Making sense of digital innovation

Zhang, Nila

2020

Zhang, N. (2020). Making sense of digital innovation. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/136949>

<https://doi.org/10.32657/10356/136949>

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A thesis submitted to the Nanyang Technological University
in partial fulfilment of the requirement for the degree of
Doctor of Philosophy

2020

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate with amendments, changes and improvements as suggested by me as the Supervisor. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

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Authorship Attribution Statement

This thesis contains material from papers accepted at conferences in which I am listed as an author.

Essay #1 is published as Nila Zhang and Gun-woong Lee, "Consumer-perceived Value of Digital Product Innovations: Evidence from Smartphones". *the 23rd Americas Conference on Information Systems 2017, Boston, USA*

Nila Zhang and Gun-woong Lee, "Consumers' Evaluation of Digital Product Innovation", *the Annual Meeting of Academy of Management (AOM) 2017, Atlanta, USA*

Nila Zhang and Gun-woong Lee, "Consumer Valuations on Digital Product Innovation:

Evidence from Smartphones", *the 18th International Conference on Electronic Commerce (ICEC 2016), Suwon, South Korea*

The contributions of the co-authors are as follows:

- I provided the initial research idea and prepared the manuscript drafts.
- The manuscript was revised by Dr Gun-woong Lee.
- I co-designed the empirical study with Dr Gun-woong Lee. The data was collected by me. I wrote a program to grab data from the website. I also wrote a program to do the text-mining and sentiment analysis.
- Dr Gun-woong Lee assisted in the empirical analysis and econometric modeling, and provide guidance in the interpretation of the empirical results.

Essay #2 is published as Nila Zhang, Siew Kien Sia, and Gun-woong Lee, "The Institutional Legitimacy of Disruptive Start-ups in Sharing Economy." *Pacific Asia Conference on Information Systems, June 2018, Yokohama Japan*

Nila Zhang, Siew Kien Sia, and Gun-woong Lee, "Sharing Economy Disruption and the Quest for New Institutional Legitimacy". *International Conference on Information Systems 2017, Dec 10-13, Seoul South Korea*

The contributions of the co-authors are as follows:

- Dr Sia Siew Kien provide the initial project direction and edited the manuscript drafts.
- I wrote the drafts of the manuscript. The manuscript was revised together with Dr. Gunwoong Lee.
- The analysis and research framework were co-designed by Dr. Sia Siew Kien, Dr. Gunwoong Lee, and me. The news data was collected by me through an online database.
- The machine learning program was written by me. The training samples and coding guideline are manually coded and summarized by Dr. Sia Siew Kien, Dr. Gunwoong Lee, and me.
- Dr Sia Siew Kien assisted in the theortical framework design, and provide guidance in the interpretation of the analysis results.

Jan 15th 2020

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Acknowledgements

Undertaking this PhD has been a truly life-changing experience for me and it would not have been possible to do without the support and guidance that I received from many people.

I would like to first express my special appreciation and thanks to my supervisor, Dr. Sia Siew Kien, whose expertise was invaluable in the formulating of the research topic and theory building in particular. Throughout the writing of this dissertation I have received a great deal of support and assistance. I deeply appreciate all his contributions of time, ideas, and most importantly moral support. In addition to mentoring my thesis, he also provides me opportunities to accumulate experience on overseas conferences and other types of research projects.

I would also like to thank my co-supervisor, Dr. Gunwoong Lee. He has provided me extensive personal and professional guidance and taught me a great deal about both scientific research and life in general. He is kind, patient, and always willing to help. I'm grateful for all the thoughtful suggestions and advices he gave to me, which could benefit me even after my graduation.

I would also like to thank my committee members, Dr. Damien Joseph, Dr. Mo Jiahui, and Dr. Ping Wang for serving as my committee members. I also want to thank them for letting my defense be an enjoyable moment, and for their brilliant comments and suggestions. I would especially like to thank Dr. Mo Jiahui. Her research inspires me to explore new ideas and topics in different areas.

During the collaboration with her in the research projects, she has not only taught me step-by-step on how to conduct high-quality academic research rigorously, especially in terms of methodology. She cares about not only my research on hand but also my career development and life experience. As my teacher and co-author, she has taught me more than I could ever give her credit for here.

I am also grateful to all of those with whom I have had the pleasure to work during this and other research project. Particularly, I would express my gratitude to Dr. Boh Waifong, the head of our ITOM division. I deeply appreciate all her contributions of time, ideas, and most importantly guidance on the developing of our research project. Besides, as the PhD coordinator, she also provides me opportunities to have a well-designed PhD course arrangement and accumulate experience on teaching.

My gratitude also goes to all the faculty members in Nanyang Business School and the ITOM department, especially Dr. Christina Soh Wai Lin, Dr. GOH Kim Huat, Dr. Wu Yuan, Dr. ANG Soon, Dr. Trevor Yu Kang Yang, Dr. Elison LIM, Dr. ZHANG Kuangjie, Dr. Sharon NG Sok Ling, Dr. Faraji-Rad Ali and Dr. Suzanne Rivard, whose courses helped me to lay a solid foundation in information systems research.

I gratefully acknowledge the funding received towards my PhD from the Nanyang Technological University Research Scholarship. I also appreciate the kind help and professional administrative support from Ms. Teng Huay Chiun,

Ms. Quek Bee Hua, Ms. Karen Barlaan, Ms. Hu Tsai Ting, Ms. Ada Ong, and many other staff in Nanyang Business School.

I am indebted to all my friends, who I have met during these four years in Singapore. Their friendship and the warmth they extended to me have made my PhD life enjoyable. In particular, I would express my gratitude to Chen Yi, Zhang Yimiao, and Yang Yanjia. It is a lovely experience to chat with them, discuss research with them, and play with them. The special thanks also go to my friends back in Shanghai, Hong Kong, and other places in the world. Thanks for listening to my complaints, sharing my happiness, and being there for me.

I owe my great thanks to my master supervisor, Dr. Chen Hailiang, who is an excellent researcher in information systems. It is the research experience, when I worked with him as a research assistant, fostered my interests in academic research. Although I have graduated and left Hong Kong, he continues to provide me guidance and support for my research and career development.

Nobody has been more important to me in the pursuit of PhD degree than the members of my family. I would like to say a heartfelt thank you to my Mum, Dad, and my late grandma for always believing in me and encouraging me to follow my dreams. It's my great fortune to have such a considerate and supportive family. I love them so much, and I would not have made it this far without them.

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SUMMARY

The rapid development of digital technologies has been reshaping the way of designing products, services, and business models by stimulating remarkable innovations to industries. Specifically, the paradigm of production in digital products has shifted from merely increasing hardware parameters to providing innovative digital capabilities and services. In line with this, conventional business models (e.g., finance, transportation, and accommodation industries) are being challenged by digital innovation. However, it is still unclear how the digital innovation (i.e. digital product innovation and digital business model innovation) interact and make sense to focal stakeholders (i.e., consumers, regulators, industrial competitors and partners). Therefore, it is necessary to collect a large volume of data on multiple organizations and various industries engaging in both production and business model innovation. To make it work, advanced information technologies (i.e. Text Mining, Machine Learning, Natural Language Processing, and Deep Learning) enable us to gather and analyze large textual dataset. This also allows us to utilize quantitative methods (e.g., econometrics modeling and data mining) to understand qualitative (and unstructured) data. Combining rich data and quantitative approaches is expected to help us to better comprehend the dynamics in related industries. As a result, my dissertation works is expected to provide both theoretical and methodological contributions to management and digital innovation literatures.

Keywords: Digital Product Innovation, Digital Business Model Innovation,
Text-mining, Consumer Evaluation, Legitimacy

INTRODUCTION

Over the decades, digital technology has become a great driver for industrial transformations, and it creates opportunities for new business models and processes, new products, and new services (Nambisan et al. 2017). Examples are plenty – since the original iPhone in 2007, Apple and smartphone vendors have continuously introduced new technologies into their products and increasing number of smart devices have been present in the market; Netflix and YouTube are on the way to replace traditional TV programs from people's homes; and Uber and Airbnb have challenged and disrupted the traditional transportation and accommodation industries globally. The rise of digitization has attracted a growing number of IS researchers to study on digital innovation.

Digital innovation is defined as “a product, process or business model that is perceived as new, requires significant changes on the part of adopters, and is embodied in or enabled by IT” (Fichman et al. 2014). Prior IS literature on digital innovation has already spotted the influence of digital innovation for organizations and, broadly, for society (Yoo et al. 2010; Yoo et al. 2012; Nambisan 2017). By and large, these studies focus on the process of digitizing organizational business and product development procedures (e.g. Swanson and Ramiller 1997; Barua et al. 2004; Srivastava and Shainesh 2015) and impacts of adopting new IT technologies (e.g. Srivardhana and Pawlowski 2007; Lee and Berente 2012; Carlo et al. 2014). In recent years, researchers have started to explore the theoretical and managerial understanding of digital product

innovation and business model innovation (Fichman et al. 2014; Ghezzi and Cavallo 2018). They fall into two main categories: (1) adopting digital technology in new product development process can help to enhance firms' internal management conditions and external competitive advantages (Krishnan and Ulrich 2001); (2) introducing innovation to firms' business model can help firms to generate market values and ensure their financial viability (Weill and Vitale 2001). The studies of these two categories are both from the adopters' perspective to discuss how organizations interact with digital innovations. However, as a premise of the adoption and interaction, how digital innovations form/evolve requires IS researchers to further explore because not all innovations can be successfully survived in the current highly competitive and fast-moving digital era (Nambisan 2017). For example, a China's bike-sharing startup, Ofo, failed and is near bankruptcy¹, and Amazon failed to introduce its smartphone, Fire Phone, with a digital innovation component, 3D camera². As such, from disruptors'/innovators' perspective, understanding factors and processes of developing successful digital innovation is important and makes sense to both academia and industries.

One of the critical elements that influence the success of digital innovation is how digital innovation interact with stakeholders' (i.e. organizations and individual consumers) to foster cognitive sense-making

¹ Yue Wang (Dec 2018), "How China's Bike-Sharing Startup Ofo Went From Tech Darling To Near Bankruptcy" accessed by <https://www.forbes.com/sites/ywang/2018/12/20/how-chinas-bike-sharing-startup-ofo-went-from-tech-darling-to-near-bankruptcy/#204b77a66e66>

² PCMag Asia (Nov 2019), "The Biggest Smartphone Fails of the Decade " accessed by <https://sea.pcmag.com/gallery/35095/the-biggest-smartphone-fails-of-the-decade>

(Nambisan et al. 2017). Cognitive sense-making is related to questions: what does the innovation mean and how does it mean to the stakeholders (Weick et al. 2005)? The disruptive/radical digital innovation extends beyond traditional cognition of product and service categories (Lyytinen and Rose 2003). The emergence of them creates many new problem-solution pairs in multiple contexts (e.g., FaceID for identification and ridesharing apps for transportation), which breaks stakeholders' existing dominant cognitive frames of traditional business models and products (Lyytinen and Rose 2003). The reframing of digital innovation may be hard to understand by relative stakeholders (i.e. organizations and individual consumers). The adoption of digital innovation does not begin at introduction to the technology but substantially after the formation of stakeholders' cognition (Seligman 2000). As such, the success and survival of digital innovative products and business models depend on how their related stakeholders understand, accept, and satisfy the new cognitive frame of existing product categories and incumbent industries. However, there is still a lack of related research to understand how digital innovation (i.e. new products and business models) can interact with relative stakeholders to get socio-cognitive sense-making, such as being legitimized in incumbent industries and satisfying target consumers. As recent studies (e.g. Nambisan et al. 2017) indicate, it is necessary for IS researchers to explore how digital innovation can gain socio-cognitive sense-making among relative stakeholders.

To understand how digital innovations form/evolve, this dissertation develops theoretical and empirical insights into the determinants of developing

socio-cognitive sense-making for digital product innovation and digital business model innovation. This dissertation is organized into two essays as listed below.

(1) Essay #1: Consumer Evaluation of Digital-Product Innovations

Given the ubiquity and rapid development of digital products, firms have to continuously introduce innovative and novel features into smart products. Novelty, however, could reduce consumers' familiarity with and acceptance of new products. This research examines how the novelty-familiarity dilemma can be resolved by means of the product design of smartphones. Specifically, we examine how complementarity in radical and incremental hardware, and complementarity in hardware and software, can mitigate the negative effects of novelty that result from consumers' lack of familiarity with radical innovations. Text-mining techniques were employed to classify product innovation designs and to evaluate consumers' sentiments about digital-product innovations in smartphones. The quantified textual information is then used to assess the impacts of distinct innovation design strategies on consumers' assessments. The findings highlight the importance of leveraging complementarity in the design of digital products to resolve the novelty-familiarity dilemma. Overall, our findings inform how the design of smart products influences consumers' evaluations.

(2) Essay #2: Legitimacy Challenges in Digital Business Model Disruption

Relying on digital technologies (e.g., smart devices, peer to peer platforms, and cloud-computing services), many tech-startups have created

innovative business models (e.g. sharing economy model, blockchain, and crowdsourcing), and have threatened to disrupt the traditional industries (e.g. transportation, accommodation, and financial industries). However, the process of such digital business model disruptions is messy, requiring the contestation between incumbents and new entrants to negotiate a new legitimacy. Sharing economy, as a typical example of digital business model innovation, is suitable for us to understand the process of new legitimacy formation. By utilizing textual analysis techniques, we identify the legitimacy topics surrounding Uber and Airbnb, two leading tech-startups in sharing economy, from news articles published between 2008 and 2018. Our exploratory findings suggest a possible framework with regulative, normative, and cultural-cognitive legitimacy challenges driving the formation of the new legitimacy in digital business model innovation, with different intensity at different development stages and in different industrial contexts. Implications for research and practice are then discussed.

The expected contributions to the extant IS literature from the perspective of socio-cognitive sense-making of forming digital innovation are as follows. First, I show that the design strategies of digital product innovation affect consumers' sense-making/satisfaction of new digital products. The first study fills research gaps in digital product design by emphasizing the importance of digital product innovation designs on enhancing consumers' sense-making, which is directly related to the future success of innovative digital innovation. Second, this research explores the factors and the process of pursuing sense-

making among different stakeholders. The second study contributes to IS literature by introducing institutional legitimacy literature in IS studies to understand the challenges and processes of how digital business model innovation can disrupt and survive in the incumbent industries. These two studies with different research objects, digital products and digital business models, answer the research question, how digital innovation can successfully form and evolve. These findings can help firms that develop innovation to understand how digital innovation can make sense among different stakeholders and how can successfully address these challenges.

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ESSAY #1: CONSUMER EVALUATION OF DIGITAL- PRODUCT INNOVATIONS

2.1 Introduction

Digital product innovation refers to the development of novel or improved products that combine digital and physical components satisfying consumer needs (Hauser et al. 2006; Yoo et al. 2010). Like Yoo et al. (2010), we refer to the development of novel digital products, distinguishing this concept from the concept of process innovation through information technologies (IT) in the extant IT innovation literature (Swanson 1994). With advances in information technologies and the pervasive adoption of high-tech innovations, product innovation plays a pivotal role in increasing firms' profits (Markides and Geroski

2004). As such, digital product manufacturers are eager to include innovative hardware components and/or features in their new products to attract consumers' attention. Leading digital device manufacturers such as Apple and Samsung, in attempting to outdo competitors, are continuously acquiring and generating cutting-edge functional hardware components and adapting them into their latest product series.

Prior literature on digital innovation has already spotted the benefits of digital innovation for modern businesses (Yoo et al. 2012; Yoo et al. 2010b). By taking advantage of digital innovation in their business processes, for instance, firms have improved their overall performance and achieved better resource allocations and organizational capabilities (Nambisan 2013). Although both academic research and industrial reports have emphasized the significant role of product innovation in improving firms' performance and in acquiring consumers' attention to newly launched products, it is still unclear when and how digital product innovation, specifically the inclusion of novel features in a new product, does really play a pivotal role in attracting/satisfying consumers' tastes, which eventually determines firms' market shares and values (Bourreau et al. 2007; Rindova and Petkova 2007). Unlike integrated products (e.g., conventional home appliances), smart digital products (e.g., smartphones and smartwatches) are generally characterized as convergent products featured with independent modules and embedded digital capabilities (Han et al. 2009; Lee et al. 2013; Yoo et al. 2010a). The modular structure of a digital product enables firms to easily upgrade a product by improving its existing components (i.e., incremental

innovation) and/or including really-new hardware components (i.e., radical innovation) in a specific module (Baldwin and Clark 2000; Gershenson et al. 2003). Besides, as part of firms' digital innovation strategies, they are increasingly creating smart products – which embed digital technologies into physical artifacts that are previously non-digital in nature (such as smartphones) (Yoo et al. 2012).

The ease of introducing new hardware components, enhancements to existing hardware components, and the embedded digital capabilities, however, bring challenges to high-tech companies and manufacturers who now have to keep pace with consumers' growing demands for greater functionality and improvements to cutting-edge digital devices (Fang 2008; Gill and Lei 2009; Henard and Szymanski 2001). The fast pace of growth and demanding consumers leads to a hyper-competitive market, where smart product companies³ have to constantly innovate to introduce attractive and distinctive products that can accommodate heterogeneous consumers' needs and tastes. However, there is still a paucity of academic studies considering the harmonious configuration of various innovative components, specifically innovative hardware components, in a digital device as the important constituent of effective digital product designs to attract and satisfy consumers. Especially, prior studies have not considered the importance of product design strategies with innovative components (i.e. introducing different combinations of innovative components in a digital device)

³ We use the term “smart product companies” to refer to companies that own smart product brands, and orchestrate the design, manufacturing, marketing and sales of smart products.

in the digital product development stage, which potentially affect consumers' positive evaluations. The success of an innovation depends eventually on whether consumers are willing to accept them, and how they may react to improvements and new functionality introduced into smart products.

To provide insights into how firms should innovate on smart products, factoring in consumer reactions to and understanding of innovative smart products, we integrate two streams of literature: research examining consumer responses to innovations, and research examining organizational innovation strategies.

The first stream of research examining consumers' responses to innovations has focused on the three aspects: (1) describing the mental, behavioral, and demographic characteristics of consumers that are associated with their propensity to adopt novel innovations; (2) understanding the diffusion and sales growth of new products over their life-cycles; and (3) providing insights into the network externality effects, where a consumer's adoption of a product may be linked with the number of other consumers using the product (Hauser et al. 2006). One important aspect that remains underexplored is the understanding of socio-cognitive processes driving consumers' ability to understand and recognize the value of innovative products (Nambisan et al. 2017; Rindova and Petkova 2007). The evaluation of product innovation depends on if and how it makes sense for consumers. There exist considerable difficulties for consumers to make sense of the value and usefulness of products that significantly change underlying components or the configuration of attributes. (Rindova and Petkova

2007). The perceived values of products depend on whether consumers can mentally translate information of product features to functional benefits. Although firms emphasize that their innovative features offer advantages to consumers, consumers may not always or initially perceive the benefits of the novel features. Different types of innovative components/features trigger different sense-making outcomes regarding novelty (Griffith 1999). The product design choices and component introduction strategies may help infuse the sense-making of a new product for consumers. Hence, it is important to understand how consumers discover new meanings and make sense of innovations in the smart product space (Nambisan et al. 2017) and which combinations of components can trigger consumers' sense-making.

Highly novel products bear a higher level of uncertainty and risk to consumers, when they evaluate the usefulness of novel products (Hoeffler 2003). In particular, novel products might require a higher degree of change in the thinking and behavior of consumers using the products (Veryzer 1998), and greater effort on the part of consumers to learn and make sense to the products. As novel and innovative products and designs are unfamiliar to potential consumers, the latter might have doubts about the quality and usefulness of the products. Prior research has highlighted that consumers are more likely to make sense with novel innovations when they have a higher level of comprehension about the product and perceive fewer risks involved in product sense-making and adoption (Moreau et al. 2001). We thus examine the role that the concept of familiarity plays in consumers' evaluations of smart product innovations.

