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User Experience-driven Innovation in Smart and Connected Worlds

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Abstract:

In our fast-paced digital economy, expectations for improved user experiences (UX) increasingly drive innovation. Thus, companies must fully grasp users' points of view when they design innovative technologies that can successfully compete in a crowded global market. These technologies must not only satisfy users' expectations but also empower them and improve their quality of life. To address this challenge in our rapidly evolving and globally expanding digital economy, we need new theories and models for technology design—ones that incorporate UX. In this paper, we address this need by developing conceptual models for UX-driven innovation. We explain how these models can enable innovative, responsive technologies that meet users' needs in real time. These models also facilitate the production of new theories that are discovered via accessing the rich, real-time data sets that our increasingly smart and connected worlds create.

Keywords: Technology Design, Innovation, User Experience, Smart and Connected systems, Internet of Things (IoT).

Fiona Nah was the accepting senior editor for this paper.

1 Introduction

In today's smart and connected environments, technological products and services play an ever-increasing role in commerce, business, government, healthcare, education, entertainment, communication, social connections, and so on. They have become essential in helping individuals conduct their personal and work-related day-to-day activities. The many companies that seek to meet the demands for these computerized tools have created crowded markets for the overall information technology industry. In these crowded markets, companies compete by providing better and more innovative user experiences (UX). By focusing on better UX to compete, UX has begun to drive innovation in today's digital economy (Wilson & Djamasbi, 2015). For example, by putting UX at the forefront of innovative design, smartphones have set the standard for what people expect from mobile devices. The impact of smartphones on user expectation is not limited to mobile industry, smart phones have changed what people come to expect from technology in general. For example, people now expect their car to have an infotainment screen on which, with just a few taps, they can place phone calls, search for destinations, and access other features. To stay competitive, the auto industry has had no choice but to meet these expectations. Accordingly, automakers now produce vehicles with advanced infotainment systems that include large touch screens and voice and gesture recognition (Monticello, 2017).

To address these innovative design challenges, we need new technology design models—ones that highlight UX as driving these innovative designs. Such new models benefit from examining technology design challenges through an innovation lens (see Figure 1). This lens, which advocates products and services that can compete successfully in the marketplace, requires us to consider both the usage world in which human-technology encounters take place and the design world in which technology design originates. While these two worlds inform and interact with each other, each also has its own paradigms, theories, practices, and constraints. A UX-driven innovation lens that considers both the design and usage worlds expands the opportunity space for designing and delivering novel technologies. It also highlights opportunities for building new theories and models that can self-adjust and/or discover new behavioral patterns in real time.

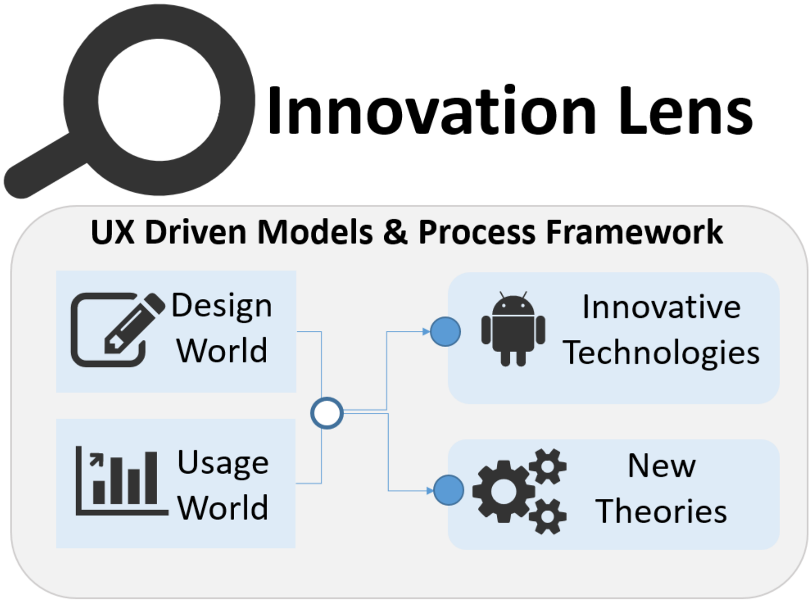


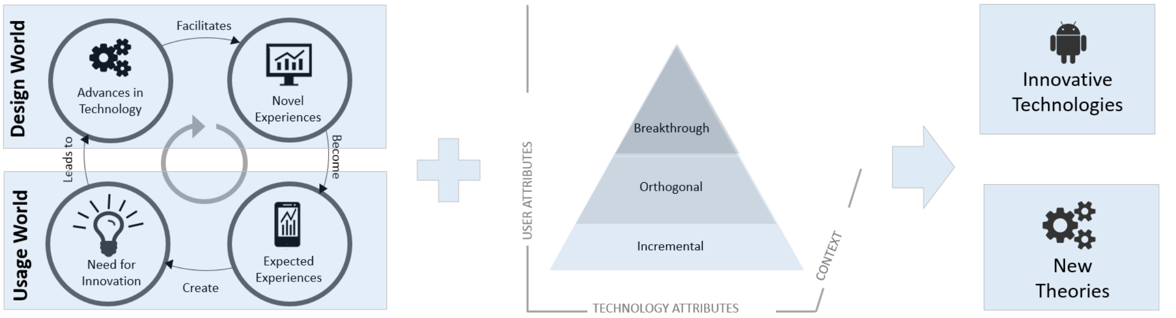
Figure 1. Innovation Lens for UX-driven Technology Design

In this paper, we explore what those opportunities are and how to exploit them by developing four conceptual models: 1) a model for UX-driven innovations (UXDI model) developed for traditional environments, 2) an extended version for smart and connected environments (UXDI-SC), 3) a process model for developing UX-driven innovations in traditional environments, and 4) another process model for smart and connected environments. All four models include both the design and usage worlds. The models for traditional environments serve as a starting point for demonstrating the opportunities in smart and connected environments. As such, the second model (UXDI-SC) constitutes a key contribution because it explores how we might capitalize on smart and connected environments' ability to support innovative real-time adaptive systems that facilitate automatic experimentation and theory building. The fourth model has similar importance because it provides a process for exploring and exploiting these opportunities. Together, these models provide insights about an effective approach for exploring the solution space for designing novel technologies. They also provide ample opportunities for developing innovative theories. Before presenting our four models, we first briefly review how UX became a driver for innovation and how looking at technology design through an innovation lens can help develop competitive products and build new theories.

