an addition to the theoretical literature focused on the improvement of the predictive power of the UTAUT model by adding the Technology readiness concept as a moderator. From the academic perspective, this research adds to the understanding of the behavior of the potential "economic" prosumers. Previous studies in the literature on the acceptance of 3D printing for home fabrication, have primarily focused on Europe and Asia whereas this study primarily focused on the USA, thus applying it to a different market than previously studied.

Statistical analysis of the survey data led to the conclusion that that out of the 17 proposed hypotheses, 12 hypotheses were supported. Performance expectancy (PE) was the lead key predictor for the male sample, with an effect size of 0.229 (Table 20.), at the 1% significance level compared to an effect size of 0.023 for the female sample at the 10% significance level. Per Figure. 13, an effect size of 0.229 is considered as greater than medium effect while an effect size of 0.023 is considered small. Facilitating conditions (FC) was the lead key predictor for the female sample, with an effect size of 0.211, at the 1% significance level. That is compared to an effect size 0.152 for the male sample at the 5% significance level. Social influence (SI) was significant at the 5% level for both the male and female samples with comparable effect sizes of 0.161 and 0.157 respectively. Effort expectancy (EE) was of significance at the 5% level for the female sample with an effect size of 0.145 (Table 20.). Hedonic motivation (HM) turned out to be of more significance to the female sample than the male sample. The effect size at the 5% significance level for the female sample was 0.109 compared to an effect size 0.034 at the 10% significance level for the male sample. Price value (PV) had no main effect for both the male and female samples.

In addition, the results showed that the Enabler construct was of significance to male sample at the 1% level with an effect size of 0.131 and at the 5% level for female sample with an effect size of 0.087. In contrast, the Inhibitor construct was of significance at the 1% level for the female sample with an effect size of 0.139 and at the 10% level for the male sample with an effect size of 0.079. Including the Technology readiness constructs (Enabler and Inhibitor) as moderators in the UTAUT2 model boosted the predictive power of the model. The two-way interaction terms (i.e. PE*EN, PE*IN, EE*EN, EN*IN, etc.) and the three-way interaction terms (i.e. PE*EN*AGE, PE*IN*AGE, EE*EN*AGE, EN*IN*AGE) were of key importance in testing the proposed hypotheses and played a key role in boosting the predictive power of the research model. Thus establishing the importance of Enablers and Inhibitors constructs as moderators in the UTAUT2 model. In doing so, the study adds to the embryonic theoretical literature that focuses on combining the UTAUT2 model and the Technology readiness concept.

From the practical perspective, as pointed out in a report by Kearney management consulting (2017), understanding the adoption behavior of 3D printing (3DP) users is the key to driving the 3D Ecosystem (Figure.20). In the same report, it was also pointed out that the solid understanding of the adoption behavior will open opportunities for global job distribution in support of local manufacturing (Figure 21) in some countries such as the USA. Thus, the results of this study will serve to inform the industry on the adoption behavior of new male and female 3DP users in the USA. While the current study was primarily focused on home 3DP users, one should recall that the Technology readiness constructs (Enablers and Inhibitors) do not differentiate between home and industrial settings (as discussed in Chapter 2.), thereby, extending the results of the study to the industry. In another report, Buckholt et al. (2019) discuss the global distribution of online 3D printing demand (Figure. 22).

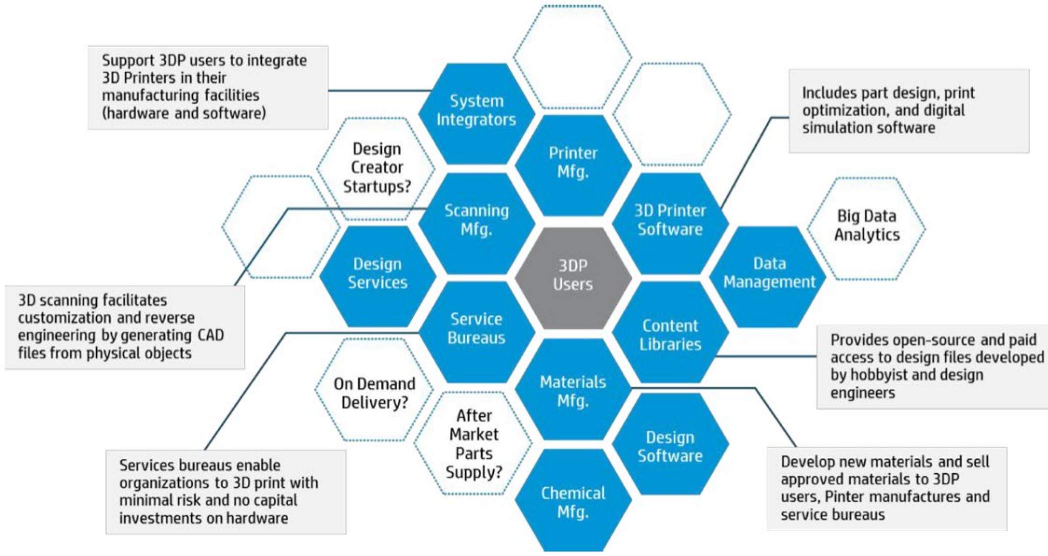

Figure 20. 3D Ecosystem (adopted from Kearney management consulting, 2017)

Figure 21. Global job distribution due to 3D printing (adopted from Kearney, 2017)

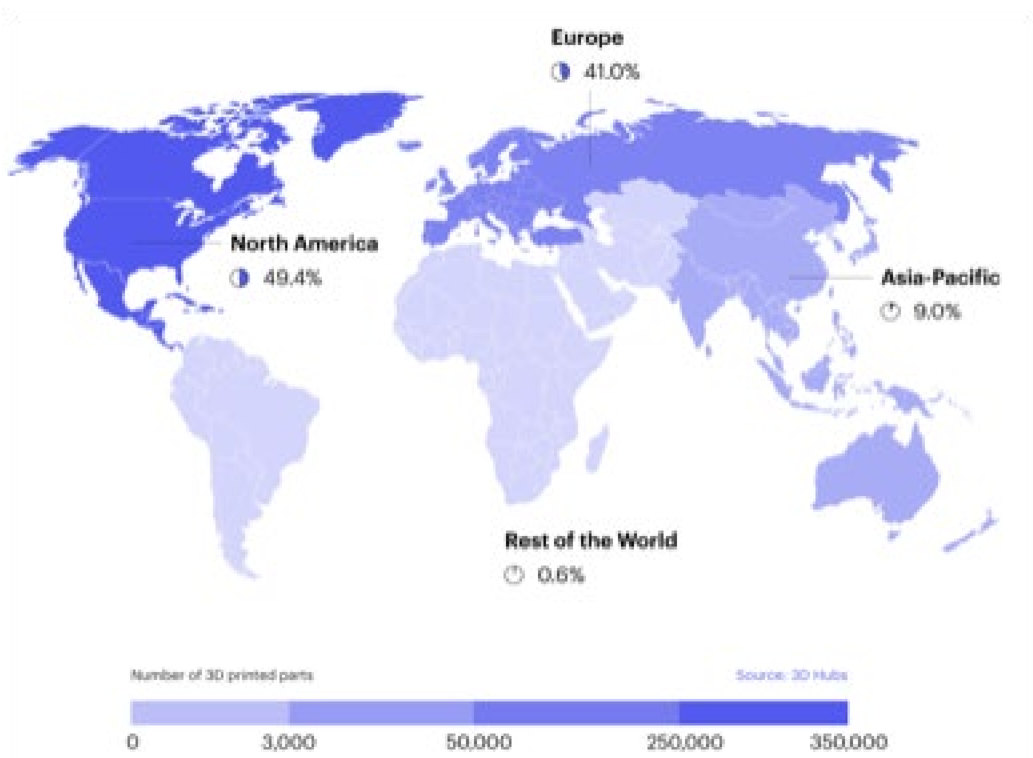

Figure 22. Global distribution of online 3D printing demand (adopted from Buckholt et al., 2019)