The second stream of research focuses on digital product innovations. Many studies have focused on identifying the key characteristics of digital product innovations (Yoo 2010) and attempted to understand what kind of innovation strategies might present the greatest likelihood of success (Pagani 2013). Adopting the Schumpeterian view of innovation (Schumpeter 1934), our work defines digital innovations as new combinations of digital and physical components (Yoo et al. 2010). Yoo (2010) highlights the need to examine firm strategies for creating digital innovations and how the design of smart products should take into account the ability to design products by combining digital technologies with physical artifacts. With the ability to mix and match different physical and digital components to generate innovative smart products (Baldwin and Clark 1994), organizations have to carefully consider how they should create innovative products that carefully make use of complementary innovative hardware components and how they should introduce newly supporting software with radical hardware components.

There is considerable scope to integrating the two research streams, as theories of product innovation cannot ignore the difficulties that consumers may have in understanding and evaluating the usefulness of novel products. Prior research has extensively studied product innovations only from firms' perspectives and paid less attention to consumers' perceptions of innovation outcomes (Ali et al. 1995; Hauser et al. 2006; Yoo 2010). Without a deep understanding of consumers' reactions to product innovation designs, firms are unable to achieve repeatable product success with superior product design

strategies. Further, the wide range of combinatorial possibilities for hardware and software components underscore the importance of factoring in the role that consumer familiarity may play in affecting their evaluation and acceptance of smart products. The consideration of consumers' sociocognitive processes is an important theoretical lens that can help provide guidance to firms as they navigate the challenges associated with determining the right set and combinations of digital and physical innovations to present to consumers in their smart products. Overall, there is a paucity of research considering how various physical and digital components should be combined in the design of smart products to attract positive consumer evaluations.

Consequently, this research aims to investigate how various product design strategies influence consumers' evaluations of digital products. In particular, the key aspects of innovative hardware components in improving consumers' evaluations of smartphones are scrutinized, given that smartphone vendors always emphasize the innovative hardware components when releasing a new smartphone. We attempt to understand how distinct product hardware innovation designs, which combine different types of hardware innovation, and provide supporting software for radical hardware components, would shape consumers' appraisals toward an innovative new smart product. This enables us to identify effective product design strategies that would foster favorable consumer assessments of smart products.

We examine the above proposed research questions in the context of smartphone products. We collected 78,167 consumer reviews on the most

popular 55 smartphones offered from 10 leading smartphone vendors and recorded the detailed hardware and software specifications of the sampled smartphones from multiple data sources. Textual analysis techniques such as content analysis and sentiment analysis methods are employed (1) to identify the distinct smartphone innovation design strategies; and (2) to assess consumers' evaluations of digital product innovation echoed in the smartphones from consumer review comments. The quantified textual information is then used to empirically investigate the association between product innovation designs and consumers' assessments of smartphones.

Overall, we believe that our findings provide salient insights for smart product firms and contribute to the digital innovation literature by linking product design strategies to consumer evaluations and acceptance.

2.2. Theory and Hypotheses

2.2.1 Consumer Familiarity in Radical vs. Incremental Innovations

Prior research has long distinguished between radical and incremental innovation as two key innovation approaches that firms adopt (Rindova and Petkova 2007). Radical innovations represent major departures from the current technology trajectory of the industry or may even offer functionalities and technologies incongruent with those in existing products (Garcia and Calantone 2002). Radical innovations typically provide new value, benefits, performance improvements and features not offered by alternative products available in the market (Danneels and Kleinschmidt 2001; Leifer 2000). Incremental innovations, on the other hand, refer to minor changes to the technology

trajectory of the industry, and typically represent minor improvements or upgrades to existing core components and functionality, generating value by creating additional benefits built upon and compatible with components that already exist in products available in the market (Garcia and Calantone 2002). In the smartphone context, “Touch ID” (i.e., a fingerprint recognition feature on the home button) adopted in iPhone 5s is an example of a radical innovation as it represents a radical departure to existing components and functionalities to the smartphone market at the point of introduction. Examples of incremental innovation in smartphones would include larger memory capacities, or longer-lasting battery life in newer smartphones.

Many innovators believe that the adoption of products will come naturally once novel features are designed into a product that meets users’ needs, as radically innovative products that generate “creative destruction” are more attractive to users (Schumpeter 1942). The value and perceived usefulness of innovations, however, is socially constructed. The pursuit of novelty involves a departure from the existing scope of understanding on the part of consumers. Innovation that brings about radical changes implies that there are many aspects that will be new to its users. Prior research has shown that innovations that change the way users interact with an artifact in unfamiliar ways can cause users to resist adopting the innovation (Hargadon and Douglas 2001). Therefore, the novelty in innovations is a double-edged sword. On one hand, it can bring significant value by introducing new and novel uses of an innovation. On the other hand, novelty implies that users are unfamiliar with an innovation and how it is used.

Consumers tend to infer the value of a product based on both their experience and knowledge of familiar features and their expectations about new features in the product. When evaluating the usefulness of radically new and novel products (Hoeffler 2003), consumers face greater uncertainty as radically new and innovative designs are unfamiliar to consumers. From a cognitive perspective, Mandler (1982) proposed that the *fit* between a product's attributes and the schemas it invokes in consumers (i.e., image or purpose of a product) leads to a consumer's sense-making and overall judgment of the product's value. The higher the level of congruence between the product attributes and the product's existing image/purpose, the greater consumers' familiarity with the attributes. Incongruity creates a cognitive challenge to the users – consumers have to find or develop a new schema to assess the potential value and usefulness of radically novel products (Rindova and Petkova 2007). For example, many smartphone users hardly discovered the merits of Face ID adopted in the iPhone X, comparing with previous Touch ID⁴, but smartphone users can easily value In-screen fingerprint readers. As such, products that are more congruent to existing schemas and familiar to consumers are likely to be evaluated more positively by consumers (Meyers-Levy and Tybout 1989).

In line with the above arguments, we define radical hardware innovations for smart products to be introductions of new hardware components that were previously not part of the smart product. The introduction of such new hardware

⁴ Face ID and Touch ID compared (2017, AppleInsider Staff) available at <https://appleinsider.com/articles/17/11/28/watch-face-id-and-touch-id-compared>

components is likely to introduce functionalities and features that are unfamiliar to consumers, triggering incongruity between product attributes and consumers' cognitive schema or image about the product. Without familiarity or relevant knowledge about the radically new features, it is difficult for consumers to assess its benefits/values, especially in highly complex digital products (Mukherjee and Hoyer 2001), thus decreasing consumers' perceived value of the innovations.

Furthermore, radical innovations also increase the learning costs for consumers, thus making it difficult for consumers to effectively utilize the smart product (Hoeffler 2003; Mugge and Dahl 2013). Learning cost refers to the cognitive effort consumers need to exert to search for and understand new knowledge to use the smart product effectively (Klemperer 1987; Mukherjee and Hoyer 2001). Since radical innovations are generally unfamiliar to consumers, such products require consumers to spend more effort to understand and use effectively.

In contrast, we define incremental hardware innovations for smart products as cumulative innovations and improved features/performance of existing hardware components for smart products. Such incremental innovations are less likely to trigger incongruity between product attributes and consumers' image of the product (Rindova and Petkova 2007), as they represent incremental improvements in existing hardware components that are already familiar to consumers. Incremental innovations fit easily within existing schemas, as such innovations present consumers with situations that are familiar, easy to understand, and associated with positive emotions derived from predictability

and familiarity (Rindova and Petkova 2007). With incremental innovations, experience and expectations based on current products enable consumers to understand the link between new features offered and the perceived benefits and utility that can be derived from the new features (Hoeffler 2003).

Incremental innovations also entail a lower learning cost compared to radical innovations. Consumers rely on their existing schema and knowledge to understand innovations. Processing information that is higher in familiarity requires less cognitive efforts (Mandler 1982). As incremental innovations imply consumers are able to transfer or build upon the knowledge of existing components, consumers need not put in a lot of cognitive effort to search for and learn new knowledge (Moreau et al. 2001). Hence, we hypothesize:

Hypothesis 1: Incremental hardware innovation is positively associated with consumer evaluation.

Hypothesis 2: Radical hardware innovation is negatively associated with consumer evaluation.

2.2.2 Effects of Complementarity

Entrepreneurs thus need to ensure that the design of their product strikes a balance between novelty and familiarity, by locating their ideas within the set of existing understandings of their consumers, and yet set their innovation apart from what already exists (Hargadon and Douglas 2001). The design of a product refers to the combination of different aspects of an object, as well as the arrangement about diverse parameters through which the object is created (Baldwin and Clark 2000). Specific to product design, it often refers to the

function and form of the object (Buchanan and Margolin 1995; Rindova and Petkova 2007). A product's design affects how individuals comprehend and respond to the product. Innovators thus have to carefully choose designs that strike a balance between novelty and familiarity. For example, by designing the incandescent light based on features of the already-familiar gas system, Edison was able to tap on the public's understanding of the current technology and lower the learning curve for the public (Hargadon and Douglas 2001).

We thus examine how leveraging the concept of complementarity helps to create product designs that can help firms to overcome the novelty-familiarity dilemma. As highlighted by Yoo et al. (2010), digital products are highly modular in nature, where individual components can be loosely coupled to create different products. This allows firms to architect linkages and match components together. This is in line with the Schumpeterian view of innovation (Schumpeter 1934), where innovations consist of recombination of components that were not previously combined. In particular, smart products can be conceived as modular products that combine several discrete hardware and software components across functional modules (Han et al. 2009; Lee et al. 2013). For instance, a smartphone consists of multiple hardware (e.g., CPU, RAM, and camera) and software (e.g., operation system and applications) modules. A smart product is most useful when various hardware and software components are working effectively in tandem. It is thus important to consider effective complementarities that make such combinatorial innovations effective, as consumer's perceived value of a modular product is affected not only by individual components in the product, but also by

inter-dependencies among the components (Baldwin and Clark 2000). Indeed, consumers' perceptions of a product are influenced by the entire configuration of attributes of a product (Rindova and Petkova 2007). This highlights the need to consider how firms might maximize the complementarity amongst different components (Schaefer 1999). In particular, we examine how firms make use of complementarity between radical and incremental hardware components, and between radical hardware and newly introduced supporting software to overcome the novelty-familiarity dilemma.

Complementarity between radical and incremental hardware components. An important aspect of a product's design is in determining which hardware innovations should be bundled together when launching a new product. This is in line with the idea of technology convergence, which refers to the integration of multiple knowledge and technological bases into a single product (Gill 2008; Han et al. 2009; Rosenberg 1976). The integration of disparate functionalities such as the ability to take a picture or a video with the mobile phone is the result of such technology convergence (Giachetti and Dagnino 2017). Having too many radical hardware innovations bundled into a new product exacerbates the challenges consumers face due to the lack of familiarity with such a novel product, as consumers will be unable to overcome the incongruity between their perceptions and expectations of the product and the new functionalities provided. Rather, we propose that there is a need to make use of complementarity between radical and incremental hardware innovations.

As noted earlier, radical hardware innovations in smart products involve

the introduction of new hardware components that are unfamiliar to consumers and increase the uncertainty that consumers face in evaluating the benefits and usefulness of the new product. On the other hand, incremental hardware innovations in smart products involve the enhancements of existing hardware components, and thus involve innovations on components users are already familiar with. By bundling radical and incremental hardware innovations together, incremental innovations could help to increase consumers' familiarity, extending the existing schema of users to help bridge the incongruent expectations posed by radical innovations. Incremental innovations thus provide users with the appropriate schema to understand the usefulness of the product's novel and radical innovations (Rindova and Petkova 2007). In other words, consumers are able to give meaning and interpret the value of the innovation as the novel products are presented in such a way that the radical innovations complement the attributes and components that are already familiar to the consumers (Hargadon and Douglas 2001). For example, the usefulness of a wireless charging technology (i.e., radical hardware innovation) in a smartphone is augmented with a fast-charging battery technology (i.e., incremental hardware innovation). This configuration will allow consumers to more easily perceive the convenience and improved experience provided by the new feature.

Prior research has also found that including new components in product innovations whose functional goals are congruent with the product's overall design goals can enhance consumers' evaluation of the product (Gill 2008). As consumers rely on their existing knowledge when learning about new products

(Rindova and Petkova 2007), complementing radical and incremental hardware innovations allow consumers to transfer their existing knowledge from a familiar domain (knowledge about existing hardware components in incremental innovations) to the new hardware components, facilitating consumers' learning about the radical innovations (Reinders et al. 2010). In accessing their knowledge about a familiar domain, consumers can compare the content and structure of their knowledge of the base and the targeted domain. In mapping elements across domains, these serve as paths via which knowledge can be transferred from the familiar to the unfamiliar domain. Hence:

Hypothesis 3: The negative effect of radical hardware innovation on consumer evaluation is weakened by combining radical and incremental hardware innovations.

Complementarity between radical hardware and software components.

Software is often designed to perform functions of hardware products, making the hardware products more attractive (Adomavicius et al. 2008). Indeed, many systems such as video game systems are composed of complementary hardware and software products (e.g. video game console and video games) (Binken and Stremersch 2009). Prior research has noted that consumers' utility derived from a product is often increased with the availability of complementary products and services (Gupta et al. 1999).

The interpretation of radical innovations thus depends significantly on the ability of firms to use supporting software to suitably invoke familiar schemas to

aid interpretations. For example, smartphones incorporating cameras often have software that uses the similar operation interface of the traditional digital cameras to invoke the familiar schema of taking a photograph with a camera. Hence, as people make sense of the new in terms of the old (Hargadon and Douglas 2001), the use of software can allow smart product manufacturers to flexibly invoke aspects of old or familiar even as they introduce radical hardware innovations that are unfamiliar to users. Complementary and supporting software can help users to transfer their knowledge from more familiar domains to understand and interpret radical hardware innovations (Rindova and Petkova 2007). As software is the key interface via which users interact with smart products, the use of complementary and supporting software is thus a key approach to manage the apparent novelty of radical hardware innovations.

Furthermore, leveraging supporting software can also reduce the learning costs that consumers may face in learning to effectively use the radical hardware innovations introduced in smart products. As supporting software is the key interface via which consumers interact with the smart product components, such software can enhance consumers' interactions with the new hardware components and reduce the complexity of using such unfamiliar components. As consumers often make high learning cost inferences and perceive radically new innovations to be complex and difficult to make sense of (Mukherjee and Hoyer 2001), reducing consumers' perceptions of the complexity of the product and facilitating their learning curve will help to foster a more positive evaluation of the smart product. Thus:

Hypothesis 4: Introducing radical hardware innovations with supporting software to a digital product is positively associated with consumer evaluations.

Finally, Figure 1 provides a summary of our hypotheses.

Figure 1. Research Framework

2.3 Methodology

2.3.1 Data Description

To empirically test the proposed hypotheses, we gathered data from multiple sources. We compiled a dataset that include (1) detailed hardware and software specifications of smartphone products from professional smartphone review websites (i.e., GSMArena.com and Phonearena.com) and (2) consumer rating scores (ranging from 1.0 to 5.0) as well as textual consumer review comments of the sampled smartphones from a leading online retailer (i.e., Amazon.com). We collected data on 55 smartphones offered from 10 leading

smartphone vendors in the U.S. smartphone market⁵ (i.e., Apple, BlackBerry, BLU, Google, HTC, Huawei, LG, Motorola, Nokia, and Samsung). The data collected was for the time frame ranging from October 2011 to September 2017. A total of 84,616 consumer reviews were collected from Amazon.com. To minimize the inclusion of irrelevant review comments, we excluded 6,449 reviews not directly concerning the features of smartphones or consumers' experiences with using the smartphones, such as comments on delivery, payment methods, and Amazon services. As a result, 78,167 reviews were selected for further analyses. Table 1 presents the number of consumer reviews and the number of products included for each smartphone vendor.

Brand	#Products	#Reviews
Apple	7	18,412
Blackberry	7	5,302
BLU	5	4,804
Google	6	9,967
HTC	5	4,845
Huawei	6	1,966
LG	5	5,089
Motorola	5	13,987
Nokia	4	2,289
Samsung	5	11,506
Total	55	78,167

Table 1. Smartphones and Consumer Reviews

2.3.2 Classification of Hardware Innovation Design Strategies

First, we identified the innovative hardware components embedded in

⁵ The selection of smartphone brands is based on the smartphone market shares in the United States (e.g., Market Shares in 2013: <https://www.statista.com/chart/1356/smartphone-market-share-in-q2-2013/>) and the Amazon Best Sellers listed in the cell phone category (<https://www.amazon.com/Best-Sellers-Cell-Phones-Accessories-Unlocked/zgbs/wireless/2407749011>). We included the firms' representative smartphone product lines that had been annually upgraded with most and latest innovative components in our sample.

smartphones and classified the components into different types of innovation based on our theoretical model, using a qualitative text-data evaluation procedure (i.e., content analysis) (Kolbe and Burnett 1991). To conduct the content analysis on smartphone innovations, we compiled detailed specification information about hardware components and software features for the 55 sampled smartphones from Phonearena.com⁶ and GSMArena.com⁷. In line with our theoretical model, we consider two types of hardware innovations: radical hardware (*HR*) and incremental hardware (*HI*) innovations. While *HR* refers to the inclusion of a novel (or really-new) hardware feature in a smartphone, *HI* concerns the improvement of an existing hardware element such as enhancements in CPU, memory, and battery capacity. In addition, we also identified new software features introduced to support the use of radically innovative hardware component(s) (*HR_SW*). Any software applications/aids introduced to help consumers better utilize radical hardware components are recorded as software supported radical hardware innovation (e.g., iPhone 6s' Live Photos for 3D touch).

To distinguish between radical (*HR*) and incremental (*HI*) hardware components available in a smartphone, we identified *HI* components based on

⁶ Phonearena.com is a well-established smartphone review website offering new smartphone information such as full specifications and in-depth comparisons with other smartphones.

⁷ GSMArena.com is a professional digital device review website. Its primary task is to provide detailed and accurate information about smartphones and their features. Since Phonearena.com does not provide actually full specifications of smartphones, missing information is supplemented by this website.

the benchmark modules ⁸ provided by Phonearena.com. A smartphone benchmark test is widely used to evaluate and compare hardware-related performances between multiple smartphones. The hardware component categories in the benchmark testing list are the essential/core components of a smartphone. Smartphone vendors generally report and emphasize how much improvement they made on these benchmark modules when introducing newer smartphones. Accordingly, if a newer smartphone made improvements in hardware feature(s) listed in the benchmark modules (as compared with those in its predecessor), we recorded them as incremental hardware innovations. A hardware component firstly introduced into a new smartphone product that cannot be classified as a component in this list is considered a radical hardware innovation. Notice that the measures of *HI* and *HR* are determined from comparisons between newly-launched smartphones and their previous versions in the same smartphone series. For example, iPhone 7 released in 2016 is featured with four *HI* components (in CPU, GPU, Camera, and Display) and two *HR* features as compared with its previous model, iPhone 6S in 2015. As an illustration, Table 2 shows the classifications for *HI*, *HR*, and *HR_SW* for the iPhone series.

