CUSTOMER ENTREPRENEURSHIP ON DIGITAL PLATFORMS: CHALLENGES AND SOLUTIONS FOR PLATFORM BUSINESS MODELS

ABSTRACT

Drawing on the mixed methods of qualitative research and agent-based simulation, this study examines (a) how end-users use digital platforms to become customer–entrepreneurs undertaking commercial activities on platforms, and (b) how platform providers can convert this customer entrepreneurship into a revenue stream. Considering that end-users have traditionally been defined as passive and uncharged actors in platform business models, an in-depth understanding of their commercial activities and the viable revenue model to monetize this emerging customer practice is warranted. Our qualitative study reveals that customer–entrepreneurs make substantial use of platform offerings to advertise their products; communicate with end-consumers; and accept payments. These commercial activities are largely exercised for free on platforms, even though they could otherwise serve as a source of revenue. On this point, our simulation results identify two pricing models achieving the generation of nearly identical revenues over time. First, platform providers may charge both advertising and transaction fees, which maximize the survival of professional customer–entrepreneurs. Second, platform businesses may levy advertising fees only, which maximizes the survival of informal customer–entrepreneurs operating on a micro-scale and part-time basis. This study offers theoretical, methodological and managerial implications for platform studies.

Keywords: Digital platform; customer entrepreneurship; digital entrepreneurship; business model; agent-based simulation.

1. INTRODUCTION

> [Facebook] launched a dedicated shopping channel on Instagram in order to capitalise on the growth of 'unofficial businesses' thriving on the service (Dodds, 2019; emphasis added).

Customers are hitherto known to act as passive end-users on digital platforms, defined as 'a set of digital resources—including services and content—that enable value-creating interactions between external producers and consumers' (Constantinides, Henfridsson & Parker, 2018, p. 381). Recently, a new breed of customers has stepped out of their traditional role to become proactive actors undertaking commercial activities on digital platforms. For example, children are earning a considerable income by creating toy unboxing videos on YouTube, rather than passively watching media content (BBC, 2019). Large numbers of students use digital platforms to sell consumer goods, rather than merely buying products (*The Economist*, 2017). We refer to this phenomenon as *customer entrepreneurship* and define it as the entrepreneurial activities of actors conventionally categorized as end-consumers or end-users in ecosystems.

Customer entrepreneurship presents challenges for platform providers because it renders a situation in which customers shift away from their roles that are pre-defined in the business models of platform providers (Cusumano, Yoffie & Gawer, 2020; Saadatmand, Lindgren & Schultze, 2019). Therefore, the intake of customer–entrepreneurs in platforms requires platform operators to enact business model innovation: changes to the elements of business models, such as (a) target customers and their roles, and (b) the revenue model (e.g., Micheli, Berchicci & Jansen, 2020; Zott, Amit & Massa, 2011). However, the extant platform studies may not explain the practice of customer–entrepreneurs on platforms and a viable revenue system in response to the emerging customer entrepreneurship. The reason for this is that, first, the literature has conventionally seen customers as target audiences (Evans & Schmalensee, 2008; Muzellec, Ronteau & Lambkin, 2015) and application users (Brunswicker & Schecter, 2019; Saadatmand, Lindgren & Schultze, 2019) that platform hosts 'sell' to external producers. As a result, we know little about the micro-processes through which customers change their traditional roles as passive consumers to become proactive entrepreneurs on digital platforms. Second, because customers have been deemed a means to attract money-side producers (i.e., the group charged for its commercial activities on platforms), the extant literature has typically assumed that customers use offerings that are available on platforms for free (Eisenmann, Parker & Van Alstyne, 2011, 2006; Rysman, 2009). As such, we lack understanding about how platform providers convert the entrepreneurial activities of customers on platforms into a sustainable source of revenue. We take a first step toward addressing these gaps, with a special focus on two major components of business models, that is, the activities of target customers and revenue systems (e.g., Andries & Debackere, 2013; Zott, Amit & Massa, 2011). Specifically, this study asks: (a) *How do end-users use social media platforms to become customer–entrepreneurs undertaking commercial activities on platforms?* And (b) *How should social media providers convert this customer entrepreneurship into a source of revenue?*

To deal with these questions, we examine customer entrepreneurship on 'social media' platforms through the sequential mixed-methods of qualitative research and agent-based simulation (Creswell, 2014). Our qualitative study selected *daigou* agents on WeChat as a case representing customer entrepreneurship on social media. Composed of Chinese expatriates around the world, daigou agents enact customer entrepreneurship by: (a) purchasing goods from local stores in advance and re-selling them to online consumers via social media platforms; and/or (b) offering platform-based personal-shopping services, such as giving shopping tips or shopping on behalf of clients. The volume of daigou sales on social media is considerable, such that it is now comparable to official, traditional sales channels (Bain and Company, 2016; Lavin, 2019). Next, building on the findings of the qualitative case study, our second study developed and ran an agent-based simulation model to identify viable revenue models by which platform providers convert customer entrepreneurship into a sustainable revenue stream.

Our findings make important contributions to both the literature and practice. First, this study contributes to the platform literature by unraveling the new role and practice of customers (or end-users) in platforms. While the extant literature has deemed customers to be a passive side that uses what platforms and their complementors offer for free, we reveal that they are increasingly playing a commercial role in platform ecosystems through the use of platform offerings (e.g., photo- and video-sharing services, messaging services and digital wallet services). Second, we also add to understanding the way in which platform providers expand business models. In detail, our findings suggest that platform providers achieve business model expansions by enabling financial transactions between participants, on top of their existing business models that mediate non-financial, information exchange between platform users (cf. Cusumano, Yoffie & Gawer, 2020; Filistrucchi et al., 2014; Trabucchi & Buganza, 2019). Finally, our simulation results identify two revenue models available in response to the emerging customer entrepreneurship.

This paper is structured in three main parts. First, we begin by reviewing platform studies. This is followed by the presentation of our qualitative research and agent-based simulation. We close by discussing our results and their implications for theory, research method and practice.

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2. THEORETICAL CONTEXT

Platform research tends to address the issues associated with two components of business model: (a) activities undertaken by 'the focal firm, its partners, vendors or customers'; and (b) 'what prices can be charged' (DaSilva & Trkman, 2014; Micheli, Berchicci & Jansen, 2020; Zott & Amit, 2010, p. 217). Specifically, as outlined in Table 1, the first research stream on platforms examines 'design elements - content, structure and governance' coordinating the activities and interplays of platform participants in a value-creating manner (Rysman, 2009; Stummer, Kundisch & Decker, 2018; Zott & Amit, 2010, p. 216); and the second research stream probes viable revenue models that enable platform providers to generate sustainable profits.

TABLE 1. Research streams on digital platforms

Research streams	Key issues and propositions
Research on design elements (i.e., content, structure and governance)	Chicken-and-egg problem-solving (e.g., Hagiu & Spulber, 2013; Stummer, Kundisch & Decker, 2018)
	Platform governance (e.g., Eisenmann, Parker & Van Alstyne, 2006; Rysman, 2009)
	Openness strategy (e.g., Brunswicker & Schecter, 2019; Ghazawneh & Henfridsson, 2013; Karhu, Gustafsson & Lyytinen, 2018; Parker & Van Alstyne, 2018; Saadatmand, Lindgren & Schultze, 2019)
	Platform quality management (e.g., Eisenmann, Parker & Van Alstyne, 2006; Rysman, 2009)
	Structure expansion (e.g., Muzellec, Ronteau & Lambkin, 2015; Trabucchi & Buganza, 2019)
Research on revenue models	Fixed or per-transaction fees (e.g., Armstrong, 2006; Caillaud & Jullien, 2003; Rochet & Tirole, 2006)
	Free value/loss leader/price discrimination strategy (e.g., Dou, He & Xu, 2016; Eisenmann, Parker & Van Alstyne, 2006; Hagiu & Spulber, 2013; Muzellec, Ronteau & Lambkin, 2015; Rochet & Tirole, 2003)
	Mixed bundling strategy (e.g., Chao & Derdenger, 2013)
	Penetration pricing (e.g., Rysman, 2009)

Taken together, the body of research on platforms offers a useful point of departure for understanding how customers behave on social media platforms and how social media providers make money from the participation of customers. First, social media participants entail customers, advertisers and complementors. Complementors, such as third-party software developers, are invited to use social media boundary resources (e.g., Instagram Graph and WeChat Pay application programming interfaces) to develop complementary offerings that enrich the value of platforms (Boudreau, 2010, 2012; Ghazawneh & Henfridsson, 2013). Advertisers undertake marketing activities on social media platforms by posting the latest products, time-limited offers and job vacancies on social network sites. Social media platforms typically pre-define the role of customers as subsidy-side participants, which use offerings available on the platforms for free, or discounted, to engage in multi-directional communicating and sharing of user-generated content, including photos, videos, audio files and links (Cusumano, Yoffie & Gawer, 2020; Eisenmann, Parker & Van Alstyne, 2011; Ooms, Bell & Kok, 2015).