As seen in Figure. 22, North America (including the USA) is a big contributor to the online 3D printing demand. The online 3D printing demand provides a great opportunity for the economic prosumer. The results of this study will also contribute to the techno-marketing of 3D printers in USA households to keep the momentum of online 3D printing demand. In general, the techno-marketing domain addresses the fact that the marketplace is simply not a continuum but rather complex in nature. The techno-marketing domain recognizes the unique prosumer behavior with respect to cutting edge technologies and applies this knowledge in the marketing of innovative technologies (Colby,2002). With the appropriate techno-marking strategy in the USA, more users will adopt 3D printing for home fabrication and increase the contribution to online 3D printing demand.

As previously discussed in Chapter 2, the Technology readiness concept has four dimensions (refer to Table 4.) which define five market segments (refer to Table 5). As

Colby (2002) elaborates, each market segment should be viewed as a " wave " of new customers that will enter the market at their respective time. With that perspective, marketers can achieve better market penetration by focusing on the Enablers and Inhibitors of each segment. Using the same approach outlined in Tsikriktsis (2004), it was possible to extract the market segments from the raw survey data as shown in Figure 23.

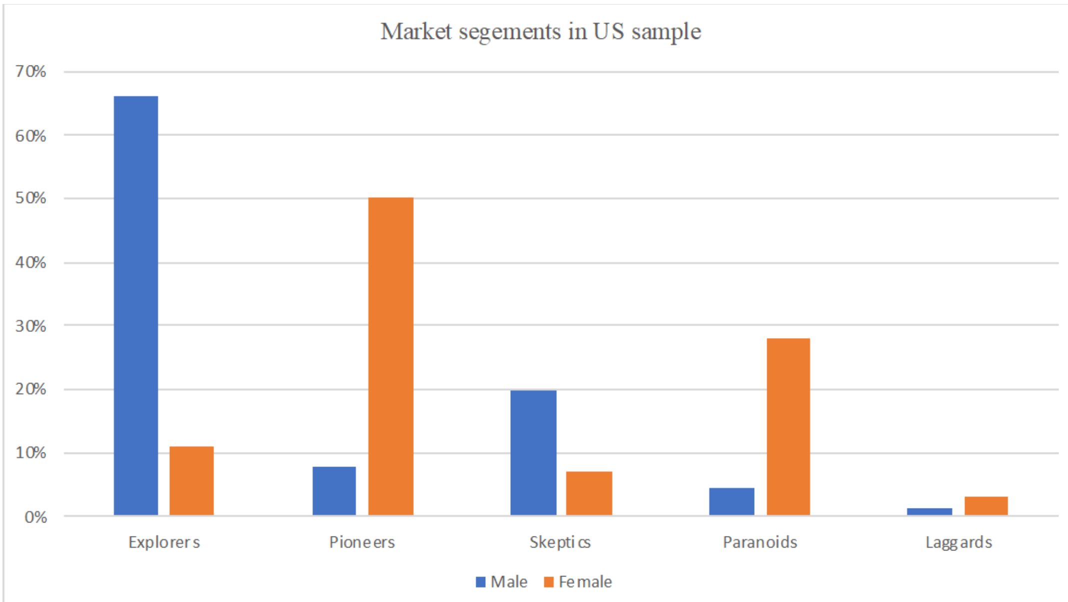

Figure 23. Home 3D printing market segments.

As Colby (2002) explains, explorers are strong influencers of the other segments. They typically like to do their own research and share the information to influence the decision of the other segments. As an example, pioneers prefer to get their information from knowledgeable friends or co-workers who could be explorers. For the male sample, the results showed that Performance expectancy (PE) was significant at the 1% level and had a larger effect size. As more than 60% of the male sample are in the explorer segment, it is sensible to find that PE as a key predictor for males. The explorer segment are typically high in optimism thus they tend to focus on the efficiencies of the technology (refer to Table 4). The results of the study also showed that Social influence (SI) was a predictor of equal importance to the male and female samples with comparable effect sizes. This is also sensible given that the leading market segments in the male and female samples (Explorers and Pioneers, respectively) rely on social influence to teach and learn. Furthermore, as Colby (2002) points out, skeptics eventually adopt new technologies as they are convinced by explorers about of the benefits of a new technology. Thus the role of Social influence is important. For 3D printing Marketers, this means that their strategy should include a focus on local maker communities where there is exposure to 3D printers and an opportunity for knowledge sharing and learning. Within these local maker communities, the 3D printer manufacturer could clearly show the benefits of the 3D printing technology by using the technology to support some local projects. These projects would be an ideal opportunity for explorers, pioneers and skeptics to interact. The news of such successful projects will propagate quickly among friends and neighbors and will address the inherent fears of within the pioneer and paranoid groups. Putting focus, through these projects, on boosting the hedonic motivation (HM), which is one of the key predictors for the female group, is another way of addressing the inhibition issue in the pioneer and paranoid groups. As Colby (2002) points out, both the pioneer and the paranoid segments need a high level of customer focus to address the high level of inhibition. Such customer focus will include making it easy to learn the technology, responsiveness to all types of questions regarding the use of the technology, assurance that the technology is intuitive will perform as required and finally compatible with other established technologies currently in use. In essence, the elements of the suggested customer focus could address the needs of Facilitating conditions (FC) and Effort expectancy (EE). For the female sample, Facilitating conditions (FC) was a key predictor of acceptance followed by Effort expectancy (EE). Thus, there should be a focus on providing customer-focused training sessions either online or at local maker community centers to specifically target the needs of the female population (the majority of which are in Pioneer and Paranoid segments). There could also be training sessions targeting the elderly female population because the results show that the three-way interaction terms reinforce the negative moderation of inhibitors as age increases in the female sample. Offering easy-to use software will also greatly improve the effort expectancy (EE) perception.

Interestingly, Hagel et al. (2014) suggested, in their report, that the best way for organizations to increase the adoption of 3D printing was to encourage the maker mindset and employ the same platforms that makers use. Thus, the techno-marketing strategies the 3D printing manufactures plan to use (based on the results of this study) at the local maker communities will eventually find their way to organizations seeking to increase the adoption rate of 3D printing. As an example, Siemens opened an innovation center in Orlando to encourage the maker mindset and encourage the use of a variety of technologies including 3D printing (Larson,2019).