2 UX-driven Innovation

User experience (UX) refers to the dynamic, context-sensitive interaction between people and technology (Hassenzahl, 2003) that results in users' affective responses (ideally satisfaction, appeal, and delight) and drives their behaviors (ideally technology adoption, continual system use, etc.). The interaction should offer a practical and engaging experience that addresses target users' needs and goals.

UX has begun to drive innovation in our digital economy due to the reciprocal relationship between technological advances and users' needs for novelty. Advances in science and engineering provide increasing opportunities to design novel technologies for personal use (e.g., Fitbit) and organizational use (e.g., the UPS On-Road Integrated Optimization and Navigation tool for package delivery) (Forrest, 2015). These novel technologies address users' needs for novelty and, thus, increasingly shift market competition from utility to user experience. This shift in the nature of market competition, in turn, means that companies must design novel products and services that offer outstanding user experiences. While designing innovative experiences constitutes a challenging task on its own, being successful in designing novel experiences creates an even greater challenge for companies: a never ending cycle of demand for more innovative and novel products (i.e., more innovation) (see Figure 2a). Every successful novel experience raises the bar for what users expect from new products, and, thus, triggers a call for new and useful experiences. Novelty tends to wear off rather quickly and becomes something that users expect in new products. An expected experience, while important for user satisfaction, can no longer foster the joy and delight that novel experiences typically trigger. Hence, the mere success in creating delightful experiences perpetuates the demand for more innovation, which, in turn, drives advances in technology (Wilson & Djamasbi, 2015).



a. Demand Cycle for UX Driven Innovation **b. UX Innovation Design Space** **c. UX Innovation Outcomes**

Figure 2. UX-driven Innovation

While such a never-ending cycle of demand poses a great challenge to technology designers, a closer look at the design space for UX-driven innovations (see Figure 2b) reveals innumerable opportunities for addressing the market need for novel solutions. Innovation refers to addressing market needs with solutions that customers find valuable (Terwiesch & Ulrich, 2009). Novelty is essential and implicit in the innovation concept. Novelty may refer to a new market need, to a new solution that can satisfy an existing need, or to a new way to match a need and a solution (Terwiesch & Ulrich, 2009; Estrin, 2009). We can group innovation into three major categories: incremental, orthogonal, and breakthrough. Incremental innovation refers to significant improvements in existing products (e.g., Web 2.0). Orthogonal innovation refers to matching existing needs and solutions in a new way (e.g., iPod). Breakthrough innovation refers to discovering something completely new—typically through basic research (e.g., the discovery of DNA) (Estrin, 2009). Designing successful products and services requires at least one of the three types of innovations and may include all three.

The design space for such UX innovations (see Figure 2b) has three major dimensions (user attributes, technology attributes, and the context), which indicates that a user experience requires an individual to use a technology designed for a use purpose in a specific context (Hassenzahl & Tractinsky, 2006; Hassenzahl, 2003). In this design space, the user attributes dimension includes individual characteristics such as gender, age, culture, affect, expertise, preferences, needs, goals, and so on. The technology attributes dimension includes variables such as technology type (e.g., specificity of purpose), interaction type (e.g., touch, gaze, gesture, voice), and physical characteristics (e.g., size and/or shape). The context dimension, which refers to the environment in which the human-technology interaction takes place, includes all conditions external to both the user and the technology, such as the task, the setting, and/or the physical environment. Delineating and understanding the design space for UX innovation, as Figure 2b depicts, facilitates the exploration of innovation opportunities that best match a firm's business strategy. Delineating the design space in this way also promotes the understanding of technology design based on its contribution to innovation (incremental, orthogonal, breakthrough). Because developing a novel technology (an artifact) itself represents a contribution to knowledge (Hevner, March, Park, & Ram, 2004), the UX innovation space for technology design can help to better categorize and theorize about such contributions to theory and practice (Figure 2c).

3 Conceptual Model for UX-driven Innovations (UXDI)

We now describe our conceptual model for UX-driven innovation (UXDI) more fully. The UXDI model considers both the usage world and the design world (see Figure 3). Behavioral theories typically focus on understanding the user perspective in the usage world. This focus on users' perspectives is important and valuable because different people may have different reactions to the same artifact, and their reactions may differ from what designers envisioned (Hassenzahl, 2003). From an innovation lens, it is also critical to consider the design world. In the design world, which typically exists in an organizational setting (e.g., company, government institution), technology designers envision and give form to technologies for users. While their perceptions about users' needs influence their design goals, organizational factors such resource availability, organizational culture, and business strategy also influence their design objectives. In the design world, a project typically receives approval only if it has acceptable return on investment (ROI), which means that a product must go beyond soliciting positive user reactions (e.g., satisfaction, delight) to also foster behavioral changes that meet key performance indicators (e.g., increased adoption rate and continued usage).