⁸ Smartphone Benchmark Component Categories: CPU, Storage, Graphics, Network, Battery, Display, Camera, Audio, and Connection (e.g., Galaxy S7: https://www.phonearena.com/phones/Samsung-Galaxy-S7_id9817)

Product		iPhone4	iPhone4s	iPhone 5	iPhone 5S	iPhone 6	iPhone6s	iPhone7
Released Date		June 24, 2010	Oct 14, 2011	Sep 21, 2012	Sep 20, 2013	Sep 19, 2014	Sep 25, 2015	Sep 16, 2016
HW	Incremental Components (HI)	CPU GPU Storage Camera Battery	CPU GPU Camera Battery Connection Audio	CPU RAM Camera Battery Display Connection	CPU GPU Battery	CPU RAM Battery Display	CPU GPU RAM Camera Connection	CPU GPU Camera Display Network Battery
	Radical (New) Components (HR)	Front Facing Camera			Touch ID (Fingerprint recognition)	Barometer NFC	3D Touch	Dust and water resistant
		Active noise cancellation with a dedicated microphone						Combining Lightning Charge and 3.5mm headphone jack
SW	OS Version	iOS 4	iOS 5	iOS 6	iOS 7	iOS 8	iOS 9	iOS 10
	SW Supporting Radical HW Components (HR_SW)	FaceTime	.	.	Identification	Apple Pay	Live Photos	.

Table 2. Digital Product Innovation in iPhones

Two undergraduate students were hired as independent coders and asked to identify and classify the innovative components evident in each product launch based on the smartphone specifications. The coders had a training session, which trained them about the classification rules based on the definitions of innovation components. A pre-test was conducted with Samsung's Galaxy S series under the authors' guidance. After confirming the coding procedures by the authors, all 55 smartphone specifications were given to each coder, and the innovation components (i.e., *HI*, *HR*, and *HR_SW*) were identified and classified accordingly.

Finally, the classifications and identifications made by the coders were evaluated by the authors. Krippendorff's alpha (1980) for measuring inter-coder reliability was calculated to test the reliability of the content analysis outcomes

from the two coders. The inter-coder reliability coefficient (i.e., $\alpha = 0.92$) exceeds the recommended value of 0.70 and shows that the classification outcomes are statistically consistent between the coders.

2.3.3 Extracting Consumer Evaluation of Smartphones from Textual Review Comments

We collected information on consumer evaluation of each smartphone product in our sample to operationalize the dependent variable(s) used in our research models. To assess multifaceted consumers' appraisals about the products, we utilized both review rating scores and the content of reviews gathered from Amazon.com. While consumers' numerical review rating scores were used to examine their overall satisfaction of the smartphone, textual review comments were scrutinized to identify consumers' opinions/sentiments about the key aspects of smartphones (i.e., hardware-related innovations embedded in the sampled devices) by utilizing advanced data/text-mining techniques.

Prior research on online consumer reviews has reported that product review ratings have a *J*-shape distribution (Hu et al. 2017; Hu et al. 2009), in which rating scores are highly skewed to positive extreme values. As such, raw review rating scores may not adequately capture the nuanced differences in consumers' perceived value derived from a product. Recent research has increasingly adopted text-mining approaches to analyze the content of consumer reviews to avoid this issue (Archak et al. 2011; Ghose et al. 2012; Lee and Bradlow 2011). Hence, we text-mined textual consumer reviews to better

characterize consumer evaluation. Specifically, by utilizing Natural Language Processing (NLP) techniques, we extract consumers' product related opinion sentences from their reviews, and then identify the sentiment of these product opinion sentences. This allows us to exclude irrelevant or less-informative consumer review contents such as comments on delivery service and shopping experience. It also makes our sentiment analysis more specific and accurate in evaluating consumers' appraisals about smartphones based on their designs.

Although extant literature on consumer product reviews has extensively utilized text-mining approaches to measure a consumer's overall sentiment/evaluation of a product from the entire review comment (Duan et al. 2008; Huang et al. 2017), the sentiment that a consumer may exhibit on different components or dimensions of the product in the review has been largely ignored. Our research goes the additional mile by first identifying the specific components that a consumer mentioned in his or her product review, and then extracting the consumer's sentiment regarding that particular hardware component. This allows us to conduct robustness tests to examine whether our arguments pertaining to consumers' perceptions of the hardware innovations hold, as we examine consumer evaluations of only hardware-related features. It also further allows us to differentiate between consumers' evaluations about the overall smartphone versus specific aspects, such as hardware components. We conduct a series of textual analyses on consumer reviews including content analysis and sentiment analysis to derive product-specific sentiment from the reviews in a systematic manner, as described below.

Opinion Sentence Identification

The first step of the analysis is to identify sentences reflecting consumers' evaluation of the smartphone product. We followed text-mining procedures used to extract product attributes from consumer reviews presented in prior studies (Büschken and Allenby 2016; Hu and Liu 2004; Lee and Bradlow 2011). Firstly, each consumer review comment was split into sentences. Next, sentences consist of only irrelevant/less-informative words or symbols (e.g., "Yes.", "None.", and "!!!") were removed from the sample. Then, we identified sentences containing terms concerning the key features of smartphone products. Since a product's features are generally described with nouns or noun phrases (e.g., camera, fingerprint, screen, battery, etc.), we further identified whether a word in a review sentence is a noun, adjective, verb, or other grammar constituents by taking advantage of the NLP technique, *part-of-speech* (POS) *tagger*, which generates a POS tag for each word in a sentence. We used the POS tagger to classify nouns and noun phrases as candidate words that may characterize product features. We extracted these nouns and used a stemmer function to convert plural nouns to singular forms (e.g., from "photos" to "photo"). We then aggregated all noun words used across the reviews, and counted their frequencies of appearance. Only words that appeared in at least 1% across all review sentences were kept. Different consumers may have different product related stories and experience, but the words used to describe product features are usually similar across consumers. Thus, the sentences including these commonly-used nouns (and noun

phrases) are reserved as opinion sentences. Finally, sentences concerning something frequently mentioned but not related to the product's attributes, such as delivery, shopping experience, and service (e.g., “*Amazon service*”, “*fast delivery*”, and “*good seller*”), were also dropped. To verify our opinion sentence identification procedure, we randomly selected 1,000 sentences from the reserved 238,996 sentences, and then manually evaluated whether these sentences reflect consumers' opinions/sentiments on smartphones. We found that about 97% of sentences are directly related to consumers' experience and/or evaluations about the sampled smartphones. As a result, we confirm that the identified opinion sentences are well-represent consumers' overall evaluations on smartphones.

Content and Sentiment Analysis

Having extracted opinion sentences that consumers used to evaluate smartphones, we next conducted content and sentiment analysis to determine the extent to which consumers were positive or negative about the smartphone product. First, we performed sentiment analysis on each consumer review sentence to extract the overall evaluation. Having removed irrelevant sentences in the first step, only opinion sentences evaluating smartphones were used for further textual analyses. A deep-learning algorithm (Manning et al. 2014; Socher et al. 2013) was employed to conduct sentiment analysis. While most conventional NLP-based sentiment analyses heavily rely on the occurrences of polarity words (e.g. the occurrences of positive/negative words such as “*good*”,

“bad”, “amazing”) in a review comment, a deep-learning-based sentiment analyzer utilizes the *Recursive Neural Tensor Network* (RNTN) method to train on a sentence structure and to assess the meanings of noun phrases presented in a review sentence so that it can produce more credible and accurate sentiment analysis outcomes (Socher et al. 2013; Tang et al. 2014). The accuracy of this algorithm (reportedly over 85%) is generally much higher than other conventional sentiment analysis algorithms (Socher et al. 2013). We developed a Java program with the Deep-Learning Java package to compute a sentiment score (ranging from 1.0 (very negative) to 5.0 (very positive)) for each review sentence. Then, the averaged value of sentiment scores for all relevant sentences in a review comment is considered the consumer’s overall sentiment of a smartphone. Table 3 presents the sampled reviews and their corresponding sentiment scores computed by our deep-learning model.

Review Sentence	Sentiment Score
“Excellent product.” “The phones cameras and screen are absolutely amazing!”	5.0
“It worked fine and properly with no issues.” “Beautiful screen and fast.”	4.0
“Screen, features all work as mentioned.” “Battery does last for days.”	3.0
“Bluetooth and camera functions do not work.” “The sim card inside was not being detected.”	2.0
“Horrible piece of hardware.” “Basically a waste of money.”	1.0

Table 3. Sampled Review Sentiment Scores

To identify consumers’ evaluation of hardware-specific innovations in smartphones, we further extracted consumers’ sentiments about hardware-related components. A bag-of-words model (Sriram et al. 2010) was employed to scrutinize the content of a review comment to identify nouns that consumers use

to identify smartphone hardware components (e.g. “The *battery life* is great”; “The *camera* is blurry liked it is scratched”). We surface the words used by consumers to characterize smartphone hardware, rather than simply using product specification descriptions provided by smartphone manufacturers for several reasons. First, hardware-related terms used in a product specification tend to be too technical and may not be consistent with the words that consumers used to describe certain smartphone components and attributes (e.g., optical image stabilization vs. “*stable camera shooting*”). Second, the terms in the specification are generally restricted to explain particular hardware features and may not contain various and differentiated terms that consumers frequently use in their reviews (e.g., chipset vs. speed, pixel vs. camera/photo). Hence, we use the content of review comments to generate the keywords groups that consumers use to characterize the smartphone components.

We conducted text analysis as follows. First, we used all nouns words identified by POS taggers in the opinion sentence identification step. Only words that appeared in at least three reviews were kept to lower the overall sparsity of words across the reviews. As a result, 7,921 unique nouns were selected as candidate terms representing hardware components. Since consumers often describe their smartphone experience with auxiliary terms, the list still included numerous nouns not specific to actual hardware components (e.g., “*problem*”, “*price*”, “*life*”, “*quality*”, and “*product*”). To address this issue, we hired another two independent coders to manually evaluate whether the identified nouns in the reviews represent smartphone hardware components. As a result, we identified

395 nouns characterizing hardware-specific features. The high reliability score (Krippendorff's $\alpha = 0.90$) ensures that the evaluation outcome is reliable and the identified key nouns corresponding to hardware components are consistent across the coders. The ten most frequently appearing nouns representing smartphone hardware components are listed in Table 4.

Noun	Frequency of Mention
<i>Screen</i>	19,842
<i>Battery</i>	17,072
<i>Camera</i>	12,908
<i>Keyboard</i>	3,142
<i>Power</i>	2,960
<i>Button</i>	2,922
<i>Display</i>	2,560
<i>Memory</i>	2,278
<i>Storage</i>	2,226
<i>Wi-Fi</i>	1,620

Table 4. Most Frequently-mentioned Hardware Components in the Reviews

Next, the review sentences are classified by matching the extracted nouns with the hardware-specific nouns identified in the above step. The average value of sentiment scores for the sentences containing hardware-related nouns only is recorded as a consumer's sentiment on the hardware components of a smartphone. Table 5 summarizes the consumers' evaluations of sampled smartphones measured from the above textual analyses.

Variable	Description	N	Mean	Std. Dev.	Min	Max
<i>Rating</i>	A consumer review score on a smartphone (1.0 to 5.0 scale)	78,167	3.883	1.550	1.0	5.0
<i>Sentiment</i>	A consumer's overall sentiment score on a smartphone (1.0 to 5.0 scale)	66,744	3.002	0.827	1.0	5.0
<i>Hardware_Sentence</i>	A consumer's sentiment score on smartphone hardware components (1.0 to 5.0 scale)	32,265	2.780	0.873	1.0	5.0

Table 5. Summary Statistics of Consumers' Evaluations

As expected, the values of consumer ratings, *Rating*, are positively skewed, while the averaged values of overall sentiment scores, *Sentiment*, and hardware-specific sentiments of smartphones, *Hardware_Sentiment*, are closer to the mean score of 2.5.

2.3.4 Measurements

Dependent Variables

Consumer evaluation of smartphone product innovations is measured with three dependent variables, operationalized by both review rating scores and the sentiments of content in the reviews. The review rating is an evaluation metric measuring a consumer's attitude toward a product. Its value is ranged from 1.0 for "I hate it" to 5.0 for "I love it". We use it as the measurement of consumers' overall satisfaction derived from consumer review scores (*Satisfaction*). Furthermore, we evaluate consumers' overall sentiments (*Overall_Sentiment*) and hardware-related sentiments (*HW_Sentiment*) about smartphones.

Satisfaction: As the distribution of consumer rating scores is highly skewed to the maximum score (5.0) with a *J*-shape distribution (mean score was about 3.9) (Hu et al. 2009), we introduced a dichotomous variable indicating the degree of consumer satisfaction on a smartphone: high evaluation (=1) if a rating score is above 3.9 and zero otherwise.

Overall_Sentiment is measured by averaging sentiment scores across all the sentences in each review, and reflects a consumer's evaluation of the entire smartphone.

HW_Sentiment is measured by averaging sentiment scores across the

sentences (in a review) concerning hardware components only.

Independent Variables

Incremental Hardware (HI). As developers usually showcase smartphone improvements based on the number of benchmark modules they have made improvements on, we take into account the number of improved hardware features in each new product launch when evaluating how much a smartphone was incrementally enhanced from its previous version. We measure the degree of incremental innovation as the percentage of improved individual hardware components (in a smartphone) out of the nine modules pre-defined in GSMArena.com's benchmarking list: $\frac{\# \text{ Improved modules in a product}}{\text{Nine Modules in the list}}$. For example, *HI* value of iPhone 7 is 0.667 ($=\frac{6 \text{ improved component modules}}{9 \text{ modules}}$)⁹.

Radical Hardware (HR): We consider the new hardware components included in new smartphone launches by making a comparison with previous versions in the same smartphone series. For example, iPhone 5S includes a hardware innovation – fingerprint recognition feature. Since most smartphones in our sample include only one novel component, we created a binary variable to indicate whether a new smartphone model includes at least one radical hardware innovation component (=1, 0 otherwise) compared to its previous model.

Radical Hardware with Software Support (HR_SW): To test H4, we generated a variable to measure whether a radical hardware innovation is

⁹ iPhone 7 improved 6 modules as compared with iPhone 6S: CPU, GPU, Network, Battery, Display, and Camera. The model comparison information is available on GsmArena.com: <https://www.gsmarena.com/compare.php3?idPhone2=8064&idPhone1=7242>.

supported by software features. For example, iPhone 6s includes a new hardware feature, “3D Touch” which can distinguish different pressure degrees when a user pushes the screen, with a related software application, “Live Photos” which launches different actions in photographing according to how hard a user push the screen.

Control Variables

As controls, we included a set of review-, product- and firm-specific factors that could potentially influence consumer evaluation of a smartphone.

First, we control for variables relating to consumer reviews: (1) *Age_Review* measures the number of days between the launch date of a smartphone and the posting date of a consumer review; (2) *Helpfulness* measures how useful a review is perceived to be in helping others to evaluate the smartphone (i.e., the number of helpfulness votes by consumers); and (3) *Verified Purchase* indicates whether a review was made by a consumer whose purchase has been verified. This variable controls for potential differences between reviews written by consumers who used a product versus those who never experienced the product.

Second, the price of a smartphone (*Price_Group*) is introduced as a product-specific attribute that could affect consumers’ assessment of the smartphone. Since the key aspects of a smartphone (i.e., HW/SW-related features), that are most likely influential in shaping consumers’ evaluations of the smartphone, are already considered as independent variables in our empirical model, a single but potentially important factor (i.e., price) driving consumers’

appraisals is introduced as a product-level control variable. We employed the data from GSMArena.com, as they have created an index to monitor smartphone prices from various sources on a daily basis. This caters to the fluctuation in the price of a smartphone across time and countries. The index classified smartphones from 1: lowest to 10: highest based on their overall price levels. For example, iPhone 6s belongs to the price group of 9, whereas Nokia Lumia950 and HTC One-X are in price groups 7 and 4 respectively.

Third, we control for a set of firm-level attributes that could influence consumer evaluations. *High_Market_Share* is a binary variable indicating whether a smartphone vendor is one of the two companies having the largest smartphone global market share in a specific year. In general, the top two smartphone vendors (e.g. in 2017, Samsung - 23.8% and Apple - 15.4%) have about 40% of the global market shares. In addition, a firm's technological orientation, which could affect its product performance (Gatignon and Xuereb 1997), is also considered. We classify smartphone vendors according to their technological capabilities in developing SW (i.e., operating systems such as iOS and Android OS) and HW (i.e., devices): (1) SW-oriented vendors who used their own OS in smartphones; (2) HW-oriented ones who manufactured and/or designed devices in smartphone development; and (3) vendors who manage both SW and HW in their products. As such, we generate two dummy variables: *Software-Oriented* (e.g., Apple, Google, and Microsoft) and *Hardware-Oriented* (e.g. Apple, Samsung, and Motorola). To verify this classification, various firm-level technological capability measures such as the number of hardware/software

patents owned by the sampled vendors and their core business areas¹⁰ were considered, and we have found that our vendor classification is consistent across different measures. Finally, *Tenure_Smartphone_Market* controls for heterogeneity in firms' experience/capability in developing smartphones, and it measures the number of years elapsed since a firm's entrance into the smartphone market (i.e., the release day of the first smartphone by a vendor).

The key research variables used for empirical analyses are summarized in Appendix A.

2.3.5 Model Specification

In order to investigate the impacts of smartphone vendors' innovation design strategies on consumer evaluations, we utilized a multi-level mixed-effect model. Since a consumer's evaluation of a smartphone (i.e., the dependent variable) is generally influenced by factors at different levels (i.e., review-specific, product-level, and firm-level attributes), a hierarchical modeling approach would be appropriate. Therefore, our empirical analyses rely on a multi-level mixed-effects model.

Empirical analyses using overall consumer satisfaction: First, we investigate associations between distinct innovation design strategies exerted in smartphones and overall consumer satisfaction with the smartphones by using the review rating scores (i.e., *Satisfaction*) as the dependent variable. We model a mixed-effects logistic linear regression (MEL) to examine a consumer's

¹⁰ The firms' industry information is gathered from their official websites and Wikipedia pages.

evaluation of a smartphone using product-level predictors (with fixed effects) and firm-specific random effects¹¹. This model is suitable as it allows us to control for both product-level innovation strategies on consumer satisfaction via fixed effects and unobserved firm-specific covariates via random effects. The model specification is as follows:

$$\text{Logit}(\text{Satisfaction}_{ijk}) = \ln \left(\frac{\text{Prob}_{\text{Satisfaction}_{ijk}}}{1 - \text{Prob}_{\text{Satisfaction}_{ijk}}} \right) = \pi_{ijk}$$

, where i = consumer; j = smartphone; k = firm

$\text{Satisfaction}_{ijk}$ indicates whether consumer i has a positive evaluation of smartphone j offered by a firm k . To examine individual consumers' satisfaction on smartphones, we develop a binomial model with a logit link function. This function links the untransformed binary dependent variable ($\text{Satisfaction}_{ijk}$) to a transformed variable π_{ijk} . Since the variance of binary variables is determined by its mean, no residual term for the error variance exists at the consumer level. The equation below is then used to estimate the transformed variable π_{ijk} .

$$\begin{aligned} \pi_{ijk} = & \beta_0 + \underbrace{\beta_1 (HI)_{jk} + \beta_2 (HN)_{jk}}_{\text{Familiarity vs. Novelty}} + \underbrace{\beta_3 (HN - SW)_{jk}}_{\text{Complementarity}} + \underbrace{\beta_4 (HN \times HI)_{jk}}_{\text{Complementarity}} \\ & + \gamma (\text{Controls})_{ijk} + \alpha_{jk} + \xi_k \end{aligned}$$

, where $\xi_k \sim N(0, \sigma_\xi^2)$

We include product-level predictors concerning consumer familiarity and novelty in hardware innovations (HI and HR), complementarity in radical and

¹¹ We construct a conditional logistic regression model to accommodate product-level heterogeneity. Then, a random intercept logistic approach is adopted to control for differences between 10 firms.

incremental hardware innovations ($HR \times HI$), and complementarity in radical innovations and software support (HR_SW) into the model. A set of control variables ($Controls_{ijk}$) at different levels are introduced. α_{jk} indicates smartphone-specific fixed effects. Finally, ξ_k is a random intercept assumed to be normally distributed with the mean of 0 and the variance of σ_{ξ}^2 , which accommodates the variation across smartphone vendors.