These results will also be of benefit to the “Women in 3D Printing” society. Realizing that the 3D printing industry is predominantly male, the goal of this international society is to encourage women in the industry to select a career related to 3D printing. Such a goal is really important because there is a need to have women return to the workforce even through freelance work. The results will aid in the understanding of the key predictors to the adoption 3D printing technology by the female population. With these results, the society can influence the techno-marketing strategies of 3D printer manufactures through the sponsorship of 3D printing conferences tailored toward the female population. In doing so, the society will aid in creating freelance work opportunities for the female population through the use of 3D printing technologies.

Limitations

The cross-sectional nature of this study made it difficult to assess if there was any change in the key predictors over time. This is a limitation that was also cited in previously published work in Europe and Asia. Another limitation is the sample size. The minimum sample size of 150 for each gender was acceptable for this study, knowing that gender is the source of heterogeneity considered in this study. While not in the scope of this study, to test for other possible heterogeneities (i.e, ethnicity, previous experience with 3D printing, location in the US, etc.) within each gender groups a much larger sample size would be required.

Future Research

As this was a cross-sectional study, it would be interesting to repeat this study again within a few years to check for any variance in the key predictors due to time. It would also be valuable to repeat the study with a sample size greater than the recommended minimum sample size of 150 per gender group to allow for mor robust testing of other unobserved heterogeneity as mentioned in the Limitations section. It would be very interesting to understand the role of ethnicity in the acceptance of 3D printing. Ethnicity introduces an extra factor of diversity in addition to gender. Previous work by Colby and Albert (2003) provided evidence that there is Technology readiness variation in the US due to the multiple ethnicities. Another key area of interest is the location within the USA. As shown in Figure 24, the current of use of 3D printing varies with the location within the USA. It would be worthwhile to understand how much variance exists in the key predictors between the states.

As can be recalled, enablers and inhibitors are situational traits and it would be interesting to find out if they vary by state or by region in the USA. This analysis will also show if there is any significant impact on the market segments .

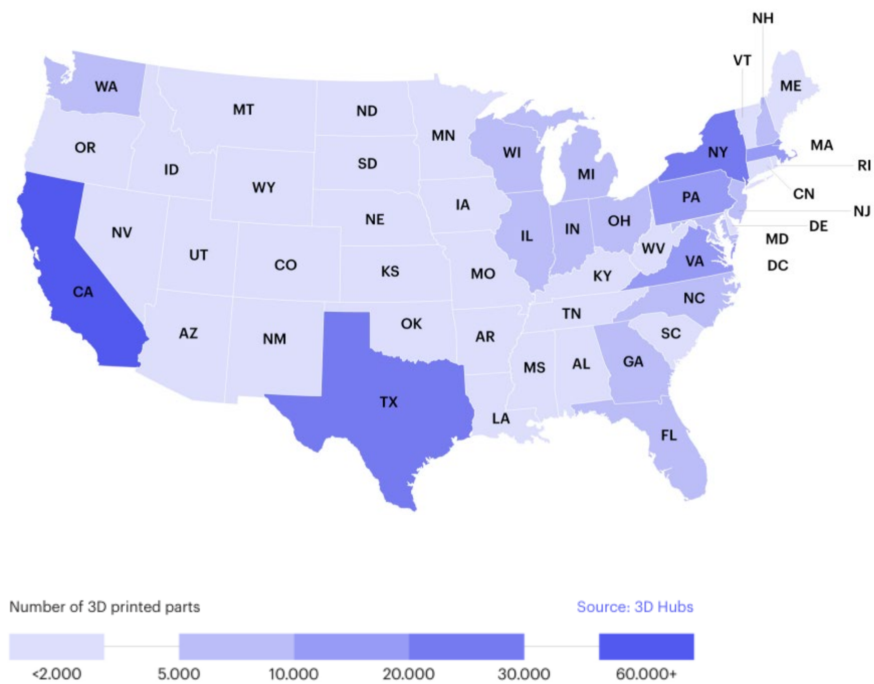

Figure 24. Number of printed parts per state (Adopted from Buckholt et al., 2019)

Outside of the US, it would be very interesting to repeat this study in Germany and the Netherlands using the same 3D printing training material and the proposed research model used in this study. The inclusion of the enabler and inhibitor constructs to replace the DIY construct used in European models will enable further analysis of the role of Technology readiness in technology adoption. As discussed in Chapter 2, the literature on the Technology readiness concept argued that was necessary to consider demographics variables and Technology readiness when considering technology adoption and use. As a country becomes more developed and the demographic differences are normalized, Technology readiness takes the dominant role in technology adoption and use. The work of Mendez, et al. (2017) was instrumental in arguing that while the US is a developed country, the demographics differences were not normalized . As such demographic variables and Technology readiness must be considered in technology adoption and use in the US. The results of this study shows that, in 2021, the demographic differences still exist and it is important to consider both variables when it comes to the US population. Thus, the results of the study confirm the conclusions of Mendez, et al. (2017). The previous studies in Germany and Netherlands on the adoption of home 3D printing also hinted on the existence of demographic differences. By repeating the study across the three countries using the proposed research model, it will be possible to compare how significantly different the role of demographics is in these three countries. Furthermore, the comparison of these three countries will shed some light on the impact of culture on Technology readiness.

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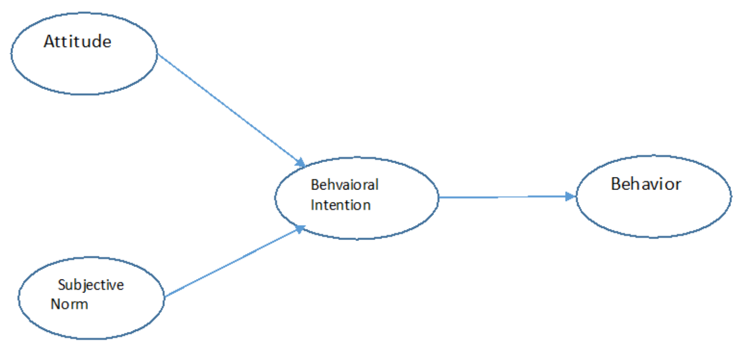
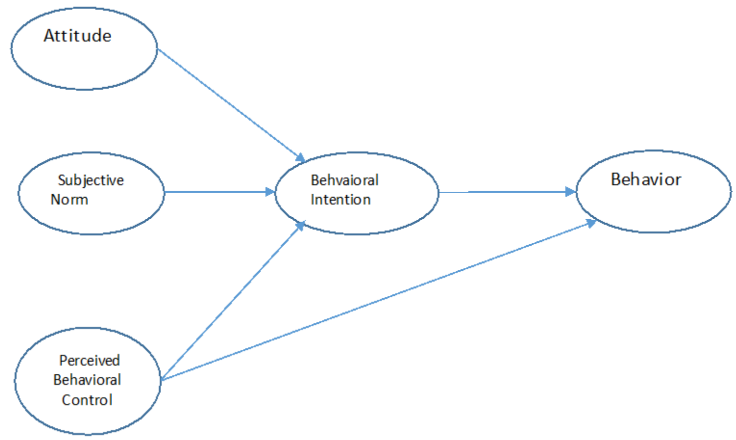
Appendix A