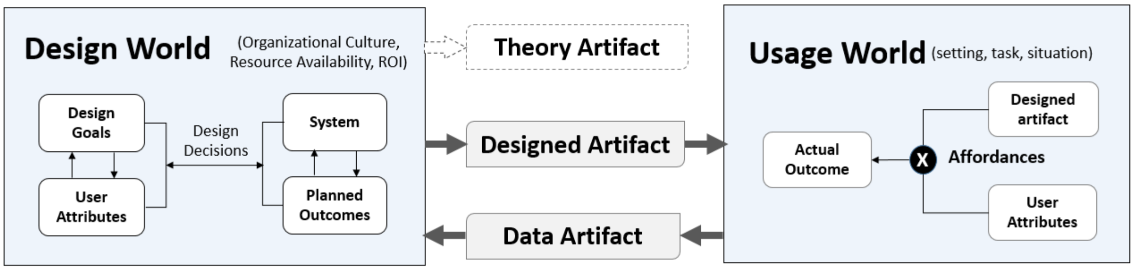


Figure 3. UX-driven Innovation (UXDI) Conceptualization in Traditional Settings

UX-driven innovation relies on more deeply understanding users' needs, goals, challenges, and so on. Such understanding is typically achieved through qualitative UX research methods such as interviews and observations. The detailed and often complex information about users is then translated into effective representative groups of users, called personas (Bajracharya et al., 2019; Bhattacharyya, Mossman, Gustafsson, & Schneider, 2019; Jain, Djamasbi, & Wyatt, 2019; Javahery & Seffah, 2012). As Figure 3 shows, this information, which is often gathered periodically, is used to drive design decisions. In the design world, this information aids with selecting the system type (e.g., mobile apps, wearables, IoT sensors) and features (e.g., content, presentation, functionality, interaction) in order to offer a practical and engaging experience that meets target users' needs and goals. That is, the system is designed with specific planned outcomes in mind. In the usage world, the designed system ideally elicits desired affective responses (e.g., satisfaction, appeal, delight), evokes desired evaluative responses (e.g., ease of use, usefulness), and drives desired behaviors (e.g., adoption, continual system use) (Djamasbi, Strong, Wilson & Ruiz, 2016; Tulu et al., 2016; Wilson, Djamasbi, Strong, & Ruiz, 2017; Nguyen, Ruiz, Wilson, Strong, & Djamasbi, 2018).

The design process in the design world creates two important artifacts: the designed artifact and the theory artifact. The former refers to the system that is ready for launch in the usage world. The latter refers to theories or models that are used, modified, or discovered when designing and developing artifacts. The designed artifact is initially informed by existing theories such as those about design, technology, and users, although these theories may be only implicit during design. By exploring the solution space, designers have the opportunity to advance existing constructs, models, and/or methodologies that they used initially (Hevner et al., 2004). These advances then form an updated theory artifact, which they may or may not be explicitly articulated (the dotted lines in Figure 3 indicate this possibility).

Once a designed artifact (e.g., a new product or service) is launched in the usage world, we can observe how its users actually experience the system in the real world settings (see Figure 3). User experience arises from the dynamic and context sensitive interaction between people and technology (Hassenzahl, 2003). The affordances concept, which (a) refers to the potential for behaviors associated with achieving an immediate concrete outcome and (b) arises from the relation between an object (e.g., an IT artifact) and a goal-oriented actor or actors (Volkoff & Strong, 2013), can help designers understand how designed artifacts lead to various different user experiences. A relational concept, an affordance arises between a particular user and a particular system (i.e., an affordance does not represent a system's features or a user's characteristic but arises from the interaction between a system's features and users' characteristics and goals) (Volkoff & Strong, 2018). When user characteristics or goals change, the affordances that arise differ. Thus, affordances can differ for different users and even for the same user at different times or under different immediate user goals.

While an affordance refers to a potential of a system to meet a user's goal(s), user experience refers to actual outcomes that occur when a user interacts with a system (Strong et al., 2014). Depending on the person's characteristics and situational need (goal), the person may see the object as helpful in different ways. For example, the encounter between a thirsty person and a mug will likely give rise to the mug's potential to quench thirst. In a breezy office, the same person's encounter with the mug may lead to a different affordance; namely, the mug's potential to serve as a suitable paper weight. In each case, the user experience from interacting with the mug may also vary to the extent the person experiences satisfaction or delight in being less thirsty or to the extent the person experienced delight in solving the breeziness problem.

Thus, Figure 3 shows affordances as a relational construct between the designed artifact and a user's internal state (user attributes) in the usage world. Note that an affordance is a potential. When a user interacts with the designed artifact, the user actualizes affordances, which results in immediate concrete outcomes, such as a user's experiences. That interaction with the designed system also provides users with the opportunity to observe whether the system has the ability to help achieve their goal. This observation has evaluative (system is useful), affective (system is appealing), and behavioral (system usage and continued usage) consequences. These consequences of a users' interaction with the system generate the user experience. They may also give rise to the user discovering additional affordances through their learning. User learning effectively changes user characteristics and, thus, generates new affordances.

Affordances' complex and situational nature (Volkoff & Strong, 2013; Volkoff & Strong, 2018) explains why the consequences of a user's interaction with an artifact in the usage world may differ from what designers envision in the design world (Hassenzahl, 2003; Kieffer, 2017). Therefore, it is crucial to collect information about the user experience of designed artifacts in the usage world (Djamasbi, 2014; Albert & Tullis, 2013). We refer to the collected information about user interactions and experiences with a system as the data artifact. The contents of the data artifact can be used to assess the alignment between the outcomes planned in the design world and actual outcomes that occur in the usage world. The information provided by the data artifact also can be used in the design world to address the demand for UX-driven innovation in the next production cycle. Both assessing the alignment between planned and actual outcomes and exploring UX-driven innovation space (Figure 2b) can contribute to knowledge and, thereby, impact the theory artifact.