Second, social media platforms generate revenue by harnessing network effects (Caillaud & Jullien, 2003; Parker & Van Alstyne, 2018). Specifically, as individual customers increasingly sign up to enjoy free offerings provided by platforms, firms yet to join the platforms start getting on board to exploit new opportunities, such as advertising (Filistrucchi et al., 2014; Tucker & Zhang, 2010), marketing (Hajli et al., 2017; Huang & Benyoucef, 2015), user-provided data (Muzellec, Ronteau & Lambkin, 2015; Trabucchi, Buganza & Pellizzoni, 2017) and sales of applications (Boudreau, 2010, 2012; Ghazawneh & Henfridsson, 2013). Platform providers tend to use a revenue model that sells advertising space to firms searching for target audiences (Evans & Schmalensee, 2008; Muzellec, Ronteau & Lambkin, 2015) and businesses looking for application users (Brunswicker & Schecter, 2019; Saadatmand, Lindgren & Schultze, 2019). For example, in the 2016–17 period, roughly sixty-five million businesses ran Facebook pages for marketing purposes and five million firms of all sizes used the advertising spaces of Facebook, enabling the social media platform to earn $26.9 billion in advertising revenue (Chaykowski, 2017).

Finally, social media operators do not provide a feature that supports on-site, financial transactions. As such, participants (e.g., customers–customers and customers–advertisers) exchange information on social media; yet such interactions typically transpire in ‘the absence of a [financial] transaction between the two sides of the market’ (Filistrucchi et al., 2014, p. 298; Trabucchi & Buganza, 2019). For example, Starbucks’ marketing activities on social networking sites are a case in point. This coffee company interacts with a number of individuals by posting its latest products, time-limited offers and job vacancies on social networking sites. Starbucks, however, does not sell coffees or other relevant products on social networking sites. Social media users wishing to buy Starbucks coffee need to click on a provided link to move onto a Starbucks online shop or to visit an actual store.

As Saadatmand et al. (2019, p. 2) recount, platform providers typically resolve the aforementioned choice calculus and make decisions about how to design their business models ‘prior to going live’. Recent platform studies, however, have suggested that platform providers often enact business model innovation—changes to the ‘cost structure, revenue system and value proposition’ of platform hosts (Micheli, Berchicci & Jansen, 2020, p. 1). For example, platforms may choose to change the orientation and recipient of the value proposition to capitalize on the business side of the platforms (Muzellec, Ronteau & Lambkin, 2015). Trabucchi and Buganza (2019) identify three strategies that platforms use to expand their business models. First, platform providers (e.g., Uber) may choose to entice a new business customer group (e.g., restaurants), in addition to an existing side (e.g., drivers), using the attractiveness of their end-user base (e.g., individuals who need rides or delivery food). Second, two-sided ‘transactional’ platforms may incorporate non-transactional markets into their existing sites in order to expand their boundaries. Third, platforms may analyze the large volume of data created through the interactions between two different customer bases (e.g., Uber drivers and Uber riders) and then provide the resulting statistics and insights to third-party business customers.

In recent years, business-like customers have increasingly been selling consumer goods on social media platforms, without the direction and governance of the platform providers. Instagram, for example, has discovered yoga instructors selling yoga retreats on the site (e.g., Kleinman, 2017). WeChat has seen myriad students touting consumer goods on the platform (e.g., Williams & Xu, 2017). YouTube has witnessed children generating considerable income by unboxing and reviewing toys (e.g., Enough, 2018).

This customer entrepreneurship requires platform providers to revamp their business models to deal with the change in the role of individual users, hitherto pre-defined as the passive consumers/users of freebies on the platforms. We suggest that the extant research may not offer a complete explanation and prescription vis-à-vis the emerging phenomenon of customer entrepreneurship because it has underplayed two important ingredients. First, the platform literature has under-studied the roles and activities of customers. Instead, the main focus was largely placed on the activities of platform owners and complementors (e.g., third-party software developers of operating systems and web browsers), with an implicit assumption that these two agents are the central locus of value creation. As such, we know much about how platform providers act in response to business model issues (e.g., Muzellec, Ronteau & Lambkin, 2015; Song et al., 2018; Stummer, Kundisch & Decker, 2018; Trabucchi & Buganza, 2019); how platform complementors behave on platforms (e.g., Boudreau, 2012; Eaton et al., 2015; Ghazawneh & Henfridsson, 2013); and how platform owners drive complementor engagement without having negative ramifications (e.g., Karhu, Gustafsson & Lyytinen, 2018; Parker & Van Alstyne, 2018; Saadatmand, Lindgren & Schultze, 2019). By contrast, we know virtually nothing about how customers undertake activities that go beyond the passive consuming and using of services provided by platform owners and their complementors (Evans & Schmalensee, 2008; Parker, Van Alstyne & Choudary, 2016; Trabucchi, Buganza & Pellizzoni, 2017). Second, platform studies have not portrayed customers as a source of revenue. Rather, individual users have been regarded as a means to attract money-side users (i.e., the user group paying for their commercial activities on platforms). The extant literature, therefore, proposed that platform hosts need to make everyday people a subsidy side, who use services available on the platforms for free or discounted (Eisenmann, Parker & Van Alstyne, 2011, 2006; Rysman, 2009). As customers have increasingly engaged in commercial activities on social media, business model innovation with regards to a revenue model is needed. However, both scholarly and practitioner communities have yet to introduce functioning pricing systems (see, for example, Dodds, 2019; Murphy, 2019; Zheng, 2019).

Our work attempts to fill the aforementioned research gaps by conducting a combination of qualitative research and agent-based simulation. Throughout this process, we address two research questions: (a) *How do end-users use social media platforms to become customer–entrepreneurs undertaking commercial activities on platforms?* And (b) *How should social media providers convert this customer entrepreneurship into a source of revenue?*

3. STUDY I: QUALITATIVE CASE STUDY

We conducted the single case study to (a) understand how customer–entrepreneurs undertake commercial activities on social media platforms (de Reuver, Sørensen & Basole, 2018) and (b) derive an empirical footing for the development of an agent-based model and its scenarios (Davis, Eisenhardt & Bingham, 2007; Forrester, 1994). Simulation studies have often used the case study method to provide empirical grounding for the development of simulation models (Garcia, 2005; Vuculescu & Bergenholtz, 2014). This section describes how we collect and analyze data and the results arising from the case-based research.

3-1. Method

3-1-1. Research context

The research context we explored was WeChat, the most widely used social networking site in China (Yu et al., 2019). This social media platform had seen the customer entrepreneurship of myriad individuals, known as *daigou* agents. Typically comprising Chinese expatriates around the globe, daigou agents purchase a variety of consumer goods, such as cosmetics, infant formula and clothing, from local stores and re-sell them to online consumers via social media platforms (Bloomberg News, 2019; Lavin, 2019). Daigou agents are so prosperous that, according to *The New York Times*, eight out of ten Chinese students in Australia alone have conducted daigou businesses on WeChat (Williams & Xu, 2017). Furthermore, the luxury goods industry estimated that over 20 percent of Chinese consumers have purchased items via the daigou channel (Bain and Company, 2016). To keep the scope of our case study manageable, we probed a single case whereby daigou agents buy Korean cosmetics from duty-free stores in South Korea and re-sell these beauty aids to consumers in China through WeChat.

3-1-2. Data collection

To understand the activities of customer–entrepreneurs on platforms, we collected data between 2015 and 2019. Specifically, drawing on a purposeful and theoretical sampling logic (Charmaz, 2006; Locke, 2001), ten daigou agents were incrementally sampled. These daigou agents were all owner–managers with different lengths of experience in daigou businesses—they had run their businesses for 2.5 years on average at the time of data collection, with one daigou agent having just started her work. Although these daigou agents typically operated on a micro-scale, some made considerable revenue—the smallest daigou agent earned $280 per month and the largest generated $800,000 per month. In the course of the data collection, we performed a total of 24 interviews with our samples. The interview questions centered around (a) how daigou agents source cosmetics for re-sale; (b) how daigou agents advertise/sell cosmetics and receive payments; and (c) how the end-consumers and retailers of cosmetics act. All interviews were transcribed verbatim, producing 360 pages of single-spaced text. The interview data was complemented and triangulated through the two-month observation of social media posts (e.g., texts, videos and photos) generated by the daigou informants (Jick, 1979; Makarevich, 2017). The observational data was digitally recorded and stored in a document of 273 pages. In addition, we collated grey literature, defined as ‘the diverse and heterogeneous body of material available outside, and not subject to, traditional academic peer-review processes’ for triangulation purposes (Adams, Smart & Huff, 2017, p. 2).