Brief Description of Eight Technology Acceptance Models

<table>
<tr><th>Table A1 : Theory of Reasoned Action (TRA)</th><th>Core Constructs</th><th>Definitions</th></tr>
<tr><td rowspan="3">The TRA model was first developed in 1975 by Fishbein and Ajzen for sociological and psychological research. The goal of the theory is to predict and explain human behavior through three main cognitive components that include attitude, social norm and intention (Sheppard et al (1988)). Davis et al (1989) applied TRA to individual acceptance of computer technology and found that the explained variance was within the limits established by other studies for different behaviors. The cross-sectional study done Karahanna et al (1999) on information technology adoption using the TRA model found that the impact of attitude on intention was stonger with increasing experience. In contrast, the impact of subjective norm on intention became weaker with increasing experience. Volunariness was a key moderator investigated</td><td colspan="2">
</td></tr>
<tr><td>Attitude toward Behavior</td><td>"an individual's positive or negative feeling (evaluative affect) about performing target behavior" (Fishbein and Ajzen (1975);cited in Venkatesh et al (2003))</td></tr>
<tr><td>Subjective Norm</td><td>" the person's perception that most people who are important to him think he should not performthe behavior in question" (Fishbein and Ajzen (1975); cited in</td></tr>
</table>

<table>
<tr><th>Table A1 (cont'd): Theory of Planned Behavior (TPB)</th><th>Core Constructs</th><th>Definitions</th></tr>
<tr><td rowspan="4">Ajzen(1991) extended the TRA Model by adding Perceived Behavioral control (PBC) as a new predictor variable. The new predictor variable is determined by the availability of resources, opportunities and skills. In the extended model , PBC has direct influence on actual beahvior as well as indirect influence on actual behavior through behavioral intentions. The application of TPB to understanding individual acceptance of technology has been investigated by Mathieson (1991) and Talylor and Todd (1995b). Morris and Vankatesh (2000) emperically investigated the moderating roles of experience and age which were not included in the original TPB model. The results demonstrated that the impact of subjective norm on behavioral intention becomes weaker with increasing level of experience. Age had a stonger moderating role on Attitutude for younger workers while having a stronger moderating role on PBC for older workers. The moderating role of gender was investigated by Venkatesh et al (2000). The results indicated that Attitude had a stronger impact among males than females. In contrast, subjective norm and PBC had a stonger impact among females than males. The study of Hartwick and Barki (1994) suggested that subjective norm had a stronger role on behavioral intention when the technology use was percived to be less voluntary. Voluntariness, Gender and Age were the key moderators in this theory</td><td colspan="2">
</td></tr>
<tr><td>Attitude toward Behavior</td><td>"an individual's positive or negative feeling (evaluative affect) about performing target behavior" (Fishbein and Ajzen (1975);cited in Venkatesh et al (2003))</td></tr>
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<tr><td>Perceived Behavioral Control</td><td>" the perceived ease or difficulty of performing the bahvior" Ajzen (1991)</td></tr>
</table>

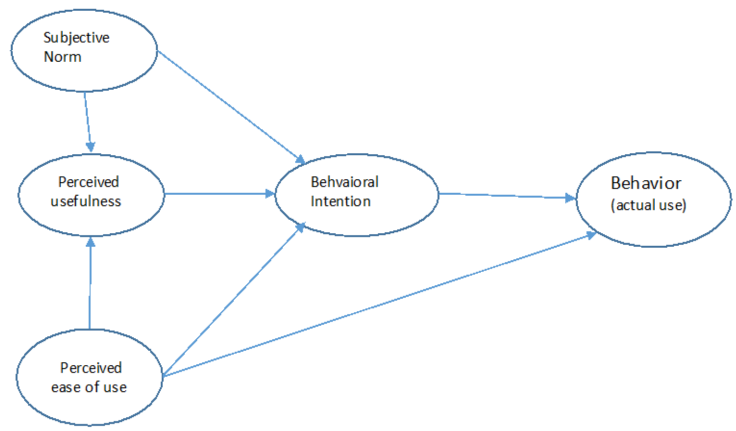
Table A1 (cont'd):Technology acceptance model (TAM)	Core Constructs	Definitions
TAM is an adaptation of TRA specifically tailored for modeling an individual user acceptance of information technology (Davis,1989). TAM explains the behavioral intention of the user via three constucts: PU, PEU and Attitude. In original model, Attitude mediates the influence of PU and PEU on behavioral intention. Venkatesh and Davis (1996) found that PU and PEU have a direct influence on behavioral intention thus eliminating the mediating role of Attitude. Venkateah and Davis (2000) extended the TAM model to add subjective norm as shown in the diagram. TAM and its extended models have been applied to a diverse set of technologies and users (Lee et al, 2003). Davis et al (1989), among others, have shown emperically that the impact of PEU on behavioral intention becomes weaker with incerased experience. Venkatesh and Morris (2000) provided emperical evidence that PU had a stronger impact for males while PEU had stronger impact for females. Furthermore the effect of subjective norm was stronger for females in the early stages of experience. Voluntariness and Gender were the key moderators conisdered in this theory		
	Perceived Usefulness (PU)	"the degree to which a person believes that using a particular system will enhance his or her job performance" (Davis,1989)
	Subjective Norm	" the person's perception that most people who are important to him think he should not performthe behavior in question" (Fishbein and Ajzen (1975); cited in Venkatesh et al (2003))
	Perceived ease of use (PEU)	" the degree to which a person believes that using a particular system would be free of effort" (Davis,1989)

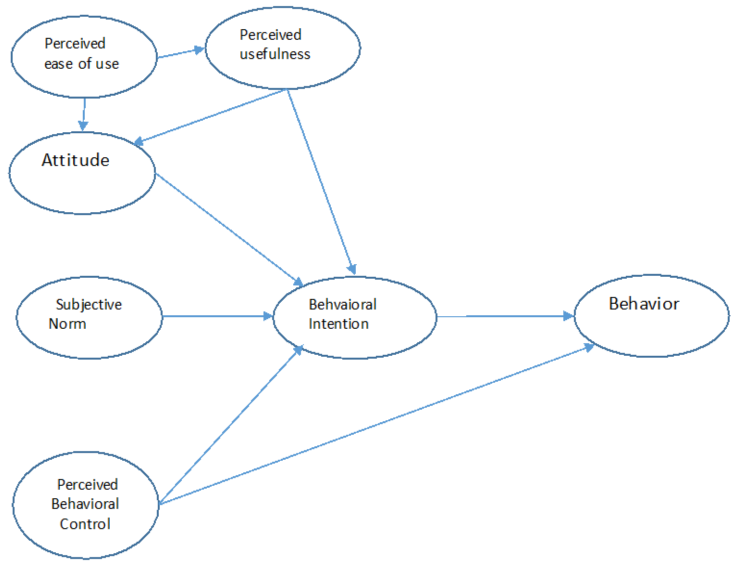
Table A1 (cont'd): Combined TAM-TPB	Core Constructs	Definitions
Taylor and Todd (1995a) added the Perceived usefulness and Perceived ease of use from TAM to the existing TPB model. Their results showed tha PU, Attitude and PBC had stonger impact on behavioral intention with increasing experience while the impact subjective norm became weaker with increasing experience. (Note : Perceived ease of use (PEU) and Peercevied usefulness (PU) are defined as in the TAM model)		
	Attitude toward Behavior	"an individual's positive or negative feeling (evaluative affect) about performing target behavior" (Fishbein and Ajzen (1975);cited in Venkatesh et al (2003))- as defined in TPB
	Subjective Norm	" the person's perception that most people who are important to him think he should not performthe behavior in question" (Fishbein and Ajzen (1975); cited in Venkatesh et al (2003))- as defined in TPB
	Perceived Behavioral Control	" the perceived ease or difficulty of performing the bahvior" Ajzen (1991)- as defined in TPB