The UXDI model also facilitates experimentation; namely, it allows the examination of the impact that specific interventions can have on actual outcomes (see Figure 4). For example, through A/B testing or other controlled trials in which different groups randomly receive different flavors (prototypes) of the same service/product, companies can measure the extent to which a new intervention succeeds. While such an approach can effectively reveal whether an intervention is successful or not (yes or no), it does not necessarily reveal which factors made an intervention successful or which made them fail to produce desired outcomes (why and how) (Sheeran et al., 2017). To answer "why" and "how" questions, we need to have more information about the causal chain of effects that lead to an outcome.

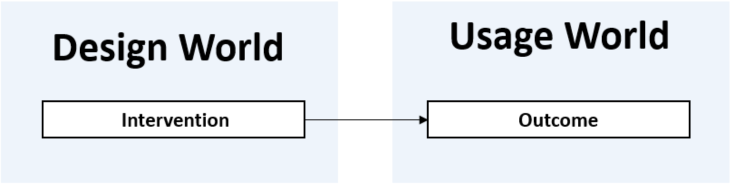


Figure 4. Assessing Whether an Intervention is Successful

To make this point clearer, consider a health and wellness app that provides theory-driven interventions for weight loss (e.g., information about healthy habits and reminders for daily exercise). With the model that we outline in Figure 4, we can assess whether these app-based interventions succeeded or not (e.g., whether users lost weight) through a fixed, controlled trial to test whether the designed app resulted in significant changes in the usage world. We would not be able to detect why the intervention succeeded or not without additional information (i.e., we need a more complex model than a simple intervention-outcome model). That additional information would track how a targeted intervention causes changes in individuals (e.g., they may gain knowledge about health and wellness or develop positive attitudes toward exercise) and/or changes in their social environment (e.g., connecting with people with similar weight loss goals). Such changes in individuals and their social environment can generate changes in health behaviors (e.g., consume food with low sugar and fat, exercise more often), which could potentially generate changes in desired health outcomes (e.g., weight loss). However, without capturing information along this chain of possible outcomes (from changes to individuals and their environment to changes in behavior and health outcomes), we cannot track and understand whether and why planned outcomes do or do not occur from interventions (see Figure 5).

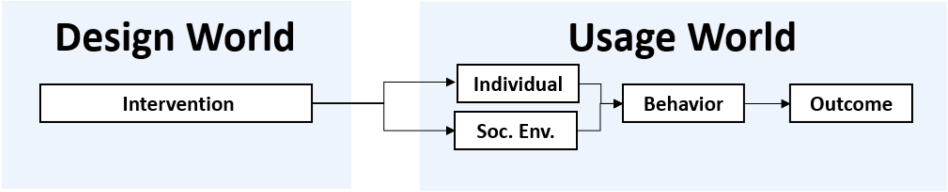


Figure 5. Assessing Why and How an Intervention is Successful

To capture the chain of possible outcomes, we need a more advanced model. In Section 4, we describe such a model—specially, a UX-driven innovation model for designing technology in smart and connected environments (UXDI-SC). Using this model, we can automatically examine such “why” and “how” questions.

4 UXDI-SC: UX-driven Innovation Model (UXDI) for Smart and Connected (SC) Worlds

Smart and connected worlds rely on the Internet of things (IoT), a system of computing devices that can share data over a network without human intervention. These computing devices typically generate a massive amount of data. Machine learning (ML) engines now often process this data to gain insight for design and/or other business decisions. With the proliferation of reliable and affordable consumer grade IoT, these smart and connected environments will surely offer increasingly smart and seamless experiences, which, in turn, will likely increase the pace of user demand for innovation (see Figure 2a). To keep up with the accelerated need for innovation, smart and connected worlds should include a similarly paced mechanism for continual experimentation to facilitate scientific examination of new service/product experiences anywhere along the causal chain. That mechanism comprises a set of interacting smart artifacts that, as Figure 6b shows, resides between the design and usage worlds and interacts with both worlds.

In traditional settings (see Figure 6a), the designed artifact and data artifact that results from use of the designed artifact connect the design and usage worlds. In these settings, after the designed artifact is launched in the usage world, the data artifact (e.g., customer feedback) is then used in the design world to improve the existing product or identify opportunities for designing new products. The data artifact can be also used to verify or extend models that were used to develop the designed artifact.

In smart and connected settings (see Figure 6b), the usage world facilitates the continual collection of behavioral data through IoT sensors and, thus, produces a rich, real-time data artifact. Such rich continual data serves as feedback for the designed artifact to adapt itself. That is, the availability of rich real-time data artifact makes it possible to develop adaptive designed artifacts, which can respond to user needs in real time (Shojaeizadeh et al., 2019). Because the real-time data artifact can collect information about the entire chain of outcomes (e.g., changes in individuals, social context, behavior, and actual outcome), it can feed machine learning engines that automatically identify triggers that impact user reactions along the chain of outcomes directly or indirectly. Those triggers, in turn, provide information for creating new or modified interventions.

Detecting triggers that impact the causal chain of outcomes in real time enables the development of adaptive designed artifacts and also facilitates the development of theory artifacts that test and revise theories. Using the rich, real-time data in the data artifact, those theory artifacts can automatically test existing models and discover new constructs or models via various methods, such as ML engines.

Together, the adaptive designed artifact with its ML engine, the theory artifact with its ML engine, and the real-time data artifact that feeds them form a set of smart artifacts. As such, smart artifacts are particularly important to information system (IS) research, which considers the development of viable designed artifacts and new theory artifacts as major contributions to knowledge (Hevner et al., 2004).