We also conducted the same analyses using the other two measures of consumer evaluation derived from the sentiment analyses (i.e., *Overall_Sentiment* and *Hardware_Sentiment*). We developed a multilevel mixed-effects linear regression model (i.e., a random-intercept model) for the dependent variables concerning consumers' sentiments/opinions on smartphones. In addition, we conducted robustness checks of our empirical analyses by including a set of additional control variables concerning firm-level fixed effects to test if the original model with firm-level random effects produces consistent findings across different model specifications. The maximum likelihood estimator (MLE) was utilized to estimate the coefficients in the models.

2.4. Results

2.4.1 Overall Consumer Evaluation of Smartphones

The estimation results of our main regression models on consumers' overall satisfaction of smartphones are presented in Table 7. Columns 1 to 3 present the estimation outcomes from MEL models evaluating the impacts of smartphone products' innovation design strategies on overall consumer

satisfaction (*Satisfaction*). Columns 4 to 6 show the outcomes derived from linear mixed-effect regression models concerning consumers' overall evaluations (*Overall_Sentiment*) on review samples with detailed comments about smartphones. The presence of multicollinearity was checked with Variance Inflation Factors (VIF). None of the VIF values exceeded 2.0, indicating that multicollinearity was not an issue in our models.

Dependent Variable:	Consumer Overall Satisfaction (<i>Satisfaction</i>)			Consumer Overall Sentiment (<i>Overall_Sentiment</i>)		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Fixed Effect: Main Predictors						
<i>Constant</i>	2.475*** (0.116)	1.983*** (0.109)	2.081*** (0.114)	2.282*** (0.030)	2.181*** (0.032)	2.225*** (0.034)
<i>Incremental Hardware (HI)</i> (<i>Familiarity</i>)	.	0.706*** (0.046)	0.586*** (0.056)	.	0.127*** (0.017)	0.069** (0.021)
<i>Radical Hardware (HR)</i> (<i>Novelty</i>)	.	-0.071* (0.029)	-0.314*** (0.072)	.	-0.043*** (0.011)	-0.158*** (0.027)
<i>HR with Software Support (HR_SW)</i> (<i>Complementarity</i>)	.	0.139*** (0.025)	0.141*** (0.025)	.	0.026** (0.010)	0.029** (0.010)
<i>HR × HI</i> (<i>Complementarity</i>)	.	.	0.369*** (0.100)	.	.	0.175*** (0.037)
Fixed Effect: Controls						
<i>Ln_Age_Review</i>	-1.406*** (0.027)	-1.465*** (0.027)	-1.469*** (0.027)	-0.274*** (0.010)	-0.286*** (0.010)	-0.288*** (0.010)
<i>Ln_Helpfulness</i>	-0.535*** (0.010)	-0.548*** (0.010)	-0.546*** (0.010)	-0.205*** (0.004)	-0.207*** (0.004)	-0.207*** (0.004)
<i>Verified_Purchase</i>	0.747*** (0.033)	0.746*** (0.033)	0.745*** (0.033)	0.259*** (0.013)	0.258*** (0.013)	0.257*** (0.013)
<i>Ln_Price_Group</i>	-0.397*** (0.034)	-0.361*** (0.035)	-0.374*** (0.036)	-0.022 (0.013)	-0.004 (0.013)	-0.008 (0.013)
Random Effect						
σ^2_{δ} (<i>Between-firm variance</i>)	-1.253*** (0.227)	-1.406*** (0.229)	-1.378*** (0.229)	-3.090*** (0.245)	-3.104*** (0.250)	-3.059*** (0.247)
AIC	88179.99	87888.73	87877.09	160515.3	160415.2	160395.2
BIC	88235.59	87972.13	87969.76	160579.1	160506.3	160495.3
N	78,167	78,167	78,167	66,744	66,744	66,744
* $p<0.05$, ** $p<0.01$, *** $p<0.001$						

Table 7. Estimation Results of Main Analysis

In order to test the formulated hypotheses, we sequentially ran each model in three iterations with different sets of predictors. As baseline models, Models 1 and 4 are random-intercept models only with review- and product-level control variables (*Age_Review*, *Helpfulness*, *Verified_Purchase*, and *Price_Group*). Models 2 and 5 evaluate the main effects of radical hardware innovation with and

without incremental hardware components (*HI*) and complementary software support (*HR_SW*). Models 3 and 6 examine the interaction effects of incremental and radical hardware innovative components ($HR \times HI$) on consumer satisfaction.

We first test the two baseline models (i.e., Models 1 and 4), which include only control variables and firm-specific random effects (σ_s^2). The estimation results indicate that reviews made earlier (*Age_Review*), and made by consumers who purchased the smartphones (*Verified_Purchase*) are likely to have positive consumers' appraisals (i.e. higher satisfaction and overall sentiment scores) on the smartphones. However, reviews featuring more helpfulness votes (*Helpfulness*), and for smartphones at higher prices (*Price_Group*) are negatively associated with consumer evaluations. Furthermore, the estimates from the two baseline models are qualitatively consistent and statistically significant except the impact of price (*Price_Group*) on consumer satisfaction. The significant firm-level random coefficients (σ_s^2) across the models indicate that our model construction effectively incorporates firm-specific effects into the models, and show the suitability of using a multi-level model approach to deal with the unobserved heterogeneity between smartphone vendors. Therefore, our mixed-effects model specifications are valid in controlling for both fixed and random effects potentially made at review-, product-, and firm-levels in a hierarchical manner.

Consumer Familiarity in Hardware Innovations: HR vs. HI: In Models 2 and 5, we evaluate the main effects of product-level innovation strategies on

consumer evaluations. While the estimates of *HI* are positive and statistically significant at 0.1%, those of *HR* are negative at the 5% (or 0.1%) significance level in the models. Specifically, each additional percentage increase in incremental hardware innovations (*HI*) increases the odds of having high evaluation score (above 4.0) by 2.026 (= EXP(0.706)) times (in Model 2), and increases the expected sentiment score by about 0.13 (in Model 5). Meanwhile, the introduction of a radical hardware component (*HR*) into a smartphone decreases the likelihood of having a high evaluation by 6.8% (= 100*(1-EXP(-0.071))) and it reduces the sentiment score by 0.043, as compared to when no hardware radical innovation is present in the smartphone. As a result, the findings support Hypotheses 1 and 2, as we find that radical hardware product innovation (i.e. *HR* only) is detrimental to consumer satisfaction, but incremental hardware product innovation is likely to foster positive consumer evaluation of smart products.

Complementarity in Hardware Components: *HR* vs. *HR* + *HI*: Models 3 and 6 investigate the complementary relationship between radical hardware (*HR*) and incremental hardware (*HI*) innovations in stimulating positive consumer evaluation. The estimation outcomes of the interaction term of *HR* and *HI* (i.e., $HR \times HI$) are positive at the 0.1% significance level in both models. The estimate of $HR \times HI$ in Model 3 indicates that each additional percentage increase in incremental hardware innovation (*HI*) improves the likelihood of customer satisfaction for smartphones with radical hardware innovation ($HR = 1$) by about 1.45 times (=EXP(0.369)). Similarly, we find a positive marginal effect of *HI* on

the sentiment score for smartphones featured with *HR* in Model 6, showing that the negative effect of radical hardware innovation on consumer evaluation is mitigated by incorporating both incremental and radical hardware innovations into smart products. The estimate of $HR \times HI$ in Model 6 indicates that each additional percentage increase in incremental hardware innovation (*HI*) improves consumer sentiment for smartphones with radical hardware innovation ($HR = 1$) by about 0.175. Therefore, Hypothesis 3 is also supported.

Complementarity between Radical Hardware and Software Components:

HR vs. HR + SW: The estimated coefficients of *HR_SW* in Models 2 and 5 are positive and statistically significant at 0.01% and 0.1% levels respectively. Each additional percentage increase in radical hardware with software supporting (*HR_SW*) increases 14.9% likelihood of having a high evaluation score (above 3.9) (in Model 2), and the expected sentiment score by about 0.026 (in Model 5). These results show that after controlling for the positive effects of incremental hardware innovations, radical hardware innovations with software support have significantly positive impacts on both consumer satisfaction and overall consumer sentiment. This shows that the availability of complementary software features to radical hardware innovations can effectively mitigate consumer-perceived risks related to the unfamiliar schema of novel components. Hypothesis 4 is thus supported.

2.4.2 Robustness Checks and Additional Analyses

We conduct a set of additional analyses to validate our main findings. First, a consumer's overall evaluation of a smartphone (measured with

Satisfaction and *Overall_Sentiment*) could be influenced by other product strategies, such as the number of available software on app stores, and perceptions about smartphone brands. As our research aims to examine how innovative *hardware components* affect consumer evaluation, an alternative dependent variable is introduced to examine the validity of our arguments relating to how individuals value the *hardware innovations* in smartphone products. We use the average sentiment score of smartphone hardware related sentences in each review as our dependent variable. The estimation results with the new dependent variable are presented in Columns 1 (R1) and 2 (R2) of Appendix B.

The results reveal that our findings are mostly consistent across different measures of consumer evaluation on smartphone product innovations. The only difference is that radical hardware innovation does not significantly influence consumer evaluation of hardware components (see R1). This may be because tech-savvy consumers, who tend to describe the technical details with specific terms about hardware components in their review comments, have more knowledge about smartphones than other consumers. On one hand, the tech-savvy consumers may have higher evaluation criteria and low evaluation of some radical innovation. On the other hand, prior literature has argued that a consumer's ability to understand and accept an innovation depends on his or her existing knowledge and experience (Venkatesh et al. 2012). Consumers knowledgeable in a specific product category (or domain) would be less influenced by the level of incongruity between a new product and its schemas

(Moreau et al. 2001; Peracchio and Tybout 1996). As such, consumers, who used specific hardware terms in the reviews, are familiar with smartphone hardware components and are not likely to have negative sentiments about a product when they evaluate *HR* separately (in R1) since they can easily evaluate the values/benefits of hardware artifacts based on their domain knowledge. Hence, overall, the evaluation of radical innovation becomes not significant. As such These consumers, however, continue to appreciate the complementing of incremental and hardware innovations ($HR \times HI$), and the use of software to support hardware innovation (HR_SW), as they can better evaluate the newly-introduced features along with the improved (familiar) hardware elements and with software support.

Second, in the main analysis, we controlled for firm-level influence by using a mixed random-effect model. To ensure the consistent estimation outcomes across different model specifications, we have included vendor-level fixed effects into the original models. The estimation results are presented in models R3 to R6 in Table 8. All the findings are qualitatively consistent with the main results. Therefore, our empirical findings are valid and robust to different model specifications.

Third, some consumers may seek novelty and others prefer familiarity. Prior studies on diffusion of innovations have revealed that early adopters are less price-sensitive and risk-taking in purchasing a new (innovative) product, and are excited by the novelty of new ideas and new functionalities featured in the product, but those who adopted the product later (i.e., laggards) are averse to

change and risk, and are thus keen on familiar features (Mahajan et al. 1990; Moore 2014). Hence, those who make purchases soon after the launch of the products can be considered to be early adopters seeking novelty, while those making purchases later are likely to be those who are more risk averse and prefer familiarity. We conducted further analysis to verify this by showing whether there are distinctive patterns in the review comments provided by the early adopters vs. those who tend to make purchases later after the product launch. The results are listed in Table 9. Overall, the results are consistent with our main findings. The only difference is that radical hardware components with software support are not significant positive in the analysis within 1 year. This may because early adopters are more critical for radical innovation.

	Within 2 years		Within 1 years	
Dependent Variable:	Consumer Overall Satisfaction (Satisfaction)			
Constant	0.060 (0.101)	0.211* (0.105)	0.148 (0.132)	0.242 (0.136)
Incremental Hardware (HI)	0.468*** (0.053)	0.192** (0.071)	0.310*** (0.071)	0.118 (0.093)
Radical Hardware (HR)	-0.158*** (0.033)	-0.595*** (0.082)	-0.257*** (0.041)	-0.571*** (0.106)
Radical HW with Software (HR_SW)	0.067* (0.034)	0.096** (0.034)	0.044 (0.044)	0.066 (0.045)
HR × HI		0.681*** (0.117)		0.506** (0.158)
Fixed Effect: Controls				
Product Fixed Effects	√	√	√	√
Review Fixed Effects	√	√	√	√
σ^2_s (Between-firm variance)	-1.961*** (0.246)	-1.918*** (0.245)	-2.075*** (0.273)	-2.031*** (0.268)
AIC	62737.87	62705.93	37916.38	37908.12
BIC	62817.15	62794.01	37991.26	37991.31
N	49427	49427	30322	30322

Table 9. Estimation Results of Robustness Checks with Different Adopters

In addition, we conducted further analyses to exclude alternative explanations for our main findings. In the main analysis, we defined radical

hardware innovation based on novel hardware features introduced to a new product offered by a particular vendor. In the smartphone market, however, such radical hardware innovations could already have been introduced into the market by other firms. As a result, it may be argued that consumer evaluations of such smartphones could be affected by comparisons with existing products having similar radical innovation components previously introduced by other firms. To rule out this concern, we redefined radical hardware innovation as new hardware features in the focal phone that were introduced for the first time in the smartphone market. This resulted in a smaller subset of radical innovations (*HR_Market*). Models R7 to R10 show the results based on this new definition of radical innovation. These results are also consistent with our main analyses.

Thus far, we have investigated the effects of complementarity in incremental and radical hardware innovation ($HR \times HI$) and in radical hardware with software support (HR_SW) separately. To measure the joint effect of complementing radical hardware with both software support (HR_SW) and incremental hardware components (HI), we introduce an additional interaction variable ($HR_SW \times HI$) into the models. First, in order to better appreciate the joint effects of complementarity in the three types of innovation components, we conducted further analyses for all smartphone products having either radical or incremental hardware innovations (R11 and R12 in Table 10). Second, to appreciate the moderation effect of software support on the complementary effect of incremental components on radical innovation, we further performed analyses on smartphones featured with radical hardware innovation only (R13 and R14 in

Table 10).

	All Products		Products with Radical Innovation Only	
Dependent Variable:	Consumer Overall Satisfaction (<i>Satisfaction</i>)	Consumer Overall Sentiment (<i>Overall_Sentiment</i>)	Consumer Overall Satisfaction (<i>Satisfaction</i>)	Consumer Overall Sentiment (<i>Overall_Sentiment</i>)
	R11	R12	R13	R14
Fixed Effect: Main				
<i>Constant</i>	1.929*** (0.111)	2.153*** (0.033)	1.635*** (0.130)	2.002*** (0.044)
<i>Incremental Hardware (HI)</i> (<i>Familiarity</i>)	0.825*** (0.064)	0.185*** (0.024)	1.095*** (0.086)	0.247*** (0.032)
<i>Radical Hardware (HR)</i> (<i>Novelty</i>)	-0.078** (0.029)	-0.047*** (0.011)	.	.
<i>HR with Software support (HR_SW)</i> (<i>Complementarity</i>)	0.309*** (0.069)	0.110*** (0.026)	0.605*** (0.085)	0.179*** (0.032)
<i>HR_SW × HI</i> (<i>Complementarity</i>)	-0.264** (0.100)	-0.130*** (0.037)	-0.542*** (0.117)	-0.178*** (0.043)
Fixed Effect: Control				
Review Fixed Effects	√	√	√	√
Product Fixed Effects	√	√	√	√
Random Effect				
σ^2_{η} (<i>Between-firm variance</i>)	-1.410*** (0.229)	-3.102*** (0.248)	-1.526*** (0.242)	-2.987*** (0.260)
AIC	87883.77	160405	60048.13	110280.1
BIC	87976.43	160505.2	60128.16	110367.5
N	78,167	66,744	53,756	46,271
* $p<0.05$, ** $p<0.01$, *** $p<0.001$				

Table 10. Estimation Results of Consumers' Review Sentiment

The significant and negative estimate of interaction term $HR_SW \times HI$ indicates that the positive complementary effect of radical and incremental hardware innovations is weakened by the inclusion of software support. Figure 2 presents how software support influences the marginal effect of complementarity in radical and incremental hardware innovation on consumer evaluation. It shows the changes in the marginal effects of incremental hardware innovation on consumer evaluation of smartphones with radical hardware innovation only

(dashed line) and those with both radical innovative hardware components and software support (solid line). Although both two lines are up-inclined, the slope of the marginal effect of incremental hardware becomes flat when radical hardware is aided by software. This indicates that the contribution of incremental hardware innovation in mitigating consumer-perceived unfamiliarity from novel features can be substituted by appropriate software support.

Figure 2. Marginal Effects of Complementarity between Radical and Incremental Hardware Innovation and Software Support

2.5 Discussion and Conclusion

This study examines how product design strategies help to resolve the novelty-familiarity dilemma prevalent in innovative digital products in the smartphone context. Our findings demonstrate that relying solely on novelty in product innovations can negatively influence consumers' appraisals of new smart products. Although radical hardware functionalities may help companies attract consumers' interests in a hyper competitive smartphone market, consumers' perceived uncertainty and unfamiliarity of these highly innovative features are

eventually translated into unfavorable evaluations of the product. The lack of familiarity and the high learning costs to consumers negatively influences consumers' evaluation of the value and usefulness of the novel features. In contrast, incremental hardware innovations appear to be better received by consumers as they build upon consumers' current understanding of the product. Furthermore, introducing supportive software features can assist consumers easily perceive the usefulness of the novel features with low learning costs, which can eventually increase a consumer's evaluations about a novel product.

Our study thus proposes two innovation strategies that firms can adopt to overcome the novelty-familiarity dilemma, both of which leverage the concept of complementarity. First, we theorize and empirically show that complementing radical hardware innovations with incremental hardware innovations will mitigate consumers' unfamiliarity with a new smart product. Along with highly innovative but unfamiliar hardware artifacts, the inclusion of existing (familiar) but improved components into a new device can assist consumers to overcome the incongruity between their perceptions and expectation of the product. The use of incremental hardware innovations allows consumers to transfer their knowledge from more familiar domains to learn and interpret radical hardware innovations. As a result, reduced uncertainty and risks involved in product adoption creates a significant positive effect on consumers' overall assessments about the new product.

Second, we theorize and empirically show that the availability of software support to complement the radical hardware innovation. Such software support

has the potential to enhance users' interactions with the radical hardware components, thus increasing consumers' understanding of radical innovations. This suggests that enhancing user-product interactions (via software) should be considered as a way to enhance consumers' usage of smart products, instead of exerting tremendous efforts on improving hardware performances without considering software support. We found that having software support makes the benefits of radical hardware innovation more obvious. In sum, our findings highlight the pivotal role of strategic product designs leveraging on complementarity to improve customers' satisfaction with smart digital products.

2.5.1 Research Implications

The results of this research have salient implications not only for the extant literature on digital product designs and product-level innovation strategies, but also for practice. From an academic perspective, our research brings together two streams of literature on research examining consumer responses to innovations and research examining organizational innovation strategies. The integration of these two streams of literature allows us to provide insights to solve the novelty-familiarity dilemma by proposing the use of complementarity as a design strategy. Our findings firmly establish the importance of strategic product design as a key to success in the smart product markets.

Our research is one of the few limited studies exploring how the physical and digital aspects of a smart product work together, based on the principles of complementarity. We find that appropriate compositions of product combining

radical and incremental hardware innovations, and combining radical hardware innovations with software support, are most optimal to resolve the novelty-familiarity dilemma, while “overdoing” complementarity in terms of combining radical with incremental hardware innovations with software support might not be effective. We thus contribute not only to a greater understanding of how physical and digital artifacts might be combined, but we also extend the new product development literature by providing additional evidence of the positive effects of complementarity and the negative effects of lack of familiarity in smart products. We believe that our research findings will bear significant implications for future research in the theorizing of effective smart product designs with innovative components.