3-1-3. Data analysis

We analyzed the data in line with common prescriptions for writing an in-depth case history (e.g., Eisenhardt, 1989; Frishammar et al., 2016) and data reduction through qualitative coding (Charmaz, 2006; Corbin & Strauss, 2015). First, the lead and second authors collated the interview transcripts and observation records in isolation. Subsequently, they met regularly to produce a narrative and visual map (Langley, 1999) outlining multi-directional interactions initiated by daigou agents. Second, we engaged in a coding process that iteratively generates: (a) first-order concepts that capture the voices of interviewees; and (b) second-order categories that synthesize the lower-order concepts into a set of theoretical concepts. In detail, we initially grouped a large amount of raw data into a handful of first-order concepts rooted in the language of our interviewees (Saldana, 2016). We then attempted to group large numbers of low-level concepts into a smaller number of theory-grounded categories. To do so, we consulted the literature on social media marketing and the grey market. For example, the literature on social media marketing informed us that daigou agents may use social media platforms to communicate responsively with myriad end-consumers on social media (Agnihotri et al., 2016; Ogilvie et al., 2018; Rodriguez, Ajjan & Peterson, 2016). The grey market literature helped us to code our data with a guideline that daigou agents, like grey marketers, may take advantage of profitable arbitrage opportunities; and they have both positive effects (e.g., exploiting untapped markets in a cost-saving manner) and negative ramifications (e.g., cannibalization of sales) for established retailers and manufacturers (Antia, Bergen & Dutta, 2004; Myers, 1999; Shao, Krishnan & McCormick, 2016). The combination of data coding and literature consultation was carried out in an iterative manner and continued until no additional theoretical categories emerged. To ensure that our case analysis captured the reality properly, we took the emerging findings back to the key informants for review, with the subsequent refinements applied to the case study results (Guba, 1981; Locke & Velamuri, 2009).

3-2. Findings

Since the early 2010s, a multitude of customers have begun selling consumer goods on social media platforms, such as WeChat and Weibo. As the *Financial Times* reported, these customer–entrepreneurs came to be known as *daigou* agents (Hawkins & Thorpe, 2019). Daigou agents were typically made up of Chinese expatriates living, for example, in Australia, South Korea and the UK. Although these individuals often generated similar or even larger sales than formal businesses (Lavin, 2019), they were non-professional everyday people. Indeed, our interviewees included students, housewives, university lecturers and government officials doing daigou work on a part-time basis. In our research context, the general operations of this new seller group contained five sequences: (a) a daigou agent visited Korean duty-free stores and bought cosmetics in bulk; (b) during and/or after the purchase, the daigou agent took pictures of the consumer goods and posted them on WeChat for advertising purposes; (c) a consumer on mainland China looked around the daigou agent's WeChat posts and chose a particular item; (d) the consumer transferred money to the daigou agent using WeChat's digital wallet service; and, finally, (e) the daigou agent shipped the product to the consumer on mainland China. Figure 1 illustrates this five-stage process.

As shown in Figure 1, daigou agents carried out several marketing activities on WeChat. For example, all of the informants posted photos of beauty aids with self-created advertising lines. Daigou agents devoted considerable efforts to social media advertising such that, for example, one of our informants generated 1,100 WeChat posts over four months. Furthermore, an increasing number of daigou agents livestreamed their visits to duty-free stores via WeChat, showing a range of cosmetics being sold in the stores and even receiving customer orders on a real-time basis. At the same time, daigou agents shared their personal lives with customers, in the same way as they conducted typical social media activities.

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FIGURE 1. The operational process of WeChat-based daigou agents

A. Purchasing

Daigou agents buy Korean cosmetic products at duty-free stores in Seoul. The figure on the left-hand side shows approximately twenty daigou agents queuing up to buy a certain Korean cosmetic product.

B. Advertising on social media platforms

Daigou agents post the photos of the purchased cosmetic products with marketing text on WeChat. The left-hand figure is a representative advertising post, and the marketing text is translated as follows:

> Price: 630 RMB. CosmicCo's (pseudonym) skin serum is currently in stock. Released as a limited edition once a year, this serum is available in an attractive, large storage ceramic jar (130ml). Apply this nutritional skincare treatment after facewash.

C. Engaging in typical social networking activities

Daigou agents post about their life on WeChat for typical social networking purposes. The figure in the left corner shows a WeChat post that one of our daigou informants shared with his followers-cum-consumers. The words in the post are translated as follows:

> Pasta and rosé wine: two things we must have in Italy!

D. Conducting transactions on social media platforms

Daigou agents sell the purchased cosmetic products to their customers, who immediately make payments via WeChat. The left-hand figure captures a representative transaction between one of our daigou informants and a consumer. The WeChat conversation is translated as follows:

Customer:	here is my payment. I forgot to do this because I was busy in the afternoon.
Daigou agent:	received.

Note: Any sensitive information is blurred.

Our case study data revealed that there were two types of daigou agent: (a) an informal agent operating on a micro-scale and part-time basis; and (b) a professional agent conducting a daigou business for a living. These daigou agents, though differing in size and commitment, presented several commonalities and differences. First, daigou agents of all sizes tended to operate without a business license and, consequently, evaded taxes and custom duties. In this way, they were able to sell the same cosmetic products more cheaply than via the official sales channels. Specifically, informal daigou agents offered the same beauty aids at 70–80 percent of the retail price, and professional daigou agents sold the same beauty products at 60–70 percent of the sticker price in the official sales channels. Second, daigou agents often stopped running their businesses when their monthly revenue dropped below $600 over three months. Finally, daigou agents made decisions about changes in price and marketing less responsively than established firms. This is illustrated by one of our informants:

> I usually post advertising content [on WeChat] once a week. Daigou business is my part-time work at best. Technically, I need to spend most of my time studying because, actually, my full-time job is a university student. Price-wise, I haven't changed it often but price management is getting more important as daigou agents compete more. So, now, I change the price, say, once a month?

Customers using the daigou channel made purchase-related decisions before contacting a daigou agent. For example, customers decided what to buy (e.g., Korean or French cosmetics) and how to buy (e.g., daigou channel or official sales outlets) having already obtained information about the product from their friends, both offline and online. Because customers made many purchase-related decisions in advance, daigou agents needed to increase sales opportunities by appearing to be trustworthy; by building a large customer/follower base; by delivering cosmetics at speed; and/or by selling cosmetics more cheaply than their competitors. The following quote of one daigou agent is illustrative:

> Daigou work is not difficult at all. Anyone can do this. The key is selling products cheaply and proving your trustworthiness… Even before I started my daigou business, I had many WeChat followers who kind of trusted my taste in cosmetics, fashion and so on. After I began doing this daigou work, my followers were transformed into potential customers… As my daigou business grew, what became gradually important was like delivery time.

Daigou agents operating in South Korea generally sourced cosmetics for re-sale from Korean duty-free stores. The product quantity that daigou agents purchased from the duty-free stores was remarkable, contributing to roughly two-thirds of duty-free sales (*The Jing Daily*, 2019; Wong, 2019). To propel this revenue stream, the duty-free stores offered commissions proportional to the amount of purchases made by daigou agents. Figure 2 illustrates the commission rates that Korean duty-free operators offered daigou agents. The numbers in the dotted box (e.g., 15 and 26) represent the commission rates expressed as a percentage. The commission rate was roughly 15 percent in 2019, and our case study informants commonly remarked that it could decrease to 5 percent, depending on several factors, such as government policies and market conditions. However lucrative they were for duty-free stores, daigou sales had their dark sides; for example, the profits arising from daigou sales were constrained by the commissions offered to daigou agents.

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FIGURE 2. The commission rates that daigou agents receive per purchase from Korean duty-free operators, as of 2019

Note: Any sensitive information is blurred.

We found that daigou agents relied substantially on social media functionalities to perform their commercial activities on social media platforms. Indeed, daigou agents on WeChat used: (a) photo- and video-sharing services to advertise cosmetics for re-sale; (b) messaging services to communicate with customers in person; and (c) digital wallet services to accept payments. These commercial activities of daigou agents took place without WeChat directing them (Zheng, 2019).

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4. STUDY II: AGENT-BASED SIMUATION

Based on the case study findings, we conducted an agent-based simulation to identify viable revenue models for monetizing the commercial activities of customer entrepreneurs on platforms. The rationale behind this methodological selection was two-fold: (a) agent-based simulation enables the exploration of behavioral changes 'over time', which is not easily captured by other methods, which produce rather static, theoretical models (Fioretti, 2013; Garcia, 2005; Garcia & Jager, 2011); and (b) it generates insights into 'a better mode of operation' by predicting the outcomes resulting from the complex interplays between multiple agents under research (Davis, Eisenhardt & Bingham, 2007; Harrison et al., 2007, p. 1239).