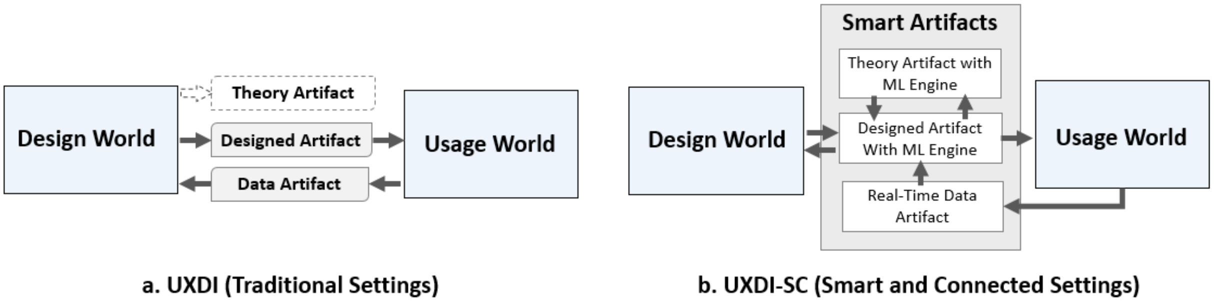


Figure 6. UX-driven Innovation Conceptualization in Traditional and Smart Settings

These smart artifacts working together constitute the mechanism for experimentation and automated learning in the smart and connected environment (see Figure 6b). The ML engines turn IoT data into meaningful information for the design world, the usage world, and the theory artifact to use. The designed artifact in this model is the arbiter between all the other components in the model. The data artifact (i.e., the steady stream of real-time data) does not go directly to the design world as it does in the model in Figure 6a; rather, the data artifact is first processed by the designed artifact. The ML engines then use this processed data in the designed artifact to provide insight for the design world. For example, using the continual stream of data, the ML engines in the designed artifact can reveal new emerging markets or identify new services that existing users will likely find desirable. Similarly, the data that the ML engines process in the designed artifact can suggest design improvements for the next development cycle.

The theory artifact can also use the IoT data that the designed artifact processes. Because the data artifact contains detailed information about individuals, their environment, their behavior, and the outcomes of the behavior, it can facilitate the development of advanced models that can lead to a more nuanced and dynamic understandings of user reactions and behavior change over time (Riley et al., 2011; Sheeran, Klein, & Rothman, 2017).

The ability to provide real-time personalization in smart and connected and environments requires a smart theory artifact that can both automatically test existing models and build new ones by, for example, suggesting experimentation (i.e., interventions) that the designed artifact can put into action. Such a smart theory artifact would include embedded, specialized ML engines and a library of behavioral models. The embedded library would hold both interventions that have been verified as successful and unsuccessful along with the conditions under which they were tested. Depending on its setup in the design world, the designed artifact can either conduct automatic experimentations that the theory artifact suggests or implement the suggested interventions only after the experts in the design world approve them. This control mechanism enables the management team to oversee the automation, enable or disable it as they see fit, and to ensure adequate control for situations that require human oversight (e.g., for critical interventions that involve health, safety, or data security).

The UXDI-SC model in Figure 6b can also help address the double-adoption problem, which postulates that individuals can achieve behavioral goals only if they adopt both the new technology and new behaviors (Kelley, Chiasson, Downey, & Pacaud, 2011), i.e., technology adoption and use (Zhang & Venkatesh, 2018), and even a delightful user experience is not enough. For example, improved health requires more than using and enjoying using a health app; health behaviors must also change. The theory and designed artifacts in the UXDI-SC model minimize the double-adoption problem by working together to provide real-time personalization (Nahum-Shani et al., 2014) and, thus, deliver interventions that lead to behavioral changes in that individual. For example, the availability of current contextual information for each individual user makes it possible to detect both positive and negative triggers for technology acceptance and behavior adoption. In turn, the detection of these triggers] allows the implementation of just-in-time adaptive interventions (i.e., dynamic interventions that change over time based on data) that target technology acceptance and behavior adoption.

As compared to the UXDI model for traditional environments, the UXDI-SC model captures the ability in a smart and connected environment to deliver dynamic and adaptive interventions and to track the entire chain of outcomes of those interventions. Such a capability can provide an excellent framework for behavior change research, which often examines only interventions that remain fixed for a trial's duration (Sheeran et al., 2017). More generally, the capabilities shown in the UXDI-SC model can lead to novel platforms for automatically refining old theories and automatically generating new models, theories, and theory-based interventions.

5 Process Models for UX-driven Innovation in Traditional and in Smart and Connected Environments

Maintaining a competitive advantage in a dynamic market place requires a development process for products and services that can effectively meet the never-ending demand cycle for innovation in those products and services. In this section, we outline a process model for developing successful UX-driven innovations to make the cycle of innovation clear and to maintain engagement in both the design world and the usage world throughout the innovation process.

Less desirable UX designs often arise due to inadequate application of design methodologies from the beginning of the project. In many projects, UX is often "treated as a downstream step in the development process" to "put a beautiful wrapper" around an already developed idea (Brown, 2008, p. 86). While making products and services aesthetically attractive helps make them more desirable for consumers, UX-driven innovation requires a significantly different approach. Rather than focusing on making an already developed idea more attractive, a UX-driven innovation process uses UX-based design methodologies from the start to frame and shape initial design ideas as they are being formed (Brown, 2008).

The UXDI process model (see Figure 7) outlines a process for designing, developing, and implementing UX-driven innovations in traditional settings. This model has its foundations in research that advocates using UX-based design methodology from the early stages in product development and research that prescribes a scientific, iterative approach to exploring a design space (Brown, 2008; Hevner et al., 2004). This UXDI process model delineates activities that should occur in the design and usage worlds. We designed this process model to be consistent with research that advocates three interrelated innovation spaces: inspiration, ideation, and implementation spaces (Brown, 2008). The inspiration space focuses on situations where companies search for a solution or new market opportunity. The ideation space focuses on developing and testing solution ideas, and the implementation phase focuses on designing a path that brings the tested and approved solutions to market (Brown, 2008).