Table A1 (cont'd): Model of PC Utilization (MPCU)	Core Constructs	Definitions
Thompson et al (1991) derived this model from Trandis' Theory of interpersonal behavior (TIB). TIB focuses on the role of social factors and emotions in forming intentions. Thomson et al (1991) were more interested in predicting usage behavior (PC utlization) rather than intention but Venkatesh et al (2003) conisdered the model to present a competing perspective to the TRA and TPB models. Experience as a modertaing variable was invesitgated by Thomson et al (1994). The study shwed that only long-term consequnces beame more salinet with increasing level of experince. In contrast, the other variables were more salient with less experience.	Job-Fit (JF)	" the extent to which an individual believes that using [a technology] can enhance the performance of his or her job" (Thomson et al, 1991;cited in Venkatesh et al (2003))
	Complexity (CP)	"the degree to which an innovation is perceived as relatively difficult to understand and use" (Thomson et al, 1991;cited in Venkatesh et al (2003))
	Long-term consequences (LC)	" outcomes that have a pay-off in the furure "(Thomson et al, 1991;cited in Venkatesh et al (2003))
	Affect toward use (AU)	"feelings of joy,elation or pleasure or pepression, disgust, displeasure or hate associated by an individual with a particular act"(Thomson et al, 1991;cited in Venkatesh et al (2003))
	Social Factors (SF)	"the individual's internalization of the refernce group's subjective culture and specific interpersonal agreements that the individual has made with others in specific social situations"(Thomson et al, 1991;cited in Venkatesh et al (2003))
	Facilitating conditions (FC)	"provision of support for user PCs maybe one type of facilitating condition that influnce system utilization" (Thomson et al, 1991;cited in Venkatesh et al (2003).

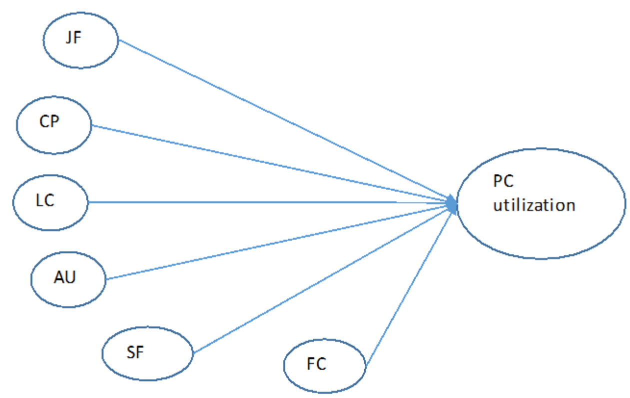


Table A1 (cont'd): Diffusion of innovation theory (DOI)	Core Constructs	Definitions
Grounded in sociology, Roger's diffusion of innovation theory has been used since the 1960s to study a variety of innovations (Tornatzky and Klein, 1982). Moore and Benbasat (1991, 1996) refined a set of constructs that would allow the utilization of the DOI theory to study individual technology acceptance. The focus was on information systems. The study of Karahanna et al (1999) showed that at lower level of experience, relative advantage, ease of use, triability, results demonstrability and visibility had stronger impact on adoption.	Relative Advantage (RA)	"the degree to which an innovation is perceived as being better than its precursor (Moore and Benbasat, 1991)
	Ease of use (EU)	"the degree to which an innovation is perceived as difficult to use" (Moore and Benbasat, 1991)
	Image (IM)	" the degree to which use of an innovation is perceived to enahnce one's image or status in one's social system" (Moore and Benbasat, 1991)
	Visibility (VIS)	"the degree to which one can see others using the system in the organization" (Moore and Benbasat, 1991)
	Compatibility (COM)	"the degree to which an innovation is perceived as being consistent with the existing values, needs and past experiences of potential adopters" (Moore and Benbasat, 1991)
	Results Demonstrability (RD)	"the tangibility of the results of using the innovation including their observabiluty and communcability" (Moore and Benbasat, 1991)
	Voluntariness of use (VU)	" the degree to wich use of innovation is perceived as being voluntary or of free will" (Moore and Benbasat, 1991)

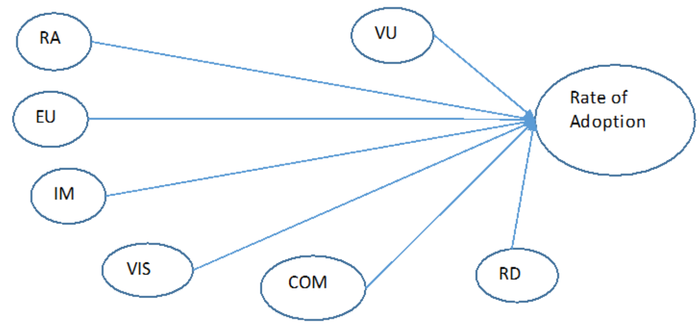


Table A1 (cont'd): Social Cognitive theory (SCT)	Core Constructs	Definitions
Grounded in sociology psychology, Bandura (1986;cited in Venkatesh et al (2003)) proposed SCT based on three main factors (behavior, personal and environment) which interact to predict group and individual behavior. Compeau and Higgins(1995b) extended the SCT model to study computer utilization. Vekantesh et al (2003) commented that the nature of the extended SCT model allow it to be used for the acceptance and use of information technology in general.	Outcome Expectations-Performance (OPERF)	Job-related outcomes that are a function of the individual's performance. The individual's perfoemance is a consequnce of behavior. (Compeau and Higgins, 1995b)
	Outcome Expectations-Personal (OPERS)	Individual's esteem and sense of accomplishment which are a function of behavior(Compeau and Higgins, 1995b)
	Self-Efficacy (SEF)	an individual's judgment of his/her ability to use a technology to accomplish a specific job or task(Compeau and Higgins, 1995b)
	Affect (AFF)	how much does the individual enjoy a particular behavior (e.g computer use).(Compeau and Higgins, 1995b)
	Anxiety (ANX)	how much are emotional or anxious reactions evoked on performing a certain behavior (Compeau and Higgins, 1995b)