4-1. Agent-Based Modelling

Our case study unravels two sets of findings: (a) a set of practice undertaken by customer–entrepreneurs to realize their entrepreneurship on digital platforms and (b) sets of practice carried out by relevant actors interacting with customer–entrepreneurs. Drawing on these findings, we built an agent-based model that captures the activities and interplays of four major agents: a user-cum-consumer; a customer–entrepreneur; a retailer; and a platform. First, user-cum-consumers (hereinafter referred to as 'consumers') refer to individual social media users who regularly buy consumer goods being touted on social media platforms and, simultaneously, perform typical social networking activities on the platforms. Second, customer–entrepreneurs denote a group of social media users posting texts, photos and videos on social media for casual networking purposes while at the same time using the platforms to advertise and transact certain products. Third, retailer agents represent an official channel from which both consumers and sellers can buy consumer goods. Retailers do not produce consumer goods themselves. Instead, they source products from consumer goods manufacturers. Finally, platforms refer to social media platforms that experience a transactional turn, whereby their social media users buy and sell consumer goods on the sites. Again, these four agents are empirically grounded in our qualitative study on WeChat (platform agents), where *daigou* agents (seller agents) acquire Korean beauty aids from duty-free operators (retailer agents) and then sell the products to their own customers (consumer agents). In what follows, we present in more detail the formulation of the agents' behavioral rules.

4-1-1. Consumers

Consumer agents buy goods via social media platforms. In our model, they are assumed to have different demographic characteristics (e.g., age and income) and engage in rational, intelligent decision-making processes (Cian, Krishna & Schwarz, 2015; Eling, Langerak & Griffin, 2015; Zhang & Nuttall, 2011) when buying consumer goods. As our qualitative study results showed, in the real cosmetics market, consumer buying processes involve: judging the expected satisfaction with a given beauty product; looking around at what others are using; and weighing up purchasing channels (e.g., customer–entrepreneurs and official retailers). This suggests that individual preference, social utility and consumer heterogeneity feature prominently in consumer choice behaviors. As such, we use utility theory (Dyer et al., 1992; Fishburn, 1970) and the consumat approach (Jager, 2000; Janssen & Jager, 1999; Kim & Yoon, 2014) for the modelling of consumer behaviors. Drawing on the combination of empirical and theoretical grounding, consumer agent *i*'s choice of purchasing channels is formulated as follows:

$$U_{ij} = \max_{l \in \mathrm{L}}\left(Y_{ijl} \sum_{k \in \mathrm{K}} \beta_{ik} X_{ijk}\right) \text{ for } \forall i \in \mathrm{I} \text{ and } \forall j \in \mathrm{J} \quad (1)$$

where $\boldsymbol{U_{ij}}$ is consumer agent *i*'s utility on product *j*; **L** is the collective group of sellers (i.e., customer–entrepreneur agents and retailer agents) in the model; **K** is the consumer preference attributes defined in the model; **I** is the collective group of consumer agents in the model; **J** is a collection of products; $\boldsymbol{X_{ijk}}$ is consumer agent *i*'s preference attribute *k,* associated with product *j*; $\boldsymbol{Y_{ijl}}$ is consumer agent *i*'s perceived attractiveness of seller agent *l*[1], who sells product *j* to consumer agent *i*; and $\boldsymbol{\beta_{ik}}$ is consumer agent *i*'s weight on preference attribute *k*. In Equation (1), the total utility that consumer agent *i* puts on product *j* is determined by the function of the agent's preference attribute *k* toward product *j*, that is X_{ijk}, and the agent's weight (β_{ik}) placed on preference attribute *k*. The preference attribute exerts an impact on consumers' choices of purchasing channels and it includes consumer price sensitivity (X_{ij1}), product accessibility (X_{ij2}), channel loyalty (X_{ij3}), technology literacy (X_{ij4}), and word of mouth (X_{ij5}). The details of these attributes and their initial value setting are outlined in Table 2.

TABLE 2. Consumer preference attributes that influence consumers' choices of purchasing channels

Parameter	Definition and literature support
Price sensitivity	Price is a key determinant of consumers' intention to purchase online (Hsu, Chang & Yansritakul, 2017; Munnukka, 2008). Consumers shopping online are known to be more price-sensitive than those using traditional stores (Schramm-Klein, Swoboda & Morschett, 2007).
Product accessibility	Product accessibility refers to the extent to which consumers can easily acquire and use products (Sinha & Sheth, 2018).
Channel loyalty	Building on the construct of loyalty (Tucker, 1964; Wallace, Giese & Johnson, 2004), we define channel loyalty as consumers' commitment to re-purchasing certain products repeatedly from their preferred channels. The channel loyalty in social media contexts is determined by the trustworthiness and number of followers of the sellers/retailers (Chaudhuri & Holbrook, 2001; Michell, Cataquet & Mandry, 1996).
Technology literacy	Technology literacy refers to individual capabilities to use technology, such as digital devices and software, in various areas of life (Ezziane, 2007).
Word of mouth	Word of mouth refers to all kinds of interpersonal communication about a firm, brand or product between receivers and communicators (Arndt, 1967; Goyette, Ricard & Bergeron, 2010). Word of mouth serves as the source of information for consumers in the purchasing decision-making processes (Brown, Broderick & Lee, 2007).

In this study, the multinomial logit model (Domencich & McFadden, 1975) was used to illustrate the discrete choice behavior of consumer agents. The rationale behind the use of the multinomial logit model was straightforward; it represents uncertain human decision-making behaviors in a simple,

[1] A seller agent is an umbrella term referring to both an customer–entrepreneur agent and retailer agent.

concise manner. Drawing on the multinomial logit model, Equation (2) computes a choice probability of product j based on the utility calculated by Equation (1).

$$P_{ij} = \frac{\exp(U_{ij})}{\sum_{j \in \mathrm{J}} \exp(U_{ij})}, \text{for } \forall i \in \mathrm{I} \text{ and } \forall j \in \mathrm{J} \quad (2)$$

In summary, our model represents how consumers determine the optimal channel to purchase cosmetic products. Each consumer agent i, having a different demographic nature and preference, enters the stage where he/she judges the potential value of the cosmetic products being sold on social media platforms by either customer–entrepreneurs or official retailers. This is formulated in equation (1). The consumer agent then purchases a certain product based on the choice probabilities of the available options, generated by Equation (2).

4-1-2. Customer–entrepreneurs

Customer–entrepreneurs conduct commercial activities on social medial platforms. Specifically, they represent everyday people using social networking sites to enjoy typical social media activities (e.g., posting, liking and sharing texts/photos/videos) and, simultaneously, to operate unofficial businesses for commercial purposes. Our case study findings submit that customer–entrepreneurs, though non-professional, carry out simple marketing activities to maximize profits. The activities of customer–entrepreneurs involve: (a) the appraisal of their financial performance vis-à-vis the immediate market conditions; and (b) subsequent decision-making on pricing adjustment and social network advertising strategies. For example, if customer–entrepreneurs find their market share shrinking, they mark down the sales price. In line with our case study findings, we assume that consumer resistance to price change is marginal because of the small-scale, friendship-based and informal natures of seller agents (see also Campbell, 1999; Nielsen, 2017). In addition to the price adjustment, customer–entrepreneurs, in the face of a decrease in sales, increase the number of advertising posts on the social networking sites they use (Brettel et al., 2015; Lindsey-Mullikin & Borin, 2017).

As our case study findings intimated, the small-scale and informal nature of the daigou agents means that their commercial activities on social media platforms do not occur on a daily basis, unlike professional, full-time merchants. Therefore, the customer–entrepreneur agents in our model make decisions about price changes and advertising intensity once a week. Likewise, the customer–entrepreneur agents are programmed to buy cosmetics for re-sale every week, with the exact purchase day chosen randomly within the week.

As with any commercial business dealing with consumers, the attractiveness of sellers (both customer–entrepreneurs and retailers) in the eyes of customers is paramount (Dennis, Marsland & Cockett, 2002; Elbedweihy et al., 2016; Tanskanen & Aminoff, 2015). Our case study data and the relevant literature (e.g., Teller & Reutterer, 2008) suggest that sellers' initial attractiveness varies along three attributes: seller trustworthiness; the number of social media followers; delivery time; and advertising effort (see Table 3). Following this initial set-up, the attractiveness of seller agents changes over time with the amount of advertising content that sellers post on social networking sites.

TABLE 3. Variables in relation to seller attractiveness

Parameter	Definition and literature support
Seller trustworthiness	Trustworthiness refers to consumers' confidence in the reliability and integrity of sellers (Hong & Cho, 2011; Mayer, Davis & Schoorman, 1995; Schurr & Ozanne, 1985). This construct plays a key role in online transactions, especially serving as a determinant of seller attractiveness (Ahearne, Gruen & Jarvis, 1999; Gibreel, AlOtaibi & Altmann, 2018; Hajli, 2014).
Follower count	Followers refer to users who subscribe to sellers' posts and updates on social networking sites. The higher the follower counts are, the more attractive the sellers are in the eyes of consumers (Tong et al., 2008).
Delivery time	Delivery time refers to the time required for sellers to deliver the ordered products to buyers. Delivery time is known as a key success factor of e-commerce businesses (Lee, 2002).
Advertising effort	This variable represents the extent to which sellers are willing to advertise on social networking sites (Van Der Wurff, Bakker & Picard, 2008) and serves as a determinant of seller attractiveness (Bell, Keeney & Little, 1975).