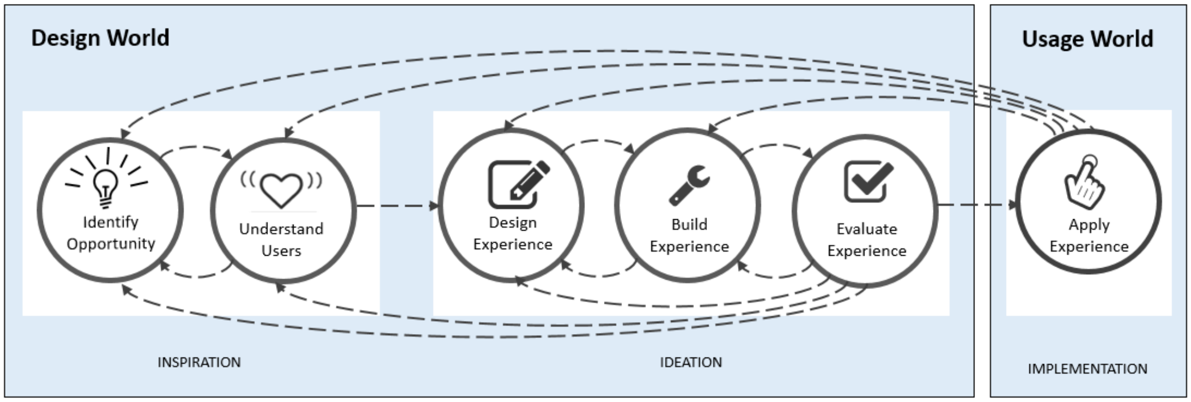


Figure 7. UXDI Process Model for Traditional Settings

Based on these ideas, the model categorizes the UX-driven technology design process into three distinct yet interconnected phases (Figure 7), the inspiration phase, the ideation phase, and the implementation phase. The first two phases in the model occur in the design world and the last phase occurs in the usage world. We need to distinguish between the design and usage worlds because, as we discuss in Section 3, each world has its own paradigms, theories, practices, and constraints. For example, design decisions, which occur in the design world, are informed by business strategy, which, in turn, is influenced by organizational culture and management mindset. User experience, which occurs in the usage world, is influenced by usage world constraints and situational and dynamic contextual factors such as the task and setting.

The inspiration phase in our model involves exploring the UX design space to identify opportunities for incremental, orthogonal, or breakthrough innovations (Figure 2b). This phase requires a deep grasp of user needs, goals, and challenges. Especially with vaguely defined problems, studying user needs and challenges offers an effective way to identify and define innovation opportunities.

The ideation phase involves designing, prototyping, and evaluating design ideas that address user needs. That is, in this phase, features and functionalities of the technology are designed, with alternative designs in the solutions space investigated as appropriate. This phase also involves choosing appropriate technologies (e.g., mobile apps, wearables, etc.) that can best deliver desired experiences. User tests for capturing and evaluating experience in this phase support the exploration of the solution space. These tests are conducted in the design world before implementing the resulting designed artifact in the usage world, and they serve as an important link between the design and usage worlds.

The implementation phase, the part of process after a technology is launched into the usage world, provides the opportunity to observe the designed artifacts in a real-world, usage context rather than in an artificial context in the design world. After all, the true impact of a design process lies in its ability to execute a vision into action (Liedtka, 2018; Brown, 2008). By launching the design idea in the usage world, this phase allows us to test how theoretical models used in the inspiration and ideation phases hold up in practice. Hence, this phase offers the opportunity to verify, extend, and/or build new theories by observing the impact of usage world constraints on use and user experiences over time. This objective can be achieved using the model displayed in Figure 6a.

The process that Figure 7 displays is an iterative course of action with many feedback loops. For example, the inspiration phase, which motivates the ideation phase, can also be informed by both the ideation and implementation phases. The circular nature of this process is due to the fact that the entire design and development process facilitates the exploration of the solution space. Through that exploration, new information is discovered about users, their needs, and their perception of what technology can do for them. The designed and theory artifacts can use this information directly and feed it back to designers in the design world. This information serves as a major source of innovation.

The iterative process in Figure 7 becomes a series of steps as the process is executed. Figure 8 provides an example of the step-by-step process for iteratively designing a new product. We can see that, after the product is designed and launched in the usage world (steps 1-3), the actual usage context or consumer data artifact (step 4) provides insight for the improvement of the designed artifact (step 5). This insight is then used in the design world to improve and launch the designed artifact (steps 2-3), which will provide data for continual improvement (step 4). The data artifact can also provide insight for persuing new market opprtunties (step 6), which then initiates the design of a new product (step 1).

In smart and connected environments, the processes that Figures 7 and 8 show require extensions (see Figures 9 and 10). That is, Figures 9 and 10 outline the same process as in Figures 7 and 8 but for UX-driven innovations in smart and connected environments. The models for traditional and IoT settings differ mainly in that, once the designed artifact is launched in smart and connected environments, the inspiration and ideation phases no longer occur only in design world. Smart artifacts, launched in the usage world, also embed an automated version of the inspiration and ideation phases, which are enabled by ML engines. This automation aggregates and analyzes data from various sensors into information for executive decisions about design improvements, market opportunities, experimentation, and so on. In smart and connected environments, the design world has a supervisory role to approve, deny, or modify insights that smart artifacts provide.

Figure 10 provides an example of the step-by-step process for designing a new connected product. We can see that, after the connected product is developed and resleased to the usage world (steps 1-3), IoT sensors provide real-time data for smart artifacts (step 4), which trigger action for personalization (step 5) or provide insights for experts to review in the design world (step 6). Experts in the design world can approve, reject, modify, or automate actions that smart artifacts recommend (step 7) and/or begin exploring new market opprtunties (step 8) and, thererby, start the pocess design for developing a new product (step 1).