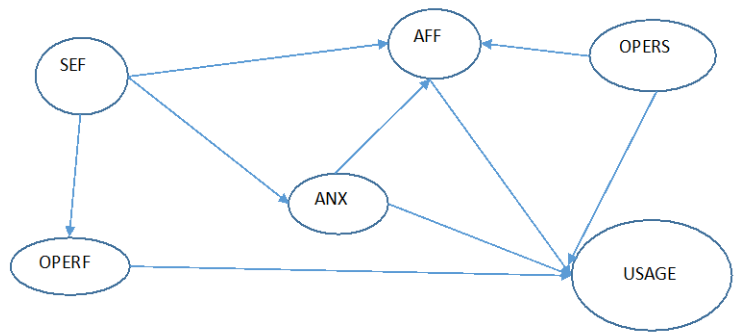
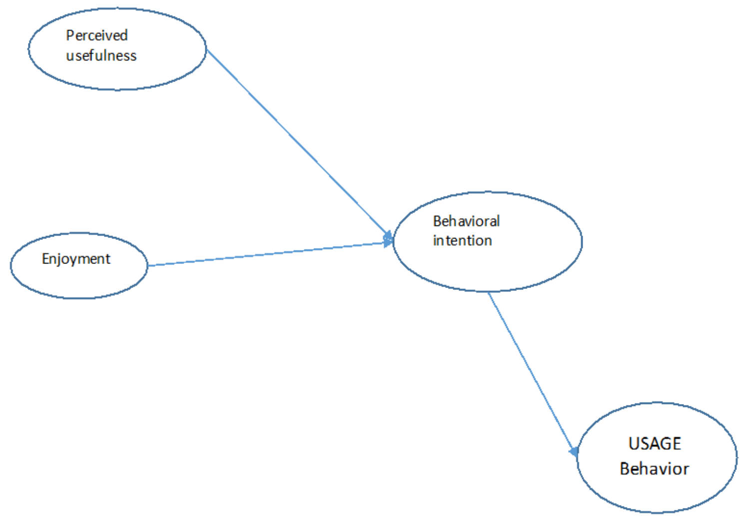


Table A1 (cont'd): Motivational Model (MM)	Core Constructs	Definitions
Davis et al (1992) applied the motivational model to the information system domain to understand new technology adoption and use. Basing their work on the existing dichotomy of extrinisc and intrinsic motivation to perform an activity, the authors use Perceived usefulness as mode of extrinsic motivation and Enjoyment as a mode of intrinsic motivation.	Extrinsic Motivation	performing an activity is percieved by the user as "instrumental in achieving valued outcomes that are distinct from the activity itself, such as improved job performance,pay or promotions" (Compeau and Higgins, 1995b) . The authors used
	Intrinsic Motivation	Individual's esteem and sense of accomplishment which are a function of behavior(Compeau and Higgins, 1995b). The authors used enjoyment as an intrinsic motivation.



Survey Questionnaire

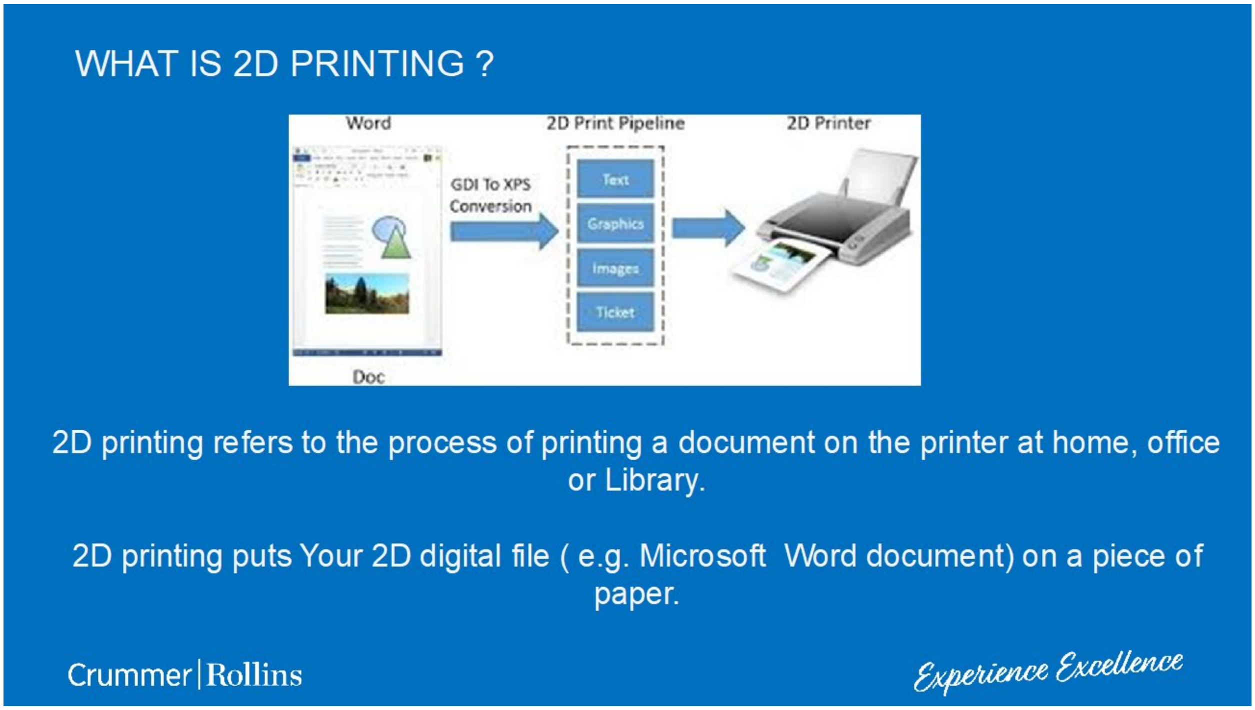
SocioDemographic and General questions
Which pronouns do you feel comfortable identifying with?
He/Him
She/Her
Other (Specify)
How would you best describe yourself ?
White
Black or African-American
American Indian or Alaskan Native
Asian
Latino
other (Specify)
How would you best rate your Income level?
< US mean income ($63,179)
>= US mean income ($63,179)
What is the highest degree or level of school you have completed?
Less than High School degree
High school degree or equivalent (e.g GED)
Associate degree
Bachelor degree
Graduate degree
What is your current Age ? (input age)
How would You best describe your Employment Status?
full time employed
part-time employed
part-time employed and Free Lancer
unemployed looking for work
unemployed not looking for work
retired
student
entrepreneur
Do you have previous experience with 3D pritning ?
None
less than 6 months
less than 1 year
greater than 1 year
Do you have a 3D printer at Home ? (elimination question)
YES
NO
Have you used 3D printing before ?
YES
NO