Empirically, prior literature has relied significantly on theoretical modeling and lab experiments to examine the key elements of innovative products in enhancing product sales performance and consumer adoptions. This research utilizes large-scale real-world datasets and empirically validates the effects of the three key principles in smart product designs – novelty, familiarity, and complementarity – on consumer satisfaction. In so doing, our study is one of the first studies, to our knowledge, to empirically substantiate the complementary effects of modular innovation strategies (i.e. hardware and software innovative components, and radical and incremental hardware innovations) in smart products.

From a practice perspective, the findings of this study will provide insights into how smart product manufacturers can utilize strategic modular

innovation design strategies to satisfy and attract consumers. Our findings suggest that the introduction of radical hardware components in a new product may not be always attractive to consumers mainly due to lack of familiarity. Rather, businesses should introduce novel hardware elements with supportive software features or with incremental hardware innovations to satisfy consumers.

2.5.2 Limitations

While we believe that our study provides theoretical and managerial insights, it is not without limitations and opportunities. First, we are unable to avoid the self-selection issue in our sample. Consumers' assessments on the sampled smartphones were extracted from consumer review ratings/comments posted on an online retailer, Amazon.com. Most of the Amazon.com reviews are written by purchased consumers, after a short period of usage. Therefore, the evaluation is only from highly involved consumers. These consumers are likely to write extremely positive (or negative) review comments on the product. Besides, we do not have related characteristics for identifying the different effects of product innovation on different types of consumers. For future research, a research design using controlled-experiments would be helpful to address this potential issue. Nevertheless, our sample presents balanced numbers of positive and negative consumers' evaluations. As such, the issue of self-selection is not the main concern in our analyses.

Second, we used 55 smartphones from the 10 leading firms to empirically validate the hypotheses. While this may not represent all smartphone products in the market, all the smartphone series used in our study are the most popular

smartphone models in each smartphone vendor's product lines (e.g., Samsung's Galaxy S Series and Apple's regular iPhone series). As our sample accounts for about 90% of market shares, we believe our sample is representative of the products available in the smartphone market.

Third, in our study, we only consider the software support for radical innovation components because incremental innovation components are well-established infrastructural components with existing software supports already built in, typically via settings in the operating systems. In our dataset, the differences among operating systems for Android smartphones are limited and most of the smartphones in our dataset use Android OS. Therefore, we did not consider the OS's software support for incremental innovation components. However, in recent years, more and more smartphone vendors start to customize their Android OS functions. In future research, it may be better to consider the complementary effects of customized/updated OS functions.

Fourth, our study uses the percentage of improved benchmark hardware components and the binary variable of radical hardware to measure the independent variables. However, it is possible that consumers may value differently for different component innovations. For example, consumers may value more on the camera's incremental innovation than audio's incremental innovation. Therefore, in future study, it would be better to further explore which kinds of incremental and radical innovations can enhance consumers' evaluation more.

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ESSAY #2: LEGITIMACY CHALLENGES IN DIGITAL BUSINESS MODEL DISRUPTION

3.1 Introduction

About a decade after the sharing economy began its rapid rise across the globe, the hustle of innovation initiatives with the exponential growth in the number of new tech-startups has triggered the new business model disruption. Different from the key attributes in traditional business models hiring regular employees, manufacturing goods, and providing services to consumers, sharing economy heavily relies on digital technologies in providing a unified platform for a sharing access to personal assets and matching demands and supplies of the shared access (e.g. ridesharing, home sharing, P2P lending) in a more direct manner. The sharing economy tech-startups, such as Uber and Airbnb, have dramatically transformed the way of transport, accommodation, and service and goods exchanges. Such new business models have lowered the barrier of suppliers' market entry (e.g. individuals can add themselves as available Uber drivers and/or Airbnb hosts rooms through an app) and simplified consumers' ordering processes (e.g. consumers simply book a car by pushing a button to call a nearest Uber driver.). A recent survey reveals that the US transportation market share has been overturned by ride-sharing firms. In 2018, the ride-sharing firms replaced the traditional firms to be the biggest player in the US transportation

market, reaching to the 72.5% share¹². PwC estimates that the revenue of the sharing economy is expected to reach \$335 billion by 2025¹³. While the innovation rhetoric about the new business model (i.e. sharing economy) has received much attention, actual disruptions to the existing industries are not sufficiently understood by both researchers and practitioners. Successful diffusion of innovation is not only a rational pursuit for stronger performance, but also a quest for legitimacy of business innovation (Aldrich and Fiol 1994; Rao et al. 2008), which is related to the death rate of young innovative firms (Singh et al 1986).

The legitimacy of a firm refers to being accepted by stakeholders, such as regulators, mass consumers, and other industry actors (e.g. rivals, funders, partners, etc.) in its related institutional environment (Bitektine 2011, Bitektine and Haack 2015). Perceived illegitimacy by these stakeholders will consequently lead to radically reforming or exiting (Dowling and Pfeffer, 1975; Rao 1994). For a new digital business model, gaining legitimacy in the eyes of the customers alone will not be enough. For example, Airbnb has been launched in Singapore since 2012 and there are about 7,000 Singapore properties listing on Airbnb. However, Singapore's housing laws has announced that short-term rental service is illegal and forbidden in Singapore. Similarly, although a large group of Uber

¹² Wolf Street Inc. (July 2018) "Uber and Lyft are gaining even more market share over taxis and rentals," accessed by <https://www.businessinsider.com/uber-lyft-are-gaining-even-more-market-share-over-taxis-and-rentals-2018-7/?IR=T>

¹³ PwC Inc. (August 2014) "The Sharing Economy: How Will It Disrupt Your Business? Megatrends: the Collisions," accessed by https://pwc.blogs.com/files/sharing-economy-final_o814.pdf

and Lyft users are in New York City, New York City Council voted to limit Uber and Lyft in 2018. Greater efforts are necessary to legitimize themselves with the others in the broader operating context which has been built up around the old system over the years. The operating context presents a set of rules, norms, and beliefs which organizations must conform to in order to gain legitimacy for survival (DiMaggio and Power, 1983; Scotts, 1995). Often, legitimacy is a challenge of institutional entrepreneurship (Aldrich and Fiol 1994). The disruptive start-ups need to “stumble upon” and leverage certain opportunities to get legitimacy, e.g., taking advantage of the regulatory void in nascent markets, to challenge the existing norms. Sharing economy is currently still in this nascent period where the possible disruptive future, not yet fully formed, coexists with the existing institutional norms, where the emerging new trajectories are continuously challenging – and are challenged by – the existing ones. Some disruptions may succeed as path-changing innovation and become a routine part of everyone’s life, while others will falter and eventually what seems promising turns to become disappointing failures.

The fact that only some disruptive innovations succeed in crossing the chasm and others fail awaits further theoretical explanations. As legitimation is a process of increasing acceptability (Maurer 1971, Deephouse and Suchman 2008), we still lack a better understanding of the process of new legitimacy formation. The main objective of this study is to understand what legitimacy challenges are faced by tech-startups and to identify how these challenges are raised/considered in different stages of development and different industrial

contexts. At the organizational level, as an aspiring tech disruptor or an established incumbent, such understanding will help them to better assess the likelihood of a tech disruption occurring and to devise appropriate strategies to influence such field-level institutionalization processes. At the macro level, such understanding should enable policymakers to do a more reflective consideration of what constitutes a good process of legitimacy formation. Policy makers can then be more conscious and careful about enabling a logic process to take place.

Despite its importance, extant literature has not paid attention to the legitimacy challenges during the organizational developing process. Most of the existing studies have focused on the legitimacy-seeking strategies (Aldrich and Fiol 1994; Suchman 1995) and consequence of legitimacy/illegitimacy, such as the value of IPOs (Cohen and Dean 2005; Pollock and Rindova 2003), stock market performance (Bansal and Clelland 2004; Lamin and Zaheer 2012), and survival rates (Baum and Oliver 1991; Ruef and Scott 1998). A few recent research works have studied the process of legitimacy formation, especially the relative importance of legitimacy dimensions during the process (Tolbert and Zucker 1996; Johnson et al. 2006; Drori and Honig 2013; Laifi and Josserand 2016). However, these studies have presented the mixed results regarding the sequence of legitimacy formation and the importance of legitimacy dimensions in each firm development stage. The potential reason for the inconsistent findings is that most prior literature is single-case studies that cannot detect the effects from different institutional environments. Taking advantage of sharing

economy firms, which entre multiple incumbent industries, we can investigate the process of legitimacy formation across various industrial contexts.

To the best of our knowledge, legitimacy has not yet been studied in the context of digital business model innovation such as sharing economy. The existing findings of traditional legitimacy literature may not apply to the sharing economy firms because digital technology helps to generate new ways (e.g. social media) for gaining legitimacy (Castello et al. 2016). Lots of new business models, such as sharing economy, Fintech, and Internet-celebrity economy, are occurred in the digital era. It is worthwhile to understand the legitimation process of innovative business models based on digital technology. Furthermore, prior literature differentiates gaining legitimacy in incumbent industries and institutionally innovating (Deephouse et al. 2017). Institutionally innovating requires entrepreneurs to create new criteria in various legitimacy dimensions (DiMaggio 1988; Aldrich and Fiol 1994), which is different from fitting and encompassing pre-existing legitimacy criteria in a stable and incumbent institutional environment (Bitektine 2011; Zimmerman and Zeitz 2002). Sharing economy as a business model innovation, however, needs to combine these two scenarios together. First, sharing economy is an institutional innovation with many tech-startups, which adopt it. Then, sharing economy is not an independent industry. The tech-startups are disrupting various existing incumbent industries. As a result, sharing economy tech-startups require both creating new institutional rules and norms for the innovative business model, and demonstrating their fitness of the relative incumbent institutional environment.

Accordingly, the goal of our research is to explore the following salient research questions: (1) What are the issues specific to the digital business model disruptions?; (2) How are the issues related to the traditional lens of legitimacy challenges?; (3) How do the legitimacy challenges evolve over time?; and (4) Are the legitimacy challenges different across contexts/industries?

To answer these research questions, we conducted a comparative longitudinal case study for the two representative tech-startups in sharing economy: Uber and Airbnb. In this study, we utilized a large volume of global news articles published from 2008 to 2018. The key tenets in theories on organizational legitimacy were utilized to classify the news articles. Two types of text-mining approach, unsupervised topic modeling and supervised deep learning, were adopted to understand and validate the framework of legitimacy challenges for innovative business models in the context of sharing economy. Based on the text-mining results, we then analyzed the sequential aspects of legitimacy topics for Uber and Airbnb. Since industrial contexts may affect the legitimization process, we further compared the Uber and Airbnb cases, which have disrupted transportation and accommodation industries. Our findings present that legitimacy challenges of sharing economy disruption fall into three categories: (1) Regulative, (2) Normative, and (3) Cultural-cognitive legitimacy. Then, we find that the importance of each legitimacy challenges varies by startups' development periods and their industrial contexts.

The key findings of this study contribute to both practice and literature on the legitimacy of business model innovation. First, we empirically validate the framework of legitimacy challenges for the future analysis of new business model legitimacy. This framework illustrates the three dimensions of legitimacy challenges and detailed issues of legitimacy from the audience of these legitimacy challenges. Second, we capture the legitimacy challenges over firms' developing stage (before their IPOs). The understanding of legitimacy challenges over time provides a guideline for tech-startups' entrepreneurs to strategically pursue legitimacy-related issues. Third, our study draws attention to the importance of industrial contexts and the endogenous process of legitimacy formation by comparing Uber and Airbnb. Therefore, we expand the extant institutional research in appreciating what kinds of legitimacy topics are faced by disruptive tech-startups in different industrial contexts.

3.2 Literature Review

3.2.1 Business Model Innovation

Business Model and Business Model Innovation

The concept of a business model is defined as an architecture of business and a value creation mechanism (Teece 2010; Amit and Zott 2001). Academic interests and practical attentions on business models have been increased since the boom of Internet in the late 1990s (e.g. Amit and Zott 2001; Magretta 2002; Timmers 1998). With the development of digital technology, a business model has been increasingly considered as the object of innovation (Johnson et al. 2008; Chesbrough 2010), because digital technology helps new ventures and tech-

startups to change the ways of value creation and business operation (e.g. sharing economy, blockchain, and social media commerce), and thereby enhances firms' competitive positions in the market (Amit and Zott 2010; Teece 2010).

Business model innovation refers to generate a new logic of organizing business and new ways to create values for firms (Casadesus-Masanell and Zhu 2013). As more consumers and value-chains are distributed to innovative business-model firms, the business model innovation breaks the normal operation and value-creation of incumbent firms in the existing industries. At a certain level, incumbent firms cannot ignore the changes bringing by the new business model, and therefore begin to consider to response and compete to it. According to institutional theory, disrupting an existing industry is a result of "organizations in conflict and coordination, and institutions in contradictions and interdependence" (Friedland and Alford 1991). As such, the emergence of tech-startups with innovative business model leads to a disruption of institutional setup in a certain industry.

Despite the growing awareness of business model innovation, the existing research is still incipient and limited. The prior research suggests that the business environment and digital technology are drivers that trigger firms to innovate their business models (Wirtz et al. 2010; Lee et al. 2012). They also find positive effects of business model innovation on firm performance of startups (Aspara et al. 2010; Hall and Wagner 2012) and disruptive effects on incumbent industries (Sabatier et al. 2012; Habtay 2012). However, how new business models can gain

legitimacy during their disruption process for sustainable development has not been studied yet.

Sharing Economy

Sharing economy is a typical example of business-model innovation, which redefines an existing service and changes the way how it is provided to consumers (Markides, C. 2006). Sharing economy, also known as the collaborative economy and peer-to-peer economy, is an innovative business model that is enabled by the intermediary role of digital technologies (Remane et al. 2016). Different from traditional business models, the sharing economy business model utilizes accessible digital technology (mobile devices and mobile apps) to match the resources and requirements among participated private peers (Plenter et al. 2017). Tech-startups of sharing economy provides mobile apps and online platforms for individual suppliers and demanders to share and use private assets. For example, Airbnb develops an online platform for hosts to share their flats and for guests to book and stay these flats. Since tech-startups adopted sharing economy business model does not provide exactly new service to their consumers (e.g. taxi service and hostel service), they attract consumers from those that existing firms focus on and snatch value-chain from established firms. Given the unique crowd-based peer to peer exchange model (Sundararajan 2016), sharing economy disruption, a business model disruption, cannot simply congruent with old institutional logics, which may create destruction on existing institutions (Tracey et al. 2011). Hence, we expect that the challenges of new

institutional legitimacy formation in a sharing economy disruption to be more severe.

According to our literature review, few studies deal with the legitimacy challenges encountered by the sharing economy disruptors. Most of the sharing economy literature focus on the roles and affordances of sharing economy platforms, such as the IT effect on the provision of rapid access to resources and labors. For example, joining sharing economy platforms, such as Uber and Freelancer.com, offers more benefits than the traditional labor market, which increases the opportunities of part-time work and employment (Arita et al. 2016; Dillahun and Malone 2015). However, there is only a small stream that investigates competition between sharing economy firms and incumbent firms. For example, Einav et al. (2016) discuss the design and regulation of sharing economy firms in the accommodation industry and provide theoretical predictions of the effects of competition from the disruptive start-ups on incumbent firms. Two studies use survey data and find that gasoline consumption and car ownership are negatively related to the raising of ridesharing firms (Cervero et al. 2007; Martin et al. 2010). Another recent study tries to explore the institutional strategies of sharing economy start-ups in three European countries to understand how legitimacy be influenced by different country contexts and firms' institutional strategies (Uzunca et al. 2018). However, these are just a small sample of the many controversial issues that have been stirred up by the sharing economy disruptors. What are the sources of legitimacy

challenges? Which among them are the persistent ones that require focused attention?

3.2.2 Legitimacy in Organization Literature

Definition of Legitimacy and Disruption

Institutional disruption is generally considered as a political process of power contest between relevant parties in the industry (Beckert, 1999; Levy and Scully, 2007), that is, a result of “individuals competing and negotiating, organizations in conflict and coordination, and institutions in contradictions and interdependence” (Friedland and Alford, 1991). It involves conflicts and contests for power among different stakeholders (Beckert 1999; Levy and Scully 2007) and the creation or alteration of systems of meaning through the use of language and symbols (Suddaby and Greenwood 2005; Munir and Phillips 2005) to attain legitimacy – “a generalized perception or assumption that the actions of an entity are proper, appropriate, and desirable within some socially constructed system of norms, values, beliefs, and definitions” (Suchman, 1995). Oliver (1991), for example, argued that disruptive innovators may respond to the institutional forces by acquiescing (habit, imitate, comply), compromising (balance, pacify, bargain), avoiding (conceal, buffer, escape), defying (dismiss, challenge, attack), and manipulation (co-opt, influence, control).

Prior organization literature defined that institutions imply stable social orders (Berger and Luckmann 1966), which define a constructed system of norms, values, beliefs, and regulatory process among a community of

stakeholders (Suchman 1995; Scott 1995), including competitors, regulators, and consumers (DiMaggio and Powell 1983; Greenwood et al. 2002). New entries, such as tech-startups, try to recognize and catch up opportunities with innovative ways to break institutions in a certain industry. While incumbent firms in the industry try to protect themselves and defend new entries. Legitimacy is the eventual outcome of conflicts and negotiations between these two parties. However, the nature of such negotiation remains unclear. What are the key issues and processes of negotiation during legitimacy? Existing literature on institutional change or institutional entrepreneurship tend to take a micro organizational (rather than a field level) perspective to these issues as they focus on the institutional responses by the focal organization or institutional entrepreneur (e.g., Henfridsson and Yoo 2013), e.g., how they can frame the value propositions, design and theorize on an appropriate organizational template, and leverage on macro discourse to gain legitimacy. The in-depth focus from the focal perspective, i.e., their purposive actions, however, somewhat downplay the perspective from the broader institutional field, i.e., the cumulative effects of the distributed interactions of all the players in the field (e.g., Henfridsson and Yoo, 2013), including the regulators, market incumbents, trade associations, unions, customers, and other new entrants.

The omission could lead to an incomplete understanding of the legitimation process, recognizing that legitimacy does not come just from the actions of the focal entrepreneurs, but also from the broader discourses and the distributed responses of the related institutions in the social setting. The larger

the accumulation of the network of distributed players, the higher the likelihood that disruptive innovation will be seen as institutionally legitimate. Moreover, these institutional entrepreneurship cases are anchored in organizational field settings that are not related to the sharing economy disruption (e.g., in the new field contexts of the global law firm (Smets et al. 2012), accounting firms (Greenwood and Suddaby, 2006), social enterprise (Tracey et al. 2011)).

Dimensions of Legitimacy Challenges

In the organization literature, several studies try to propose dimensions of legitimacy (Suchman 1995; Scott 1995; Archibald 2004). Although the classifications of legitimacy dimensions in the past research are slightly different in the aspects that they emphasize, all of their classifications share the same fundamental perspective, which is related to getting acceptance from the organizations' stakeholders. As one of the first research delineates the legitimacy dimension, Scott (1995) has proposed three basic dimensions of legitimacy challenges (1) regulative legitimacy challenges, (2) normative legitimacy challenges, and (3) cultural-cognitive legitimacy challenges in the social setting, which new institutions may face when disrupting a mature industry. The regulative legitimacy challenges concern the relevant laws and formal rules that actualize regulative obedience and protest disputes in the existing institutional environment (Scott, 1995). Regulative legitimacy is accomplished by aligning new actors with symbolic systems, comprising legal and quasi-legal rules (i.e. what institutions can/cannot do) (Scott, 2001). This type of legitimacy requires new actors to negotiate with authorities with legislators, councils, and

governments. Regulative legitimacy challenges are important in sharing economy disruption, since innovative business models may not follow the legal process (e.g government ban, council protest, law broken). Normative legitimacy challenges refer to common norms, appropriate behaviors, and acceptable practices in the existing industry (i.e. what institutions should/should not do) (Dimaggio and Powell 1983). This legitimacy challenge dimension usually confirms at the industry level, relating to competition and cooperation dynamics in the industry. The survival of the innovative sharing economy business model should rely on the challenges and support from their partners and competitors. The last type of legitimacy is formed at the individual level, which is called cultural-cognitive legitimacy. This legitimacy refers to prevailing cultural beliefs of a new practice among its social audience (Scott, 1995). Different from normative legitimacy, it addresses the symbolic nature of human activities in the society. To form this legitimacy, sharing economy players need to cultivate people's taken-for-granted habits and common knowledge (i.e. what users typically do). As the new business model disruption hits the organizational field, it seems reasonable that the existing cultural-cognitive, normative, and regulative legitimacies are shaken, as the various players jostle, contest and renegotiate a new legitimacy.