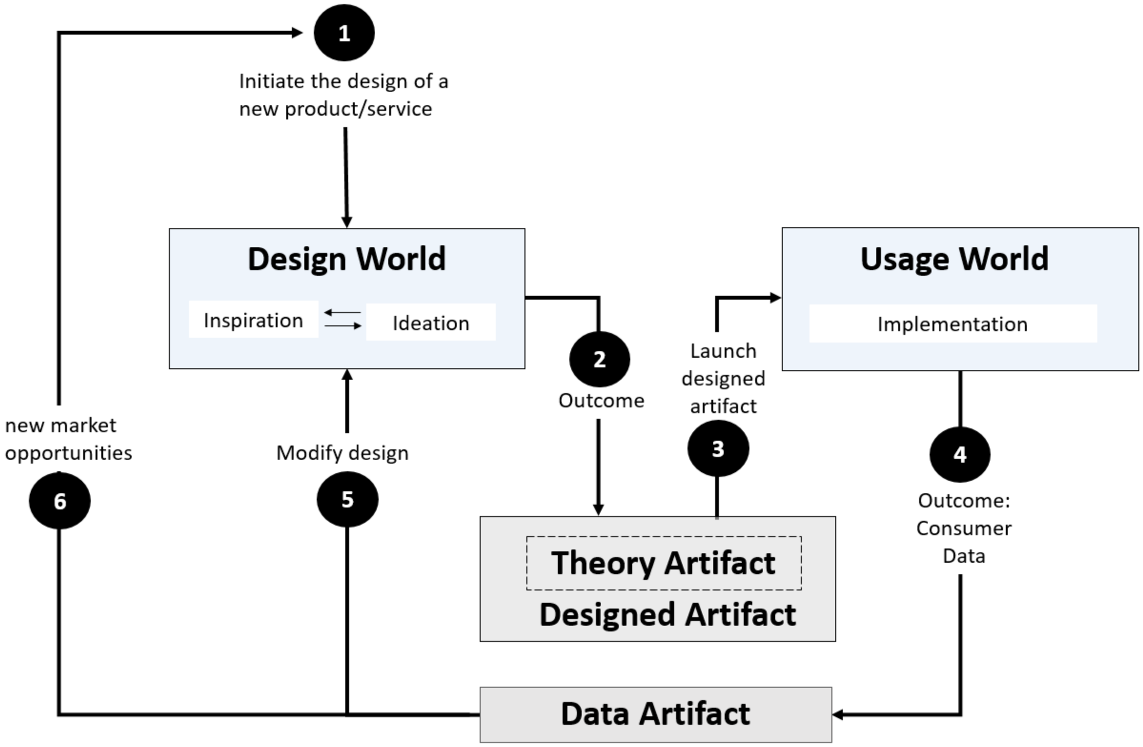


Figure 8. A Step by Step Example of UX-driven Innovation Process for Designing a New Product in Traditional Settings