The perceived attractiveness of seller agents is formulated as follows:

$$Y_{ijl} = \sum_{s \in \mathrm{S}} \alpha_{ils} T_{ijls}\,, \text{for } \forall i \in \mathrm{I}, \forall j \in \mathrm{J}, \text{and } \forall l \in \mathrm{L} \quad (3)$$

where $\boldsymbol{Y_{ijl}}$ is the attractiveness of seller agent *l* in the eyes of consumer *i,* who seeks to buy product *j*; **S** is a collection of seller attributes that influences the attractiveness of the seller agent *l* (see Table 3); **L** is a collective group of seller agents; **I** is a set of consumer agents; **J** is a collection of beauty products; $\boldsymbol{T_{ijls}}$is consumer agent *i*'s attractiveness attribute *s,* associated with product *j* being sold by seller agent *l*; and $\boldsymbol{\alpha_{ils}}$ is consumer agent *i*'s weight on attractiveness attribute *s* related to seller agent *l*. Although the attractiveness of the seller agent stems from sellers' behavior (e.g., delivery time and advertising intensity), for operational reasons, this attribute is integrated into the formulation of consumer agent *i*'s purchasing channel choice, as expressed in Equation (1).

4-1-3. Retailers

Retailer agents sell consumer goods via social media platforms, in addition to their traditional channels. Retailers are analogous to customer–entrepreneur agents in the sense that two agents share the common behaviors of what Hagiu and Wright (2015) refer to as re-sellers. Just like re-sellers, both retailers and customer–entrepreneurs source products from suppliers; they decide the marketing and pricing strategies of the supplied goods; and, finally, they re-sell them to end-customers. Given this operational similarity, the perceived attractiveness of retailer agents is formulated as the same as that of seller agents expressed in Equation (3). Despite several similarities, the following characteristics set retail agents apart from customer–entrepreneur agents. First, retailers in our model generate most of their revenue by selling cosmetic products to customer–entrepreneur agents rather than consumer agents. Our case study findings show that the product quantity that customer–entrepreneurs buy from duty-free stores come to roughly two-thirds of sales volume of duty-free operators (*The Jing Daily*, 2019; Wong, 2019). This is in sharp contrast to customer–entrepreneur agents that make sales from end-customers only. Second, although retailer agents have increasingly established sales outlets on social media platforms, this new online channel is in its infancy. Our model therefore assumes that the retailer revenue generated from the platform-based channel is marginal. The major revenue source of retailers is their long-established physical stores, whereas customer–entrepreneur agents sell products online only.

Given that retailers and customer–entrepreneurs are both downstream players wishing to sell as many cosmetics as they can to end-customers, they often compete for the same consumer segments. Despite this competitive nature, interactions between customer–entrepreneurs and retailers are characterized by co-opetition (Pekovic, Grolleau & Mzoughi, 2019) because customer–entrepreneur agents buy cosmetics for re-sale from retailer agents. The more sellers that buy products from retailers, the more revenue retailers will earn. As our case study reveals, duty-free stores run sales incentive programs in which daigou agents receive commissions proportional to the amount of purchases they make. However helpful they are for duty-free stores, daigou sales have their downside. Specifically, while duty-free operators (retailer agents) can see increases in revenue, profits may remain steady or even decrease insofar as commissions are provided to daigou agents (customer–entrepreneur agents).

The behavior of a retailer agent is summarized as follows: (a) assessing its own market share and sales performance; (b) buying products from a consumer goods manufacturer; (c) selling the consumer goods to either consumer agents or customer–entrepreneur agents; (d) offering commissions to the customer–entrepreneur agent who buys cosmetic products from the retail agent; (e) discontinuing the sales incentive scheme if profits remain constant; and (f) changing the sales price or advertising intensity depending on its sales performance.

4-1-4. Platforms

At the center of our model, platforms enable multi-directional interactions between consumer, customer–entrepreneur and retailer agents. Most importantly, platform agents charge fees to agents selling products on the platforms. As such, customer–entrepreneurs and retailers need to pay per-transaction fees to social media platforms. The charges vary from free to moderate prices depending on the platform providers. In addition to the transactional functionality, platforms serve as an online forum in which agents are able to post a variety of advertising content to entice consumers (see Figure 1). Equation (4) represents the daily revenue (D_r) that a platform agent generates by charging advertising fees to a seller agent.

$$D_r = \delta N_e \sum_{j \in \mathbf{J}} \sum_{l \in \mathbf{L}} N_{jl} \tag{4}$$

where $\boldsymbol{N_{jl}}$ is the number of advertisements that seller agent *l* generates to promote product *j*; $\boldsymbol{\delta}$ is an advertising fee; and $\boldsymbol{N_e}$ is the number of times potential consumers are exposed to the advertisement of seller agent *l*, which is expressed as follows:

$$N_e = \gamma N_a N_f \tag{5}$$

where $\boldsymbol{\gamma}$ is the frequency of a user's daily social media use; $\boldsymbol{N_a}$ is the average number of times social media users are exposed to advertisements posted on social media sites; and $\boldsymbol{N_f}$ is the average number of followers that a social media user has. The rationale behind the modelling of daily advertising-generated profit (D_r) is two-fold: first, we assume that the followers of a certain seller are likely to become prospects, as they are exposed to the advertisements of the seller (Dehghani & Tumer, 2015; Kim & Ko, 2010). Second, such a transition from followers to prospective customers is propelled if the followers are using social media often and, hence, repeatedly being exposed to the advertisements (Ayanwale, Alimi & Ayanbimipe, 2005; Kumar & Raju, 2013). Table 4 outlines how we define each parameter and its initial value.

TABLE 4. Parameters in relation to platforms' advertising revenue

Parameter	Definition and literature support
Advertising fee $\delta = \$100$ (Chen, 2017)	Advertising fee refers to the prices that platform providers charge to sellers operating on the platforms.
Number of seller advertisements $N_{jl} = 5$ (Mezzo Media Research, 2019)	Number of seller advertisements refers to the number of advertisements that sellers generate to promote their products.
Daily social media use $\gamma = 10$ (Statista, 2018)	Daily social media use refers to the frequency of a social media user's daily social media use.
Number of followers $N_f = 150$ (Workmacro, 2018)	Number of followers refers to the average number of followers of a social media user, such as an customer–entrepreneur or retailer (Workmacro, 2018).
Exposure to advertisement $N_a = 3.3$ (Mezzo Media Research, 2019)	Exposure to advertisements refers to the average number of times social media users are exposed to advertisements posted on social media sites (Mezzo Media Research, 2019).

4-2. Scenario Description

We conducted simulation experiments for two different, yet interconnected, purposes. In the first scenario, the simulation was run to understand how transaction fees, which are currently not charged on real-world social media platforms (e.g., Dodds, 2019; Zheng, 2019), influence the financial performance of customer–entrepreneurs. This first scenario contrasts two cases in which: (a) a platform provider allows customer–entrepreneurs to conduct commercial activities on the platform for free; and (b) the platform charges a 4 percent per-transaction fee to customer–entrepreneurs.[2] In the second scenario, we run the second simulation to explore viable revenue models by which platform providers convert customer entrepreneurship into a source of revenue. In this second scenario, platform providers

[2] To estimate the 4 percent transaction fees, we use the pricing rules used on Amazon (i.e., 6–20 percent) and eBay (i.e., 9 percent for beauty products) over the past few years as a proxy. Given that social media platforms are new players in an e-commerce landscape, as opposed to Amazon and eBay, we set the seller fees lower, at 4 percent.

attempt to make revenue by: (a) charging 4 percent transactions fees and, simultaneously, selling advertising space to customer–entrepreneurs; and (b) only charging the advertising activities of customer–entrepreneurs.[3] We draw on our case study findings to derive these scenarios, thereby assuming a particular context in which customer–entrepreneurs sell Korean facial serums to another group of social media users on mainland China.

In both scenarios there are two types of consumer regularly buying cosmetics either from customer–entrepreneur channels or an official retail outlet. As outlined in Table 5, they differ in demographics and lifestyle. The first group of consumers (Consumer group A) represents a young segment of people born between the 1980s and 1990s, who are highly educated, make relatively frequent trips overseas, and often purchase luxury goods and foreign products directly from source countries. Consumer group A act as early adopters of social media shopping because they are highly capable of using digital technologies (e.g., smartphones and social media) and they often gain information about desirable products via social media channels. The second group of consumers (Consumer group B) represents a traditional segment born in the 1970s, meaning that they are the parent generation of Consumer group A. These consumers are less educated, travel less frequently, and are less proficient in digital technologies than Consumer group A. For these reasons, this older group has relatively high channel loyalty, prioritizing traditional e-commerce channels over emerging social media outlets when buying products online. The incomes of Consumer group B (the older generation) are substantially higher than those of Consumer group A (the younger generation) because of the differences in social/career status. As such, Consumer group A is more price-sensitive than its older counterpart. However, the purchasing power of each group does not differ considerably, because, as Luan et al. (2019, p. 6) put it, the parents of Consumer group A 'top up… half their personal income' so that these young consumers can purchase luxury products and consumer goods to sell overseas. Following these characteristics of the two consumer groups, we set the relevant values, as outlined in Table 5.