Legitimacy Challenges over Time

While the legitimacy aspects are discussed a lot in past research, only a few research illustrates how these legitimacy challenges occur and are negotiated during the development of a new venture. Tolbert and Zucker (1996) identify

three stages of institutional legitimation process. The first stage is the habitualization stage. In this stage, firms need to show the utility and viability of disruptive innovation to convince organizational decision-makers to accept it. This stage is about normative legitimacy, which requires to gain industrial acceptance. The second stage is the objectification stage, which is related to the diffusion of innovation. In this stage, innovation needs to gain some social consensus, such as acceptance from news media, stock market, and other organizations. This stage is an extension of normative legitimacy in the first stage and cultural-cognitive legitimacy. The third stage is the sedimentation stage, which is fully embedded in the social system. The three stages introduced by Tolbert and Zucker (1996) only focus on normative and cultural-cognitive legitimacy. Different from Tolbert and Zucker (1996), Greenwood et al. (2002) emphasize the role of regulative legitimacy in the first two stages of legitimation process and the competition from other new organizations in the third stage. Johnson et al. (2006) also pay attention to the regulative legitimacy but they identify four stages for the legitimacy process and emphasize the diffusion and general acceptance in social contexts.

However, to date, there is still no consistent framework of legitimacy dimensions and formation process. Since legitimacy challenges must come and follow a particular order (Zimmerman and Zeitz 2002), understanding the legitimacy process is essential to firms' survival rates (Baum and Oliver 1991; Ruef and Scott 1998). Further studies on the importance of various legitimacy challenges during firms' development stages are required (Deephouse and

Suchman 2008). The sharing economy is a suitable context to study the legitimacy challenges over time because sharing economy as an emerging business model innovation is still on its way to legitimation.

Legitimacy Research in IS

Turn to the IS literature, legitimacy is firstly introduced by Klein and Hirschheim (1989) as an important influence factor of IS success. They give a definition to legitimacy, “a social process by which institutions, practices, and ideas gain social acceptance” and discuss how gaining legitimacy from organizational users is related to the success/failure of IS projects. After that, only a small set of IS studies mentioned about legitimacy. Majority of these legitimacy research study how IT innovation evolve and become legitimized in the existing institutions over time (Baptista 2009, Lyytinen et al. 2009, Nielsen et al. 2014) and how IT platforms, such as B2B platforms and crowdfunding platforms, can get legitimacy to attract organizational adoption (Ingram et al. 2019; Son and Benbasat 2007). Although these studies have explored the nature and process of the legitimacy of IT innovation, most of them study the legitimation of IT within an organizational context and focus on the importance of legitimacy on IT adoption. These existing legitimacy studies in IS literature are either only from adopters’ perspectives or not systematically discussed types of legitimacy and the related legitimacy-seeking strategies (Brown, 1998; Kohli and Kettinger, 2004). Currently, a new small stream of IS research has started to explore the legitimacy-seeking strategies for innovative IT technology such as Blockchain and Healthcare IT (Flynn and Puarungroj 2006; Lynn et al. 2018).

Since lots of disruptive IT innovations appear recently, more literature on the process of legitimization-seeking is required. Therefore, our study was designed to contribute to IS literature from an industry-level perspective, while also exploring the challenges and process in new legitimacy formation of digital business model innovation in a sharing economy disruption.

3.3 Methodology

3.3.1 Research Context

To answer our research questions, we conducted a separate case analysis for the two most successful tech startups of Uber and Airbnb. As the pioneers of innovative business model disruption, Uber and Airbnb are the two biggest triggers of sharing economy growth. Over the past ten years, Uber has expanded its ride-sharing service from North America to 85 countries, covering 903 cities¹⁴. In early 2019, Uber is successfully filed for its IPO at a company valuation of \$120 billion¹⁵. Similarly, Airbnb is also quite successful and is preparing to IPO at a valuation of \$38 billion¹⁶. Besides, Airbnb is the first sharing economy firm that has made profits since 2016¹⁷. Although leading sharing economy firms will continue to be IPO, the extent to which they are seen

¹⁴ UberEstimator.com (April 2019) available from <https://uberestimator.com/cities>

¹⁵ Trefis Team and Great Speculations. (December 2017). How Uber Could Justify A \$120 Billion Valuation. Forbes. Retrieved on Dec 3, 2018, from <https://www.forbes.com/sites/greatspeculations/2018/12/03/how-uber-could-justify-a-120-billion-valuation/#6afoabod7f9b>

¹⁶ Denise Lee Yohn. (April 2019). Why the Corporate Valuations Of Rent The Runway, Airbnb And Lyft May Be Completely Wrong. Forbes. Retrieved on Apr 2, 2019, <https://www.forbes.com/sites/deniselyohn/2019/04/02/why-the-corporate-valuations-of-rent-the-runway-airbnb-and-lyft-may-be-completely-wrong/#76a9c3a06453>

¹⁷ Leigh Gallagher (February 2017). Airbnb's Profits to Top \$3 Billion by 2020. Fortune. Retrieved on Feb 15, 2017, from <http://fortune.com/2017/02/15/airbnb-profits/>

as legitimate remains questionable, as evidenced by the racial discrimination on Airbnb, irate taxi drivers, worsening traffic, and mounting housing costs. Even today, the sharing economy model is still surrounded by various controversies.

Therefore, the case of Uber and Airbnb are the most suitable and typical cases to understand the challenges of new legitimacy formation in the innovative business model disruption. The case analysis is done based on a comprehensive archival analysis of news headlines. Online news coverage is an appealing data source as news that highlight such legitimization issues are published and accessible to the public over a period of time. Prior literature has also suggested that news media is a valid source for studying legitimacy (Bansal and Clelland 2004; Lamin and Zaheer 2012). Given the high-profile status of Uber and Airbnb, extensive coverage of their developments and impacts has been regularly chronicled in news media. Finally, we utilized a set of text-mining approaches to analyze and understand legitimacy-related challenges/efforts faced by the disruptive sharing economy start-ups in a comprehensive manner.

3.3.2 Data

Our sample (i.e., news articles) was gathered from a comprehensive news article database, Lexis-Nexis Academic. Lexis-Nexis Academic contains thousands of publications from over 17,000 credible news, business and legal sources over the world. The news sources in this database cover the majority of global news media such as the New York Times, Wall Street Journal, The Pioneer (India), China Daily, and so on. At the same time, this database offers an

advanced search engine to assist users in finding exactly relevant news articles. In our research, we searched and selected the news articles by limiting to the documents written in English from May 2009 (Uber launched) to March of 2018. We also limited the news articles which mentioned the term “Uber” in their headlines or at least five times in their contents. Due to the voluminous search results and their massive textual contexts, we only used the headlines of these news articles to classify them into several key themes, where the headlines can point aspects of Uber’s legitimacy challenges. For Airbnb, we also used the same searching strategies to select comparable news articles from September 2008 (Airbnb launched) to March of 2018. Our dataset consists of 40,829 Uber news articles and 10,854 Airbnb news articles from 1,778 news sources. Since newspapers tend to have articles from the same source or with the same content, there must be multiple duplicate news articles. To minimize the duplicated news headlines, the headlines for the same news content were eliminated from the sample with the function provided by Lexis-Nexis Academic, and then, we manually checked the headlines and deleted rest duplicated news headlines. Then, we also eliminated less-informative (fewer than three words) news headlines. As a result, 36,246 Uber headlines and 9,501 Airbnb headlines were selected for further analyses.

3.3.3 Textual Analysis

Figure 3. Textual Analysis Steps

Since we have about 50,000 headlines in the sample, it is not easy to code/manage all the headlines manually. We, therefore, relied on text-mining approaches to analyze the large unstructured textual dataset. In our study, both supervised and unsupervised text-mining techniques were applied to identify legitimacy topics and to classify legitimacy challenge dimensions. To validate our text-mining approaches in analyzing legitimacy topics of sharing economy, we applied inverted sequential procedures to analyze Uber and Airbnb. Since the difference between new business model legitimacy and traditional industrial innovation legitimacy is not certain, we firstly used Uber's news headlines to comprehend potential legitimacy topics by using an unsupervised text-mining approach. Then, we compared these identified issues with the commonly presented legitimacy dimensions in the prior literature. We generated a framework for classifying the legitimacy challenges of disruptive digital business model innovation. After that, we used a supervised machine learning approach (i.e., classification) to classify Uber and Airbnb's news headlines according to the proposed framework. In order to evaluate whether our classification is correct, finally, we applied an unsupervised approach (i.e., topic modeling) to

Airbnb’s classified headlines for investigating legitimacy topics in each category. In the next sections, we detail the key procedures of unsupervised and supervised text-mining approaches.

Unsupervised Machine Learning

Our unsupervised text-mining approach builds upon Latent Dirichlet allocation (LDA), which is a statistical method for discovering latent “topics” from a large collection of textual datasets (Blei and Latterty 2007). The LDA model can automatically discover topics, which headline sentences contain, in terms of the probability distribution over words for each topic. The underlying mechanism of LDA is the assumption that each word in each textual data probabilistically falls into one topic category of the dataset. Given the large volume of textual data, the words and topic categories are jointly estimated. Here, we use R packages to analyze our textual data with the LDA model. The key procedures are depicted in Figure 4.

Figure 4. Unsupervised Text Mining Procedures

In the data pre-processing step, we firstly tokenized the unstructured textual data to structured formats by splitting sentences into words, lowercase the

letters, and remove punctuations, symbols, and numbers. Then, we removed the less-informative stop words, and replaced the words with their root forms (i.e., word stems) based on WordNet database (Fellbaum 1998). We also dropped the region names (e.g., USA, New York, China, and India) in the headlines to focus on extracting general topics. Finally, we also get rid of less-frequent words that appear in less than 0.1% headlines (at least 20 headlines). After processing the textual data, we defined the number of desired topics. To set an optimal number of topics, we used the “ldatuning” R package featured with the four statistic models (i.e. Griffiths2004, CaoJuan2009, Arun2010, Deveaud2014) estimating the most preferable number of topics for LDA model. The range of the optimal number of topics was defined by the minimum number of CaoJuan2009 and Arun2010 results, and the maximum number of Griffiths2004 and Deveaud2014 results. Then, we tried different numbers in the calculated range for our LDA-analysis. In the LDA-analysis step, the Gibbs Sampling process based on Markov-chain Monte Carlo (MCMC) (Griffiths and Steyvers 2004), was adopted for training the machine to inference the latent topics from the headlines. The detailed analyses for the identified legitimacy topics of Uber and Airbnb are discussed in the Results sections.

Supervised Machine Learning

In the first unsupervised text-mining step, legitimacy topics for sharing economy were extracted. According to the unsupervised machine learning results in the first step, we found that all these legitimacy topics arise from the three

sources, governments, industrial players, and users (i.e., passengers and drivers), which are consistent with the three fundamental legitimacy challenge dimensions: regulatory, normative, and cultural-cognitive legitimacy suggested by Scott (1995). As such, we adopted Scott (1995)'s theoretical framework. Besides, we defined detailed topics in each legitimacy dimension in the sharing economy context. Next, the topics were adopted as classification rules for legitimacy challenges.

To classify these three legitimacy challenges, we introduced a mixed approach including a (theory-driven) content-analysis and a supervised machine learning technique. Following the supervised text-mining procedure, our data analysis contains the four main steps: 1) random sample and manually coding, 2) data pre-processing, 3) model training and selection, 4) full dataset classification, as described below (as shown in Figure 5):

Figure 5. Supervised Machine Learning Procedures

First, we randomly selected 1,000 headlines out of our dataset as a training set for manual coding. Three independent coders were asked to classify the sampled headlines into three categories in accordance with the legitimacy

classification framework that we generated in the first step. Based on the human coding procedures suggested by Neuendorf (2016), we developed a series of instructions and coding guidelines for coders to ensure the consistent criteria in the classification. The detailed classification criteria and exemplar headlines for each dimension are discussed later in the Results section of the Uber case.

Then, the final classification of samples was evaluated by the authors. Krippendorff's alpha (Krippendorff 2004) was calculated to test the inter-reliability among the three coders. The reliability score was 0.87, which was over the suggested value of 0.70. Finally, we used a majority vote to determine which category a headline belongs to.

We tested the classification performances (for Uber) based on the most widely-accepted ten classification algorithms with the sampled 1,000 headlines. Prior literature suggests using an iterative cross-validate procedure to determine the optimal training model (Smyth 2000, Still and Bielek 2004). We set a 200-round iteration test to obtain a reliable and accurate calculation of classification performance for each algorithm. In each round of tests, firstly, the machine randomly selected 500 headlines as a training set to train the classification model. Then, the trained model was used to classify the rest of the 500 headlines as a testing set. Finally, the machine's coding results were compared with those made by the coders to compute the classification performance score. The average score of 200-round testing was used as an evaluation of classification performance. Then, we compared the performance scores over these 10 algorithms. Overall, a

deep-learning algorithm (i.e., Keras) achieved the most decent performance with high accuracy rates (*Acc*), *F-Score*, and *ROC Area* which were all roughly about 0.80 for the three categories. We adopt this 80% accuracy because prior literature has done a comprehensive robustness test for the acceptability of the bias concerns and possible endogeneity issues arising from using text-mining results with around 80% accuracy (Netzer et al. 2012, Wang et al. 2013).

To ensure that the selected algorithm was also suitable for classifying Airbnb's news headlines, we tested the classification performance for Airbnb with the best-performing deep-learning algorithm. The performance of a deep learning algorithm (Keras) for Airbnb was also acceptable and similar to that of the Uber case. The classification performance is listed in Table 10. Therefore, the deep-learning algorithm was selected as the classification method for both Uber's and Airbnb's entire dataset.

Algorithm	Regulative			Normative			Cultural		
	Acc	F-Score	ROC Area	Acc	F-Score	ROC Area	Acc	F-Score	ROC Area
BAGGING	0.78	0.67	0.70	0.67	0.63	0.72	0.76	0.67	0.70
BOOSTING	0.78	0.63	0.69	0.58	0.57	0.71	0.76	0.52	0.70
GLMNET	0.75	0.69	0.74	0.63	0.63	0.76	0.74	0.65	0.74
MAXENT	0.76	0.69	0.74	0.64	0.66	0.29	0.76	0.66	0.36
RF	0.79	0.70	0.69	0.67	0.66	0.74	0.78	0.67	0.70
SLDA	0.79	0.60	0.70	0.66	0.59	0.72	0.79	0.57	0.68
SVM	0.79	0.70	0.72	0.66	0.65	0.25	0.78	0.65	0.26
TREE	0.77	0.67	0.66	0.65	0.53	0.65	0.78	0.64	0.64
NAÏVE	0.81	0.59	0.71	0.66	0.56	0.64	0.79	0.46	0.64
KERAS for Uber (Deep Learning)	0.84	0.89	0.86	0.77	0.79	0.84	0.81	0.87	0.82
KERAS for Airbnb (Deep Learning)	0.84	0.90	0.87	0.78	0.81	0.86	0.81	0.88	0.84

Table 10. Text Mining Algorithm Classification Performance

We first used Uber's entire dataset to perform a classification of legitimacy topics. 35,410 headlines were classified into one specific category. About 391 headlines were assigned into two categories. These headlines were

generally written in long sentences with confusing/non-definable words (e.g., “*Athlete Criticizes Those Who Dropped Out of Olympics; Preview of Bolling's Book 'Wake Up America'; Left Putting Up Roadblocks to Ride Sharing Companies*”). Furthermore, 445 headlines were predicted to none of these 3 legitimacy challenges, which included irreverent terms to Uber. Finally, we had a total of 35,410 Uber’s news headlines, which were classified and used for further analyses. Next, we applied the same approach to Airbnb’s entire dataset and had similar outcomes in Uber’s case. The *normative* legitimacy challenge presented the largest number of 4,301 headlines. 93 headlines were not assigned into any category and 68 headlines belonged to more than one category. The final dataset of Airbnb for further analysis contains 9,340 headlines. The percentage of misclassification rate for Uber and Airbnb were both below 3.0%. To further validate our final classification accuracy for further analyses, we randomly selected 500 news headlines from classified news headlines, and manually code these headlines. We compared our manually coding results with the machine’s coding results. The accuracy is over 94% (94.6%)¹⁸. Overall, the classification results were acceptable.

3.4 Results

3.4.1 Uber’s Case

¹⁸ The increasing accuracy may be related to the increasing number of training samples. In the test, we randomly select 500 training samples and test in the rest 500 headlines. In the full dataset, we use the whole 1000 training dataset to train the model and to classify the whole dataset. The increasing training dataset size leads to a better classification result (Netzer et al. 2012).

Legitimacy Topics for Uber

Figure 6. Optimal Number of Topics

We firstly explored the potential legitimacy topics in the sharing economy from Uber's case. According to the procedure of topic modeling, the optimal number of topics was calculated and the results are shown in Figure 6. To find the optimal number of topics, the above part of the graph uses a minimizing solution and the below part uses a maximizing solution. The lines without an inflection point are invalid and not considered as a reference for the optimal number of topics. As a result, we came to the conclusion that the optimal number of topics is between 6 and 16 topics.

Next, we fitted the LDA model with different numbers of topics from 6 to 16. The identified optimal choice was 12 topics. The numbers lower than twelve caused an information reduction and those larger than twelve included redundant information. As such, the LDA model with twelve topics gave us the most distinctive and best interpretable topics from the sampled new articles.

Table 11 summarizes the detailed legitimacy topics and examples of the news headlines.

Topic ID	Legitimacy Topic Description	Top 10 Terms (Ordered by frequencies)	Headline Example
#1	Business Cooperation and Extension	<i>partner, transport, free, payment, bike, mobile, expand, option, team, market</i>	"AsiaRooms Partners Uber for Free Transfers in Singapore" "Uber uses Visa Commerce Network to launch offers in 10 U.S. markets."
#2	Licence Issues	<i>licence, operate, ban, court, rule, govt, transport, appeal, fine, legal</i>	"TfL refused to renew the car-hailing company's licence on public safety grounds." "Egyptian Court Rules Uber, Careem Illegal"
#3	Internal Business Issues	<i>ceo, kalanick, travi, deliverier, chief, leave, execut, board, boss, founder</i>	"Uber's board considers reducing voting power of former CEO" "Uber founder Travis Kalanick resigns as CEO under investor pressure"
#4	Privacy Issues	<i>data, safe, user, breach, tech, secure, feature, hack, custom, privacy</i>	"Data is Uber's business. But protecting it may be its biggest weakness." "Uber and other tech companies store vast amounts of data about users. But can they be trusted?"
#5	Features & Promotions	<i>price, fare, surge, charge, cost, pay, rate, cut, custom, free</i>	"Uber is delivering free ice cream in Manchester." "Uber testing cheaper fares for people willing to wait longer."
#6	Industrial Protests	<i>taxidriver, protest, strike, ban, fight, street, war, call, industri, block</i>	"Paris taxi drivers block streets in Uber protest." "London's black-cab drivers use rival app to compete with upstart Uber."
#7	Regulative Rules	<i>regulate, law, bill, rule, insure, council, airport, transport, legal, operate</i>	"Ride-hailing firms use major influence over lawmakers to pass industry-friendly rules" "Fate of Uber's legality at Dulles and National airports to be decided Wednesday."
#8	User Safety Issues	<i>woman, passenger, rape, sexual, assault, polic, charg, accus, allege, claim</i>	"Uber taxis banned in major city after driver accused of raping passenger." "Uber driver 'shoots passenger DEAD' on motorway in Denver."
#9	Investment and Fund Raising	<i>invest, rival, billion, deal, market, fund, sell, raise, stake, buy, merger</i>	"Saudi Arabia investing USD3.5 Billion in Uber taxi booking service." "Softbank's \$1bn deal with Uber; Uber deal could be largest private stock sale ever"
#10	Technological Innovation	<i>test, crash, vehicle, autonom, driverless, fatal, fly, arizona, kill, pedestrian</i>	"Uber flying taxis move a step closer to take-off after company hires NASA aircraft engineer." "Uber shut off braking tech in robot car."
#11	Impacts of Sharing Economy	<i>gig, economy, employ, business, worker, tech, disrupt, challeng, industri, regulate</i>	"The emergence of a shared economy has fuelled new businesses and is changing the property landscape worldwide" "Online gig economy platforms like Uber could boost world economies."
#12	Law Suits	<i>law, tech, sue, court, action, class, judge, settle, claim, secret</i>	"Uber faces class action lawsuit filed on behalf of Ontario taxi drivers." " French labor court backs Uber in driver contract dispute."