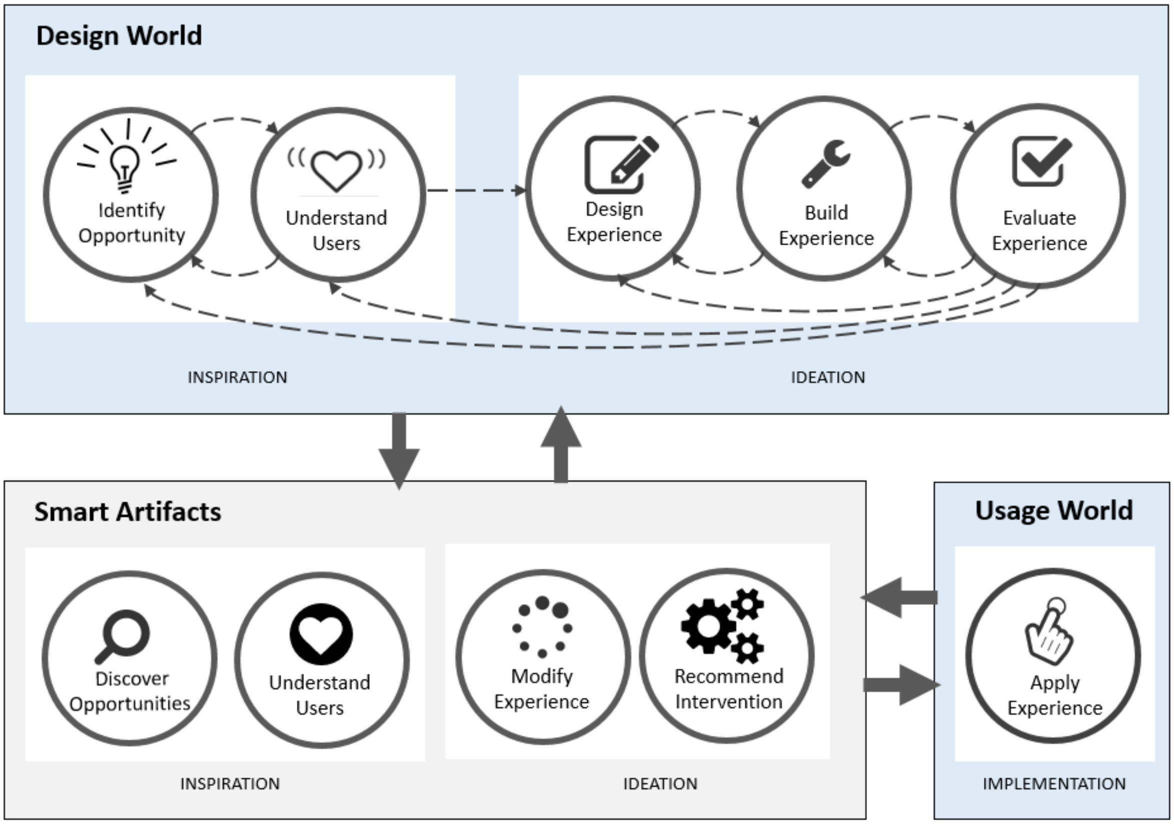


Figure 9. UXDI-SC Process Model for Smart and Connected Settings

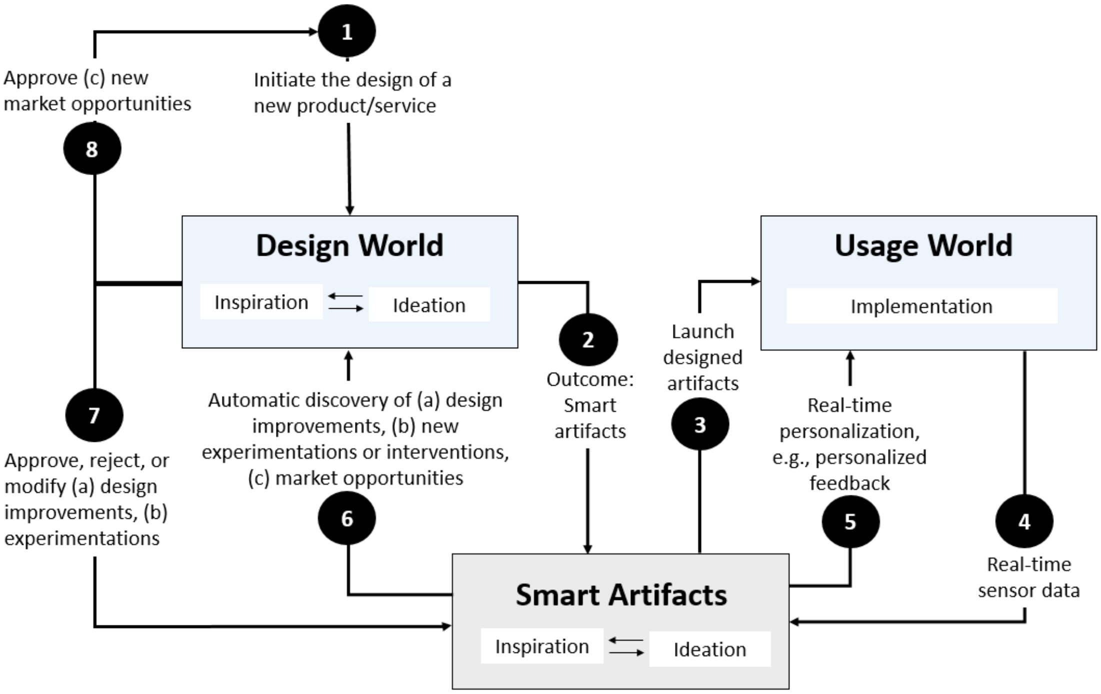


Figure 10. A Step-by-step Example of UX-driven Innovation Process for Designing a New Product in Smart and Connected Settings

6 Conclusion

A reciprocal relationship between advances in technology and novel user expectations creates a never-ending cycle of demand for innovation, which the fast pace of our digital economy exacerbates. Fortunately, the proliferation of smart and connected technologies provides opportunities for addressing the continual demand for innovation with an equally fast and continual process that promotes exploration of the innovation space through automatic experimentation.

UX-driven design must aspire to build solutions that go beyond meeting user needs; it must aspire to build solutions that empower users and improve their quality of life (Brown, 2008; Bajracharya et al., 2019; Bhattacharyya et al., 2019; Jain et al., 2019). A recent study demonstrates that putting users at the forefront of design is critically important in making successful design decisions (Jain et al., 2019). Doing so also serves as an organizational key performance indicator (KPI) for assessing the degree to which organizational assumptions about consumer needs align with actual market needs (Jain et al., 2019). The conceptual models that we outline in this paper also provide other KPIs (e.g., continual assessment of planned and actual outcomes) that will likely prove essential for staying relevant and competitive in today's fast-paced, digital economy.

Despite the call for UX-driven design as a key approach for empowering users and improving their quality of life (Brown, 2008; Bajracharya et al., 2019; Bhattacharyya et al., 2019; Jain et al., 2019), many systems that organizations use internally fail to deliver the user experiences that people have come to expect and demand from consumer products and services. One reason for a lack of UX focus in organizations may involve their requiring individuals to use those systems (mandatory use). Using popular mobile applications and website services, however, have changed what employees consider good user experiences (Wilson & Djamasbi, 2015). Requiring employees to use systems that fail to deliver an adequate UX can cause frustration and lead to ineffective technology usage and, hence, poor return on investment (ROI). Both frustration and poor ROI have significant negative impact on organizational outcomes. Hence, UX-driven innovation is relevant and important for not only customer-facing technologies that individuals voluntarily choose to use but also systems that employees must use internally in an organization.

In this paper, we develop four conceptual models for UX-driven innovations, two for traditional environments and two for smart and connected environments. We outline how we can capitalize on the power of smart and connected environments to 1) develop novel experiences that are continually tested and improved by automatic experimentation and 2) build advanced theories. The models that we outline in this paper represent a first step toward building a comprehensive scientific framework for UX-driven design. Future research is needed to refine the models we present in this paper through their use to guide UX-based innovation. Because the models we discuss in this paper include both design and usage worlds, collaborative industry-academic research is needed to gain both a more holistic and nuanced picture of opportunities that are inherent in UX-driven innovation, particularly those offered by smart and connected environments.

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