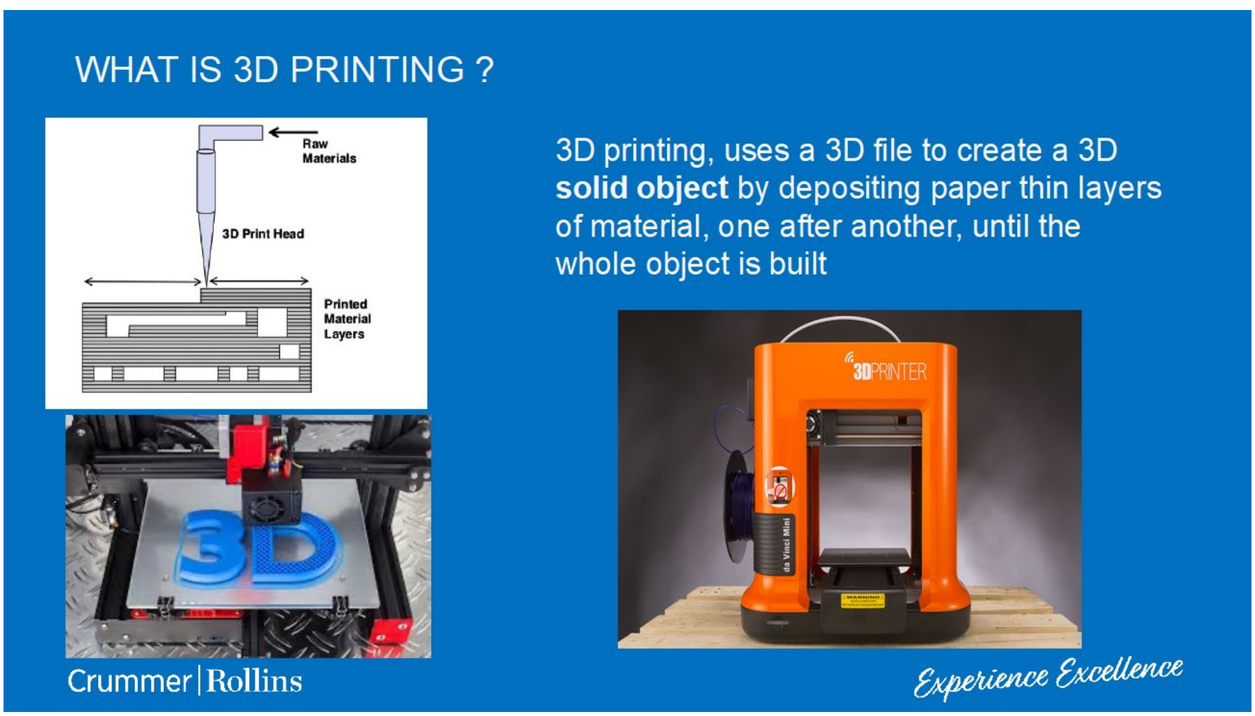
UTAUT Constructs	Survey Questions	Source
Behaviioral intention (BI)		
Intention to use 3DP at home (ITU)		
ITU1	I intend to start using 3DP in the future	Hartmann and Vanpoucke (2017)
ITU2	The probability is high that I will try to use 3DP in the future	Vankatesh et al (2003,2012)
ITU3	The probability is high that I plan to start using 3DP frequently in the future	
Purchase intention (PI)		
PI1	I would intend to purchase a 3D printer for home-use	
PI2	My willingness to buy a 3D printer is high	Halassi et al (2018)
PI3	The likelihood that I would buy this 3D printer is high	
PI4	I am likely to pruchase any 3D printer	
PI5	I would tell my friends to purchase a 3D printer for home use	
Performance expectancy (PE)		
PE1	I think 3DP is useful	Hartmann and Vanpoucke (2017)
PE2	Using 3DP could help me accomplish things more quickly	Vankatesh et al (2003,2012)
PE3	Using 3DP can increase my prodcutivity	
Effort Expectancy (EE)		
EE1	Learning how to use 3DP will be very easy for me	
EE2	My interactions with 3DP is clear and understandable	Hartmann and Vanpoucke (2017)
EE3	I think 3DP is easy to use	Vankatesh et al (2003,2012)
EE4	I think it is easy for me to become skilled at using 3DP	
Facilitating conditions (FC)		
FC1	I would be willing to invest in the resources necessary to use 3DP	Hartmann and Vanpoucke (2017)
FC2	I would be willing to invest in the knowledge necessary to use 3DP	Vankatesh et al (2003, 2012)
FC3	3DP is compatible with other technologies I use	
Social influence (SI)		
SI1	I expect that people, who are important to me, will think that I should use 3DP	Hartmann and Vanpoucke (2017)
SI2	I exppect that people, who influnce my bahavior, will think that I should use 3DP	Vankatesh et al (2003, 2012)
SI3	I expecct that people, whose opinions that I value, will prefer that I use 3DP	
Price Value		
PV1	3DP is reasonably priced	Hartmann and Vanpoucke (2017)
PV2	3DP is good value for the money	Vankatesh et al (2003, 2012)
PV3	At the current price, 3DP provides a good value	

Technology Readiness Constructs	Survey Questions (Parasuraman & Colby, 2015)
Optimism (OPT)	
OPT1	New technologies contribute to a better life
OPT2	Technology gives me more freedom of mobility
OPT3	Technology gives people more control over their daily lives
OPT4	Technology makes me more productive in my personal life
Innovativeness (INN)	
INN1	Other people come to me for advice on new technologies
INN2	In general, I am among the first in my circle of friends to acquire new technolgoy when it appears
INN3	I can usually figure out high-tech products and services without help from others
INN4	I keep up with the latest technological develpoment in my areas of interest
Discomfort (DIS)	
DSI1	When I get technical support from a provider of a high-tech product or service, I sometimes feel as if I am being taken advantage of by someone who knows more than I do
DSI2	Technical support lines are not helpful because they do not explain things in terms I understand
DSI3	Sometimes, I think that technology systems are not designed for use by ordinary people
DSI4	There is no such thing as a manual for high-tech products or service that is written in palin language
Insecurity(INS)	
INS1	People are too dependent on technology to do things for them
INS2	Too much technology distracts people to a point that is harmful
INS3	Technology loweres the quality of relationships by reducing personal interaction
INS4	I do not feel confident doing business with a place that can only be reached online

Appendix C

3D Printing Training Material





3D model

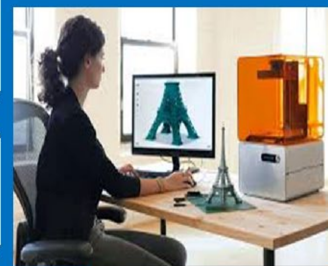
- Use free online 3D printing software to create 3D Model
- Or You can download a 3D model from a reliable source (some are free and others You have to pay for)
- Or use a portable scanner or your smartphone to scan the object and generate a 3D model . Wow ! Is that fun or what ?

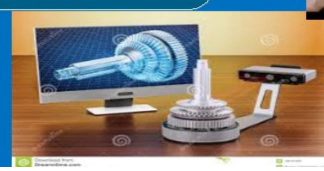
3D file

- Adjust the scale of the model to fit your 3D printer
- Using the 3D printing software slice the 3D model into paper thin layers that can be printed. You select a few print settings, and the software will do the rest. That will be your 3D file.
- Send the 3D file to the printer

3D print

- Load the material you intend to use. Some printers can use only plastics, others only ceramics and others only use metals
- Press START to begin printing
- Remove solid part from printer, clean up any excess material, inspect, and Enjoy!





Why do You need a 3D printer at home ?
Nowadays, 3D printers are affordable, safe and easy to operate. You have the opportunity to become a 3D printing entrepreneur and make money at home. Many free online resources show you how to do that.

How much does a 3D printer cost?
It all depends on the size, material and dimensional accuracy of the object to be printed.