Table 11. Legitimacy Topics of Uber from News Headlines

Legitimacy Challenge Framework

Broadly, the identified twelve topics highlight the key sources of legitimacy for Uber, and they are generally “relatable” to what most people are known during the development of Uber. Since the prior literature has already defined that legitimacy is evaluated by related stakeholders by comparing to specific institutional criteria (Scott 1995). Accordingly, we classify the topics into the three categories presented in Scott (1995)’s legitimacy dimension model. First, we find that half of these legitimacy topics are related to the operation of Uber as a business, such as internal business issues (e.g., replacing Kalanick as CEO), external business issues (e.g., business cooperation and expansion, investment and fundraising, and industrial protesting from incumbents), future business development (e.g., technological innovation), and new business impacts (e.g., changing and disrupting existing business model). All these business- and operation-related issues can be classified into the normative legitimacy challenge because normative legitimacy reflects shared norms and values within a societal environment of a new venture. Another big category of legitimacy audience is the direct users of sharing economy firms. This category includes three topics, pricing and promotion, user safety issues, and data privacy issues. The data privacy issue has become a common and rising concern of Internet-based companies and services. These issues are cultural-cognitive legitimacy challenges in Scott (1995)’s model, which is related to widespread innovative knowledge and practices among individual users and social audiences. The last legitimacy challenge is caused by governments and regulators such as issues on licensing, regulating, and lawsuits. Such legitimacy is usually accomplished by

aligning with relevant legal rules in the existing contexts (Scott 2011). As a result, we generate the legitimacy challenge framework (as well as legitimacy challenge classification criteria) of the sharing economy, as shown in Table 12.

Legitimacy Challenges	Legitimacy Topics
Regulative Legitimacy	<ul style="list-style-type: none"> -Constraints imposed by regulatory authorities, e.g., operating license, regulative rules, tax. -Law Suits, e.g., contract dispute; class action
Normative Legitimacy	<ul style="list-style-type: none"> -Business cooperation and extension -Industrial protests and competition -The attraction of investment funding -Internal business issues -Technological innovation (future business developments) -Impacts of Sharing Economy (Macro-discourse)
Cultural-cognitive Legitimacy	<ul style="list-style-type: none"> -Perceptions on various product features and promotions -Consideration for user issues (e.g., safety, data privacy)

Table 12. Legitimacy Challenge Framework

Based on this table, we conducted a supervised text-mining (i.e., classification). Overall, the findings suggest that *normative* legitimacy has the largest number of news headlines but *regulative* and *cultural-cognitive* legitimacy challenges have almost the equal number of news headlines (as shown in Figure 7). However, whether the normative legitimacy challenge is most important and significant during the firm's development process as compared to the other two legitimacy challenges is still unknown. The details of legitimacy challenges over time are discussed in the next section.

Figure 7. General Pattern of Legitimacy Challenges

Legitimacy Challenges over Time of Uber

Figure 8. The Pervasiveness of Legitimacy Topics over Time (Uber)

In this section, we compare the percentage of each legitimacy challenge in the same period (quarterly). The total number of legitimacy topics continued to increase over the study period of 2011-2018, as shown in Figure 8. Among the different legitimacy challenges, the dominant legitimacy challenge had been the normative legitimacy. To statistically compare/evaluate the overall patterns of legitimization, we performed a set of T-tests comparing the three legitimacy

challenges. The T-test results are presented in Table 13. The coefficients indicate the differences between normative legitimacy and other two legitimacy challenges (Column All in Table 4) show that the percentage of normative legitimacy challenges are significantly ($p < 0.01$) larger than the percentage of other legitimacy dimensions in the same period. This finding suggests that normative legitimacy challenges are the most heated contestation of legitimacy (e.g., in expanding market share, in attracting funding, or in alignment with macro discourse). Industry-level legitimacy, therefore, is in a prior position to shape the overall legitimacy of a tech-startup. On the other hand, regulative legitimacy has the smallest percentage among the three legitimacy challenges in the same period. The potential reason is that regulative issues generally occur later than industry-related (e.g. fundraising and competition) and user-related issues (e.g. promotion for usage).

	All			Early			Late		
	Mean of difference	t-statistic	p-value	Mean of difference	t-statistic	p-value	Mean of difference	t-statistic	p-value
Normative - Regulative	0.184	11.061	0.000	0.197	6.789	0.000	0.175	9.600	0.000
Cultural - Normative	-0.144	-8.813	0.000	-0.078	-2.622	0.010	-0.185	-13.722	0.000
Cultural - Regulative	0.039	2.053	0.023	0.119	3.361	0.002	-0.010	-0.593	0.279

Table 13. T-test Results between Early and Late Stage (Uber)

As illustrated in Figure 8, however, the cultural-cognitive legitimacy covered 50% legitimacy topics in 2011 and kept decreasing over time. It seems that users' habit formation and forming certain user colonies are the first concern for disruptive organizations in the early stage of disruption. Accepted by social

audiences leads Uber had more bargaining power to disrupt the incumbent industry and acquired legitimacy in the early stage. In the later stage driven by “people-powered technology”, Uber can constantly control and manage such issues by alleviating safety concerns and offering feature improvements, e.g., introducing some safety features. Finally, the regulative legitimacy topics kept increasing mainly due to the heavy protections of taxi industries from governments and the increasing employment contract lawsuits raised by Uber’s drivers.

Early stage - Late stage	Mean of difference	t-statistic	p-value
Regulative	-0.050	-1.889	0.037
Normative	-0.028	-1.522	0.072
Cultural-cognitive	0.079	3.586	0.001

Table 14. T-test Results for Changes of Each Dimension

Since the legitimacy dimension patterns are different between early and late stages as observed in Figure 8, we conducted a T-test of percentages of legitimacy challenges in the same period (quarter) for further understanding the dynamics in the focus of legitimacy topics. The T-test results are summarized in Table 13 and Table 14. We differentiated early and later firm development stages based on their funding sources and business performances. The cutting point of Uber’s early stage in the year 2015. Before 2015, all the funds of Uber are from venture fundings (Series A – E). Since 2015, Uber has raised funds from Debt

Financing, Private Equity and Secondary Market ¹⁹ . These fundraising transactions often occur when a private company becomes highly valuable and is identified as an established firm by business evaluators (e.g. banks and investors)²⁰. Therefore, we defined the early stage (before 2015) and the later stage (2015-2018) as the matured stage.

In general, the normative legitimacy is the most important challenge that should pay attention to because in both early and late stages the percentage of normative legitimacy challenges are significantly ($p < 0.01$) larger than others. By comparing the regulative and cultural-cognitive legitimacy challenges, however, we find that the percentage of cultural-cognitive legitimacy challenges is larger ($p < 0.01$) than that of normative legitimacy challenges in the early stage, but there is no significant difference in the later stage. This finding suggests that firms concern more about how to attract users to use their innovative service in the early stage, but more regulative legitimacy challenges occur in the later stage. In Table 14, furthermore, we find that the percentage of regulative legitimacy challenges are significantly ($p < 0.05$) increased in the later stage as compared to those in the early stage. Rather, the percentage of cultural-cognitive legitimacy challenges increase in the later stage, comparing to that in the early stage. Besides, although the number of normative legitimacy challenges is more than others in

¹⁹ Uber's Fund Raising Data Source: https://www.crunchbase.com/organization/uber/funding_rounds/funding_rounds_list

²⁰ Glossary of Funding Types: <https://support.crunchbase.com/hc/en-us/articles/115010458467-Glossary-of-Funding-Types>

the early stage (as shown in Table 4), the normative legitimacy challenges still slightly increased in the later stage as shown in the second row of Table 14 ($p < 0.1$).

Legitimacy Challenges	Early Stage		Later Stage	
Regulative	Rules and Regulation	37.75%	Rules and Regulation	37.55%
	Licensing Issues	47.41%	Licensing Issues	34.42%
	Lawsuits	14.82%	Lawsuits	28.03%
Normative	Internal Business Issues	16.31%	Internal Business Issues	16.82%
	Sharing Economy Rhetoric	20.49%	Sharing Economy Rhetoric	17.46%
	Investment and Fund Raising	13.79%	Investment and Fund Raising	16.98%
	Technological Innovation	6.83%	Technological Innovation	15.92%
	Business Cooperation and Expansion	17.24%	Business Cooperation and Expansion	16.54%
	Industrial Protests	25.33%	Industrial Protests	16.28%
Cultural-cognitive	Safety Issues	44.59%	Safety Issues	46.35%
	Promotion & Features	54.23%	Promotion & Features	50.43%
	Privacy Issues	1.17%	Privacy Issues	3.22%

Table 15. Issues of Legitimacy Challenges in the Early vs. Later Stages

To understand how the normative legitimacy challenges keep increasing and whether detailed issues of legitimacy challenges change in early and later stages, we additionally performed a content analysis based on our topic-modeling analysis outcomes on each legitimacy challenge. The issues of each legitimacy challenge for each stage are presented in Table 15.

Although all the issues were found in both early and later stages, the percentage of each issue in the three legitimacy challenges was dissimilar to each

other. The news articles show that rules and regulation issues were equally identified both in the early and the later stages along with the global expansion of Uber, it continuously confronted the rules and regulation issues, such as “*When Is a Taxi Not a Taxi?; The new car service company Uber exposes the idiocy of American cities' cab regulations (2011)*”, “*Uber is coming to taxis in New York, if law allows. (2012)*”, “*Why does Seoul mayor oppose Uber? (2014)*”, “*Uber banned in Portugal (2015)*”, “*Uber to be legal in Edmonton after city council vote (2016)*”, “*New Regulations for Ride Apps Begin in Sao Paulo (2018)*”, etc. On the contrary, more licensing issues were featured in the early stage when the Uber app was just launched and entered the taxi market. Most of the cities did not impose any licensing-related laws on this innovative service. In the later (matured) stage, however, numerous cities had a clear attitude (laws) on the disruptive business model innovation of Uber. Some cities revised the legal provisions for offering Uber licenses. For example, “*Uber Regains Its License to Operate in London*”; “*Uber Won't Renew Permit for Self-Driving Cars in California*”. Because the regulation system for Uber services became mature in the later stage, many taxi drivers and units started to stick to the laws to maintain their rights in the later stage, such as “*Taxis to file lawsuits against ride hailing app, authorities*” and “*Uber pays \$3M to settle suit with New York drivers.*” As lawsuits are issued from various parties, the increasing percentage of lawsuits in the regulative legitimacy challenges led to the increase of overall regulative legitimacy challenges in the later stage.

When it comes to normative legitimacy, we observed many industrial protests, fundraising, and business cooperation topics in the early stage. For example, “*Paris taxi drivers block streets in Uber protest*”; “*Uber could raise \$25B in next funding round*”; and “*Expensify Partners with Uber to Bring SmartRides to Business Travelers Worldwide*”. While developing its business in the early stage, Uber had faced protests and competitions from the incumbents. Therefore, Uber looked for funds and cooperation to gain supports for its competition to the incumbent rivals. In the later stage, as the market of Uber became stable, Uber focused more on its future developments (e.g. investing in driverless car innovation). Meanwhile, the market has been disrupted by Uber since the early stage, the impact of this new business model has been found and emphasized more in the early stage but these impacts were continually discussed in the later stage. Overall, the weights among all the six normative legitimacy topics were balanced in the later stage than in the early stage. As a result, the volume of normative legitimacy challenges was slightly larger in the late stage (as shown in Table 14).

Tolbert and Zucker (1996) suggest that cognitive legitimacy is the last legitimacy challenge. However, we find that cultural-cognitive legitimacy is important both in the early and later stages. Uber spent large portions of funds on pricing and promotions in the early stage to attract potential users. For example, “*Uber cuts fares by 20 percent in New York in price war with taxis*”. Because Uber focused on the market extension in the early stage, they did not put much effort into the potential safety issues. In the early stage, therefore, Uber

confronted a lot of safety issues after a rapid extension, such as “*Indian police arrest Uber driver accused of rape.*” In the late stage, however, after acknowledging the potential safety issues, Uber has updated its app features to minimize safety-related issues, such as “*Uber India launches new cognitive security feature called real-time ID check*”. Besides, Uber cannot always rely on burning money to gain cognitive legitimacy and to compete with numerous similar apps that appeared in the market. Consequently Uber paid more attention to feature developments to gain cultural-cognitive legitimacy in the later stage. For example, “*Uber introduces new 'Uber For Business' for customized travel experience.*” As evidence, moreover, privacy issues become the most common concerns for consumers using mobile apps and websites in the current big data era. More data breach related issues were found in the later stage.

3.4.2 Airbnb’s Case

As for Airbnb, we firstly conducted a supervised text mining analysis based on the legitimacy dimension framework. Then, topic modeling analysis was utilized for the classified Airbnb new headlines to confirm legitimacy topics of each legitimacy challenge dimension as we found in Uber’s case.

Legitimacy Challenge Framework of Airbnb

Figure 9. General Pattern of Legitimacy Challenges for Airbnb

Following the framework suggested in the previous section, we classified Airbnb's news headlines into the three legitimacy challenge dimensions: regulative, normative, and cultural-cognitive legitimacy challenges. Overall, we find that the biggest legitimacy challenge is normative legitimacy challenge as compared to those of the regulative and cultural-cognitive legitimacy. However, the number of regulative legitimacy challenges and cultural-cognitive challenges are comparable.

Legitimacy Topics of Airbnb

For each legitimacy challenge dimension, we used the same number of topics in the suggested framework as the topic number to do the topic modeling analysis. Then, we tried different numbers around the focal number (e.g. Regulative legitimacy has two topics in the framework, as shown in Table 12). We varied the number of topics from 1 to 4 in the topic modeling analysis on the regulative legitimacy news headlines. Then, we chose the most interpretable model for each dimension. Table 15 presents the detailed topics and examples of news headlines.

Legitimacy Dimension	Topic Description	Top 10 Terms (Ordered by frequencies)	Headline Example
Regulative	Rules and Regulation	<i>shortterm, rule, regular, law, house, illegal, council, list, property, ban</i>	"Regulating Airbnb: Vancouver Residents Must Obtain Annual Licence And Pay One-Time Activation Fee." "L.A. moves to regulate short-term home rentals."
	Tax issue	<i>tax, regulate, deal, govt, collect, pay, shortterm, agreement, sign, bill</i>	"Short-term rentals don't follow the same rules or pay hotel taxes." "Airbnb rules anger some suite owners; Landlords worry about loss of income due to new regulations."
Normative	Investment and Fund Raising	<i>Raise, fund, billion, invest, found, growth, hotel, expand, plan, create</i>	" Investors Pour \$450 Million Into Airbnb." " Airbnb valued at \$13 billion as it discusses employee stock sale: WSJ."
	Business Cooperation and Expansion	<i>travel, partner, launch, experience, business, tour, offer, service, expand, share</i>	"Airbnb Partners With Jumio to Help Power New Identification Verification Product." "Airbnb launches Trips, introduces tours and travel activities in Experiences."
	Sharing Economy Rhetoric	<i>economy, hotel, uber, share, travel, growth, business, tech, industry, disrupt</i>	"The Rise of the One-Room Hotel." "Airbnb Generated \$632 Million in Economic Activity in New York."
Cultural-cognitive	User Issues	<i>host, guest, party, house, race, woman, neighbour, flat, discriminate, landlord</i>	"Texas homeowner claims Airbnb guest from hell threw a wild house party that caused \$18K in damage." "AirBnB host claims to use hidden cameras to take secret sex videos of their guests."
	Features and Promotions	<i>stay, night, list, offer, travel, home, holiday, book, hotel, property</i>	"Airbnb has created the ultimate penthouse, offering a one-night stay in Norway." "Bed down with Van Gogh, your Airbnb host for the night."

Table 15. Topics on Legitimization Issues of Airbnb

Since the total number of Airbnb's headlines are largely fewer than that of Uber's, the number of subtopics for Airbnb legitimacy topics are also fewer than Uber. Although there are only seven topics in the legitimacy challenges of Airbnb, they bear much resemblance to the legitimacy challenges surfaced in the case of Uber (i.e., sharing economy rhetoric, rules and regulation, features and promotion, and business cooperation and expansion). Issues related to guests and

hosts on home damages, privacy, and safety are combined somewhat at a higher level as user-related issues. A unique issue for Airbnb is closely related to tax regulations on short-term rentals. Although the tax-related issue does not appear in Uber's topics, it still fits into the regulative legitimacy. The Uber's case also includes tax issues, but they are only a small portion of regulative issues for Uber, which seem equivalent to the license issue for Airbnb. Besides, the industrial protest issues for Airbnb are rare. This may be related to the diversity of services and target guests in the accommodation industry. Overall, the findings from Airbnb news headlines can validate the proposed legitimacy challenge framework of digital business model innovation.

Different from Uber, Airbnb's legitimacy topics did not continuously increase after 2016, which was the first year when Airbnb turned a profit²¹ (as

presented in Figure 10). This suggests that the legitimation process becomes stable after being accepted by the market. Similar to Uber, the normative legitimacy has been the most pervasive issue for Airbnb across the periods, which is significantly higher than other legitimacy dimensions (see the T-test results in Table 16). We only find slightly significant ($p > 0.1$) and larger (difference $< 3\%$), however, when the cultural cognitive legitimacy is compared with the regulative legitimacy. In addition, we do not find significant differences between the regulative and cultural cognitive legitimacy both in the early and later stages. Both of them are less appeared in the headlines than the normative legitimacy. These findings suggest that Airbnb did not exert extensive efforts on the cultural-cognitive legitimacy and regulative legitimacy. The one possible reason would be that short-term rentals have already existed (been available) for a long time in the accommodation industry. The acceptance rate of the online short-term rental platform would be high for both individuals and regulators. Airbnb is a new format of short-term rental service, which allows individuals to freely offer homestay services via Internet or mobile devices.