(Continued on next page)

[3] We set the advertising fee at $100 in line with the 'cost per thousand views' plan of WeChat (Chen, 2017).

TABLE 5. Consumer agents: characteristics and value setting

Dimension	Consumer group A	Consumer group B
Population ratio	42.75%	57.25%
Age	Born between the 1980s and 1990s	Born in the 1970s
Income	\$10,000–34,000	\$100,000
Education	Bachelor or graduate degree	High-school graduate
Travel frequency	At least once a year	Once every three years
Price sensitivity (X_{ij1}) and its relevant weight (β_{i1})	Having relatively higher price sensitivity; $X_{ij1} = 3$; $\beta_{i1} = 0.60$	Having relatively lower price sensitivity; $X_{ij1} = 1$; $\beta_{i1} = 0.49$
Product accessibility (X_{ij2}) and its relevant weight (β_{i2})	Purchasing desirable products from various sales channels; $X_{ij2} = 3$; $\beta_{i2} = 0.11$	Purchasing desirable products from limited sales channels; $X_{ij2} = 2$; $\beta_{i2} = 0.10$
Channel loyalty (X_{ij3}) and its relevant weight (β_{i3})	Early adopters of new sales channels; $X_{ij3} = 2$; $\beta_{i3} = 0.08$	Loyal to existing sales channels; $X_{ij3} = 3$; $\beta_{i3} = 0.13$
Technology literacy (X_{ij4}) and its relevant weight (β_{i4})	Digitally native; $X_{ij4} = 3$; $\beta_{i4} = 0.14$	Moderately proficient; $X_{ij4} = 3$; $\beta_{i4} = 0.10$
Word of mouth (X_{ij5}) and its relevant weight (β_{i5})	Sources of product information being social media and friends; $X_{ij5} = 3$; $\beta_{i5} = 0.14$	Sources of product information being Internet news articles and friends; $X_{ij5} = 2$; $\beta_{i5} = 0.18$

Notes: (a) the value of X_{ijk} is normalized on a three-point scale basis (1: low; 2: moderate; and 3: high); (b) the relevant weight refers to consumers' weight on preference attributes (e.g., price sensitivity and channel loyalty); (c) our case study results and the grey literature are used for setting values (e.g., Dou, Wang & Zhou, 2016; Korea Trade Commission, 2016; Luan et al., 2019; Schmitt, 1997).

Our scenarios assume that both customer–entrepreneur agents and retailer agents are selling Korean cosmetics to consumers on the platform. Based on our case study findings and the relevant literature, we assume that there are two different groups of customer–entrepreneur: (a) informal customer–entrepreneurs that operate on a micro-scale and part-time basis; and (b) professional customer–entrepreneurs that conduct commercial activities on platforms for a living. First, customer–entrepreneurs of all sizes have a substantial price advantage over their market competitors, particularly cosmetics retailers. Customer–entrepreneurs, intentionally or unintentionally, fail to register businesses, evade customs duties and appropriate firms' intangible resources, thereby saving a great deal of operating costs and selling the same cosmetic products at lower prices. Our case study reveals that informal customer–entrepreneurs sell the same beauty products at 70–80 percent of the regular retail price, and professional customer–entrepreneurs offer the same cosmetics at 60–70 percent of the sticker price available at official retail channels (see also Chan, Wouters & Wu, 2016; Pandey, 2016). Consumers are, therefore, more likely to buy cosmetic products from customer–entrepreneurs rather than official outlets, all else being equal. Second, the perceived trustworthiness of both informal and professional customer–entrepreneurs is assumed to be high because this new form of sales channel rests upon friendship-based transactions (Lavin, 2019; Nielsen, 2017). Third, it takes a week or longer for informal customer–entrepreneurs to deliver the ordered goods to customers on mainland China, whereas professional customer–entrepreneurs can do the same deliveries within a week. Fourth, our scenarios assume that both informal and professional customer–entrepreneurs devote considerable efforts to posting advertising content on social media, because this is the only route for them to communicate with consumers. Finally, customer–entrepreneurs have their own customer base ranging from 100 to 5,000 people depending on the size of their businesses. Given that customer–entrepreneurs sell via only social media, the number of customers that a certain customer–entrepreneur has is the same as the number of social media followers that this agent has. Finally, our scenarios assume that customer–entrepreneurs exit the market if they earn monthly revenue that is lower than $600 for three consecutive months. This assumption is grounded in our case study observation.

In our scenarios, consumers can access official cosmetics retailers on platforms to buy desirable cosmetics. Compared to customer–entrepreneurs of all sizes, official retailers have advantages in terms of trustworthiness, the number of social media followers, delivery speed and advertising effort. Table 6 outlines how customer–entrepreneurs and official retailers differ along several dimensions. Furthermore, as we intimated through the case study findings, customer–entrepreneurs constantly acquire products for re-sale from official cosmetics retailers. The amount of cosmetics that customer–entrepreneurs buy from retailers operators is remarkable, such that, for example, 60–80 percent of duty-free sales are made by customer–entrepreneurs (*The Jing Daily*, 2019; Wong, 2019). For this reason, duty-free stores offer commissions proportional to the amount of purchases made by customer–entrepreneurs. Drawing on this empirical evidence (see Figure 2), the customer–entrepreneurs in our scenarios are assumed to earn 5–15 percent in commission on every purchase they make in official cosmetics retail stores.

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TABLE 6. Customer–entrepreneur agents and retailer agents: characteristics and value setting

Dimensions	Informal customer–entrepreneurs ($l = 1$)	Professional customer–entrepreneurs ($l = 2$)	Retailer agents ($l = 3$)
Price advantage	20–30 percent off	30–40 percent off	Regular price ($25)
Trustworthiness (T_{ijl1}) and its relevant weight (α_{il1})	Relatively moderate trustworthiness; $T_{ijl1} = 2$; $\alpha_{il1} = 0.35$	Relatively high trustworthiness; $T_{ijl1} = 3$; $\alpha_{il1} = 0.35$	Relatively high trustworthiness; $T_{ijl1} = 3$; $\alpha_{il1} = 0.35$
Follower count (T_{ijl2}) and its relevant weight (α_{il2})	Relatively low number of followers; $T_{ijl2} = 1$; $\alpha_{il2} = 0.26$	Relatively moderate number of followers; $T_{ijl2} = 2$; $\alpha_{il2} = 0.26$	Relatively high number of followers; $T_{ijl2} = 3$; $\alpha_{il2} = 0.26$
Delivery time (T_{ijl3}) and its relevant weight (α_{il3})	A week or longer; $T_{ijl3} = 2$; $\alpha_{il2} = 0.15$	Less than a week; $T_{ijl3} = 3$; $\alpha_{il2} = 0.15$	Less than a week; $T_{ijl3} = 3$; $\alpha_{il2} = 0.15$
Advertising effort (T_{ijl4}) and its relevant weight (α_{il4})	Posting ads frequently; $T_{ijl4} = 3$; $\alpha_{il2} = 0.24$	Posting ads frequently; $T_{ijl4} = 3$; $\alpha_{il2} = 0.24$	Posting ads frequently; $T_{ijl4} = 3$; $\alpha_{il2} = 0.24$

Notes: (a) the value of T_{ijls} is normalized on a three-point-scale basis (1: low; 2: moderate; and 3: high); (b) the relevant weight refers to consumers' weight on attractiveness attributes (e.g., trustworthiness and delivery time); (c) our case study results and the grey literature are used for setting values (e.g., Chan, Wouters & Wu, 2016; Lavin, 2019; Nielsen, 2017; Pandey, 2016; The Jing Daily, 2019).

In addition to the hitherto mentioned agent-specific characteristics and relevant values, key assumptions in common across all scenarios are as follows: (a) customer–entrepreneurs and retailers sell facial serum at $25 on the same social networking site; (b) customer–entrepreneurs buy facial serum for re-sale from retailers, which, in turn, offer 5–15 percent in sales commission on every purchase; (c) the number of consumers in the market is 100,000 people and remains fixed over a 3-year period; and (d) all consumers buy facial serum every month from customer–entrepreneurs or retailers via the social media platform.

Drawing on the grey literature on the cosmetics market trend (e.g., Korea Trade Commission, 2016; Luan et al., 2019; Nielsen, 2019), we estimate that the number of consumers in the platform-based market is 100,000 people. Specifically, the literature submits that the number of Chinese females who can buy cosmetic products is approximately 416 million; 2.5 percent of such consumers purchase beauty aids via online sales channels; the ratio of facial serum sold in the Chinese cosmetics market comprises 3 percent; and the market share of Korean cosmetics in China accounts for 30 percent. In addition to the number of consumers, we assume that this consumer population is fixed over time. In this way, we can run a simulation under a somewhat closed system, whereby the effectiveness of pricing policies under experiment is clearly observable.