$350

-Example Design and sell toys for kids

$1,300

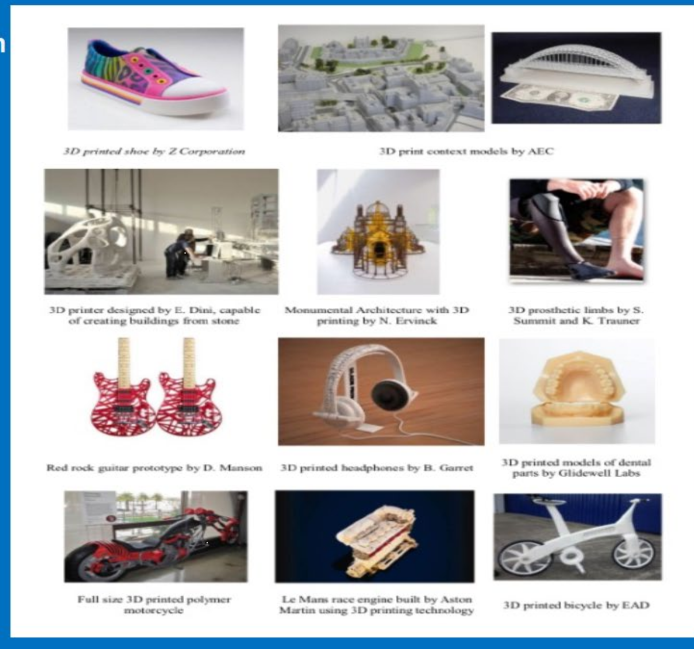
Example: design and sell printed shoes or sandals

$9,995

example : design and sell customized metal jewelry or spare parts

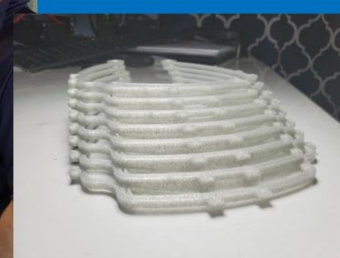
Are there examples of what 3D printing can be used for ?
The limit is your imagination. If you turn your ideas into 3D models, You can 3D print them

Do You need to be an expert in 3D modeling?
No, You do not! There are community driven websites that share free models. There are free online software that allows you to create your own 3D models out of a 2D image or an idea. It may take as little as 30 mins to learn. Or you can simply scan the object using your phone to create the 3D model.



What else can 3D printing be used for ?
The limit is your imagination! If you turn your ideas into 3D models, You can 3D print them. You can become an entrepreneur.

When doctors and nurses in our country were in dire need of protective gear in the covid-19 pandemic, an imaginative Volunteer became a Social Entrepreneur. By using a free community-made 3D model, help from friends and supporters, He used his 3D printing machines at home to print protective face shield frames and assembled face shields to support his local hospitals.



Appendix D

Consent Form

CERTIFICATE OF INFORMED CONSENT

Please read the following information and, if you are willing to participate, sign and date this form:

This research investigates the factors that would influence your decision to buy and use a Desktop 3D printer at home. Desktop 3D printing at home can be for the purpose of a hobby or for the purpose of developing your home business. Answers to the survey questions collected during the process of this research will serve purpose of developing a model to understand intention toward the adoption of Desktop 3D printing in US households. Such an understanding is of high importance to Policy makers and 3D printer manufactures to understand how to encourage You to develop your home business with Desktop 3D printing and create jobs. Please be as accurate as You can in answering the survey questions because your opinion counts.

I voluntarily agree to participate in this study. I understand that I can withdraw from the study at any time without penalty and that I can decline to answer any questions without prejudice to me. I also understand that any information obtained from me during the course of my participation will remain confidential and will be used solely for research purposes.

____

Name (please print) ______________________________ Signature

______________________________ Date

If you would like a summary of the results when ______________________________

this study is completed, please list an e-mail or postal address to the right and one will be sent to you:

____

Appendix E

Definition of Statistical terms

Collinearity. It is a measure to assess if there is any collinearity between the predictor constructs (independent variables). This happens if any of the constructs are highly correlated. A variance inflation factor above 5 indicates a potential collinearity problem. In this event, eliminating predictor constructs, merging predictor constructs ore creating higher-order constructs should be considered to treat the problem.

Convergent Validity. It is the extent to which indicators (measures) of a specific construct converge or share a high portion of variance. To evaluate Convergent Validity of reflective constructs, researcher consider the outer loadings of the indicators and the average variance extracted (AVE) (Hair, 2017). The recommended value for outer loading is 0.70. Indicators with outer loading less than 0.70 should be considered for elimination if there is no impact on the content validity. AVE is a measure of how much variance the construct explains in its indicators. A recommended value of 0.50 is used in research (Hair et al., 2017).

Discriminant Validity. It is a measure of the extent a construct is truly distant from other constructs in the same model. Establishing discriminant validity implies that a construct is unique and captures phenomena not represented by other constructs. The heterotrait-monotrait ratio (HTMT) is the preferred recommended approach in the literature (Hair et al., 2017;2018). In essence HTMT is an estimate of what the true correlation between two constructs will be if they were perfectly measured. A HTMT value above 0.85 suggests lack of discriminant validity. In SMART PLS 3.0, a statistical discriminant validity test using bootstrapping is implemented. Using bootstrapping a distribution for the HTMT statistic is derived. Based on this distribution a confidence interval is calculated and if the interval contains the value 1 then there is lack of discriminant validity.

Effect size (f^2). It is a measure of the change in R^2value when a specified predictor construct (independent variable) is omitted from the model. The rule of thumb is there is no effect if the effect size is less than 0.02 (Hair et al., 2017).

Effect size (q^2). Similar to the effect size f^2 approach for assessing R^2 Values, the effect size q^2 assesses the impact on predictive relevance Q^2 when a predictor variable is omitted from the model.

Internal Consistency Reliability. It is a form of reliability used to determine if the items measuring a construct are similar in their scores. SMART PLS 3.0 uses two approaches to calculate the Internal Consistency Reliability. The traditional approach is to use the Cronbach's alpha. However, as Cronbach's alpha demonstrated to be sensitive to the number of items used on the scale, it tends to underestimate the Internal Consistency reliability (Hair et al., 2017). The alternative is the Composite Reliability. The true value of reliability lies between Cronbach's alpha (lower bound) and the Composite reliability (Hair et al., 2017). A value below 0.60 indicates lack of Internal Consistency Reliability while a value above 0.90 indicates all indicators are measuring the same phenomenon in the construct and are not like a valid measure of the construct

Path Coefficients. These are the estimated path relationships between the constructs in the model. They correspond to the standardized betas in a regression analysis.

Predictive relevance (Q^2). This value is a measure of how the path model exhibits predictive relevance when it predicts the dependent variable using data not used in the model estimation. In essence, Q^2 is a measure of out-of-sample predictive power (predictive relevance). A $Q^2 > 0$ for a reflectively measured dependent variable indicates the model's predictive relevance.

R^2 values. These values are a measure of how much variance is explained in the dependent variable with the given model. The acceptable R^2 values depend on the model complexity and research discipline however, Hensler et al. (2009) and Hair et al. (2011) provide the rule of thumb : 0.25 Weak, 0.50 moderate, 0.75 significant.