	All			Early			Later		
	Mean of difference	t-statistic	p-value	Mean of difference	t-statistic	p-value	Mean of difference	t-statistic	p-value
Normative - Regulative	0.243	12.534	0.000	0.270	9.218	0.000	0.200	12.009	0.000
Cultural - Normative	-0.216	-12.731	0.000	-0.238	-10.078	0.010	-0.183	-8.389	0.000
Cultural - Regulative	0.026	1.420	0.081	0.032	1.166	0.127	0.018	0.828	0.210

Table 16. T-test Results between the Early and Later Stages for Airbnb

Similar to Uber, we also performed T-tests on the changes in issues of each legitimacy challenge in the early and later stages. We separated the early

and later stages for Airbnb by the year 2016. In 2016, Airbnb has raised funds from Debt Financing and Second Market, and Airbnb also turned a profit. Therefore, they can be considered as signals of acceptance of Airbnb from the market and investors. The T-test results are presented in Table 17. We do not find any significant changes in regulative and cultural-cognitive legitimacy in the early and later stages. Only the normative legitimacy topics slightly increased ($p < 0.1$), in from the early to later stages. This can be explained by increasing business extension and attention to sharing economy.

Early stage - Late stage	Mean of difference	t-statistic	p-value
Regulative	-0.028	-0.922	0.183
Normative	0.041	1.673	0.055
Cultural-cognitive	-0.014	-0.584	0.283

Table 17. T-test Results for Changes of Legitimacy Dimensions for Airbnb

Then, we conducted a content analysis based on our topic-modeling results for Airbnb. The legitimacy topics of each legitimacy challenge dimensions for each stage are summarized in Table 18.

Legitimacy Challenge	Early Stage		Later Stage	
Regulative	Rules and Regulation	53.74%	Rules and Regulation	48.58%
	Tax Issues	46.26%	Tax Issues	51.42%
Normative	Sharing Economy Rhetoric	42.14%	Sharing Economy Rhetoric	33.91%
	Business Cooperation and Expansion	29.34%	Business Cooperation and Expansion	31.93%
	Investment and Fund Raising	28.52%	Investment and Fund Raising	34.16%
Cultural-cognitive	Features & Promotion	54.63%	Features & Promotion	53.98%
	User Issues	45.37%	User Issues	46.02%

Table 18. Sub-topics of Legitimacy Dimension for Airbnb

Regarding the regulative legitimacy of Airbnb, we find that although the percentage of regulative legitimacy does not significantly change, the importance of regulative issues is changed during the development of Airbnb. In the early stage, Airbnb faced protests from the existing regulation rules because some cities have already forbidden short-term rentals for a long time. For example, *“Short-term rentals have officially become illegal-and sneaking around the law has officially become epidemic”* and *“Court rules vacation rental site illegal in New York.”* In the later stage, after negotiating with regulators for legal operations, Airbnb faced more operational related regulative issues, such as tax issues (e.g., *“B.C. government announces tax agreement with Airbnb”*), and Airbnb also tried to deal with the regulative issues, such as *“Airbnb tax collections start March 1 in Tulsa”*. However, both rules and regulations and tax issues arise from governments. Therefore, the percentage of regulative challenges does not significantly change between the early and later stages.

For the normative legitimacy, Airbnb looked for funding opportunities and cooperative relationships/partnerships to develop and legitimate its business in the accommodation industry. For example, *“Airbnb raises cash to expand Budget-Travel service”* and *“Airbnb inks \$475 m from Sequoia and Andreessen Horowitz”*. In the later stage, the business cooperation/partnership became more important because the service that provided by Airbnb was limited, and therefore Airbnb started to heavily rely on partnership and expansion strategies to expand their business and market share. For example, *“Airbnb expands its experience program to Quintana Roo”* and *“Airbnb to double staff in China.”* In the early

stage, meanwhile, sharing economy was a new disruptive phenomenon, which attracted much attention from society and media. The impact of this new business model has been found and emphasized in the early stage, such as *“America's new business model: Sharing; The social media-mobile convergence helps people connect to rent homes, cars, tools, and services.”* and *“Airbnb's San Francisco showdown may set rules for gig economy”*.

For the cultural-cognitive legitimacy, different from Uber, Airbnb did not emphasize pricing scheme but promoted their unique services in the early stage, such as *“Airbnb introduces ability to rent an entire country”*, *“50 Airbnb birdhouses designed to mark website's coolest locations”*, and *“Airbnb introduces new accommodation listing tool for event and conference organizers”*. After being expanding its service to numerous countries and cities, more user-related issues were observed in the later mainly due to the increasing number of users. For example, *“Airbnb host claims to use hidden cameras to take secret sex videos of their guests”* and *“Study finds racial discrimination by Airbnb hosts.”* Meanwhile, Airbnb tried to handle these user issues by providing solutions such as *“Airbnb's Self-Policing Strategy against Discrimination”*. Moreover, Airbnb built cooperative relationships with government-related organizations to gain legitimacy such as *“Airbnb partners with anti-trafficking NGO to prevent sexual exploitation in its properties.”*

In sum, we do not observe significant changes in the three legitimacy challenges between the early and later stages.

3.4.3 Comparisons Uber and Airbnb

General Framework of Legitimacy Challenges

The legitimacy challenges surfaced from topic modeling of news headlines for both Uber and Airbnb confirms the notion that legitimacy is a political process of negotiation among different stakeholders in the institutional environment (Beckert 1999; Levy and Scully 2007).

At the micro level, there are three types of stakeholders that challenge the legitimacy of sharing economy disruptors. The first stakeholder is the target users of a new business model. Both Uber and Airbnb offer a platform and services to their users. For Uber, the target users are individual drivers and passengers. For Airbnb, hosts and guests are the target users. Challenges to the legitimacy of their existence come in the realized value they offer to the users (i.e., pricing, promotion, service quality) and their perceived concerns (i.e., safety, privacy issues). These challenges are closely related to the cultural-cognitive legitimacy among the three basis legitimacy dimensions (Scott 1995). The second group is business-related stakeholders. The sharing economy disruptors face internal and external business issues. They try to ensure that they are seemingly well-managed internally (e.g., the firing of Uber's co-founder Travis Kalanick to boost public confidence). They need to demonstrate that they are able to attract investment and raise funds to advance their business. In addition, the disruptors need to maintain their innovative image by investing in future business innovation (e.g., innovating on driverless cars). The third type of stakeholders is the industry incumbents (either existing firms or workers). The possible displacement or co-

existence must be continuously contested through protests or lobby actions by both parties. These legitimacy challenges are related to the normative legitimacy (Scott 1995). At a more macro level, furthermore, these legitimacy topics will add to the macro discourse on the sharing economy rhetoric in shaping the general legitimacy perception on the impacts of sharing economy on the economic and social environments (e.g., economic growth, traffic congestion, housing prices, and job creation).

There is another macro level of legitimacy, regulative legitimacy. All the regulative legitimacy topics are required to be negotiated within the context of legal authorities. This is manifested through the difficulties encountered in licensing, compliance with rules and regulations, and various lawsuit actions. In the case of Airbnb, we also observe tax issues surfacing strongly for regulatory compliance.

In conclusion, the legitimacy dimension framework is valid as proposed in Table 3.

Differences of Legitimacy Challenges across Industrial Contexts

While the legitimacy challenges of both Uber and Airbnb fit into the framework, we still observe a few differences between the two cases. First, the volume of Uber news is much larger than the volume of Airbnb news. The time period of Airbnb news is from 2008 to 2018. The time period of Uber news is from 2009 to 2018. The time length of these two firms is similar but Uber has four times more news headlines than Airbnb. Second, the number of topics of

Uber is doubled the number of topics of Airbnb. Third, Airbnb does not have any legitimacy issue for the incumbent category. We address the potential reasons for these differences as follows:

The first reason is mainly due to the industry differences between the two tech start-ups. Uber has disrupted the taxi industry by providing almost equivalent service to users at a lower cost. This makes customers away from traditional taxis. A recent report shows that rideshare firms have reached the 72.5% market share of US ground transportation segments²². On the other hand, the lodging industry offers different levels of services to customers. Airbnb is unable to substitute services provided by the higher-end luxury hotels. A prior study has found that only lower-end hotels (e.g., hotels not targeting business travelers) faced challenges from Airbnb (Zervas et al. 2017). As such, Airbnb experienced fewer protests from the established incumbents in the industry. Moreover, the taxi industry is somehow monopolistic. In most countries and cities, there is a limited number of taxi companies with valid licenses. These firms are usually grouped as a union and reach an agreement on the taxi price. The launch of Uber breaks the agreement among these firms in the taxi industry by providing lower prices. Therefore, Uber faces more protests and conflicts from incumbents in the industry. However, the lodging industry hardly makes such monopolistic actions/decisions. It seems a more open market as compared to the taxi industry.

²² Wolf Richter and Wolf Street. (July 2018). Uber and Lyft are gaining even more market share over taxis and rentals. Retrieved on July 30, 2018, from <https://www.businessinsider.com/uber-lyft-are-gaining-even-more-market-share-over-taxis-and-rentals-2018-7/?IR=T>

There are various types of accommodations such as hotels, inns, and motels, and they target different customer groups. These incumbents generally compete with each other. The emergence of Airbnb just introduces a new competitor to the industry.

Second, the organizational culture and business strategies of Uber and Airbnb are dissimilar in general. Uber is likely aggressive in its business strategies (e.g., Uzunca et al., 2018). Uber offers various promotions and large price discounts to increase the demand for its services. Growing its large user base is the core strategy that Uber uses to legitimize itself. Airbnb, on the other hand, adopts different strategies in its quest for legitimacy. Airbnb organizes its hosts into a community for them to share information for hospitality standards and service guidelines (Sundararajan 2014). Airbnb has been active in dealing with conflicts such as tax and safety issues (Uzunca et al. 2018). The community-building initiatives help Airbnb improve its brand image and ability to manage the user-level concerns. In addition, Airbnb proactively cooperates with local authorities. For example, Airbnb works with fire stations in the UK to improve fire safety for its hosts. Airbnb also collects taxes on its platform for the government. Therefore, the volume of regulative legitimacy did not increase in the later stage since Airbnb tried to cooperate with regulators and be more positive in dealing with regulative issues as comparing to Uber.

3.5 Discussion and Conclusion

This article reviews the evolvement process of two leading firms in sharing economy: Uber and Airbnb. The text-mining and empirical analyses confirm the legitimacy framework with the three pillars (i.e., regulative, normative, and cultural cognitive legitimacy) driving the legitimation of sharing economy. Overall, we find that normative legitimacy is the most frequent and important legitimacy issue of digital business model innovation. The normative legitimacy topics can be summarized into three categories, sharing economy rhetoric, external business cooperation and investment, and internal business issues. To successfully disrupt and survive in the incumbent industries, firms with innovative business models need to pay attention to getting acceptance among societies and industries. Comparing Uber, Airbnb has fewer normative legitimacy topics, which built a better business development environment. Furthermore, our findings suggest that these three types of legitimacy intensities vary according to the different disruption stages and industries. In the highly competitive industries where firms offer similar and highly duplicate service, disruptor firms need to pay more attention to cultural-cognitive legitimacy to build a strong user foundation in the early stage. While in the industries with a high degree of institutionalization, regulative legitimacy issues should be considered in the late stage, because the innovative business model related regulation would be formed in the late stage.

We believe our study bears salient contributions in building theoretical grounds for academic researchers and in offering managerial/practical implications to practitioners in sharing economy. For theoretical generalizability,

we collected data from different industries (i.e. transportation and accommodation industries) to compare the legitimacy formation framework in different industrial contexts. As such, we can answer the questions, are these tech disruptions in the hotel and taxi industry manifest similar patterns in how the new legitimacy is negotiated? Our study, therefore, contributes to the current legitimacy literature by exploring the conditions of different legitimacy. Moreover, we classified data to quantitatively test the inter-relationship among three types of legitimacy and appreciate their influence on the business success of disruptors in a long-term period. As a result, we generate a framework with time and industries to explain the process of legitimacy in the new business model disruption. We believe our study is the first study to empirically explore the legitimacy process of business model innovations. For practical implications, understanding the negotiation process in forming a new legitimacy is useful to guide practices of these institutional entrepreneurs, given the strenuous regulatory requirements, established industry norms, and entrenched cultural-cognitive habits. Both disruptors and incumbents are required to formulate a set of strategies to proactively shape and influence the institutionalization process of the new legitimacy.

Our study also has some limitations. First, our study only compares two representative firms in two industries. The generalization of our study needs to be further improved. It would be better to include more firms within and across different industries. Then, by comparing firms from the same or similar industries and from different industries, we can further explore and confirm the patterns and

relationships of three types of legitimacy challenges in different contexts. Second, since the limitation of open data on tech-startups' performance outcomes, such as sales, profit, and market share, we cannot do the empirical analysis on the relationship between legitimacy challenges and performance outcomes over time. Future research may address this limitation by introducing empirical analysis to explore how the legitimacy challenges relate to firms' development performance.

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CONCLUSION

In this dissertation, I have studied two types of digital innovations, product innovation and business model innovation. Though these two types of digital innovations, I study how digital innovations can make sense among different stakeholders and filling gaps in the existing literature, and finally identified some strategies for satisfying consumer product evaluation and legitimizing business model innovation. The empirical results of the first essay suggest that developing digital product innovation should balance novelty and familiarity, as well as, utilize software supports to enhance consumers' sense-making for the radical innovations. The second essay suggests that developing a digital business model innovation, firms need to deal with legitimacy challenges from three types of stakeholders, consumers, governments, and industrial competitors and partners. Furthermore, I explore the overtime and cross-context changes of legitimacy challenges.

The findings of the studies will have several significant implications for extant literature on digital innovation. From an academic perspective, this research fills the gap of existing research on how digital innovation forms and evolves from a social-cognitive sense-making perspective (Nambisan et al. 2017). This research is the first step to investigate the strategies and factors of legitimizing digital innovation among focal stakeholders. From a practitioner perspective, this research will inform digital innovation firms in formulating strategic product innovation designs and managerial strategies of innovative

business models. Moreover, the findings will provide guidelines to new market entrants and enable them to develop better strategies for their digital innovation.

The methodology of this dissertation is also advanced. Both of two essays adopt machine learning approaches to handling large unstructured dataset. It contributes to IS research by utilizing comprehensive text mining and machine learning approaches to transform qualitative textual data to quantitative data for empirical analysis. Especially, I use machine learning approach to extract specification information from rich unstructured data, for example, extracting hardware innovation related sentiments among the overall review comments and automatically extracting legitimacy topics among news headlines. Although the machine related approaches are advanced, they still have limitations. Although I have customized the approaches, and manually checked accuracy and reliability, the systematic errors from machine learning approaches cannot be avoided.

APPENDIX

Appendix A. Summary Statistics of Research Variables in Essay #1

	Variable	Description	N	Mean	Std. Dev	Min	Max
Dependent Variables	<i>Satisfaction</i>	1 if a rating score is higher than 3.9 0 otherwise	78,167	0.710	0.454	0	1
	<i>Overall_Sentiment</i>	A consumer's overall sentiment score for a smartphone (1.0 to 5.0 scale)	66,744	3.002	0.827	1.0	5.0
	<i>Hardware_Sentiment</i>	A consumer's sentiment score on hardware components in a smartphone (1.0 to 5.0 scale)	32,265	2.780	0.873	1.0	5.0
Key Explanatory Variables	<i>Incremental Hardware (HI)</i>	Percentage of improved hardware modules in a smartphone (0.0 to 1.0)	78,167	0.631	0.198	0.222	1.0
	<i>Radical Hardware (HR)</i>	1 if a smartphone has at least one radical (new) hardware innovation, 0 otherwise	78,167	0.465	0.499	0	1
	<i>Radical Hardware With Software support (HR_SW)</i>	1 if a smartphone has a radical hardware innovation supported by software component(s), 0 otherwise	78,167	0.223	0.416	0	1
	<i>Radical Hardware in the Market (HR_Market)</i>	1 if a smartphone has a radical hardware which is it is first to introduce into the market, 0 otherwise	78,167	0.191	0.393	0	1
Review-level Controls	<i>Age_Review</i>	Number of days between a smartphone's launch day and the review post day	78,167	1.454	1.084	0	7.178
	<i>Helpfulness</i>	Number of helpful votes given to a review by other consumers	78,167	3.753	29.100	0	1529
	<i>Verified_Purchase</i>	1 if a review is made by a consumer with a verified purchase of a smartphone, 0 otherwise	78,167	0.940	0.238	0	1
Product-level Controls	<i>Price_Group</i>	Price group of a smartphone, as classified by GSMArena.com (1: Lowest to 10: Highest Price Group).	78,167	6.068	2.049	2	10
Firm-level Controls	<i>High_Market_Share</i>	1 if a smartphone vendor is one of the two companies having the largest smartphone market shares in a given year, 0 otherwise	78,167	0.279	0.449	0	1
	<i>Hardware_Oriented</i>	1 if a smartphone vendor is a hardware-oriented firm (e.g., Samsung), 0 otherwise	78,167	0.872	0.334	0	1
	<i>Software_Oriented</i>	1 if the smartphone vendor is a software-oriented firm (e.g., Google), 0 otherwise	78,167	0.460	0.498	0	1
	<i>Tenure_Smartphone_Makret</i>	The number of years elapsed after a firm entered into the smartphone market	78,167	11.454	3.080	7	16

Appendix B. Estimation Results of Robustness Checks

	Firm-level Innovation						Market-level Innovation			
Dependent Variable:	Consumer Hardware Sentiment (<i>Hardware_Sentiment</i>)	Consumer Overall Satisfaction (<i>Satisfaction</i>)	Consumer Overall Sentiment (<i>Overall_Sentiment</i>)	Consumer Overall Satisfaction (<i>Satisfaction</i>)	Consumer Overall Sentiment (<i>Overall_Sentiment</i>)	Consumer Overall Satisfaction (<i>Satisfaction</i>)	Consumer Overall Sentiment (<i>Overall_Sentiment</i>)			
	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
Fixed Effect: Main										
Constant	1.853*** (0.053)	1.889*** (0.054)	1.439* (0.619)	1.372* (0.632)	2.171*** (0.140)	2.138*** (0.143)	2.114*** (0.112)	2.194*** (0.116)	2.230*** (0.032)	2.246*** (0.032)
Incremental Hardware (HI)	0.258*** (0.026)	0.199*** (0.033)	0.690*** (0.048)	0.545*** (0.060)	0.128*** (0.018)	0.061** (0.022)	0.609*** (0.046)	0.564*** (0.048)	0.097*** (0.017)	0.086*** (0.018)
Radical Hardware (HR) (HR_Market for R7 to R10)	-0.024 (0.016)	-0.131** (0.040)	-0.067* (0.029)	-0.335*** (0.073)	-0.043*** (0.011)	-0.164*** (0.027)	-0.173*** (0.034)	-0.634*** (0.123)	-0.047*** (0.014)	-0.181*** (0.050)
Radical HW with Software (HR_SW) (HR_Market_SW for R7 to R10)	0.042*** (0.015)	0.047*** (0.015)	0.147*** (0.026)	0.155*** (0.026)	0.025* (0.010)	0.031** (0.010)	0.190*** (0.029)	0.192*** (0.029)	0.073*** (0.011)	0.074*** (0.011)
HR × HI (HR_Market × HI for R7 to R10)		0.164** (0.057)		0.412*** (0.102)		0.185*** (0.038)		0.738*** (0.190)		0.210** (0.075)
Fixed Effect: Control										
Product Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Review Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Fixed Effects			✓	✓	✓	✓				
Random Effect										
σ^2_{ϵ} (Between-firm variance)	-2.484*** (0.235)	-2.456*** (0.236)	-1.682*** (0.235)	-1.661*** (0.235)	-3.218*** (0.266)	-3.195*** (0.263)	-1.360*** (0.228)	-1.325*** (0.228)	-3.128*** (0.250)	-3.151*** (0.248)
AIC	80719.43	80712.95	87890.01	87875.74	160421.6	160400	87890.13	87876.99	160408.2	160402.3
BIC	80803.25	80805.15	88010.47	88005.48	160549.1	160536.7	87973.53	87969.66	160499.3	160502.5
N	32,265	32,265	78,167	78,167	66,744	66,744	78,167	78,167	66,744	66,744
** $p<0.05$, ** $p<0.01$, *** $p<0.001$										