4-3. Simulation Results

4-3-1. Scenario I: The effects of transaction fees

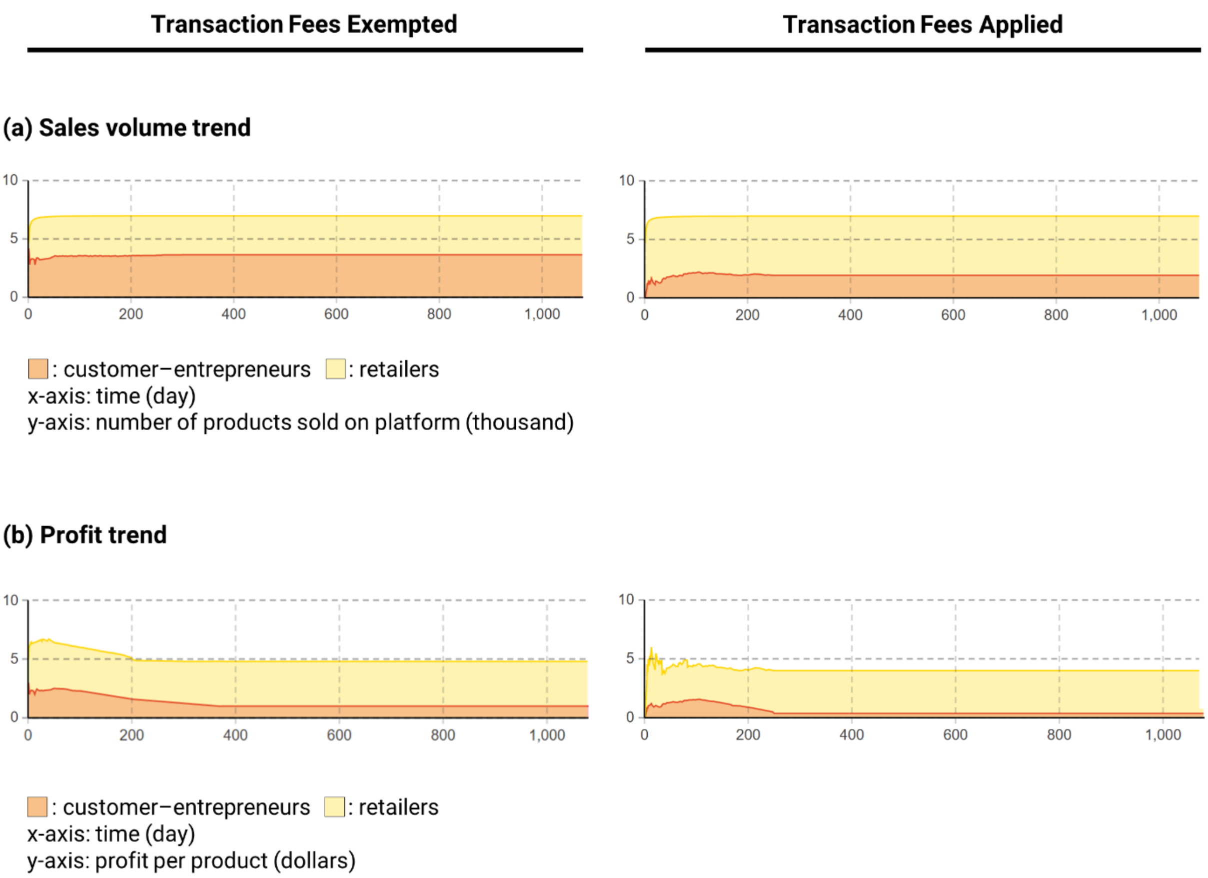
Our simulation experiment assumed a scenario in which all sellers on social media are not charged for their commercial activities. Under this scenario of no transaction fee, we find that the number of products being sold by customer–entrepreneur agents eventually comprises over half of the market (i.e., 51.28 percent), which may otherwise be monopolized by official cosmetics retailers (see Figure 3a-left). Yet, the commercial activities of customer–entrepreneur agents do not harm the sales performance of retailer agents, which remained nearly constant over a three-year period (see Figure 3a-left). The reason behind this trend is straightforward considering that: products sold by customer–entrepreneur agents are bought from retailer agents, and consumers who don't buy cosmetics from customer–entrepreneur agents acquire cosmetics via retailer agents. Understood as such, the rise of customer–entrepreneurs on social media platforms seems to result in a win–win game for the parties involved because customer–entrepreneurs acquire products from retailers (which is beneficial to retailers' sales) and sell products cheaply (which is beneficial to platform users buying products on social media).

The no-pricing plan, however, results in an unfavorable outcome for the parties involved if the sales performances are measured by unit profits. As illustrated in Figure 3b-left, during the first 72 days, the unit profit of both customer–entrepreneur agents and retailer agents showed a moderate upward trajectory. After this early stage, however, not only retailer agents but also customer–entrepreneur agents saw remarkable drops in their profits per unit. The reason for this co-destruction is that: (a) the retailer profit decreases over time because retailers offer 5–15 percent in sales commission on every purchase of customer–entrepreneurs; and (b) the competition between customer–entrepreneurs becomes severe, causing these business-like customers to keep decreasing their sticker prices (i.e., from \$25 to \$15 in the experiment) to entice consumers.

Our scenario also concerns a case in which the platform agent charges 4 percent of the cosmetics price to customer–entrepreneur agents for every transaction. Although this scenario is fictitious, it makes sense because real-world social media, such as Instagram, starts trying out pricing strategies to monetize the commercial activities of social media sellers (Dodds, 2019; Murphy, 2019). Figure 3-right shows the experiment results. The sales performance of customer–entrepreneur agents, measured by the number of products sold, increases during the initial 100 days and levels off afterwards. Despite the early increase in the sales of customer–entrepreneurs, the transaction fee ultimately gives rise to a less beneficial outcome for the customer–entrepreneur agent, compared to the end result of the no-pricing rule in sales terms. Indeed, the scenario with the transaction fee, at 1,095 days, results in 38.12 percent of consumer agents buying cosmetics from customer–entrepreneur agents via the platform, whereas the no-transaction-fee mode at the identical time sees 51.28 percent of consumer agents purchasing beauty aids from customer–entrepreneurs on the platform. By contrast, retailer agents do not see an outstanding change even when transaction fees are charged.

Figure 3b-right illustrates that the profits of both customer–entrepreneurs and retailers increase for the first three months. However, the profit of customer–entrepreneurs dips considerably after the initial rise, resulting in 30 percent lower three-year-profits than those under the no-transaction-fee policy. Retailer agents, likewise, make lower profits in a case with a transaction fee, too.

FIGURE 3. Changes in the financial performance of retail and seller agents over a three-year period under the scenario of an active pricing strategy



4-3-2. Scenario II: A per-transaction pricing plan

To understand how the platform agent makes any money, we further simulate two revenue models: revenue model 1, in which the platform agent charges both the advertising and transaction activities of customer–entrepreneur agents; and revenue model 2, in which the platform agents levy the advertising fees only. Again, per-transaction fees are set at 4 percent of the cosmetics price, and advertising fees are set at $100 until the advertising material has been viewed 1,000 times. In the first revenue model the simulation shows that the platform agent generates a total of $7,126 daily revenue, 400 days after it charges both advertising and transaction fees for customer–entrepreneur agents (see Table 7). This revenue model results in a situation in which professional customer–entrepreneurs dominate the market, with only 8 percent of informal customer–entrepreneurs surviving. The second revenue model allows the platform agent to earn revenue nearly identical to that in the first revenue system, even in the absence of transaction fees (see Table 7). The reason for this is that the survival rates of both professional and informal customer–entrepreneur agents are substantially higher if transactions fees are waived.

TABLE 7. Total revenue of platform agents and the survival rate of customer–entrepreneur agents

Dimensions	Revenue Model 1	Revenue Model 2
Total revenue from 400 days onwards	$7,126	$7,000
Advertising revenue	$4,300	$7,000
Transaction fee revenue	$2,731	-
Survival rate		
Professional customer–entrepreneurs	78%	92%
Informal customer–entrepreneurs	8%	48%

(Continued on next page)

5. DISCUSSION

This work has addressed the question of how end-users use platform offerings to realize entrepreneurial opportunities, and how platforms can capitalize on this emerging customer entrepreneurship. To answer this inquiry, our study has used a mixture of the case study method and agent-based simulation, resulting in several noteworthy findings. We now discuss, in detail, the implications of these findings.

5-1. Theoretical Implications

The first implication speaks to the extant understanding of the customer role in the platform. One of the most important business model components includes the role of participants, which is typically pre-defined by the platform businesses (Rysman, 2009; Saadatmand, Lindgren & Schultze, 2019; Zott, Amit & Massa, 2011). Unlike the extant research portraying the role of individual end-users as passive participants that consume the offerings available on platforms (e.g., Filistrucchi et al., 2014; Trabucchi, Buganza & Pellizzoni, 2017), our findings reveal that a new breed of customers is increasingly taking a proactive, entrepreneurial role in platforms. Specifically, we observe that customers on social media use platform offerings not only to engage in social networking but also to create and capture value through: (a) advertising products and services; (b) communicating with end-consumers; and/or (c) accepting payments from end-consumers. In the case that these customer–entrepreneurs use social media to re-sell goods, we suggest that the existence of the platform is a key enabler for customer entrepreneurship because customers are unlikely to undertake commercial activities without the offerings of platforms that almost eliminate operational hurdles (e.g., developing online stores, identifying potential consumers and setting up payment systems).

The second implication concerns the way in which platforms expand their business models. As Trabucchi and Buganza (2019) point out, platforms tend to expand their business models by encouraging non-financial transactions between participants, in addition to an existing business model that enables financial transactions between the parties on board. The authors provide the example of Booking.com, which initially intermediates financial transactions between travelers and hotels, but this platform now also sells services based on 'user-generated big data' to hotels wishing to interact with target audiences (Bleier & Eisenbeiss, 2015; Trabucchi et al., 2018, p. 42; Yu et al., 2019). Our findings add to this extant understanding by revealing an opposite mode of business model expansion whereby platforms enable financial transactions between participants, on top of their existing business models that facilitate non-financial, information exchange between platform users (cf. Cusumano, Yoffie & Gawer, 2020; Filistrucchi et al., 2014). This mode of business model expansion stands in contrast to the presupposition of platform studies that deems business model innovation to be the product of intentional-choice platform providers (see, for example, Hagiu & Wright, 2015; Muzellec, Ronteau & Lambkin, 2015; Rysman, 2009). Rather, we show that platform hosts may also unintentionally face a need for business model innovation, as a result of the change in the pre-defined role of the participant group without the direction and permission of platform providers.

Third, the aforementioned 'bottom-up' change in platform business models, by implication, forces platform providers to modify a revenue model that represents a central component of business models (Andries & Debackere, 2013; Micheli, Berchicci & Jansen, 2020). Our simulation results propose that platform providers may generate revenue from customer entrepreneurship through two different approaches. On the one hand, platform providers may charge for both the transaction and advertising activities of customer–entrepreneurs. Under this first revenue model, transaction and advertising fees reduce the profit margin of customer–entrepreneurs and, therefore, informal actors operating on a micro-scale and part-time basis become less motivated to remain in the market. As a result, professional entrepreneurs that engage in commercial activities on platforms for a living are likely to populate the market. Platforms, then, achieve business model innovation, and yet they will face direct competition from established e-commerce platforms, such as Amazon marketplace and eBay. On the other hand, platform providers may allow customer–entrepreneurs to sell consumer goods on the sites for free, but, instead, charge fees for advertising activities. Our simulation results show that this revenue model allows platform providers to make money comparable to the preceding revenue system, and, at the same time, enables many informal customer–entrepreneurs to survive. By implication, platform providers using this second revenue model can possess a unique business model in which informal end-users, such as yoga instructors in the UK (Kleinman, 2017), elderly people in Kuwait (Greenfield, 2013) and university students in Australia (Williams & Xu, 2017), sell products to their own consumers through platforms.

5-2. Methodological Implications

This study adds to the methodological repertoire available for understanding issues associated with platform businesses, by presenting a rare application of agent-based simulation coupled with the case study method. Previous work on platforms generally falls at some point on the end of a continuum between theoretical economic modelling (e.g., Caillaud & Jullien, 2003; Rochet & Tirole, 2003) and case study research (e.g., Muzellec, Ronteau & Lambkin, 2015; Trabucchi & Buganza, 2019). The two methods are anchored in discernible levels of granularity, whereby the economic modelling focuses on the development of high-order models by 'stripping away unnecessary detail' (Carter, 2001, p. xii), and the case study method gives primacy to the fine-grained description 'faithful to the empirical situation' (Glaser & Strauss, 1967, p. 33). Our study takes a middle-ground approach that conducts a series of: deep dives into the complex reality of platforms through the qualitative case study method (de Reuver, Sørensen & Basole, 2018); simulation modelling based on the case study results; and simulations of contrasting scenarios to provide insights into 'a better mode of operation' (Davis, Eisenhardt & Bingham, 2007; Harrison et al., 2007, p. 1239). Despite some limitations of this approach, which will be discussed in the next sub-section, we believe that this methodological attempt reveals three potential benefits: (a) first, it elevates the passing of time to the central place of analysis; (b) second, it enables the modelling and simulation of unique phenomena where hard data is virtually not available; and (c) finally, it serves as an effective managerial learning tool.

5-3. Managerial Implications

Our findings provide implications for managers dealing with the business model issues of platforms. First, a constant advance on digital technologies/platforms/infrastructures is increasingly bringing to the forefront 'the democratization of entrepreneurship' (Aldrich, 2014; Nambisan, 2017). This means that a more diverse type of customer–entrepreneur will enter platforms, bringing with them unfamiliar practices in the eyes of platform providers. Managers must devote considerable efforts to understanding the challenges and opportunities derived from the practice of customer–entrepreneurs. Second, in the era of customer entrepreneurship, a need for business model innovation does not always surface in a top-down manner. Rather, end-users may voluntarily shift away from their pre-defined roles, requiring platform providers to make changes in the existing business models. Managers, as such, should be mindful about the chance of bottom-up business model innovation. Finally, we propose that platform providers wishing to monetize the emerging customer entrepreneurship may fare better if they waive transaction fees for the sales of customer–entrepreneurs and, instead, focus on the development of lucrative advertising revenue systems. By so doing, platforms hosts can construct a unique e-commerce business model that: (a) comprises everyday people (e.g., students and housewives), rather than professional sellers, selling products on platforms; (b) generates a total revenue nearly equivalent to that incurred when transaction fees are also charged; and (c) avoids direct competition with incumbent e-commerce platforms.

5-4. Future Research Directions

Our work has several limitations that future research will need to address. First, this study takes a first step toward understanding the activities undertaken by a particular type of business-like customer, which falls within the broader category of digital entrepreneurs: ‘any agent that is engaged in any sort of venture, be it commercial, social, government, or corporate that uses digital technologies’ (Cavallo et al., 2019; Sussan & Acs, 2017, p. 66). As Nambisan (2017, p. 1032) recounts, however, ‘a greater number and diverse set of people’ will engage in digital entrepreneurship as a result of the advance on digital technologies, platforms and infrastructures. Future research, therefore, could take a step forward by exploring, for example, how customers enact digital entrepreneurship on other forms of platform, such as YouTube and Airbnb, and how customers lacking prior business experience acquire the knowledge and skills to undertake commercial activities on platforms. Second, this study focuses on the issues arising from the interdependencies between customer–entrepreneurs and platform providers. In addition to this dyadic linkage, customer–entrepreneurs engender multi-pronged ramifications for other ecosystem actors. For example, customer–entrepreneurs re-selling products on platforms engender ramifications for product–manufacturing firms (e.g., The Economist, 2017). Customer–entrepreneurs are often alleged to breach the laws in relation to business registration, tax, copyright and child privacy, suggesting a need for policy intervention (see, for example, BBC, 2019; Hawkins & Thorpe, 2019). Future work may examine how other ecosystem players manage the issues resulting from the emerging phenomenon of customer entrepreneurship. Third, customer entrepreneurship on digital platforms is a new phenomenon, such that even platform providers have yet to come up with a stable pricing plan (e.g., Dodds, 2019; Murphy, 2019; Zheng, 2019). Therefore, validation through a large amount of real-world data or time-series data is currently impossible. To overcome this limitation, the present study uses the data gathered from small-N qualitative research and guesstimates based on practitioner-oriented literature, leaving room for future improvement on the validation of our simulation results. Finally, although utility theory (Dyer et al., 1992; Fishburn, 1970) and the consumat approach (Jager, 2000; Janssen & Jager, 1999; Kim & Yoon, 2014) are known to explain a broad range of customer behaviors, a potential future study might draw on other relevant theories to develop more rigorous agent-based models.

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6. CONCLUSION

In a series of qualitative research and agent-based simulation, this study examines business model issues derived from an emerging phenomenon of customer entrepreneurship in which end-users use digital platforms to conduct commercial activities. First, we conducted longitudinal, qualitative research to understand the practice of customer–entrepreneurs on platforms. Our results demonstrate that customer–entrepreneurs use the offerings of platforms (e.g., photo- and video-sharing services, messaging services and digital wallet services) to advertise their products; communicate with end-consumers; and receive payments. This finding stands in contrast to the conventional proposition of the platform literature, which has suggested that the role of end-users is pre-defined as a passive/uncharged user group in platform business models. Second, we run agent-based simulation to understand how platform providers can convert customer entrepreneurship into a source of revenue. Our simulation results identify two viable revenue models: (a) one in which platform providers charge both advertising and transaction fees, maximizing the survival of professional customer–entrepreneurs; and (b) one in which only advertising fees are levied, maximizing the survival of informal customer–entrepreneurs operating on a micro-scale and part-time basis. This finding adds to the extant understanding of platform revenue models.

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